Temporal dilemma, time preferences and natural resource extraction

by

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This PhD thesis has not been submitted for the conferral of a degree elsewhere.

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Abstract

This dissertation sheds lights on two important questions related to temporal dilemma with respect to natural resource (fisheries) extraction:

(i) How does the presence of temporal dilemma impact resource users´ extraction behavior?

(ii) What is the relationship between individual time preferences and resource extraction behavior?

For both cases I consider two different aspects of extraction behavior: (i) effort level decision, and (ii) extraction method choice.

Chapter 2 looks at the impact of temporal dilemma on the distinct but inter-related problems of over-extraction and destructive extraction in natural resource use settings. I employ standard CPR experiments without time delay (control groups) and CPR experiments with time delay (time treatment groups) in conservation earnings to investigate whether or not participants were likely to extract greater amount of resource in the presence of temporal dilemma.

Our results suggest that delaying the benefits of conservation – an experimental feature which brings the experiment closer to reality, as conservation benefits always occur with a time delay – mainly impacts participants' extraction decision by making them more likely to try out destructive extraction methods. I find that the number of people, who do not opt for destructive extraction method even once during gear choice rounds, was significantly less in the time treatment groups as compared to control groups. On the other hand, I do not find any evidence of difference in effort level between time treatment groups and control groups when participants could not chose their extraction method.

Chapter 3 combines experimental methods and questionnaire data to understand the relationship between individual time preferences and natural resource (fisheries) extraction. I elicit individual time preference with incentivized choice experiments and link the resulting time preference measures to extraction data from questionnaires and CPR experiment.

Our findings suggest that the relationship between time preferences and CPR extraction is not as straightforward as predicted by classical economic theory. In contrast to earlier studies, I find that fishers' time preferences are positively correlated to their extraction rates. Our surprising findings can partly be explained by the disinvestment effect of time preferences and by fishers´ cognitive abilities.

Chapter 4 looks at the use of destructive fishing methods and its relationship to individual time preferences. Due to intertemporal nature of fisheries extraction activities, standard economic theory suggests that an individual's valuation of future income (individual time preferences) can play a major role in determining the gear used for extraction. Based on earlier theoretical work I identified two ways in which individual time preferences can impact the adoption of destructive extraction (fishing) methods; (i) the conservation effect which posits that patient individuals are less likely to use destructive

extraction methods since they are more likely to account for the loss of future income that is accompanied by using these methods, (ii) the disinvestment effect which argues that patient individuals are more likely to use (costly) destructive extraction methods since they have greater ability to invest in their extraction capabilities.

I use an agent-based model to understand the relationship between time preferences and adoption of destructive fishing gear. Our model suggests that the nature of destructive gear (i.e. whether it is a cost-saving gear or more costly gear) along with the level of social dilemma determines whether patient or impatient individuals are more likely to adopt such a gear. Additionally agent´s beliefs regarding future resource condition and other agent's extraction level can have a major influence in some cases. Our results clarify the conditions under which conservation effect becomes more dominant as compared to the disinvestment effect and vice versa.

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Chapter 1:

Introduction

Fisheries are an important sector of Zanzibar´s economy. Most of the fishing pressure comes from about 18-19,000 artisanal fishers, who contribute about 96% of the total marine catch. Fisheries are not only the most important source of income for these rural communities, they are also a highly valuable source of nutrition, as a significant part of this catch is consumed locally by the fishers and their families (Muhando and Jiddawi 1998, Jiddawi and Stanley 1999).

However, according to an influential study, the inshore fisheries in Zanzibar show signs of over-exploitation and degradation. As a result, the average catch-rate per fisher has decreased over the years (Jiddawi and Stanley 1999). According to the Ministry of Fisheries and Livestock, congestion in the inshore fisheries and over-extraction by fishers are the main reasons for this decline in the productivity. Jiddawi and Khatib (2008) also report that total number of fishers operating in Zanzibar has increased substantially in the last decade, and simultaneously, the fishing effort has intensified, with fishers applying more extractive methods. This has led to a situation where fisheries are being extracted at an unsustainable level (Mkenda and Folmer 2001). Additionally, a recent study found that illegal fishing techniques like dynamite fishing, using spears and/or drag-nets have caused substantial environmental damage not only to the fisheries, but also to the related ecosystems such as coral-reefs and mangroves (Watkiss et al. 2012). According to officials from the Ministry of Livestock and fisheries Zanzibar, “the most common illegal fishing methods include the use of small mashed nets and traps, beach seine, spear guns, chemicals from plants locally known as utupa and fishing without a license” (Yussuf 2012). This is especially worrying, as the widespread use of such destructive fishing methods challenges the sustainability of the entire ecosystem.

Over-fishing and use of destructive fishing methods are inter-connected yet distinct problems, so it is important to make the differentiation clear. For the purpose of this dissertation I define them as following:

Over-fishing refers to the non-sustainable use of resources such that extraction from the resource is considered greater than its regeneration rate. Destructive fishing refers to a situation where a gear is used in the wrong habitat, while destructive methods refer to fishing methods whose impact is so indiscriminate and/or irreversible that they are universally considered destructive irrespective of the environment in which they are used (FAO 2005-2014).

Zanzibar is not the only example of fisheries suffering from the twin problems of over-fishing and the use of destructive fishing methods. Globally, the collapse of fisheries is discussed widely, with the most attention paid to overfishing and destructive fishing (Clark et al. 2005, Sethi et al. 2005). According to the United Nations Environment Program, about 25 percent of fisheries worldwide are in jeopardy of collapse. Given the reliance on fisheries for local communities in many developing countries, and in particular, Zanzibar, it is extremely important to understand the reasons behind this decline.

Both over-fishing and destructive fishing result in lower productivity of the underlying resource, as well as lower overall earnings. This begs the question as to why rational agents would engage in either overfishing or destructive fishing. Theoretical studies have highlighted the importance of the social dilemma situation in natural resource use settings to explain the tendency to over extract (Hardin 1968). The negative impact of high individual extraction is a classic case of externality, where the negative impact of an individually beneficial action is shared by society. Thus, the core problem is that individuals´ selfish interests collide with what is best for society as a whole. Empirical research on small-scale fisheries in particular, and CPR extraction more generally, also focus on the social dilemma. Under certain conditions, however, different factors can mitigate the problem of the social dilemma, frequently referred to as the "tragedy of commons," such as the inclusion of private property rights, and cooperation among communities (Ostrom 1990). On the individual level, differences such as social preferences and/or levels of trust also affect the tendency to cooperate (Gächter et al. 2004, Fischbacher and Gächter 2008).

While the social dilemma is important, it must be emphasized that it is not the only reason a rational agent may engage in extracting unsustainably and/or using destructive extraction methods. Indeed, Clarke (1972) shows that individuals can extract unsustainably even without the social dilemma situation, due to the fact that resource extraction involves an inter-temporal optimization problem. Namely, there is a conflict between an individual´s short-run interest and her long-run interest. The need for present consumption competes with the wish to save resources for the future. The key underlying issue is that natural resource extraction brings earnings during the current period, whereas the benefits of conservation (or sustainable extraction) can only be accrued in the future. I refer to this as a temporal dilemma. While the delay in benefits of conservation is a feature of natural resources, the temporal dilemma itself relies on human decision making. As a matter of fact, Clarke (1972) suggests that in cases without the social dilemma, a resource users´ valuation of future benefits (individual time preferences) determines her extraction behavior.

This dissertation sheds lights on two important issues related to the temporal dilemma with respect to natural resource extraction. The first part investigates the impact of the temporal dilemma on resource users´ extraction behavior, while the second part focuses on understanding the relationship between their time preferences and their extraction behavior. There is clear link between these two research topics. As explained earlier, Clarke's (1970) assertion that resource users can engage in unsustainable extraction due to the temporal dilemma is based on the assumption that there is a (positive) relationship between individual time preferences and extraction behavior. However, note that research topic 1 looks at the impact of a structural factor (presence of the temporal dilemma) on individual and group behavior, whereas research topic 2 is interested in how individual level differences in time preferences can lead to differences in extraction behavior. Consequentially, while both research topics are clearly linked to each other, they also maintain subtle differences in emphasis.

I devote Chapter 2 of this dissertation to addressing the questions raised by research topic 1. Specifically, I ask, how does fishers' extraction behavior change depending on the presence (absence) of temporal dilemma? Furthermore, I examine whether the impact of temporal dilemma differs for the effort level choice as compared to gear choice decision.

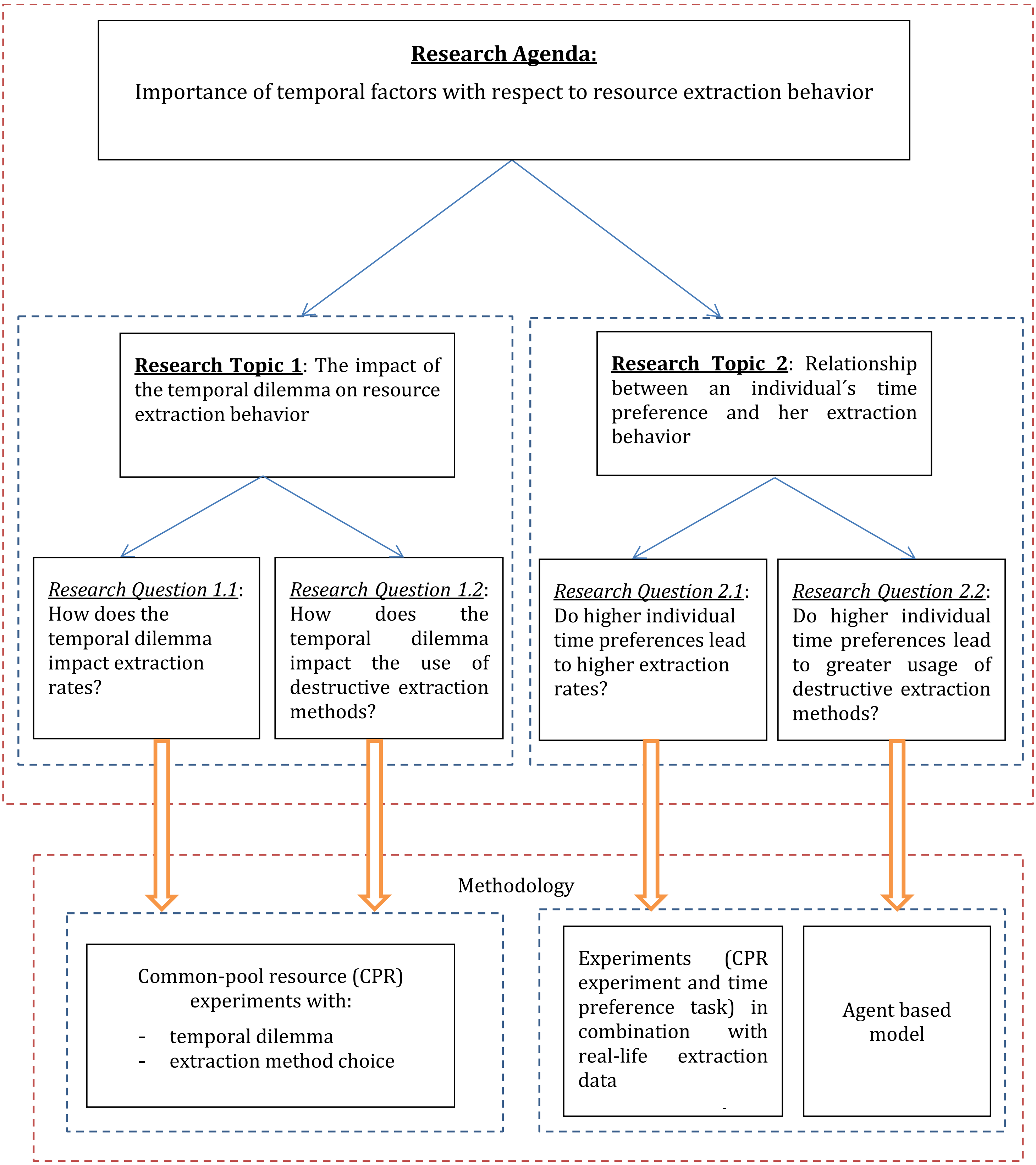
In chapters 3 and 4, I proceed to answer the questions raised by research topic 2. In chapter 3, I empirically investigate whether fishers´ time preferences are related to their extraction rates. In chapter 4, I employ an agent based model in order to explore how time preferences impact the decision to adopt destructive extraction methods.

Explaining research design and methodology

The main topic of this dissertation revolves around different aspects of the temporal dilemma (both structural as well as individual) and the various ways in which it can influence resource users' extraction behavior (effort level choice and extraction method choice). In this section, I reflect on how this basic theme comes up in different forms in each individual chapter as well as the methodological problems and difficulties associated with gauging different aspects of the temporal dilemma. This provides a good basis for understanding my methodological choices.

Figure 1.1 provides a brief summary of the research agenda, including the methods used to investigate different research questions.

Figure 1.1: Research Summary



Research topic 1: Temporal dilemma and extraction behavior

The first objective of this research is to understand the impact of the temporal dilemma or, in other words, what happens when there is a time delay in conservation benefits while the benefits of extraction are available immediately. A key challenge in investigating this issue is to figure out how to study participant behavior with and without the temporal dilemma. Ideally, we would be able to observe real-life behavior in both these settings to understand the impact of the temporal dilemma. However, we don´t have this opportunity since in real-life the temporal dilemma is present in practically all natural resource extraction settings. Another option is to either implement, or observe implementation of a project that incentivizes future stock-building by delivering benefits in the current time period as compared to the standard natural resource scenario where no such incentives exist. Here, the idea would be to examine panel data before and after the implementation of the program or to find comparable locations where some locations fall under the project while others do not. However, practically finding comparable areas and/or panel data is a very hard task, and almost impossible given the paucity of such programs. Aside from this practical concern, even more fundamentally, such a comparison would not necessarily inform us about the true impact of the temporal dilemma, as a number of uncontrollable factors can impact the extraction rates, even for a very simple program.

Given the problems associated with using observational data, I consider experimental approaches to study the impact of the temporal dilemma. Experiments allow researchers to carefully manipulate the factors under examination to understand their impact on different outcome variables. In recent years, experimental approaches have featured more prominently in social science and especially in the field of economics. For more details on experiments in economics I refer the readers to Harrison and List (2004) and Levitt and List (2009).

At a very basic level, the experimental design uses common-pool resource experiments to measure extraction rates under different conditions. The common-pool resource experiment is widely used to understand natural resource users' extraction behavior as it incorporates the negative externalities from extraction, and depicts the social dilemma situation inherent in natural resource settings (Gardner and Walker 1994). The common-pool resource experiment literature has been criticized for its reliance on student populations to gain insights about real-life behavior (Henrich et al. 2010). Some argue that student behavior does not reflect the behavior of actual resource users in real-life situations. At crux of this argument is the idea that CPR experiment presents students with an unrealistic and, whereas natural resource users have to deal with these circumstances on an almost daily basis (Ghate et al. 2013). I overcome these objections by conducting experiments with actual resource users (fishers) in Zanzibar, and explicitly framing the CPR experiment as a fisheries extraction scenario.

In order to incorporate the temporal dilemma scenario in the CPR experiment, I delay the benefits of conservation while delivering the benefits of extraction immediately. In a standard CPR experiment, participants decide to extract at the level of their choice, which yields personal earnings. Each participant´s total earnings therefore depend on (i) the extraction level (extraction earnings), and (ii) the level of resource not utilized by the resource users (conservation earnings). In the experiments, I divide the participants into two sets of groups: (i) control groups who play the standard CPR experiment, and (ii) the treatment groups, who receive their personal earnings from extraction immediately. However, the participants in the treatment groups receive their share of earnings from the non-utilized resource (conservation earnings) after a gap of 14 days.

Delaying the benefits of conservation in experimental settings can lead to changes in different factors. First, future consumption may not have the same value as present consumption in the time delay scenario. Second, future earnings may involve increased uncertainty and trust issues. And finally, there may be substantial differences in transaction costs between present and future earnings in an experimental setting. For the purposes of this study, I am only interested in the first aspect of time delay. As a result, I try to minimize the other two aspects as much as possible. In order to achieve this, I delivered both of their experimental earnings from extraction and their experimental earnings from conservation via cell phone credit, rather than cash payments. For more information on how the use of cell phone credit enables the isolation of the first aspect, please refer to Chapter 2.

With respect to the use of cell phone credit as a payment mechanism, it should be noted that almost all of the participants use pre-paid cell phone services rather than post-paid fixed contracts. The marginal value of extra credit is higher in pre-paid plans as compared to post-paid fixed contracts. In addition to its use for regular cellphone services (such as messaging or calling someone), fishers in Zanzibar use cell phone credit to buy everyday items at the local grocery stores through informal transfer systems. These informal payment systems are complemented with more formal mobile payment systems that allow subscribers to use their cell phone credit as a debit account. In recent years, a mobile banking boom has spread throughout Africa, often playing a bigger and more significant role than the traditional banks, particularly in terms of providing basic banking services to new customers from rural economies (Economist 2014). This especially applies to the participating fishers in this study, where earnings in the shape of cellphone credit are especially important for daily economic transactions.

One of the key objectives of this study is to differentiate between effort level decision and extraction method choice. In order to capture these factors in my experimental design, I include a treatment where participants can choose the extraction method, in addition to the standard effort level choice. These extraction methods differ in terms of the private benefit accrued, as well as the amount of damage caused to the common resource. Chapter 2 gives more details on the experimental design.

Research topic 2: Time preferences and extraction behavior

The second part of this dissertation investigates the relationship between individuals´ time preferences and their extraction behavior. As before, I examine two different aspects of extraction behavior: (i) extraction rates, and (ii) the choice of extraction methods, paying special attention to the use of destructive extraction methods. In order to investigate the impact of time preferences on these different aspects of extraction behavior, I employ a number of methodological approaches. For the most part this is necessitated by the fact that destructive extraction methods are illegal, making it difficult to obtain reliable responses from participants. Secondly, the snap-shot nature of the experimental setting makes it less likely to obtain deep insights into how destructive extraction methods gain prevalence, as well as the role of individual time preferences in their adoption. In this section, I first describe the challenges related to empirically investigating the relationship between time preferences and extraction rates. I then proceed to provide a brief summary of the reasons for an agent based model in the case of this study, and why it was chosen over other types of modeling techniques in order to understand the relationship between time preferences and individuals' adoption of destructive extraction methods.

With respect to the empirical investigation of this study, a major challenge is to obtain reliable measures of both individuals´ time preferences as well as their extraction rates. Broadly speaking, there are two approaches to measuring individual time preferences: (i) collecting observational data, and (ii) conducting experiments. The observational measures of time preferences offer the advantage of being based on real life outcomes. However, the problem with using these measures is that it can be difficult to disentangle true time preferences from noise related to the behavior in question. To mitigate this problem, I obtain time preference measures with the use of a multiple price list (MPL), an experimental task specifically designed to focus only on the true time preferences of participants' behavior. This is motivated by the fact that the measures obtained from this methodology have been shown to be more reliable than other types of time preference tasks. For more details on the advantages of using MPLs refer to Chapter 3.

The main problem in obtaining data on extraction rates, however, is that fishers extract resources over a period of time. So, ideally I would want to gauge the average extraction rate for each individual over a long period of time to ensure that I would not be misled by seasonal or idiosyncratic variation. However, this data is very difficult to obtain. I therefore rely on fishers to provide their extraction rates for different seasons and then use the average value as the aggregate measure of extraction rate. At a more fundamental level, the reliance on self-reported data from fishers bears its own problems. Several authors have argued that fisheries extraction is significantly underestimated due to the multitude of problems associated with self-reported data such as response bias, omitted responses, missing data, etc. (Sumaila et al. 2006, Pauly and Zeller 2016). For this reason, I complement the questionnaire data with CPR experiments, where participants make extraction decisions under controlled incentivized settings.

Although combining real-life self-reported extraction data with CPR experiments allows me to capture different aspects of extraction behavior, and provides a more reliable understanding of extraction rates, weaknesses remain in this methodological approach. Self-reported data suffers from an incentive problem, while the CPR experimental data is based on a snap-shot view of fisheries extraction. Future researchers should look at better and more extensive ways to obtain more reliable measures of extraction rates.

As explained earlier, the empirical part of research 2 focuses on the relationship between time preferences and extraction rates, however, it does not tell us a great deal about the use of destructive extraction methods and its relationship to time preferences. What drives people towards destructive gears is an extremely important and relatively under-researched question. Earlier studies argue that a combination of poverty and myopic behavior is mostly responsible for the adoption of destructive fishing gears (Silva 2006, Cinner 2009). Although poverty is potentially an important and enabling condition, a lingering question remains. Namely, what motivates one set of (largely poor) fishermen to opt for these destructive fishing gears, while others, facing similar conditions do not? The difficulty of obtaining data on destructive extraction methods has limited our understanding of the role different factors may play in this decision making process. For this reason I look at modeling approaches to fill this gap in literature.

The purpose of the model is to provide a better understanding of the adoption process of destructive extraction methods. As explained in the introduction, the basic question is: why would an individual want to use destructive extraction methods, even though using destructive methods not only reduces the total resource for others, but also causes a significant decrease to one's own future earnings potential? Since destructive fishing gears are often characterized by their ability to generate short-term profits at the cost of severe long-term damage, it stands to reason that individual time preferences can play a key role in determining who opts for destructive extraction methods, and under what conditions.

One way to model the relationship between time preferences and adoption of destructive fishing gear is to use a partial differential equations-based model. The problem with this approach is that it neglects several key aspects of the decision-making process with regards to extraction method choice. Typically, such models are focused on the aggregate level and do not take into account the complex dynamics of social decision-making processes. Secondly, these models focus on the ideal cases, providing a benchmark that could be used to guide policy-making. However, they fall short when it comes to describing actual behavior, as they do not explicitly consider the multitude of motivations across different individuals.

Agent based modeling overcomes these problems by providing a bottom-up approach, where the atomic model element is the individual herself (Kiesling et al. 2012). With the use of an agent based model, I was able to capture two significant aspects of fishers' decision-making. First, resource users differ in terms of how they make their extraction decision. Specifically, some have greater access to credit, some are more experienced, and some rely on their peers, while others are more inclined to take initiative. Agent based modelling allows us to capture these different approaches to decision making in a rigorous and systematic way. Second, natural resource extraction is marked by uncertainty and lack of information. Individual resource users cannot be absolutely certain whether or not the resource is going to collapse, what would be the reaction of other resource users, whether they are going to increase or decrease extraction in the case of a resource depletion or boom, etc. Similarly, resource users do not have accurate information about the extraction method, that is, if the extraction method is more productive or less productive than their current method, whether they have to learn how to use the new extraction method in order to achieve greater benefits, and so on.

In light of all of this, agents have to make assumptions and form beliefs about the state of the world; what is going to happen in the future, what are their alternatives and options? Given the lack of perfect information, these expectations and assumptions are based on either an individual´s own experience, or they are based on the experience of other individuals. Agent based modelling allows for this possibility by incorporating a social network of agents that defines how agents are linked to each other, and in turn, how information flows from one agent to another. This particular feature is an extremely important element of my model.

Combining agent based modelling and experiments

By employing both the model and empirical methods, I seek to understand similar yet distinct questions related to extraction rates and gear choice decisions. One of the motivations of this study was to combine an experimental methodology with agent based modeling (ABM). In this section, I briefly list some of the problems associated with using experimental data for agent based modeling, and the path taken during the course of this dissertation. For a more detailed review of different approaches to using agent based modeling and experiments in tandem, readers should refer to Duffy (2006).

One way to combine experimental data with ABMs is to use this data to validate the model. Janssen (2012), Baggio and Janssen (2013), and Oh and Mount (2011) are prominent examples. However, this method severely limits the types of research questions which can be studied. Both the experiments and the agent based model have to be designed with the specific purpose of validating the agent based model, rather than obtaining deeper insights about the phenomenon under question. Furthermore, the current state of research on the methods of validation and what constitutes as validation are underdeveloped and need more careful consideration. The second approach is to use experimental data to calibrate various aspects of the agent based model, particularly the ones dealing with agents´ decision making process. In my model, this would involve using data on an agent´s time preferences and describing how they are linked to other factors such as age, wealth etc., as well as their impact on extraction behavior. However, rather than follow this approach directly, I take inspiration from my experimental work and apply the findings of the empirical case study to the context of destructive gear choice. The advantage of this approach is that human subject experiments can impose some very strict constraints on what a researcher can do, so, agent-based models can be employed to understand and contextualize the findings of these experiments. This allows me to not only focus on a different aspect of extraction behavior (adoption of destructive extraction methods as compared to extraction rates), but also generate novel predictions and hypothesize about the scope of the experimental findings. As a result, I am able to gain a better understanding of the impact of time preferences on the adoption of destructive extraction methods.

Concluding remarks

This dissertation as a whole makes original thematic and methodological contributions, while at the same time deepening our understanding of the relationship between temporal factors and natural resource extraction behavior. Below I discuss each one of these contributions separately.

This dissertation sheds light on some underreported aspects of the natural resource extraction problem by introducing new, innovative elements to standard experimental games. First, by using a time delay in the CPR experiment I capture the importance of temporal dilemma in a more meaningful way. Second, the use of cellphone credit for payments overcomes some of the major problems associated with time delay. Third, it deviates from earlier experimental work on common-pool resources by differentiating between effort level decision and gear choice decision. This is especially important when looking at the impact of temporal dilemma. Finally, building on empirical work, my agent based model looks at the implications of time preferences on extraction method choice. In particular, I adapt models of technology diffusion to the specific context of an individual's adoption of destructive extraction methods.

These methodological innovations not only push the boundaries of state of the art research on natural resources, they also improve our ability to understand different facets of natural resource extraction, thereby providing new insights.

First, with respect to the impact of the temporal dilemma on resource extraction behavior, I find that: (i) the extraction rates are similar for individuals in both the control and time treatment groups, and (ii) the probability of participants choosing the more destructive gear is much higher in the time treatment groups as compared to the control groups. Taken together, these findings indicate that the temporal dilemma is more important with respect to the gear choice decision as compared to the effort level decision. Chapter 2 compares these findings with other studies on the temporal dilemma, and also provides potential explanations.

Second, with respect to the impact of time preferences on extraction behavior, both the empirical work and model highlight the importance of the disinvestment effect (where high time preferences lead to low extraction rates due to lower investment in extraction capability), and the more standard conservation effect (where high time preferences lead to higher extraction rates due to lower valuation of future income opportunities). In Chapter 3 I report the empirical observation that patience is linked with higher extraction rates. In chapter 4 my model builds on this finding by looking at the disinvestment and conservation effects in the context of fishers' gear choices. Both the empirical finding and the model suggest that the somewhat counterintuitive disinvestment effect should be given more careful consideration as it can play an important role in determining natural resource users' extraction behavior.

Third and finally, this study is one of first to link both structural (such as the level of social dilemma) and individual factors (such as cognitive ability, beliefs and assumptions about others and the natural resource) to determine how time preferences may affect extraction behavior. This is especially true in the case of gear choice decision. Based on my empirical work, I report the novel finding that fishers' cognitive ability plays a key role in explaining why, in contrast to the predictions of classical economic theory, patient fishers extract more as compared to impatient fishers. Similarly, my model provides testable hypotheses regarding the role of agents´ beliefs and expectations in shaping the relationship between time preferences and the adoption of destructive extraction methods.

Policy implications:

While this dissertation does not engage in examining policy outcomes directly, it does offer a few suggestions which I map out in this section. Firstly, my empirical results suggest that policies which try to address the temporal dilemma (such as programs which offer upfront benefits to incentivize stock-building, etc.) may have a greater impact on the destructive extraction problem as compared to the over-extraction problem. Secondly, any solution to the temporal dilemma can be compromised by structural factors such as the level of social dilemma and/or resource users' beliefs, and these factors have to be addressed simultaneously to have a more meaningful impact. Lastly, policies which neglect the possibility that the disinvestment effect prevails over the conservation effect risk doing more long-term damage. This is a typical outcome if natural resource users do not intend to remain in (natural resource extraction) business for long periods of time, or if they do not expect the government policy to stay the same (confidence and commitment problems), and/or if they believe that human actions are not the main driver of changes in natural resource condition.

Limitations and future research opportunities

In this subsection, I begin by briefly explaining some noteworthy limitations which arose during the course of this research, followed by future research possibilities. The methods used in this dissertation have several limitations, with each of the different methods bearing their own particular problems. I discuss the specific limitations of each methodology in the individual chapters. In this subsection, I focus on the broader issues.

This study looks at the particular context of small-scale fisheries, and naturally, our findings are mostly applicable to this context. Although more developed fisheries may share some important characteristics with these small scale fisheries, I would advise caution in using the results of this study to devise policies for these developed fisheries. Indeed one of the main results of this study is to highlight the importance of contextual factors in determining the relationship between temporal factors and extraction behavior.

Another limitation present in this dissertation is the fact that less attention is paid to some important factors that are influential in determining the relationship between the temporal dilemma and extraction behavior. The most obvious examples are market interest rates, outside income opportunities, urbanization, etc. The reasons for not explicitly considering these (and other such variables) were twofold: first, some of these factors are not especially relevant for small scale fisheries in general, and second, I am more interested in the basic mechanisms through which temporal factors can impact extraction behavior. Moreover, most of these missing variables work through impacting the mechanisms under study. Indeed it would be an interesting and fruitful effort to study the relationship between some of these variables and the mechanisms through which temporal factors, both individual and structural, affect extraction behavior.

Finally, using human subject incentivized experiments and combining them with an agent based model involves its own challenges. Some of these difficulties are discussed in an earlier section. Suffice it to say, my dissertation is an example of how they can be used in tandem to offer deeper insights, not necessarily how they can be combined together to produce a joint outcome. The main challenge in this respect is it to find a topic where experiments can meaningfully contribute to the way resource users´ decision-making processes are represented in the agent based model. For the most part, experiments are suitable for examining treatment effects. Experiments can also reveal differences in the decision-making process across different resource users; although obtaining the functional form of such differentiation requires repeated experimentation, where subsequent experiments are fine-tuned based on earlier findings. For practical reasons, this is a difficult task to achieve in the field, and therefore lab experiments may provide a more suitable avenue for such a venture.

Overall, the major contributions of this dissertation are (i) the examination of often neglected temporal factors, both at the structural and individual level, and (ii) the analysis of extraction behavior, which is revealed to be influenced by different variables. In doing so, I add another dimension to the existing literature and raise several important questions. Each individual chapter highlights these potential research questions, and ways in which they could be studied.

In this section I elaborate on a couple of broader, strategic issues raised by this study. First, while this study looks at extraction method choice, I am mainly concerned with the relationship between extraction method choice and temporal factors (both individual and structural). There is a need to have a better, more nuanced understanding of extraction method choice, especially when it comes to destructive extraction methods, which can cause irreparable damage to natural resources. Currently, both the theoretical and empirical literature on destructive extraction method choice is very limited. Given the urgency of the topic, more effort should be devoted to understanding the behavioral underpinnings of choosing destructive extraction methods. Second, this dissertation is interested in understanding the link between temporal factors and extraction behavior. However, this should be considered a first step. A logical next step would be to look at the interaction between different temporal factors and extraction behavior. For example, an interesting extension of chapter 3 would be to look at the interaction between agents with different time preferences. This would involve asking questions such as, do patient individuals behave differently when they are paired with impatient individuals as compared to when they are paired with similar, patient individuals? Indeed, while these issues are not the focus of this dissertation, both my experiments and model in particular are capable of incorporating and investigating these issues. Also, this dissertation does not study the processes which result in the formation of time preferences, or expectations and beliefs about the future. And finally, I look at the adoption of destructive extraction methods, but not how these innovations take place. Future studies should give serious consideration to these issues.

Chapter 2:

Temporal dilemma, resource extraction and use of destructive extraction methods: experimental evidence from Zanzibar*

2.1 Introduction

Natural resources (such as fisheries, forests, water resources, etc.) entail two key issues with respect to sustainable extraction and conservation: (i) social dilemma (tragedy of commons), and (ii) temporal dilemma (present value maximization) (Messick and Brewer 1983, Hendrickx et al. 2001).

Social dilemma exists due to the subtractability and high exclusion costs of natural resources. In an open access renewable resource scenario, no one has the incentives to conserve the resource (or extract sustainably) as the benefits of conservation are shared by all, whereas the benefits of extraction are for individual extractor alone (Gordon 1954, Hardin 1968). Different solutions have been proposed to mitigate the social dilemma situation (also known as the "tragedy of commons"), such as private property rights, cooperation among communities etc. (Ostrom 1990). On the individual level, differences such as social preferences, altruism and/or trust level determine the tendency to cooperate and conserve natural resources (Messick and Brewer 1983, Ostrom et al. 1994, Budescu et al. 1997).

Temporal dilemma in natural resource settings arises due to the conflict between individual´s short-run consumption needs versus her long-run wish to save resources for future consumption (Brown 2000). The key underlying issue is that natural resource extraction brings earnings during the current period, whereas benefits of conservation (or sustainable extraction) can only be accrued in the future.

It is important to understand the impact of temporal dilemma as the social as well as policy implications of temporal dilemma are different from the social dilemma. Failure to recognize the impact of temporal dilemma may result in policy measures which do not address the core problem and in extreme cases may create unintended negative outcomes. Temporal dilemma exists at an individual level so factors (such as communication, punishment, group size etc.) which facilitate resource conservation by mitigating social dilemma do not address the negative impact of temporal dilemma. Clark (1973) shows that even under perfectly enforced individual property right regimes, natural (renewable) resources can

* This chapter is co-written with Achim Schlüter.

be extracted unsustainably due to temporal dilemma. Furthermore, understanding the impact of temporal dilemma can lead to new innovative policy options, which would have better chances of achieving required level of resource conservation. For example, one way of addressing temporal dilemma could be to offer transfers from future profits to compensate natural resource users for the transition costs of stock rebuilding, thus mitigating the desire to overexploit (Grafton et al. 2007).

While a great deal of experimental research has been carried out to understand the social dilemma in natural resource settings (Ostrom et al. 1994), there has been a relative lack of interest in understanding the impact and drivers of the temporal dilemma in the context of natural resource management. The experimental research on temporal dilemma in natural resource settings has largely adopted one of the two approaches.

First way of adding temporal dimension is to play dynamic Common-pool resource (CPR) or public good games, where externalities from one round get carried over to the next one. Herr et al. (1997) is the seminal example of this approach. They play CPR experiments with time-independent appropriation externalities which are restricted to within a decision period and time-dependent appropriation externalities which occur both within and across decision periods. Messick and Brewer (1983) and Mannix (1991) use similar approach to examine the relative importance of temporal dilemma as compared to social dilemma.

While these studies address the intertemporal nature of extraction externalities to a certain extent, they do not address the fact that conservation benefits are not available to resource users immediately. In these experiments the benefits of conservation are available at the end of the experiments in the shape of earnings from shared resource. The second approach deals with the time delay aspect of temporal dilemma more directly, by changing the nature and time of the earnings from cooperation. Kortenkamp and Moore (2006) play a public goods game, where participants contribute to a local environmental group. In their study, time is manipulated by describing the mission of the environmental group as either focused on improving the environment for current city residents, or, the next generation of residents. Similarly, Jacquet et al. (2013) play a standard public good game where benefits of cooperation were; (i) delivered immediately, (ii) delayed by one day, (iii) delayed by one week, and (iv) delayed by several decades and spread over a much larger number of potential beneficiaries (in the shape of planting trees).

Present study looks at the temporal dilemma in the context of CPR (fisheries) management by conducting common-pool resource (CPR) experiments with and without temporal dilemma. These experiments were conducted in different villages of Zanzibar. We add to the existing literature on temporal dilemmas in the following ways.

First, studies described above were conducted with students in universities. Henrich et al. (2010) explain how this can create problems, as student behavior is often not reflective of overall population, especially for communities engaging in artisanal natural resource extraction. Also, students may not have experience of the underlying issues, and thus, their reaction to being in temporal dilemma within the context of CPR scenario may differ from those who have experience with CPRs (Cárdenas and Ostrom 2004, Ghate et al. 2013).

Second, we frame the experiment as common pool resource scenario involving resource extraction rather than public good games. There is some evidence that participants respond differently to CPR games as compared to PG games (Cox et al. 2013). Temporal dilemma is more prominent in natural resource use situation than public goods, so we believe it is important to understand whether adding temporal dimension to standard CPR game affects participant´s behavior.

Third, since we are specifically interested in natural resource use, so we attempt to disentangle the temporal dilemma problems related to over-extraction from the problems related to destructive extraction. This distinction is necessitated because participants may use different criteria when deciding about the extraction method as compared to their effort level decision. In our experiments, we include both the decision about effort level (how much effort to devote to extraction activities) and the choice of extraction method (which extraction method, or in case of fisheries fishing gear to use). In real life natural extraction scenario, the impact of over-extraction becomes noticeable over a long period of time, whereas the impact of using destructive extraction method is visible in a short time period. As a result, we expect that the presence of temporal dilemma will have different impact on these two interrelated yet distinct aspects of natural resource extraction.

Looking at our results, we do not find any evidence that delaying the benefits of conservation has any significant impact on the individual or group level extraction. This is true for both the amount of resource extracted in the first round as well as the overall extraction level, so learning effects are unlikely to be the main reason behind this lack of difference. However, participants who had the ability to choose between different extraction methods, extract more in the CPR experiment with temporal dilemma than those with the standard CPR experiment. We find that this greater extraction result from the fact that participants are more likely to move away from the (relatively) environment-friendly extraction method to relatively more destructive extraction method in groups with temporal dilemma.

2.2 Research design

Theoretically, assuming positive individual discount rates, we should see greater extraction in experiments with temporal dilemma. This is based on standard economic theories, which suggest that the value of conserved resource is greater in control groups as compared to groups with temporal dilemma treatment where benefits from conserved resource are only available after a time delay. Earlier empirical research also points out that cooperation is harder to achieve in the presence of temporal dilemma. Both Jacquet et al. (2010) and Kortenkamp and Moore (2006) find that rate of cooperation in public goods games, is lower in groups with temporal dimension than in groups without it. Similarly, studies using dynamic CPR experiments find that participants extract more in experiments with intertemporal externalities as compared to experiments without intertemporal externalities (Herr et al. 1997).

In light of earlier empirical and theoretical research we hypothesize that;

(i) Individuals in groups with temporal dilemma (treatment groups) extract more as compared to individuals in groups without temporal dilemma (control groups), and that this difference is magnified when extraction externalities are greater.

(ii) (Relatively) destructive extraction method is chosen more frequently in temporal dilemma groups (treatment groups) in comparison to groups without temporal dilemma (control groups); as the value of conserved resource is lower in treatment groups as compared to control groups.

2.2.1 Field site

In order to test our hypothesis, CPR experiments were conducted in 20 sessions in 5 different districts of Zanzibar. Fisheries are an important sector of Zanzibar´s economy. Fisheries constitutes the most important source of income and nutrition for rural households in Zanzibar (Muhando and Jiddawi 1998, Jiddawi and Öhman 2002). Most of the fishing pressure in Zanzibar comes from about 18-19,000 artisanal fishers contributing about 96% of total marine catches(Livestock 2010). These artisanal fishers depend on the marine resources for their income and food requirements.

According to an influential study, the inshore fisheries in Zanzibar shows sign of over-exploitation as indicated by decrease in average catch-rate (Jiddawi and Stanley 1999). Congestion and over-extraction by fishers are supposed to be the main reason for this decline in fisheries. Another major issue is the use of illegal and destructive fishing gear. According to officials from the Ministry of Livestock and fisheries Zanzibar, “the most common illegal fishing methods include the use of small mashed nets and traps, Beach seine, spear guns, chemicals from plants locally known as utupa and fishing without a license” (Yussuf 2012). These illegal and destructive fishing techniques cause substantial environmental damage not only to the fisheries, but also to the related ecosystems such as coral-reefs and mangroves. This implies that the future sustainability and the profitability of the fisheries are being affected by a combination of overfishing and destructive fishing activities. This suggests, that, fishers engaging in excessive and/or destructive fishing activities are substituting possibility of increased future income for greater present consumption.

2.2.2 Experimental sessions

During each experiment session, CPR experiment was conducted along with time-preference task.† Participants were recruited from local fishing markets. All the participants engage in fishing activities in one way or the other, approximately 95% of the participants depend on fishing activities as their primary source of income. Around 30% of the participants are totally dependent on fishing as their source of income, while the rest complement fishing with other income generating activities such as agriculture, livestock, skilled labor etc. Average age of participants was around 41(±15) years, with mean fishing experience being around 21 (±14) years. Table 2.1 presents summary of socio-economic and demographics statistics.

Table 2.1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Age	40.90	14.74	17	80
fishing experience	21.23	13.88	1	70
Household members	7.41	4.41	0	40
education level	1.50	1.03	0	4
Crewsize	5.75	7.78	0	70

		Percentage (%)		
Cell phone		87.30		
Electricity		35.71		
Transport		56.75		
Gear ownership		76.19		
Boat ownership		63.89		
Dago/Migratory fisher		27.78		
Alternative livelihoods:	None (32.94)	Farming (44.44)	Skilled worker (9.52)	Unskilled worker (11.90)

A key issue in organizing CPR field experiments with time dilemma is method of delivery of future earnings. This originates from the fact that any type of delayed benefits have to address three main issues: (i) future consumption may not have the same value as present consumption for the individual, (ii) future earnings may involve uncertainty and trust issues, and (iii) there may be substantial difference in transaction costs between present and future earnings. We are only interested in the first aspect, and try to minimize the other two aspects as much as possible. For this reason, we organize the payments

† See Chapter 3 for more details

through cell phone credit.[‡] First, it allows us to keep the transaction costs to a minimum, and more importantly constant across time periods. Second, it also helps in addressing the trust and uncertainty issues. At the end of each session participants were given receipt of the money earned during the experiment. This receipt carried the delivery date of the rest of their earnings. Participants were also given contact number in case they don´t receive their earnings. Each day randomly selected participants were contacted to make sure that the money was received by the participants.

80% of the participants had a cell phone with them during the experiment sessions. All the participants gave a contact number to which their earnings could be forwarded. Those who did not own a cell phone (around 10%) gave their spouses or children´s contact number. All results hold, even if we eliminate those who do not own a cell phone or those who were not carrying a cell phone with them from our analysis.

At the end of CPR experiments, participants also took part in social preference and risk preference tasks. These tasks were incentivized through cash payments. Participants were told about their total earnings from each activity at the end of the experiment session. Experiments were designed to make sure that both the average cash earnings and average phone credit earnings were equal to average income from a full day's work (8000 TZS = 5 USD).

2.2.3 Experimental design

We employ standard CPR experiment design based on Cox et al. (2012). The experiments were framed as fisheries extraction scenario. Groups of n=6 individuals face appropriation decisions from a "Common-pool resource" (fisheries). The total amount of resource available for each group is worth 2000 tokens (where 1 experimental token = 10 TZS) in each round. Group members know each other and could engage in costless communication at the end of first round.

Individuals simultaneously and privately decide how many tokens to extract from the common resource by deciding about the effort level devoted to extraction activities. Each additional unit of effort brings monetary rewards depending on the extraction method (e). Extracting resources causes damage to additional resource units. The extent of this damage depends on the extraction method (d). The amount of resource not extracted is shared equally between all the group members.

Player´s earnings are given as:

$$\pi_i = [\mathrm{e}_m * (x_i)] + [\left(R - \textstyle\sum_{i=1}^{n}(d_m * x_j)\right)/n] \qquad (2.1)$$

Where x_i is the effort level, e_m is the earnings-to-effort ratio and d_m is the destruction-to-effort ratio for gear *m*, X_i the earnings from resource extraction is given as $X_i = [\mathrm{e}_m * (x_i)]$, and Y_i the benefits of

‡ Most of cell phone use in Zanzibar is on a pre-paid or pay-as-you-go basis. Also cell phone users can use this cell phone credit to purchase items for daily consumption (such as groceries etc.) in addition to its primary purpose of cell phone services provision.

conservation i.e. share of non-extracted resource divided (equally) among the group members. Y_i is given as: $Y_i = Y = [(R - \sum_{i=1}^{n}(d_m * x_j))/n]$.

The social dilemma aspect comes from the fact that an individual's self interest lies in taking the maximum possible amount from the resource; however this results in resource wastage as destruction-to-effort ratio (d_m) is greater than earnings-to-effort ratio (e_m). On the other hand, social utility is maximized if all participants abstain from resource extraction, since in that case the benefits from resource are shared equally between group members and no resource is wasted.

In order to account for the temporal dilemma, we include a treatment (labelled as Time treatment). In control groups, earnings from both private extraction (X_i) as well as earnings from conserved resource (Y) are delivered at the end of experimental session, whereas in Time treatment groups earnings from private extraction (X_i) are delivered at the end of experimental session while earnings from conserved resource (Y) are delivered later (after 14 days). In this way, we are able to account for the fact that conservation benefits are not available to natural resource users in the present time period. Our experimental design allows us to compare the impact of temporal dilemma on individual as well as group level extraction.

Another key part of our experimental design is to decompose natural resource user´s extraction decision in two components (i) effort level decision, and (ii) extraction method choice. In order to capture this aspect in standard CPR experiments we introduce a choice treatment where participants can choose the gear as well the effort level.

We focus on three different prototype gears referred to as Gear1, Gear2 and Gear3. Gear1 is effort-intensive relatively environment-friendly gear, whereas Gear2 and Gear3 are equally efficient at effort input; however Gear2 is more destructive than both Gear1 and Gear3. Table 2.2 briefly explains the characteristics of these prototype gears.

Table 2.2: Gear characteristics

	Gear1	Gear2	Gear3
Catch-effort ratio (e_m)	10	20	20
Damage-effort ratio (d_m)	15	30	30
Damage-catch ratio (D_m)	1.5	2	1.5

Experiments lasted 15 rounds and were conducted in three different stages. Each group played the baseline activity first, where labor intensive extraction method (Gear1) was used. The other two stages differed for groups depending on whether they were in the choice treatment or not. In groups with no choice; activity B and activity C entailed making extraction decision with Gear2 and Gear3 respectively. In groups with choice treatment, participants could choose between Gear1 and Gear2 in Activity D and Gear1, Gear2, and Gear3 in Activity E. Each activity lasted for five rounds, and ordering of activities was determined randomly for each group.

Table 2.3 presents the experimental design in greater detail.

Table 2.3: Experimental Design

	Treatment Group A	Treatment Group B	Treatment Group C	Treatment Group D
Choice treatment	No	No	No	Yes
Time Treatment	No	Yes	No	Yes
Activity A (5 rounds)	Gear 1 only	Gear 1 only	Gear 1 only	Gear 1 only
Activity B (5 rounds)	Gear 2 only	Gear 2 only	-	-
Activity C (5 rounds)	Gear 3 only	Gear 3 only	-	-
Activity D (5 rounds)	-	-	Gear 1 & 2	Gear 1 & 2
Activity E (5 rounds)	-	-	Gear 1, 2 & 3	Gear 1, 2 & 3
# of groups	10	10	10	10
# of participants	60	60	60	60

2.3 Findings

For our main analysis, we look at the CPR extracted by the participants. This is different than the amount consumed, due to the fact that, some resource is wasted as a result of extraction depending on the gear being used. This allows us to look at participant's extraction decision standardized across different gears. Our results do not change qualitatively whether we use CPR extracted or CPR consumed as the dependent variable.

Figure 2.1: Average group extraction in each round of different activities

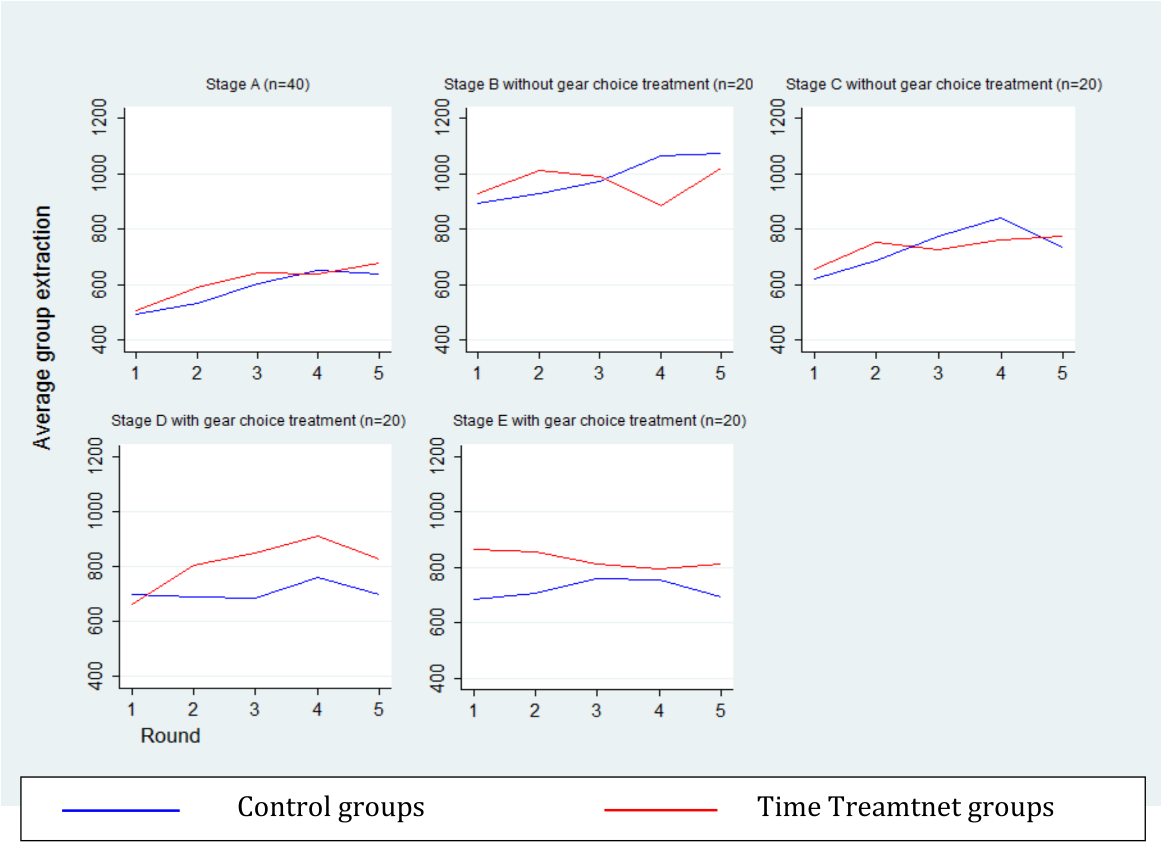


Figure 2.1 shows progression of resource extraction over experimental rounds for both control and treatment groups. The figure suggests that in the baseline activity, groups with time treatment extracted more as compared to control groups, however the difference is very small and the progression of amount of resource extracted is similar in both groups (no obvious learning effect difference). For most activities, we observe a slight difference between the amount of resource extracted in the first round of control groups as compared to amount of resource extracted by the treatment groups, however they converge as the rounds progress, except in activities with gear choice treatment (activity D&E) where this difference is magnified.

Overall, figure 2.1 indicates three interesting patterns which we explore further in our statistical analysis: (i) very small difference in extraction between control and treatment groups in the first round of the experiment (ii) seemingly similar overall extraction in all rounds for both treatment and control groups, and (iii) the difference in extraction between control and time treatment groups when participants had the ability to choose between different gears compared to when they couldn´t.

2.3.1 Extraction decision

Since participants did not know whether the experiment was to be repeated or not, and because participants could not communicate to each other before the start of the experiment, we treat the first round as a single-shot experiment. The mean extraction level in the first round of CPR experiments is 63.75 (42.29) tokens for individuals in control groups, whereas it is 70.25 (47.98) tokens for individuals in groups with time treatment. However, this difference is not statistically significant (Kruksal-wallis test p-value = 0.43).

Table 2.4-Column (1) present OLS models with the amount of resource extracted by an individual in the first round of experiment as dependent variable. The main variable of interest is *Time treatment,* which is a binary variable indicating whether or not individuals were part of the treatment group. In appendix A (table 2.7) we provide more detailed models with (i) just the main independent variables, (ii) controlling for individual preferences, (iii) socio-economic controls and views about fisheries, and (iv) controlling for individual time preference. Across specifications we do not find any significant difference between control or treatment groups even after controlling for socio-demographics factors.

Table 2.4: OLS regression models for Resource extracted in the CPR experiment

	Damage (1st Round)	average Damage (Round 1-15)		
		All groups	No-choice groups	Choice treatment groups
	(1)	(2)	(3)	(4)
Time Treatment (=1)	4.980 (9.820)	9.181 (6.948)	-7.691 (17.06)	**25.16***** **(8.085)**
Cons	**79.52**** **(29.61)**	**110.3***** **(22.04)**	**81.49***** **(25.80)**	**115.8**** **(42.03)**
Socio-demographic controls	Yes	Yes	Yes	Yes
R2	0.192	0.125	0.273	0.137
No. of observations	239	239	119	120

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For overall experiment (i.e. 15 rounds) mean extraction level is 73.02 (2.95) tokens per round for individuals in control groups, whereas it is 79.66 (3.15) tokens per round for individuals in groups with time treatment. We find weak support that this difference is statistically significant (Kruksal-wallis test p-value = 0.065). Table 2.4- Column (2) looks at the aggregate models where dependent variable is average resource extracted during the whole experiment (i.e. 15 rounds). Column (3) and Column (4) look at groups without and with gear choice option respectively. Table 2.4 Column 2-4 suggest that difference between time treatment and control groups is only significant for groups with gear choice.

The coefficient of *Time Treatment* variable is positive and statistically significant for Column (4) only, indicating that participants in groups with time treatment extracted substantially larger amount but only in gear choice treatments.

In order to account for the potential differences in learning effect in time treatment and control groups, we calculate panel models for each activity. Table 2.5-Column (1) presents results from activity A. Column (2-3) present results from activity B and C respectively for groups who could not chose their extraction method. Column (4) and Column (5) present models for activity D and E respectively, for groups who had the possibility to choose between different extraction methods.

Table 2.5: Panel models for Resource extracted in different activities during the experiment

	(1)	(2)	(3)	(4)	(5)
	(Activity A)	(Activity B)	(Activity C)	(Activity D)	(Activity E)
	Damage done to the resource				
Time Treatment (=1)	6.752 (6.885)	-10.80 (20.19)	-4.331 (14.86)	**27.94**** **(11.76)**	**26.11***** **(9.179)**
Choice Treatment (=1)	6.347 (6.968)	-	-	-	-
Round	**6.722***** **(0.948)**	3.966 (3.468)	**4.739***** **(1.209)**	**4.267**** **(2.038)**	-1.025 (1.678)
constant	**40.41*** **(23.43)**	**142.5***** **(39.93)**	35.84 (32.37)	**105.2**** **(50.61)**	**133.6***** **(45.70)**
Socio-demographic indicators	Yes	Yes	Yes	Yes	Yes
R2 (between)	0.0888	0.2124	0.2698	0.1155	0.1230
No. of participants	239	119	119	120	120
No. of observations	1195	595	595	600	600

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5 suggests that time treatment led to greater extraction in activities where participants could choose their gears, as indicated by positive and statistically significant coefficient of *Time Treatment* variable in Column (4) and Column (5). We do not observe any difference between extraction levels of individuals with or without time delay in activities where participants had no choice in terms of extraction method (Column 1-3).

2.3.2 Gear Choice

Given the fact, that, temporal dilemma had an adverse impact on participant´s ability to restrain from extraction activities only in rounds where they could choose between different extraction methods, in this sub-section we investigate participants´ extraction method decision in time treatment and control groups. In order to make sure that we capture different aspects of gear choice, we use two different measures of gear choice, these include: (i) the likelihood of choosing the destructive gear in one of the five rounds in gear choice activities, and (ii) number of times a player chose the more destructive gear during each gear choice activity. The first measure looks at the number of players who chose the more destructive gear at least once during an activity involving gear choice, while the second measure looks at the frequency of using destructive gear in each activity.

First we look at Activity D where the choice was between a gear which is more environmentally friendly but more effort intensive versus a gear which is less effort intensive but environmentally more destructive.[§]

Figure 2.2: Frequency of choosing destructive gear

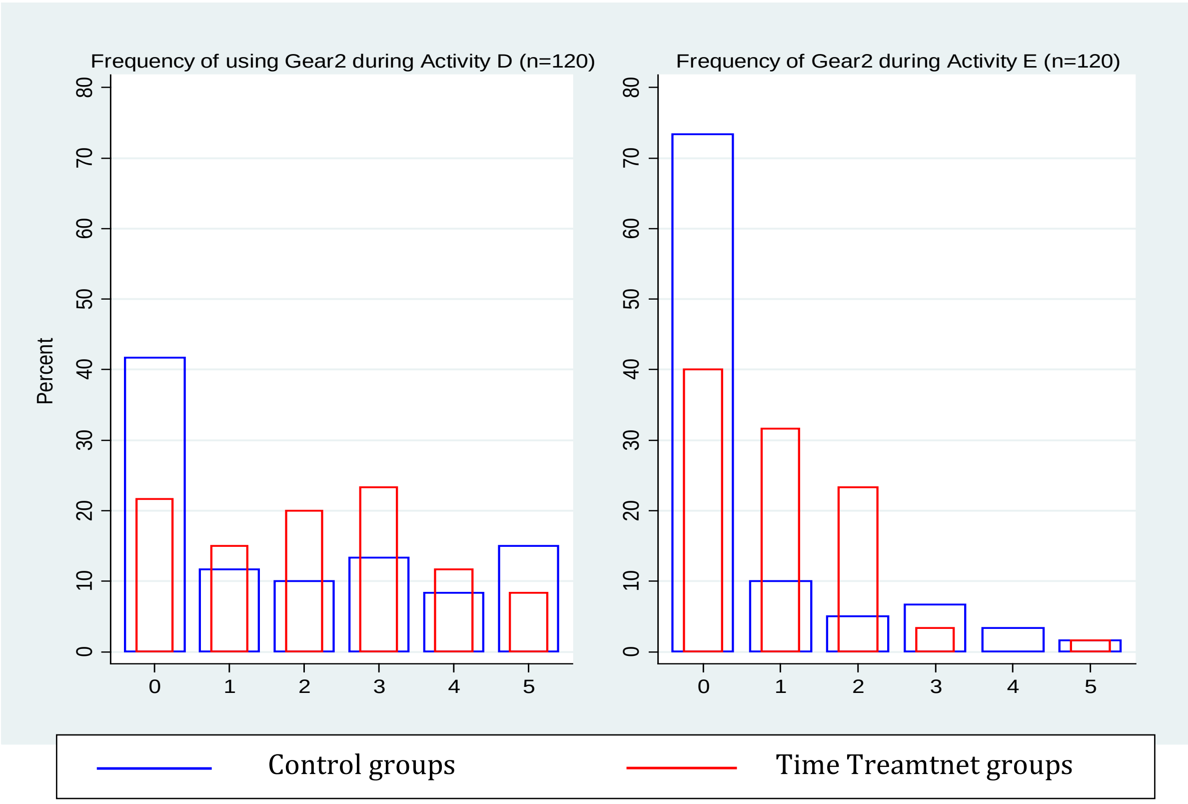


Figure 2.2(a) shows the frequency of destructive gear choice in Activity D for treatment and control groups, indicating that the use of destructive gear was more common in treatment groups as compared

[§] It should be noted that participants had no monetary benefit in restricting their effort level, as effort was not incentivized to the control groups. Additionally, we find that this difference is greater for participants who chose gear 2 in some of the rounds, but not necessarily in majority of the rounds. Indeed, the proportion of participants using destructive gear consistently (in all or in almost all of the 5 rounds) is very similar for both treatment and control groups. Figure 2.3(b) looks at the frequency of destructive gear choice in Activity E for treatment and control groups. We observe the same pattern with the use of destructive gear in Activity E as in Activity D; although the frequency of using gear 2 is much lower than in Activity D.

Given this observation, we further investigate participants' extraction method choice using statistical analysis. Fisher´s exact (pearson´s chi-square) test indicates that the number of players who chose destructive gear at least once, during Activity D is significantly higher in time treatment groups as compared to control groups ($p < 0.05$) . This is confirmed by probit models which look at the likelihood of choosing destructive gear in at least one of the rounds during Activity D and Activity E (table 2.6 Column (1) and Column (2)). We also find that the frequency and intensity of using gear 2 does not differ substantially between control and treatment groups.

Table 2.6: Regression models for Extraction method choice

	(1)	(2)	(3)	(4)
	probability of using gear 2 during Activity D[1]	probability of using gear 2 during Activity E[1]	frequency of using gear 2 during Activity D[2]	frequency of using gear 2 during Activity E[2]
Time Treatment (=1)	**0.670**** **(0.310)**	**1.024***** **(0.318)**	0.339 (0.444)	0.375 (0.246)
Cons	1.061 (1.045)	**-2.545**** **(1.017)**	**2.976***** **(0.946)**	-0.613 (0.760)
Socio-demographic indicators	Yes	Yes	Yes	Yes
sigma _cons	-	-	**1.847***** **(0.190)**	**1.066***** **(0.117)**
R^2	0.1054	0.1908	0.0228	0.0472
N	120	120	120	120

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

Notes: column 1-2 probit regression models with *probability of using gear 2* during Activity D & E respectively as the dependent variable. Column 3-4 tobit regression models with *frequency of using gear 2* during Activity D & E respectively as the dependent variable

Overall, our results suggest that for both Activity D and Activity E, the likelihood of a player choosing Gear2 increased, when the participants did not receive their conservation earnings immediately (time treatment). This is indicated by the statistically significant coefficient for Time treatment variable in Column (3) and Column (4). However, the situation is more complicated with respect to frequency of using destructive gear. We do not find any significant increase in the intensity of choosing the more destructive gear between control and treatment groups. This suggests that, addition of temporal dilemma resulted in more participants considering to move away from the traditional effort-intensive environment-friendly gear and experiment with the destructive gear.

2.4 Concluding remarks

The most noticeable aspect of our results is (i) the lack of difference between control groups and time treatment groups with respect to effort level choice, and (ii) significant difference in gear choice between control groups and time treatment groups.

The lack of difference in effort level choice could be due to the relatively short time delay between extraction and conservation earnings (14 days). In real life, temporal dilemma spans over a long time period, taking years or even generations. In other words, the benefits of conservation are often not realized in the near future, whereas in our study the delay in earnings was limited to 14 days only. The main motivation for limiting the temporal dilemma to just two weeks was to ensure that participants had trust that their delayed earnings will be available to them[**]. Furthermore, this short delay also allowed us to keep transaction costs similar between earlier and delayed earnings[††], and decreased the uncertainty attached with future payments.

While at first glance this finding may appear to contradict earlier evidence, nevertheless it is broadly in line with results from Jacquet et al. (2010) and Kortenkamp and Moore (2006). For example, Jacquet et al. (2010) find that, for intra-generational discounting (temporal dilemma) the delay in conservation earnings induces only a small difference in cooperation levels which is not statistically significant. Indeed, they only observe a large and significant difference for intra-generational temporal discounting, where conservation benefits are not only immediately unavailable to the participants, but the nature of future benefits is different as well. This is similar to the result by Kortenkamp and Moore (2006) who also look at the inter-generational aspect of temporal dilemma. We believe future studies should focus on different aspects of temporal dilemma such as: (i) the nature of the delayed benefits (i.e. whether delayed benefits come in terms of direct or indirect earning); and (ii) different aspects of delayed

[**] Pilot study showed that trust issues start emerging as the delay in earnings became longer

[††] Even though the payment method (via cell phone) makes sure that the transaction costs are not different however employing longer time period for delayed earnings would have meant that transaction costs between earnings would become substantial as the use and price structure of cell phone operators change quite regularly. It could be argued that temporal dilemma at some level involves increased future transaction costs; however we are interested in purely the temporal aspects.

earnings i.e. whether pure time discounting or transaction cost or uncertainty related issues are more important for temporal dilemma in natural resource settings.

On the other hand, results from gear choice decision indicate that, even for short time delay, there could be significant differences between control and time treatment groups. One possibility is that the choice of extraction method is more vulnerable to temporal dilemma, as in real-life the impact of gear choice is visible in a very short amount of time, whereas, the impact of higher effort level takes a longer time to become noticeable. Another related possibility is that fishers may use different criteria for different types of decision making. It is possible that temporal dilemma plays only a minor role for effort level decision, and that effort level decision is informed more by personal habits and the level of social dilemma. Whereas, the gear choice decision may have an important inter-temporal component due to personal preferences (such as individual´s time preferences, value given to the resource, etc.), and has less to do with social dilemma. Indeed, an interesting extension of our study would be look at gear choice decision for various levels of social and temporal dilemma.

The main contribution of our study is to highlight the importance of temporal dilemma and gear choice decision. Future studies on natural resource extraction should take these differences into account. In particular, the relationship between temporal dilemma and resource user's choice of extraction method deserves more consideration. The advent of urbanization and better communication links has intensified the technological progress in resource extraction methods. New innovative ways of extracting resources are rapidly becoming available to artisanal fishers. In many cases, these innovations are a threat to the sustainability of the resources (examples in fisheries include use of dynamites, spears guns and/or mosquito nets). Our research indicates that due to temporal dilemma participants are more willing to try out these destructive extraction methods.

The main policy implication of our paper is that solving the (short-term) temporal dilemma may not affect the over-extraction problem which is a longer time-horizon problem, as compared to, the destructive extraction problem which is a short time-horizon problem. So, policies which focus on short-term impact of temporal dilemma may work well for minimizing destructive fishing, but it may not have any impact on the longer term problem of over-extraction. Whether these policy implications pan out in real life as suggested by the theory needs more careful consideration.

Appendix A

Table 2.7: CPR extraction in first round

	Damage			
	(1)	(2)	(3)	(4)
Time Treatment (=1)	4.330 (11.58)	5.968 (12.47)	4.980 (9.820)	6.024 (9.733)
Activity	-	-	-	-
2.Activity	**73.03***** **(18.28)**	**70.20***** **(19.69)**	**68.10***** **(21.55)**	**70.37**** **(24.68)**
3.Activity	**39.18**** **(17.27)**	28.55 (32.55)	16.14 (30.49)	13.82 (33.83)
4.Activity	**28.82*** **(15.03)**	24.45 (19.18)	21.90 (19.57)	27.42 (18.43)
5.Activity	**39.89*** **(21.79)**	33.52 (37.51)	24.62 (37.25)	26.56 (37.51)
cellphone (=1)	-31.05* (14.40)	-30.28* (15.66)	-30.93 (18.24)	-34.22* (17.49)
ordering	-	1.778 (5.644)	3.346 (5.765)	3.451 (6.531)
Risk averse (=1)	-	-2.037 (8.478)	-7.767 (8.427)	-6.198 (9.752)
untrustworthy (=1)	-	14.90 (9.218)	15.38 (9.152)	17.24 (10.65)
Age	-	-	-0.387 (0.283)	-0.325 (0.302)
education	-	-	0.665 (5.649)	-0.867 (5.705)
MR sustainability	-	-	**-12.20**** **(4.878)**	**-14.52***** **(4.262)**
Fishing hours	-	-	5.196 (3.052)	**6.291*** **(3.245)**
IDF	-	-	-	**43.44***** **(10.53)**
Present biased (=1)	-	-	-	-0.240 (13.92)
Future biased (=1)	-	-	-	**-38.92***** **(10.24)**
Cons	**107.1***** **(16.52)**	**96.05***** **(22.77)**	**79.52**** **(29.61)**	48.12 (30.93)
R^2	0.140	0.149	0.192	0.252
N	240	240	239	239

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regression models with *damage done to the resource* in first round as the dependent variable

Table 2.8: Aggregate CPR extraction

	Mean damage					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Treatment (=1)	11.04	10.79	9.181	9.410	-7.691	**25.16*****
	(6.979)	(6.944)	(6.948)	(6.921)	(17.06)	**(8.085)**
cellphone (=1)	**-27.33*****	**-27.8*****	**-27.3*****	**-28.6*****	**-32.1*****	**-29.02***
	(8.593)	**(8.554)**	**(8.71)**	**(8.75)**	**(9.692)**	**(15.64)**
ordering	-	**4.063****	3.865*	**4.006****	**6.656***	2.515
		(2.013)	(1.984)	**(1.979)**	**(3.138)**	(2.865)
Risk averse (=1)	-	-9.137	-13.60*	**-12.37***	**-24.57***	3.032
		(7.397)	(7.343)	**(7.374)**	**(12.14)**	(7.753)
Untrustworthy (=1)	-	6.926	6.398	7.255	2.666	4.993
		(7.025)	(6.967)	(6.950)	(10.65)	(9.178)
Age	-	-	-0.215	-0.192	0.0814	-0.595
			(0.249)	(0.249)	(0.326)	(0.456)
education	-	-	2.247	1.170	3.099	-1.584
			(4.136)	(4.168)	(8.161)	(7.325)
MR sustainability	-	-	-7.289*	**-7.721***	**-14.06****	2.237
			(4.305)	**(4.378)**	**(5.092)**	(5.650)
Fishing hours	-	-	5.043***	**5.459*****	**7.981****	1.567
			(1.923)	**(1.932)**	**(3.370)**	(2.380)
IDF	-	-	-	**20.67****	23.54	**34.98***
				(10.38)	(15.60)	**(16.98)**
Present biased (=1)	-	-	-	-4.350	-8.646	1.558
				(8.638)	(14.57)	(17.15)
Future biased (=1)	-	-	-	-11.27	-23.19	-4.069
				(9.440)	(14.06)	(15.74)
constant	**141.7*****	**131.1*****	**110.3*****	**96.61*****	**81.49*****	**115.8****
	(8.461)	**(11.99)**	**(22.04)**	**(23.30)**	**(25.80)**	**(42.03)**
R^2	0.051	0.079	0.125	0.145	0.273	0.137
N	240	240	239	239	119	120

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regression models with *average damage done to the resource* during the whole experiment (15 rounds) as the dependent variable

Table 2.9: Panel model CPR extraction

	Damage				
	(1) (Activity A)	(2) (Activity B)	(3) (Activity C)	(4) (Activity D)	(5) (Activity E)
Time Treatment (=1)	6.752	-10.80	-4.331	**27.94****	**26.11*****
	(6.885)	(20.19)	(14.86)	**(11.76)**	**(9.179)**
Choice Treatment (=1)	6.347	-	-	-	-
	(6.968)				
Round	**6.722*****	3.966	**4.739*****	**4.267****	-1.025
	(0.948)	(3.468)	**(1.209)**	**(2.038)**	(1.678)
Age	-0.0246	-0.192	0.0328	-0.666	-0.557
	(0.247)	(0.415)	(0.376)	(0.529)	(0.533)
Edu	3.761	-1.499	3.990	-1.765	-3.330
	(4.151)	(8.457)	(8.403)	(8.293)	(9.196)
ordering	2.093	**7.455***	**6.407****	4.228	2.778
	(1.960)	**(4.068)**	**(3.269)**	(3.413)	(3.174)
Risk averse (=1)	-6.400	**-29.66****	**-20.80****	1.020	-5.428
	(7.335)	**(14.87)**	**(10.04)**	(8.850)	(12.35)
Untrustworthy (=1)	3.611	-1.907	15.53	9.351	0.300
	(6.863)	(13.50)	(10.90)	(12.23)	(10.89)
cellphone (=1)	**-17.37****	**-45.39*****	**-28.96*****	-25.28	**-35.98****
	(8.715)	**(14.12)**	**(9.735)**	(21.56)	**(16.46)**
MR sustainability	-5.337	**-17.74****	**-13.80****	2.719	1.164
	(4.355)	**(8.669)**	**(5.575)**	(8.667)	(6.002)
Fishing hours	**6.288*****	**6.630***	**9.100****	-0.605	3.070
	(1.914)	**(3.422)**	**(3.709)**	(2.598)	(3.033)
constant	**40.41***	**142.5*****	35.84	**105.2****	**133.6*****
	(23.43)	**(39.93)**	(32.37)	**(50.61)**	**(45.70)**
R^2 *(between)*	0.0888	0.2124	0.2698	0.1155	0.1230
No. of players	239	119	119	120	120
No. of obs.	1195	595	595	600	600

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Random-effects panel regression models with *damage done to the resource* during each round of the whole experiment (15 rounds) as the dependent variable

Table 2.10: Extraction method choice

	(1) probability of using gear 2 during Activity D	(2) probability of using gear 2 during Activity E	(3) frequency of using gear 2 during Activity D	(4) frequency of using gear 2 during Activity E
Time Treatment (=1)	**0.670****	**1.024*****	0.339	0.375
	(0.310)	**(0.318)**	(0.444)	(0.246)
cellphone (=1)	**-1.133****	0.447	**-1.193****	**0.371***
	(0.476)	(0.395)	**(0.549)**	**(0.203)**
ordering	0.0659	0.170	0.0936	0.0749
	(0.0845)	(0.107)	(0.112)	(0.0794)
Risk averse (=1)	0.0576	-0.265	0.494	-0.103
	(0.200)	(0.303)	(0.340)	(0.243)
Untrustworthy (=1)	-0.132	**-0.558****	-0.214	**-0.461***
	(0.204)	**(0.238)**	(0.218)	**(0.268)**
Age	-0.0133	0.000957	-0.0122	-0.000739
	(0.00995)	(0.00836)	(0.0152)	(0.00803)
education	0.160	0.212	0.158	0.260*
	(0.187)	(0.223)	(0.210)	(0.140)
MR sustainability	0.0684	**0.213****	0.100	0.120
	(0.122)	**(0.0972)**	(0.164)	(0.0941)
Fishing hours	0.0169	0.147	-0.108	0.105
	(0.0615)	(0.0976)	(0.107)	(0.0712)
Constant	1.061	**-2.545****	**2.976*****	-0.613
	(1.045)	**(1.017)**	**(0.946)**	(0.760)
Sigma _cons.	-	-	**1.847***** **(0.190)**	**1.066***** **(0.117)**
R^2	0.1054	0.1908	0.0228	0.0472
N	120	120	120	120

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: column 1-2 probit regression models with *probability of using gear 2* during Activity D & E respectively as the dependent variable. Column 3-4 tobit regression models with *frequency of using gear 2* during Activity D & E respectively as the dependent variable

Chapter 3:

Time preferences and natural resource extraction behavior: an experimental study from artisanal fisheries in Zanzibar*

3.1 Introduction

Classical economic theory suggests that resource extraction is an inter-temporal maximization problem, where time preferences are crucial in determining the overall extraction rate (Hotelling 1931). Time preferences enter the decision making process, whereby individuals weight present consumption versus future consumption. Over-extraction in the current time period reduces the future availability of the resource. It is generally accepted that high time preferences accelerate extraction by decreasing the value given to the future (Koopmans 1974, Dasgupta and Heal 1979).

From earlier empirical research, we know that there is significant variation across resource users with regards to their time preferences (Curtis 2002, Tanaka et al. 2010, Johnson and Saunders 2014, Teh et al. 2014), and their resource extraction behavior (Cinner et al. 2009). This suggests that, people with higher time preferences extract more as compared to people with lower time preferences (Clark 1973, Chakravorty and Gunatilake 2000, Sumaila and Walters 2005). In their seminal work examining the relationship between time-preference measures and resource extraction, Fehr and Leibbrandt (2011) show that resource users who exhibit impatient behavior (high time preferences) are more likely to accelerate resource depletion. In a similar vein, Johnson and Saunders (2014) find that time preference measures are able to predict resource management preferences. These empirical studies demonstrate that individuals with higher time preferences are more likely to engage in unsustainable resource extraction.

However, earlier empirical research is limited in two ways: (1) most empirical studies use non-incentivized or primary reward-based tasks that do not account for the degree of heterogeneity in time preferences (e.g. Fehr and Leibbrandt (2011)); and (2) extraction measures are either self-reported, or, as in the case of Fehr and Leibbrandt (2011)– too simplistic to be generalizable to more sophisticated, artisanal natural resource extraction scenarios.

Following this line of research, the present study examines the relationship between individual time preferences and natural resource user extraction rates. We focus on the case of a fishery resource, arguably a CPR system of major global importance. We contribute to this literature by using a more

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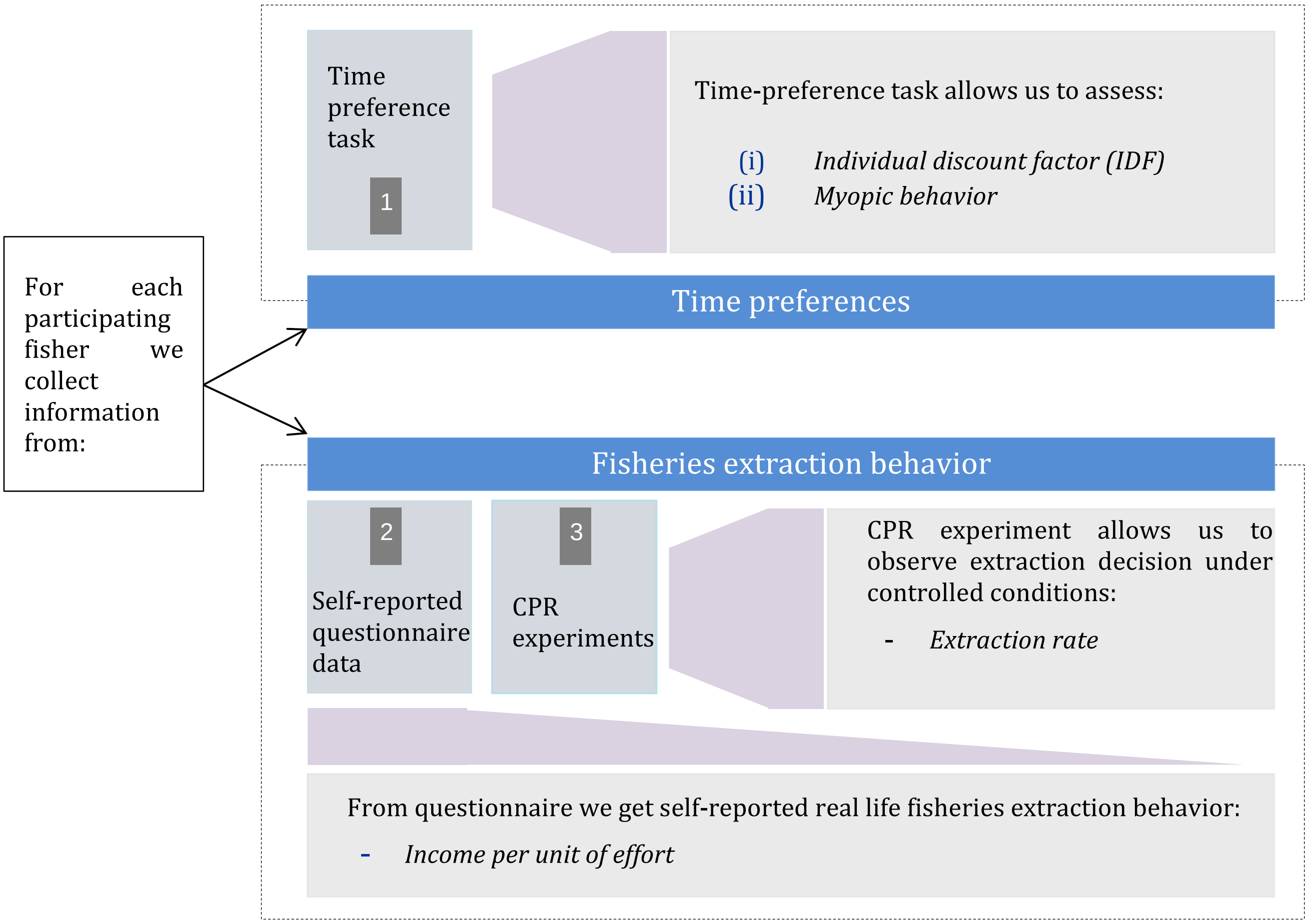
realistic measure of time preferences based on multiple price lists (MPLs), and by combining questionnaire and experimental data, which, taken together, increases the robustness of our findings.

Our results suggest that the relationship between time preferences and natural resource extraction is not as straightforward as assumed by the classical economic theory. We find that time preferences are negatively correlated to extraction rates. Our findings are partly explained by the disinvestment effect of time preferences and by fishers´ cognitive abilities.

3.2 Research Design

Based on earlier theoretical and empirical work (see Introduction), we guide our study on the hypothesis that fishers exhibiting higher time preferences are more likely to report higher extraction rates. The research strategy is illustrated in Fig. 3.1.

Figure 3.1: Summary of research design



First, we measured individual time preferences using incentivized multiple price lists, hereafter referred to as the time preference task (Coller and Williams 1999, Tanaka et al. 2010). Second, we collected data on individuals´ (i) real-life extraction behavior, and (ii) extraction behavior under controlled experimental settings.

During each session, we first conducted the time preference task, which was followed by the experiments. We organized the payments through cellphone credit. Each day, randomly selected participants were contacted to make sure they received their payment.

Before the end of the session, participants took part in a risk preference incentivized task (Maier and Rüger 2010). Experiments were designed to make sure that both the average cash earnings and average phone credit earnings covered the average income from a full day's work [8000-10,000 TZS = 5-6 USD].

We conducted our study in 5 different fishing districts in Zanzibar, in 20 villages, with a sample size of 240 fishers. Around 15-20% of participants made inconsistent choices in the time preference task and were not considered in our empirical examination, therefore, for our main analysis, we focus on the remaining 188 fishers.

All of the participants were fishers recruited from local fishing markets. Almost 95% of the participants depend on fishing activities as their primary source of income. The average age in our sample is 41 (±15) years, and average fishing experience is 21 (±14) years. For further details on the composition of our sample, refer to Table 3.5 in Appendix B. We used the accepted protocols for both experiments and questionnaires (short experimental protocols are given in supplementary appendix, while detailed protocols are available upon request). Before the start of experimental session, participants gave oral consent to participate in the research activities and to receive their experimental earnings in the form of cellphone credit, as well as providing their cellphone number. Similarly, at the end of experimental session, participants gave written consent acknowledging; (a) that they had willingly participated in the experiments and the questionnaires, (b) that they had no objection/problem with the collection and usage of data for research purposes, and (c) their earning from the experiments (both the amount delivered to them immediately after the experiment and the amount which was to be delivered to them on a later date as well as the date itself). All data were analyzed anonymously. We collected identifying information from the participants. This allowed us to contact randomly selected participants and make sure that they had received their earnings. Secondly, it allowed the participants to contact us in case they did not receive their earnings. The data were anonymized by the first author. No other person had access to this identifying data, which was destroyed after all payments had been carried out.

3.2.1 Time-preferences

We use an incentivized multiple price list (MPL) task to measure individual time preferences (for similar approaches see Tanaka et al. (2010)). Time preference measures obtained from MPLs have been shown to (i) be stable at the individual level over time (Kirby 2009, Wölbert and Riedl 2013, Chuang and Schechter 2014, Meier and Sprenger 2015), (ii) correlate with measures derived from other methodologies (Chabris et al. 2008, Reuben et al. 2010, Chuang and Schechter 2014), and (iii), induce the same neurological responses as primary reward-based tasks (McClure et al. 2004, Kable and Glimcher 2007, McClure et al. 2007). Furthermore, they are a better predictor of life outcomes than non-incentivized measures (Chabris et al. 2008, Burks et al. 2012), and finally, MPLs avoid the risk of temptation-based negative aspects of primary reward-based tasks (Reuben et al. 2010).

In this task, subjects are required to make 10 choices between smaller rewards (X) delivered at time t1 (option A), and larger rewards (Y) delivered at time t2 (option B), where t2 is always greater than t1. Choices are grouped into two lists: (1) t1=day 0 and t2= day 14; and (2) t1= day 1 and t2= day 15. For each choice, Y remains constant while X varies from smaller to larger amounts.

At the beginning of each session, participants were informed that only one out of the 10 choices would be randomly selected for payment.

The MPL task allows us to account for two different dimensions of individual time preferences: (1) *patience* (*impatience)*, which is captured by the individual discount factor (IDF), and (2) myopic behavior, which indicates that an individual is present biased. We calculate our two measures as follows. For each list, we estimate the individual discount factors (IDFs) based on the choice at which an individual switches from opting for the smaller, more immediate payment to the larger, later payment. In the extreme cases, if a participant always choses option X in the list, we designate her $IDF_{t1,t2}$ to be 0.125. On the other hand, if a participant always chose option Y then we designate her $IDF_{t1,t2}$ to be 1. This procedure results in two distinct discount measures, $IDF_{0,14}$ and $IDF_{1,15}$. We use the average of these as the first time preference measure, hereafter "IDF". Having two lists allows us to identify myopic behavior, and distinguish present-biased participants: an individual is classified as present-biased when her $IDF_{0,14} < IDF_{1,15}$.

Fishers in our sample exhibit an average IDF of 0.63, and around 20 percent of our participants can be classified as present-biased (Table 3.1). These estimates are similar to the ones found in earlier studies on fishers´ time preferences (Curtis 2002, Johnson and Saunders 2014).

Table 3.1: Summary of Time Preferences and Extraction Behavior

	Variable	Average	Std. dev.	%	Min	Max
Time Preferences						
	IDF	0.63	0.36	-	0.125	1
	Present-biased	-	-	20%	0	1
Extraction Behavior						
Self-reported data:	*income per unit of effort (Tsh./hours)*	3496.34	3047.21	-	286	16667
CPR experiment:	*extraction rate (tokens per round)**	75	50	-	0	160

* The experiment was run with tokens. At the end, participants received 10 Tanzanian Shillings (TZS) per token earned.

3.2.2 Extraction Data

3.2.2.1 Self-reported

We collected extraction data from extensive questionnaires. We asked fishers their average income and their average effort levels (hours per day) for the normal, slow, and high seasons. The extraction behavior was calculated based on the averaged value of these income and effort variables. The questionnaire also includes socio-economic and demographic information (see Table 3.5 in Appendix B).

Based on discussions with local fisheries experts, we use the income measure as it was considered to be the most reliable and standardized way of eliciting the information regarding extraction behavior. Extraction rate is then captured by income per unit of effort or productivity-. This is an indicator for (1) fishers´ intensity of effort, and (2) fishing skills, which encompass proper maintenance and operation of gears and boats. Table 3.6 in Appendix B provides the general descriptive statistics for this data.

3.2.2.2 CPR experiment

We conducted a CPR experiment based on Cox et al. (2013). The experiment was framed as an extraction activity from a common fishery. Participants took part in the experiments in groups of 6, where group members were known to each other. Individuals simultaneously and privately decided on how many tokens to extract from the common resource.

Player earnings are given as:

$$\pi_i = (X_i) + Y \tag{3.1}$$

where $Y = (R - \sum_{i=1}^{n} x_i)/n$

X_i are the earnings from resource extraction which is a function of individual extraction level (x_i), Y are the earnings from conservation, R is the amount of the common resource, and *n* is the number of individuals sharing the resource.

Extraction from a CPR involves a trade-off between future and present consumption; the benefits of conservation are delivered in the future, while the benefits of extraction are available immediately. In a standard CPR experiment, this aspect is neglected since participants are paid their extraction and conservation earnings at the end of the experiment. Our design accounts for this time lag by including a treatment, hereafter “Time treatment”, where earnings from private extraction (X_i) are delivered immediately at the end of the experimental session. However, earnings from conserved resource (Y) are delivered 14 days after the end of the experimental session. Table 3.2 illustrates the current design.

The mean extraction rate for the CPR experiment is TZS 4000 (for reference, 1 USD = 1650 TZS). For more details see Table 3.1.

Table 3.2: Experimental Design

	Treatment Group A	Treatment Group B
Time Treatment	No	Yes
# of groups	20	20
# of participants	120	120
# of rounds	5	5

3.3 Results

3.3.1 Fisheries extraction and time-preferences

To test our hypothesis that fishers´ time preferences are positively correlated to their extraction behavior, we begin by looking at the self-reported extraction data. We carry out the study focusing on fishers' productivity, indicated by the income generated from their extraction per unit of effort (IUF), where one unit of effort corresponds with one hour of fishing activities. We estimate regression models where *IUF* is the dependent variable, and *IDF* and *Present-biased* are the main independent variables of interest. Table 3.3 reports the OLS results.

Table 3.3: OLS regression models for fisheries income

	(1)	(2)	(3)	(4)	(5)
	Ln (income per unit of effort)				
IDF	0.142 (0.198)	-	0.157 (0.199)	0.124 (0.197)	0.0401 (0.200)
Present-biased (=1)	-	**-0.293*** **(0.152)**	**-0.300**** **(0.152)**	**-0.288*** **(0.156)**	**-0.371**** **(0.170)**
Risk-averse (=1)	-	-	-	-0.248 (0.162)	-0.270* (0.159)
Cons	**7.887***** **(0.132)**	**8.038***** **(0.0849)**	**7.939***** **(0.135)**	**8.128***** **(0.182)**	**8.522***** **(0.402)**
Sociodemographic indicators	No	No	No	No	Yes
R-sq.	0.003	0.015	0.018	0.031	0.107
N	187	187	187	187	186

Cluster-robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Result 1: Myopic fishers exhibit lower extraction rates

We run five different specifications. In Columns (1) and (2), we present the results of regression models whereby IDF and present-bias are the independent variables in isolation, respectively. In Column (3), we include both IDF and present-bias, and in Column (4) we control for attitudes towards risk. Finally, in Column (5), we noticeably increase the explanatory power of our model by controlling for sociodemographic characteristics.

Classical economic theory would predict that more impatient and myopic fishers show higher extraction rates (cf. Introduction). Contrary to the theoretical predictions, we find that impatient and myopic fishers exhibit lower extraction rates, as indicated by; (i) the positive coefficient for IDF and (ii) the negative coefficient for present-bias. However, when looking at significances and magnitudes, only present-bias drives our findings, with IDF remaining insignificant. This suggests fishers' valuation of future consumption does not define their extraction rates.

The relationship between time preferences and extraction rates can be affected by attitudes towards risk (Eggert and Lokina 2007, Andreoni and Sprenger 2012). Using Maier and Rüger (2010)'s multiple price method we identify fishers who are risk averse and those who are not. Controlling for risk preferences (Table 3.3, Column (4)), we observe that the coefficient for risk is negative, which indicates that risk-averse fishers are less productive than their non-risk-averse peers, however this doesn't change our result regarding the effect of present bias on extraction rates. Moreover, Result 1 is robust when controlling for sociodemographic indicators and fisheries-related variables, such as age, education level, boat type, etc. (see Appendix B table 3.7 for further details).

3.3.2 CPR experiment and time-preferences

Previous research emphasizes the problems associated with self-reported data when it comes to analyzing fishers' extraction behavior. Indeed, illegal and under-reported fishing is one of the biggest challenges facing fisheries management (Sumaila et al. 2006, Agnew et al. 2009). According to recent estimates, actual extraction rates in some regions of Africa are 30-50% higher than the officially reported catch rates (Pitcher et al. 2002, Agnew et al. 2009, Pauly and Zeller 2016). In order to overcome the limitations associated with this methodological approach, we implement a CPR experiment where participants make extraction decisions in a controlled setting using tangible, monetary incentives.

Result 2: Impatient fishers exhibit significantly lower extraction rates

We test our hypothesis using fishers' extraction rates collected from the CPR experiment. We estimate a pooled OLS regression model with extraction per round as the dependent variable. Table 3.4 presents the results. We assume that fisher´s preferences remain constant over the five rounds of our experiments; however, as a robustness check we estimate a random-effects model as well (Appendix B Table 3.8.2). Nevertheless, our findings remain consistent in both models. As before, full models with sociodemographic indicators and fisheries-related variables are shown in the Appendix B. Table 3.4(a) and Table 3.4(b) report the results for the control and the treatment group, respectively. Note again that the treatment groups received their conservation earnings after a 14 day delay (cf Research design).

Table 3.4: Pooled OLS regression models for damage done to the CPR

	Table 3.4 (a)			
	Control groups			
	(1)	(2)	(3)	(4)
IDF	0.1 (5.9)	-	0.4 (5.8)	-6.2 (6.1)
Present biased (=1)	-	-7.7 (5. 9)	-7.7 (5.9)	-6.5 (5.9)
Risk averse (=1)	-	-	-	**9.2**** **(4.61)**
Cons	**71.3***** **(5.8)**	**72.7***** **(4.8)**	**72.5***** **(5.9)**	**70.3***** **(10.7)**
Sociodemographic indicators	No	No	No	Yes
R^2	0.024	0.023	0.025	0.055
No. of players	94	94	94	94
No. of obs.	470	470	470	470

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Table 3.4 (b)			
	Time treatment groups			
	(5)	(6)	(7)	(8)
IDF	**23.8***** **(6.2)**	-	**23.6***** **(6.3)**	**22.2***** **(6.2)**
Present biased (=1)	-	3.6 (5.3)	2.3 (5.3)	4.2 (5.2)
Risk averse (=1)	-	-	-	**-19.9***** **(5.4)**
Cons	**64.8***** **(6.7)**	**78.9***** **(5.8)**	**64.4***** **(6.8)**	**98.5***** **(11.6)**
Sociodemographic indicators	No	No	No	Yes
R^2	0.046	0.024	0.048	0.120
No. of players	94	94	94	94
No. of obs.	470	470	470	470

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For Time treatment groups (Table 3.4(b)), we find that the coefficient for IDF is positive and statistically significant (at the 5% level), indicating that on average, more patient fishers exhibit higher extraction rates. The coefficient of IDF is 20% of the maximum possible amount that can extracted per round, which suggests a large difference in extraction rates between patient and impatient fishers.

For the control group we find no evidence of extraction rates being related to fishers' IDF or to fishers' myopic behavior. This finding is to be expected, as standard CPR experiments do not include heterogeneous time preferences in their designs, and thus do not provide realistic incentives to study the effect of time preferences on extraction rates. Indeed, the motivation of including the time treatment was to address this limitation.

Even though our results are not aligned with the theoretical prediction, they do prove to be consistent with each other: both self-reported and revealed data show that higher patience is not associated with greater resource conservation.

3.4 Discussion

A recent strand of literature investigating the effect of time preferences on natural resource extraction behavior shows that impatient individuals engage in more intensive resource extraction activities. Our findings suggest otherwise; that patient fishers extract more than impatient ones. In this section, we provide potential explanations for this result, and follow with a discussion on the limitations of our study.

1. Disinvestment Effect

Farzin (1984) argues that time preferences can impact extraction behavior in two distinct and countervailing ways: (i) the conservation effect, where high time preferences (i.e., impatience) render future consumption substantially less attractive; and (ii) the disinvestment effect, where high time preferences lead to lower investment in extraction technology. Indeed, building up capacity to extract large amounts of fish requires substantial investment in buying and maintaining fishing equipment. A rational fisher discounts the future value of her investments, and then chooses how to allocate her resources between present consumption and investment for the future. Taking this into consideration, an impatient fisher will overweight the value of her benefits in the present, finding present consumption hard to resist. In every period, an impatient fisher will prefer to consume today, thus enjoy her benefits today, instead of investing in fishing gears and collecting the benefits in later periods. Fisheries in Zanzibar are generally characterized as small-scale and artisanal, where most fishers do not count on large amounts of disposable income, having a negative impact on their ability to increase their fishing capabilities. Based on the promise of higher future income, patient fishers are more willing to accept reduced current consumption and invest in fishing capabilities than more impatient ones. Given that the difference in productivity between patient and impatient fishers stems from using high impact and costly gears, the disinvestment effect dominates the conservation effect in small-scale artisanal fishery settings such as the one under study.

<u>2. Cognitive abilities</u>

Previous studies argue that intelligence level is linked to both cooperative behavior in prisoner's dilemma (or Public goods games) (Proto et al. 2014) and patience (Al-Ubaydli et al. 2013). We explore further along these lines by looking at the relationship between extraction level and cognitive ability. Given the high correlation between general intelligence and working memory (Suss et al. 2002, Conway et al. 2003), we ran an incentivized memory task as a proxy for cognitive ability and then regressed it against (1) fishers' extraction rates, and (2) fishers' time preferences. Note that this measure of cognitive ability is different and independent from participants' comprehension of experiments, which was assessed using questions related to experiment protocols. Our results (Appendix B Table 3.9(a) and Table 3.9(b)) show that the average performance in the memory task is (i) negatively associated with extraction rates in the experiment, and (ii) positively associated with IDFs. In other words, fishers exhibiting higher cognitive ability are more patient and extract more. We argue that patient fishers, who also have higher cognitive ability, view natural resource extraction from a completely different perspective than impatient fishers with lower cognitive ability. Fishers with higher cognitive abilities are better able to predict others' actions, and therefore adapt their own behavior in order to pursue their desired outcome, particularly in an experimental setting (Gill and Prowse 2014). They exploit fisheries in order to smooth their consumption over time and to do so they invest in fishing capabilities, which allows them to extract more in the future. This investment provides greater flexibility and opportunity, thereby reducing the risk of non-extraction in the future, for instance, in the case of an exponential increase in the fisher population. In contrast, fishers with lower cognitive abilities do not plan for the future, and instead apply a subsistence-based heuristic, which leads to lower extraction levels. Therefore, cognitive ability, in conjunction with the disinvestment effect, provides a reasonable explanation as to why patient fishers are less inclined to engage in resource conservation.

In this way, our consideration of cognitive ability adds a more nuanced perspective to the discussion on time preferences and resource extraction.

<u>Limitations and future research suggestions</u>

Our research expands on the relationship between time preferences and resource extraction behavior, yet it has several limitations. First, although we attempted to test the disinvestment effect by assessing fishers' costs, only a portion of our sample could provide somewhat reliable estimates. Nevertheless, regression analysis based on this sub-sample revealed that, in accordance with the disinvestment effect, patience was associated with higher investment in fishing equipment (see Appendix B Table 3.10). Therefore, we suggest future studies investigate this issue more closely.

Second, we cannot be certain how the conservation and disinvestment effects interact in the long run, i.e., more than 14 days. Since the benefits were delayed for such a short period of time in our experiments, individuals may have given greater consideration to their effort and investment decisions. As resource conservation is generally regarded as a long-term issue, a longer time horizon may lead to greater environmental consideration in the decision-making process.

Third, and finally, our research design does not allow us to completely rule out the possibility that cognitive ability is the main driver behind higher extraction rates. Although we measure cognitive ability using a memory performance task, it does not capture the multi-faceted nature of general intelligence. In addition, in order to disentangle the effects of cognitive ability and patience, future studies should carefully manipulate experimental design to gauge a variety of resource extraction settings.

3.5 Concluding remarks

Our study sheds light on the importance of the disinvestment effect and resource users´ cognitive ability, both of which play a key role in determining the effect that time preferences have on resource extraction behavior. While our results do not come to the same conclusion as earlier studies, they complement and expand on earlier research by emphasizing the significance of the above-mentioned factors. Future researchers should take into consideration the questions raised by our study, as they demonstrate that the relationship between individual time preferences and resource extraction behavior is a complex one, where contextual characteristics can be highly influential.

Appendix B

Table 3.5: List of variables

IDF.	0-1	An individual´s discount factor which he/she uses to evaluate present value of future outcomes
Present biased (=1)	0 or 1	Whether or not the individual is dynamically inconsistent
Risk averse (=1)	0,1	Whether or not the individual is risk averse
Untrustworthy (=1)	0,1	Whether or not the individual trust others; thinks are trustworthy or not
Cellphone (=1)	0,1	Whether or not the individual owns a cellphone
Fishing skills	1-5	Self-declared fishing skills (Extremely good-extremely poor)
Age		Number of years
Alternate livelihood		0 = no other livelihood; 1 = farming; 2 = skilled labor 3 = unskilled labor; 4 = own business
Education		0 = no formal education 1 = primary; 2 = secondary; 3 = tertiary
Electricity (=1)		Whether or not the individual has electricity at home
Vessel ownership		Whether or not the individual owns the vessel: 1 = owned by the individual herself; 2 = partly owned; 3 = borrowed 4 = crew member; 5 = other arrangement
Boat type		The type of boat used for fishing: 1 = canoe; 2 = outrigger canoe; 3 = Dhow; 4 = Mashua; 5 = Dingy; 6 = Ngwanda; 7 = others
Crew size		Number of people in the boat crew
Avg. IC performance		Individuals Average Performance in 4 rounds of memory task

Table 3.6: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Age	40.90	14.74	17	80
fishing experience	21.23	13.88	1	70
Household members	7.41	4.41	0	40
education level	1.50	1.03	0	4
Crewsize	5.75	7.78	0	70

		Percentage		
Cell phone		87.30		
Electricity		35.71		
Transport		56.75		
Gear ownership		76.19		
Boat ownership		63.89		
Dago/Migratory fisher		27.78		
Alternative livelihoods:	None (32.94)	Farming (44.44)	Skilled worker (9.52)	Unskilled worker (11.90)

Table 3.7: Time pref. and Income per unit of effort from fishing

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (income per unit of effort)					
IDF	0.142 (0.198)		0.157 (0.199)	0.124 (0.197)	0.0401 (0.200)	0.132 (0.208)
Present biased (=1)	-	**-0.293* (0.152)**	**-0.300** (0.152)**	**-0.288* (0.156)**	**-0.371** (0.170)**	**-0.507*** (0.177)**
Risk averse (=1)	-	-	-	-0.248 (0.162)	-0.270* (0.159)	-0.224 (0.159)
untrustworthy (=1)	-	-	-	-	0.105 (0.149)	0.194 (0.157)
Age	-	-	-	-	**-0.013** (0.00519)**	**-0.0137** (0.00534)**
Edu	-	-	-	-	0.0415 (0.0847)	0.0180 (0.0874)
Electricity (=1)	-	-	-	-	0.208 (0.159)	0.225 (0.163)
Alternate livelihood						
1.alternatelivelihood	-	-	-	-	0.117 (0.164)	0.145 (0.170)
2.alternatelivelihood	-	-	-	-	**-0.458* (0.234)**	**-0.452* (0.234)**
3.alternatelivelihood	-	-	-	-	-0.261 (0.286)	-0.244 (0.292)
4.alternatelivelihood	-	-	-	-	-0.0927 (0.265)	0.128 (0.295)
Fishing skills	-	-	-	-	0.0373 (0.0828)	0.00499 (0.0909)
Boat type	-	-	-	-	-	0.000265 (0.000510)
Crew size	-	-	-	-	-	0.00616 (0.00656)
_cons	**7.887*** (0.132)**	**8.038*** (0.0849)**	**7.939*** (0.135)**	**8.128*** (0.182)**	**8.522*** (0.402)**	**8.370*** (0.463)**
R-sq	0.003	0.015	0.018	0.031	0.107	0.164
N	187	187	187	187	186	176

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
OLS regression model where dependent variable is *income per unit of effort* from fishing activities

Table 3.8: Time preferences and extraction in CPR experiments

Table 3.8.1 (a): time preferences and extraction in CPR experiments: pooled

	Control groups				
	(1)	(2)	(3)	(4)	(5)
	Extraction rate				
IDF	0.138 (5.902)		0.404 (5.886)	-0.0443 (5.852)	-6.222 (6.100)
Present biased (=1)		-7.684 (5.879)	-7.696 (5.880)	-8.744 (5.765)	-6.488 (5.899)
Round number					
2.round_number	-0.213 (6.483)	-0.213 (6.460)	-0.213 (6.466)	-0.213 (6.316)	-0.213 (6.286)
3.round_number	1.596 (7.005)	1.596 (6.964)	1.596 (6.970)	1.596 (6.902)	1.596 (6.749)
4.round_number	8.936 (6.916)	8.936 (6.894)	8.936 (6.901)	8.936 (6.708)	8.936 (6.564)
5.round_number	7.766 (6.901)	7.766 (6.892)	7.766 (6.900)	7.766 (6.761)	7.766 (6.618)
Risk averse (=1)	-	-	-	3.499 (4.698)	**9.181**** **(4.609)**
untrustworthy (=1)	-	-	-	**19.13***** **(4.359)**	**19.13***** **(4.540)**
Age	-	-	-	-	-0.190 (0.268)
Edu	-	-	-	-	0.436 (2.787)
Electricity (=1)	-	-	-	-	-3.441 (4.727)
Alternate livelihood					
1.alternatelivelihood	-	-	-	-	**18.19***** **(5.120)**
2.alternatelivelihood	-	-	-	-	4.611 (11.15)
3.alternatelivelihood	-	-	-	-	**-12.97*** **(7.742)**
4.alternatelivelihood	-	-	-	-	**-42.38***** **(7.301)**
Cons	**71.29***** **(5.840)**	**72.77***** **(4.767)**	**72.52***** **(5.920)**	**60.14***** **(7.698)**	**70.28***** **(10.67)**
R^2	0.007	0.011	0.011	0.050	0.099
No. of players	94	94	94	94	94
No. of obs.	470	470	470	470	470

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Pooled OLS regression model where dependent variable is *extraction rate per round*

Table 3.8.1 (b): time preferences and extraction in CPR experiments: pooled regression models

	Time treatment groups				
	(6)	(7)	(8)	(9)	(10)
	Extraction rate				
IDF	**23.78*** (6.192)**	-	**23.61*** (6.219)**	**24.75*** (6.247)**	**22.20*** (6.180)**
Present biased (=1)	-	3.652 (5.355)	2.292 (5.309)	2.124 (5.141)	4.072 (5.079)
Round number					
2.round_number	5.745 (7.523)	5.745 (7.668)	5.745 (7.529)	5.745 (7.454)	5.745 (7.336)
3.round_number	9.787 (7.530)	9.787 (7.569)	9.787 (7.524)	9.787 (7.466)	9.787 (7.362)
4.round_number	5.957 (7.468)	5.957 (7.538)	5.957 (7.478)	5.957 (7.406)	5.957 (7.295)
5.round_number	4.681 (7.515)	4.681 (7.604)	4.681 (7.519)	4.681 (7.496)	4.681 (7.368)
Risk averse (=1)	-	-	-	**-16.34*** (5.124)**	**-19.99*** (5.375)**
untrustworthy (=1)	-	-	-	2.936 (4.707)	4.309 (4.704)
Age	-	-	-	-	-0.527*** (0.174)
Edu	-	-	-	-	-5.443** (2.667)
Electricity (=1)	-	-	-	-	-5.647 (4.777)
Alternate livelihood					
1.alternatelivelihood	-	-	-	-	11.63** (5.792)
2.alternatelivelihood	-	-	-	-	13.49* (7.346)
3.alternatelivelihood	-	-	-	-	20.25*** (7.551)
4.alternatelivelihood	-	-	-	-	-37.45*** (9.776)
Cons	64.85*** (6.693)	78.93*** (5.782)	64.42*** (6.805)	73.70*** (8.269)	98.57*** (11.62)
R^2	0.035	0.005	0.035	0.057	0.111
No. of players	94	94	94	94	94
No. of obs.	470	470	470	470	470

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Pooled OLS regression model where dependent variable is *extraction rate per round*

Table 3.8.2 (a): time preferences and extraction in CPR experiments: random effects model

	Control groups				
	(1)	(2)	(3)	(4)	(5)
			Extraction		
IDF	0.138 (10.99)		0.404 (10.95)	-0.0443 (10.62)	-6.222 (11.05)
Present biased (=1)		-1.466 (21.46)	-1.759 (22.01)	-1.970 (22.95)	-5.402 (27.30)
Round number	**2.468**** **(1.165)**	**2.468**** **(1.165)**	**2.468**** **(1.166)**	**2.468**** **(1.169)**	**2.468**** **(1.178)**
Risk averse (=1)	-	-	-	3.499 (8.627)	9.181 (8.096)
Untrustworthy (=1)	-	-	-	**19.13**** **(7.901)**	**19.13**** **(8.229)**
Age	-	-	-	-	-0.436 (0.297)
Edu	-	-	-	-	0.436 (5.151)
Electricity (=1)	-	-	-	-	-3.441 (8.278)
Alternate livelihood					
1.alternate livelihood	-	-	-	-	18.19* (9.427)
2.alternate livelihood	-	-	-	-	4.611 (18.91)
3.alternate livelihood	-	-	-	-	-12.97 (13.29)
4.alternate livelihood	-	-	-	-	**-42.38***** **(12.70)**
Cons	**67.51***** **(8.401)**	**68.99***** **(5.341)**	**68.73***** **(8.614)**	**56.35***** **(12.61)**	**66.49***** **(18.81)**
R^2	0.0217	0.0187	0.0218	0.0362	0.0579
No. of players	94	94	94	94	94
No. of obs.	470	470	470	470	470

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel regression model where dependent variable is *extraction rate per round*, so each individual player has 5 observations

Table 3.8.2 (b): time preferences and extraction in CPR experiments: random effects model

	Time treatment groups				
	(6)	(7)	(8)	(9)	(10)
			Extraction		
IDF	**23.78****		**23.61****	**24.75****	**22.20****
	(10.84)		**(10.89)**	**(10.61)**	**(10.13)**
Present biased (=1)		3.652	2.292	2.124	4.072
		(9.385)	(9.229)	(8.624)	(8.233)
Round number	0.957	0.957	0.957	0.957	0.957
	(1.336)	(1.336)	(1.338)	(1.341)	(1.351)
Risk averse (=1)	-	-	-	-16.34*	-19.99**
				(8.824)	(9.111)
Untrustworthy (=1)	-	-	-	2.936	4.309
				(7.790)	(7.661)
Age	-	-	-	-	-0.527*
					(0.289)
Edu	-	-	-	-	-5.443
					(4.314)
Electricity (=1)	-	-	-	-	-5.647
					(7.998)
Alternate livelihood					
1.alternate livelihood	-	-	-	-	11.63
					(9.525)
2.alternate livelihood	-	-	-	-	13.49
					(13.30)
3.alternate livelihood	-	-	-	-	20.25*
					(11.71)
4.alternate livelihood	-	-	-	-	-37.45**
	-	-	-	-	(14.69)
Cons	**67.21*****	**81.29*****	**66.78*****	**76.06*****	**100.9*****
	(8.895)	**(6.540)**	**(9.173)**	**(11.85)**	**(18.61)**
R^2	0.0717	0.0317	0.0762	0.1067	0.1850
No. of players	94	94	94	94	94
No. of obs.	470	470	470	470	470

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel regression model where dependent variable is *extraction rate per round*, so each individual player has 5 observations

Table 3.9: Regression models for performance in memory task explaining extraction rates and time preferences

	Table 3.9(a)	Table 3.9(b)
	IDF	Extraction rate
IC perf	**0.0503****	**1.305****
	(0.0270)	**(0.608)**
Risk averse (=1)	-0.203	**-7.438****
	(0.153)	**(3.409)**
Untrustworthy (=1)	-0.118	**8.107****
	(0.146)	**(3.229)**
Age	-0.0109*	**-0.387*****
	(0.00580)	**(0.125)**
Alternate livelihood		
1.alternatelivelihood	0.231	**9.522****
	(0.180)	**(3.838)**
2.alternatelivelihood	0.0657	**11.05***
	(0.257)	**(6.428)**
3.alternatelivelihood	0.105	6.110
	(0.236)	(5.433)
4.alternatelivelihood	-0.845	**-44.88*****
	(0.712)	**(4.027)**
Edu	0.115	-2.888
	(0.0856)	(1.831)
Electricity (=1)	0.00816	-1.094
	(0.151)	(3.415)
Social pref.	-	-
1.Social pref.	-0.245	-
	(0.903)	
2.Social pref.	-0.247	-
	(0.891)	
3.Social pref.	-0.384	-
	(0.893)	
Vessel ownership	-0.000674	-
	(0.000505)	
Crew size	-0.00992	-
	(0.00900)	
Time Treatment (=1)	-	9.076*
		(3.176)
round number	-	
2.round number	-	2.766
		(4.808)
3.round_number	-	5.691
		(4.994)
4.round_number	-	7.447
		(4.914)
5.round_number	-	6.223
		(4.950)
Cons	0.995	**90.34*****
	(0.949)	**(10.54)**
sigma	0.834***	
	(0.0863)	
R^2	0.053	0.085

No. of players	188	940
No. of observations	188	188

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
1: tobit model, dependent variable is *Individual discount factors*
2: Pooled regression model where dependent variable is *extraction rate per round*

Table 3.10: Investment and time preferences

OLS regressions with ln (Investment) as the main dependent variable

	(1)	(2)
	Ln (investment)	
IDF	**1.325****	**1.290****
	(0.568)	**(0.543)**
Present biased (=1)	0.707	0.602
	(0.529)	(0.554)
Risk averse (=1)	-0.311	-0.258
	(0.380)	(0.398)
Untrustworthy (=1)	0.432	0.371
	(0.421)	(0.455)
Age	0.00725	0.0110
	(0.0148)	(0.0158)
Edu	-0.102	0.00174
	(0.236)	(0.247)
Electricity (=1)	0.692	0.628
	(0.435)	(0.437)
Alternate livelihood		
1.alternatelivelihood	-0.136	-0.120
	(0.499)	(0.495)
2.alternatelivelihood	**1.506****	**1.789****
	(0.695)	**(0.746)**
3.alternatelivelihood	-0.352	-0.296
	(0.848)	(0.823)
4.alternatelivelihood	1.280**	1.822**
	(0.504)	(0.781)
Fishing skills	-	0.275
		(0.220)
Dago fisher (=1)	-	0.722
		(0.513)
Cons	10.22***	9.316***
	(1.017)	(1.155)
R^2	0.145	0.166
N	125	124

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: (1): OLS regression model where dependent variable is *investment in fishing equipment*

Chapter 4:

When patience leads to destruction: the curious case of individual time preferences and the adoption of destructive fishing gears*

4.1 Introduction

Destructive fishing is considered to be one of the most important problems in marine governance (Clark et al. 2005, Sethi et al. 2005). According to the United Nations Environment Program, about 25 percent of fisheries worldwide are in jeopardy of collapse due to destructive fishing (Shakouri et al. 2010).

The threat of destructive fishing, such as use of poison, dynamite and illegal nets, is especially devastating for inshore fisheries in tropical and developing countries where small communities are engaged in subsistence fishing (Belton and Thilsted 2014). The collapse or even serious degradation of local fisheries due to the use of destructive fishing gears has a very negative impact on the material well-being of these communities. As a result, there have been frequent attempts to persuade fishers who are using destructive gears to change their behavior, and switch to more environmentally-friendly fishing gears (Signa et al. 2008). In most cases this involves policy measures, such as gear-exchange programmes or monetary incentives for resource conservation(Verheij et al. 2004). These policies are based on the assumption that a major motivation for using destructive fishing gear is impatience or short-sightedness (low discount factors) and the lack of availability of high capital stocks.

This assumption is based on standard economic models of renewable resources, going back to Hotelling (1931), which frame natural resource extraction as an intertemporal optimization problem, where discount factors[1] indicate the value given to expected future consumption. This implies that, higher discount factors mean higher valuation of expected future consumption, which leads to lower rates of extraction and vice versa (we refer to this as conservation effect).

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* Chapter 4 is co-written with Marco Janssen, Achim Schlueter and Hauke Rueter.

[1] Throughout the article we use the term discount factor (IDF); where 0 is impatient and 1 means patient. IDF is inversely related to discount rates, so IDF = $(1 + \rho)^{\wedge -1}$; where ρ is the individual discount rate.

However Farzin (1984) offers a different point of view and argues that, for high cost of extraction, the relationship between discount factors and resource extraction is opposite to the generally held one, meaning that higher discount factors result in higher extraction levels and vice versa. This is based on the view, that, patient fishers´ are able to invest more in their extraction capabilities (we refer to this as disinvestment effect).

We add to this discussion by applying the underlying logic of these models to the specific context of the adoption of destructive fishing gears in small-scale artisanal fisheries. Our main objective is to distinguish between scenarios where the policies based on conservation effect are justified and the conditions under which they are not justified, by providing a better understanding of fisher's motivation to adopt destructive gears and its relationship to individual time preferences.

This research question is motivated by empirical research in Zanzibar which suggests that patient fishermen have higher extraction level since they can invest more in their extraction capability (see Chapter 3). This surprising finding triggered some interesting and unanswered questions. Does the relationship between time preferences and extraction levels change depending on the circumstances? What role do external factors play in this decision-making? How do beliefs and perceptions impact this relationship? While these questions are motivated and based on empirical research in Zanzibar fisheries, they are not limited to this case. The use of destructive fishing gear is common in other regions as well, such as different parts of East Africa (Guard and Masaiganah 1997, Cinner 2009, Wells 2009), Indonesia and other parts of Southeast Asia (Cassels et al. 2005, Burke et al. 2006), parts of South Asia (Rajasuriya et al. 2004) along with other developing and developed country fisheries.

For the purpose of this paper we limit ourselves to focus on the case of destructive fishing gears in small scale communities with open or shared access to the resource.

Our model shows that the impact of discount factors on adoption of destructive fishing gears is mediated by two key factors (i) the nature of destructive gear i.e. whether the destructive gear is cost-cutting low-profit gear or whether it is high-cost high-profit fishing gear, and (ii) the level of social dilemma, meaning the number of people who share the same resource. Additionally, we find that individual beliefs about the actions of other resource users and future resource condition can have a significant influence on whether the conservation effect prevails or not.

Overall, our model helps in in clarifying the conditions under which the above mentioned policy measures may be expected to work as intended and conditions where other alternative policy measures should be adopted.

4.2 Background information

4.2.1 Destructive extraction methods

Destructive methods are defined as fishing methods, gears or practices whose impact is so indiscriminate and/or irreversible that they are universally considered destructive irrespective of the environment in which they are used (FAO 2005-2014). In more concrete terms, these destructive fishing gears typically have a higher propensity to physically damage habitats like corals reefs, capture a high proportion of juvenile fish and target species that are crucial for sustainability of the system as a whole (McClanahan and Mangi 2001, McClanahan and Mangi 2004, Mangi and Roberts 2006, Mangi et al. 2007).

Examples of destructive gears in small scale fisheries include beach seine, ring nets, explosives/dynamites, spear-guns and poison(Jiddawi and Öhman 2002, Cinner 2009).

4.2.2 Destructive fishing methods and time preferences

In economics, time preferences refer to the relative valuation placed on income/consumption at an earlier date compared with its valuation at a later date. Earlier research shows that there is a considerable degree of heterogeneity in individual time preferences, some value future consumption very highly while others do not (Tanaka et al. 2010). Similar pattern can be observed for fishers as well (Teh et al. 2014).

According to standard economic models, fishers with high value for present consumption are likely to extract more resources (Koopmans 1974). This is especially true in the case of destructive fishing methods. Unlike overfishing, the damage caused by using destructive fishing gear is highly visible and occurs in very short period of time (Cinner 2009). Fishers using destructive fishing method are much more aware of the fact that they are causing serious long term damage to the resource, and that the future productivity of the resource is going to be very low as a result of their actions. So it stands to reason, that, a key determinant of adopting destructive fishing method would be the subjective value given to future profitability and sustainability of the fish stock. This suggests that we should expect that people with higher subjective value of future consumption (patient fishers) are less likely to use destructive fishing gears. On the other hand, those who give lower subjective value to future consumption (impatient fishers) are more likely to use destructive fishing gear, as they can enjoy higher immediate consumption even at the cost of potentially large decrease in future consumption. This is termed as the conservation effect of time-preferences.

However, these standard economic models do not account for the fact that, adoption of destructive gears typically requires initial investment (both capital and time in learning to operate the new gear) (Farzin 1984). Destructive fishing methods can be more expensive, either in terms of fixed or variable costs than the traditional methods. Investing a substantial amount of money in buying a destructive gear means, that this money is not available for present consumption. This consideration is especially important for artisanal fishers, who in general don’t possess large reserve capital (Cinner 2009). Overall, this point of view suggests that higher preference for present consumption is negatively associated with the possibility of using destructive gear, as these gears generally require larger initial investment. This is termed as the disinvestment effect of time-preference.

Consider, for example, the extreme case of dynamite fishing, one of the most destructive fishing methods. A typical blast kills all fish within 50-70 m radius. After the explosion, a small proportion of fish float to the surface to be collected by the fishermen. In this way, fishers are able to collect more fish per unit of effort compared to other traditional (or even non-traditional) gears. However, this increase in present income comes at the cost of future productivity of the ecosystem. According to Guard and Masaiganah (1997), dynamite fishing causes three major problems; (i) a lot of fish is wasted as a result of blasts since fishermen only get a small fraction of the fish killed, others just sink or are trapped (ii) dynamite fishing is untargeted so a lot of juvenile fish and fish eggs are destroyed, and lastly (iii) reduction of demersal plankton as well as serious destruction of corals leading to loss of productivity as the regeneration rate of corals affected by dynamites is very low. All of this result in decreasing the growth rate of fish stock, leading to lower productivity and stock levels in the future[2]. According to standard economic models, an impatient fisher is more likely to use dynamite fishing since he/she would not care about the loss of future income as much as a patient fisher.

However, dynamites are often more expensive than other traditional gears. For example in Kenya/Tanzania, dynamite required for one blast may cost somewhere around $ 5-10. On the other hand a big/small trap costs around half the amount and lasts for 3-6 months on average whereas the dynamite costs are only for one day (Mangi et al. 2007). In short, dynamite fishing is a much more expensive proposition requiring a substantial amount of initial capital investment. So according to the disinvestment effect, we should expect that fishers who are patient and can afford to wait for future consumption, are more likely to invest in fishing gear which makes dynamite fishing possible.

We have two competing accounts of the impact of individual time preferences on the decision to adopt destructive fishing methods. In this paper, we try to understand the conditions and assumptions under which the conservation effect overtakes disinvestment effect and vice versa.

4.2.3 Adoption of destructive extraction methods as technology diffusion phenomenon

The stereotypical description of artisanal communities is fishers engaged in traditional or primitive methods threatened by the advent of large-scale modern fishing industry. However, in many cases, these artisanal fishers are aware of small-scale innovations in extraction methods. These innovative, yet destructive fishing methods are adopted relatively slowly, and generally the adoption is not universal

[2] This is just in terms of fisheries related loss. According to Pet-Soede et al. (1999) cumulative private gain from using destructive gears is 4 times smaller than foregone social benefits (including non-fishing benefits such as tourism etc.).

with most fishers sticking to conventional methods. In general, these methods start from a small area and spread to different fishing sites over time (Wells 2009).

In this sense the adoption of destructive fishing methods shares a lot of similarities with technology diffusion process.[3] Technology diffusion research seeks to understand how new products spread throughout a society over time (Rogers 2010). Bass (1969) is one of the most prominent examples of this approach. For a detailed review of this stream of literature see Meade and Islam (2006).

In recent years, agent based modeling approach has been used extensively to build models explaining key features of the innovation diffusion process (for a comprehensive review Garcia and Jager (2011), Kiesling et al. (2012)). Agent based modeling approach to diffusion offers two key advantages over the traditional models; (1) Agents make decisions based on their own preferences, and decision rules. However in contrast to more traditional (differential equation based) models these rules and preferences differ for different agents. (2) Agents are affected by what is happening around them, as agents are connected to others in the form of a social network. Decisions made by others in the social network affect agent´s own choices.

We take the basic approach from these agent based models of technology diffusion and apply them to the specific context of adoption of destructive fishing gears in small-scale artisanal fisheries.

4.3 Model

Our model consists of three major components and one ancillary one:

I. Natural resource; fish stock in our case
II. Agents; fishers in our case
III. Resource extraction technologies; fishing gears in our case

And lastly a social network structure which determines how agents are connected to each other.

The role of network structure in diffusion of technologies has been a well-researched subject (see for example Rahmandad and Sterman (2008)). We implement a scale-free network. The main reason for using this particular network structure is that it represents key features of social interaction among fishers in many small-scale artisanal fisheries. In small-scale fishers a handful of individuals play a key role in influencing the decisions regarding fishing activities. In some cases they influence fishermen's decision by providing material support to other fishermen who face financial or other physical constraints (Crona et al. 2010, Ruddle 2011). However in many cases their role as information aggregators is the most important one. Unskilled or inexperienced fishers often take their cues from

[3] At this point it should be noted that although some of the destructive fishing method are truly innovative in the sense that they use newer technologies or apply new ways of using old gears, however others are just methods which fall out of favor over a period of time. As we are more interested in how these destructive gears may spread as compared to how they originate so we believe using technology diffusion models captures the basic processes of spreading of destructive methods more effectively.

these successful and well-connected individuals (Bodin and Crona 2008, Ferrol-Schulte et al. 2014). Indeed this is true for other resources as well (such as farmers) where key well-connected individuals enjoy disproportionately larger role in determining agricultural practices and reap substantially higher margins (Fafchamps and Minten 1999, Conley and Udry 2010).

For the purpose of this paper we focus mostly on the gear properties and agents´ decision-making processes which form the major components of the model, while keeping the social network constant. For more detailed analysis of the impact of social network on technology diffusion refer to Valente (1995), Valente and Davis (1999), among others.

4.3.1 Adoption of destructive fishing gear: agent-based model

Consider a case of small-scale artisanal fisheries, which has the following characteristics;

1) Resource (fish stock) which is defined by the standard logistic population growth function:

$$\Delta R / \Delta t = g * R_t * (1- R_t/K) \qquad (4.1)$$

where g is the intrinsic growth rate of the resource, K is the carrying capacity and R_t is the condition of resource in time period t.

2) "N" (=500) total population of agents (fishers) in the model; while "n" number of agents share the same resource. Agents extract this resource for their personal consumption.
3) Different gear types, which are defined by the following characteristics:

$$G_m = f(L_m, D_m, C_m) \qquad (4.2)$$

where L_m is the profit-to-effort ratio (profits per unit of effort), D_m the damage-to-effort ratio (the damage done to the resource per unit of effort) and C is the related fixed costs.[4]

We assume that gears target the same resource and that each resource unit extracted is priced at the same level. Extracting resources result in increased wealth and consumption which is desirable for agents.

The amount of effort devoted to extraction determines the current earnings along with the gear used for extraction. So agent i´s earnings in time period t (p_{it}) are determined by the effective effort level (X_{it}), total effective effort level (in the same time period) of other agents sharing the common resource ($X_{Jt} = \sum_{j=-\mathrm{i}}^{n} X_{j_t}$), and the current resource level (R_t). Effective effort level is the product of effort level (x_i) and gear (G_m) used by the agent, where gear1 or G1 is the traditional/ environment-friendly gear and gear2 or G2 is the destructive gear. Since we are mainly interested in the gear adoption process, we assume that agent's´ effort level (x_i) is fixed over time.

Current earnings (p_{it}) are given as:

[4] The earnings from each gear are net earnings meaning that they include (day-to-day) operating costs; we assume that these operating costs reflect both the monetary and nonmonetary costs (such as physical labor) of operating the gears.

$$p_{it} = \left(\frac{X_{it}}{\left(\sum_{j=-\mathrm{i}}^{n} X_{j_t}\right)^{v}}\right)^{a} * \ (R_t)^{b}$$

$$= \left(\frac{x_i * \mathrm{L}_m}{(\sum_{j=-\mathrm{i}}^{n} X_{jt})^{v}}\right)^{a} * \ (R_t)^{b} \qquad (4.3)$$

Where v is the coefficient indicating congestion in terms of fishing effort[5], a & b are coefficients for earnings and resource level respectively which determine the total current earnings; a + b < 1 which depicts the decreasing marginal return of effort and resource level.

Earnings from fisheries extraction results in higher wealth (W).[6] Wealth at the start of time period *t* is given as:

$$W_{it} = W_o + \sum_{j=1}^{t-1} \mathrm{Si} * \ p_{ij}$$

$$\Delta \mathrm{W_i} / \Delta \mathrm{t} = \mathrm{S_i} * \ p_{it} \qquad (4.4)$$

Where W_o is the initial wealth level which is determined randomly at the start of the simulation. S_i is the savings rate which is given as $S_i = f(\delta_i, s_i)$ where s_i is the individual specific saving rates, and δ_i is the individual discount factor representing an individual's time preference.

Extraction activities result in destroying part of the resource. The damage done to the resource (V) by all agents in current time period depends on the effort level and gear being used:

$$\mathrm{V}_t = \left(\sum_{i=1}^{n} (\mathrm{Dm}_{it} * \mathrm{x}_i)\right)^{c} * (R_t)^{d} \qquad (4.5)$$

Where Dm_{it} is the damage-to-effort ratio (damage per unit of effort) of the gear G_m being used by agent *i* in current time period, such that D_m for gear1 (traditional gear) is always less than D_m for gear 2 (the destructive gear).

Eq. 4.1 gives us the resource available to agent population for extraction in next period as[7]:

$$R_{t+1} = R_t + g * (R_t) * \left(1 - \frac{(R_t)}{K}\right) - V_t$$

4.3.2 Agent´s decision-making process (Gear choice decision)

At the start of simulation, all agents use the same traditional gears. Additionally, we assume that the system is in equilibrium, meaning that agents (fishers) are extracting at a level which is economically

[5] This reflects the fact that if all fishers apply a lot of effort in the same time period their individual earnings in the current time period go down due to the congestion effect (Brown 1974).
[6] Agents start with different levels of wealth at the start of the simulation.
[7] This form of equation 1 is equivalent to Gordon-Schaefer fisheries model for discrete time steps

and biologically sustainable.[8] Agents alternate between three states: not susceptible, susceptible, and switched. Agents in the “not susceptible” state keep using the same gear they were using before without making any calculations. Agents in the “susceptible” state decide whether to stick with the gear they are using or to switch to the alternative gear. Agents in the “switched” state have already made the switch to the alternative gear.[9] Agents only consider switching once they become susceptible. Here we report results from the most basic version where agents become susceptible as soon as the destructive fishing gear is introduced.[10]

The central concern in this article is the role of time preferences in determining the adoption of destructive fishing gear, so we assume that agents consider future implications of their actions and make plans accordingly. In deciding whether to switch to a more destructive gear (gear 2), agents consider the present and the future earnings from switching[11]. However as agents do not possess perfect information about the present or the future so they calculate expected percentage of higher benefits from switching (E[Z]) based on their beliefs about future state of the world:

$$E[Z_{it}] = (E\,[P_{it}\,(G2) - E\,[P_{it}\,(G1)] - disc.[C_{it}]\,)\ /\ E\,[P_{it}\,(G1)] \qquad (4.6)$$

Where $E[P_{it}(G2)]$ is the expected total earnings/profits from using gear 2, $E[P_{it}(G1)]$ is the expected total earnings from using gear 1, and disc. (C_{it}) are the costs associated with switching to gear2, all calculated in time period *t*.

Expected total earnings by each gear depend on expected earnings in current time period $E[p_{it}]$, and the present value of expected future earnings $E[p_{iT}]$.

$$E\,[P_{it}(G_m)]\ =\ E[p_{it}]\ +\ PV(E[p_{iT}])\ = E[p_{it}] + \sum_{h=1}^{T} \delta_i{}^{h} *\ E[p_{i(t+h)}] \qquad (4.6.1)$$

Where δ_i is the individual time preference or discount factor used to evaluate the present value of future earnings[12], T is the planning time horizon of the agent, and $E\left[p_{i(t+h)}\right]$ is the expected earnings in the h^{th} time step from current time period (*t*). Notice that these total earnings are based on agent's expectation in time period *t* about what is going to happen in planning time horizon *T*.

Expected earnings in the current time period t are given by:

$$E[p_{it}] =\ [(x_i * Lm'_{it})\ /\ (X'_{Jt})^{v}]^{a} *\ R_t{}^{b} \qquad (4.6.2.1)$$

[8] Meaning that total extraction level by all agents is roughly equal to maximum sustainable yield and fisheries population growth rate

[9] Note in the baseline model agents don´t switch back to the traditional gear. However in the gear-switch-back model agents can switch back to the traditional gear based on different criteria. The “switched” state allows us the possibility to have different heuristics (rules) for the switch from destructive to traditional gear as compared to the switch from traditional to destructive gear.

[10] We use four different criteria for this vulnerability to switch. The results reported here are from only one of them, for more details see appendix C

[11] Agent's planning time horizon (T number of time steps) is limited. Motivated by interviews with fishermen in Zanzibar, we assume that agents make plans about 4-6 major fishing seasons or in other words two to three years. Changing/Increasing agent's time horizon does not alter our finding qualitatively.

[12] We use exponential discounting in our baseline models.

Where x_i is the fixed effort level, Lm'_{it} is the *assumed* profit-to-effort ratio of gear *m* by agent *i* in time period *t*, R_t is the current resource level and X'_{Jt} is the *assumed* effective total effort by others in the current time period. It should be noted here that agents do not know the real profit-to-effort ratio (L_m) of any gear and have to form expectation about gear productivity (Lm'_{it}) in each time period where they consider switching. Agents´ expectations regarding the productivity of the gear they are currently using are based on their own earlier experience. Whereas, for new gears or gears not being used by the agent, their expectations are based on experience of those using these gears. This expected gear productivity (Lm'_{it} is calculated based on local information from agent's social network so it may differ for different agents and over time.

Expected future earnings ($E[p_{i(t+h)}]$) depend on the effective effort level and the *expected* future resource level($R'_{i(t+h)}$):

$$E[p_{i(t+h)}] = [(x_i * Lm'_{it}) / (X'_{J(t+h)})^v]^a * (R'_{i(t+h)})^b \qquad \forall\ h>0 \qquad (4.6.2.2)$$

Where $R'_{(t+h)}$ and $X'_{J(t+h)}$ are assumptions made by the agent regarding the expected future resource level and the expected extraction level of others respectively. The expected future resource condition $R'_{(t+h)}$ estimate depends on agent´s assumption about the resource growth rate (g_i'), what others are going to do in future ($X'_{J(t+h)}$) and her own actions:

$$R'_{i(t+h)} = f\ [\ (x_i * D_m), X'_{J(t+h)}, g_i'\ ) \qquad \forall\ h>0$$

Similarly the relative costs from switching are given as:

$$C = C(G2) - C(G1)$$

Where C(G1) and C(G2) are costs associated with gear1 and gear2 respectively[13]. Even though agents incur this fixed cost in the time period where they decide to switch (i.e. current time period), we assume that agents see this as an investment with depreciable value for the life span of the gear. The discounted costs (C_{it}) are the agent´s evaluation of the cost of switching in time period *t* using T_c as her planning horizon:

$$\text{Disc. } (C_{it}) = (C) - (\delta_i^{Tc} * RV) \qquad (4.6.3)$$

Where the time period T_c refers to the nearest of either the agent's planning horizon (T) or the time period when the agent expects the resource to collapse. RV is the difference in resale value of gear 2 as

[13] Note that we assume that both gear1 and gear2 have the same life span which is the same as agent´s planning horizon (T). We use two different options for switching point (i) agents only consider switching when their old gear needs to be replaced/repaired (ii) agents consider switching in any given time period. The cost for gear1 changes depending on the option/model, since in the second option/model gear1 costs may only become relevant in future time periods which means they are discounted costs. We use option 1 as the baseline model. However using option 2 does not change our results.

compared to gear 1[14]. In effect, agents weigh the benefits of using gear 2 while assuming that any investment in gear2 will bring benefits until time period T_c therefore spreading part of the additional costs of switching to gear2 over this time horizon.

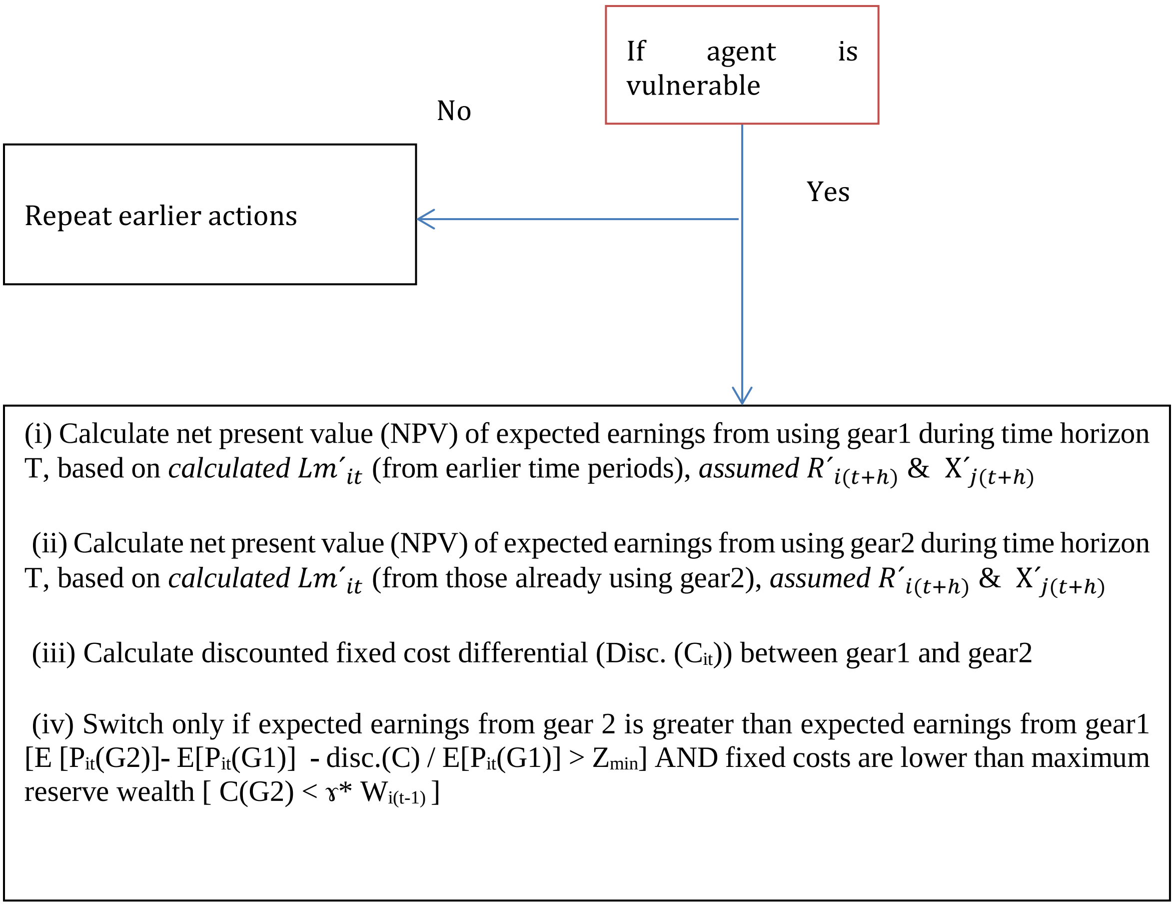
Ultimately the agent only switches to destructive gear if:

$$E[Z_{it}] = (E\,[P_{it}\,(G2) - E\,[P_{it}\,(G1)] - disc.[C_{it}]\,)\,/\,E\,[P_{it}(G1)] > Z_{min} \text{ and } C(G2) < \gamma^*\,W_{it}$$

Z_{min} is the minimum benefit threshold where the agent decides to change from traditional gear to the destructive gear[15], W_{it} is agents´ total wealth and $\gamma^* W_{it}$ is predefined fraction of agent's´ total wealth which the agent is willing to use for investment in fisheries related capabilities.

Figure 4.1 depicts agents´ decision-making process with respect to the switching decision:

Figure 4.1:Agents´ decision-making process with respect to the switching decision



Our modelling approach allows experimentation with different types of assumptions about agents´ beliefs and representing agent heterogeneity. Moreover, we can depict real life situation where fishers

[14] We assume that the resale value of the gear at the end of its lifespan depends on its initial costs only, however it is possible to consider other possibilities in our model. If Tc < T, then resale value is calculated using Straight-line depreciation method.

[15] Z_{min} is equal to 0.05 in our baseline model meaning agents switch even if G2 only provides marginally greater earnings. We experiment with different values of Z_{min} however it does not have any qualitative impact on the relationship between time preferences and adoption of destructive gears.

do not have perfect information about the productivity of the gears. In order to make an informed guess about the productivity of different gears, fishers have to rely on other fishers especially those in their social network. These calculations are based on information received from others, so they change over time as the underlying conditions change. This implies that agents can learn from both the successes and failures of others. This learning effect is a key component of our agent-based model and distinguishes it from other modeling approaches.

4.4 The impact of time-preferences on adoption of destructive gears

An agent's time preference is indicated by the value given to expected future earnings. In our model this is represented by the variable *discount factor* (δ_i). Lower values of discount factor indicate impatience, whereas higher values indicate greater patience.

In order to make their gear choice decision, agents make plans over a fixed period of time (*T*). Destructive gears destroy the growth potential of the resource, thereby decreasing future availability and profitability of the resource. Agents calculate the negative impact of using destructive fishing gear on both the resource itself, as well as, their own future earnings. In this way, agents are able to take into account the conservation effect of discount factors.

The disinvestment effect is captured in our model in two ways: (i) agents discount the fixed costs of buying gears over the life cycle of the gear, or, as long as the resource remains productive (whichever is earlier; T_c), meaning agents account for the resale value of the gear at the end of this time period, and (ii) agent´s saving rate is a function of their discount factor, so agent with higher discount factors are able to save a larger amount of their earnings.[16] As the switching decision depends on the wealth level of agents, so time preferences play an indirect role in determining whether or not agents possess enough financial capital to afford the more expensive destructive gear.

4.4.1 Computational experimental design

The main purpose of our paper is to look at the impact of time preferences on adoption of destructive fishing gears. This implies answering two key questions;

(1) Under what conditions, agent with higher discount factor (i.e., patient fishers) chose the more destructive fishing gear?

[16] Based on earlier research

(2) Under what conditions, agents with higher discount factor (i.e., patient fishers) are more likely to opt for destructive fishing gear as compared to the agents with lower discount factor (i.e., impatient fishers), and vice versa?[17]

In order to answer these questions, we conduct a series of computational experiments. These experiments manipulate factors which can be described in two broad categories; (i) structural factors, such as gear type and level of social dilemma, and (ii) agent's decision-making processes. We are mainly interested in following three variables:

1. Nature of destructive gear
2. Level of social dilemma
3. Agents beliefs and assumptions

For each of these variables, we run simulations only varying the discount factor along with the variable in question to see how it impacts the relationship between discount factor and adoption of destructive gears. Note, in the baseline model we assume that all agents in a given simulation, have the same discount factor.

Table 4.1 gives the initial model parameterization.

Table 4.1: Model parameters summary

n-of-fishers (N)	500	Number of agents/fishers
n-of-innovators (I)	1% of N	Number of fishers who come up with the destructive gear
resource-size (R_o)	40,000	Value of resource at the start of simulation
growth-rate (g)	1.7	Resource growth/reproduction rate
a, b	0.45,0.375	Coefficients for return to effort, state of the resource. Used to generate a decreasing marginal return function.
savings-rate (s_i)	0.3	Agent´s pure saving rate
x_i	-	Individual effort for each agent is fixed, such that, in the initial time period, total extraction by all agents is equal to population growth i.e. $\sum X_i \approx$ pop-g
$\hat{U}$	0.05	Utility threshold level for switching to destructive gear

[17] Notice that the number or proportion of people using the destructive fishing gear is not the main concern; rather total number of people using destructive fishing gear is important insofar as it related to discount factor (patience and impatience).

ɤ	0.3	Proportion of wealth; ɤ*W is represents the maximum amount of wealth agent is willing to use for buying fishing equipment
W_o	0-2000	Agent's wealth; initial values are assigned randomly
T_i	12	Agents´ planning time horizon. Agents consider the consequences of their actions over this planning horizon. T = 12 time steps indicate 3 years.

All experiments were conducted with the parameter values given in table 4.1. Two of our variables are determined randomly at the start of the simulation; agent's initial wealth level (W_o) and the innovative agents who start using destructive gear (I). In order to make sure that our results are not driven by the initial random assignment of these variables, we conduct 20 repetitions for each set of experiments.

Note for all experiments, we allow a 10 time step burn-in period, where agents do not make any decision regarding gear choice. At the end of 10th time step, "*I*" individuals are randomly selected as innovators. These innovative agents start using destructive fishing gear from the next time step. Since, we are mainly interested in short to medium term effects, we stop each simulation run at 120th time step.

For analyzing the role of destructive gears (4.1) and the level of the social dilemma (4.2), we keep different assumptions of agents constant for simplicity reasons; we then analyze the role of various assumptions in the following section (4.3).

4.4.2 The nature of destructive gear

With respect to different types of destructive gears, we differentiate between two major prototypes of destructive gears[18]:

Prototype 1: Destructive gears having lower fixed costs, and lower profits as compared to environmentally-friendly traditional gear

Prototype 2: Destructive gears having higher fixed costs and higher profits as compared to environmentally-friendly, traditional gear

This is motivated by the fact that in real-life small-scale fisheries, destructive fishing gears can range from highly profitable to those which are even less profitable than the traditional gears. Similarly, in terms of capital costs (both fixed and maintenance), some destructive fishing gears (such as beach seines and dynamites) are much more expensive than traditional gears, while others (such as spear guns or poison) are less capital intensive even compared to most basic traditional gears. Similar comparison can

[18] We ignore the other two possibilities as they are less interesting with respect to our research question i.e. the role of time preferences with respect to gear choice decision.

be made between labor cost required to maintain and operate destructive fishing gears (for more details see Mangi et al. (2007)).

In our model gears differ based on:

- Earnings per unit effort (L_m)
- Destruction per unit effort (D_m)
- Cost differential (C)

We define the low-cost low-profit destructive gear such that: L_m (G2) < Lm (G1), D_m (G2) > D_m (G1), and C < 0. On the other hand high-cost high-profit destructive gear is defined as: L_m (G2) > L_m (G1), D_m (G2) > D_m (G1), and C > 0.

For the baseline model we fix the earnings per unit effort (L_m) and destruction per unit effort (D_m) values for both prototypes of destructive gear and only vary cost differential values.[19]

Table 4.2: Gear properties

reward-effort-ratio (L_m)	Traditional gear	1
	Low-cost low-profit destructive gear	0.95
	High-cost high-profit destructive gear	1.5
destruction-effort-ratio (D_m)	Traditional gear	1
	Low-cost low-profit destructive gear	2
	High-cost high-profit destructive gear	2
fixed-cost differential(C)	Low-cost low-profit destructive gear	- (15-50)
	High-cost high-profit destructive gear	50-150

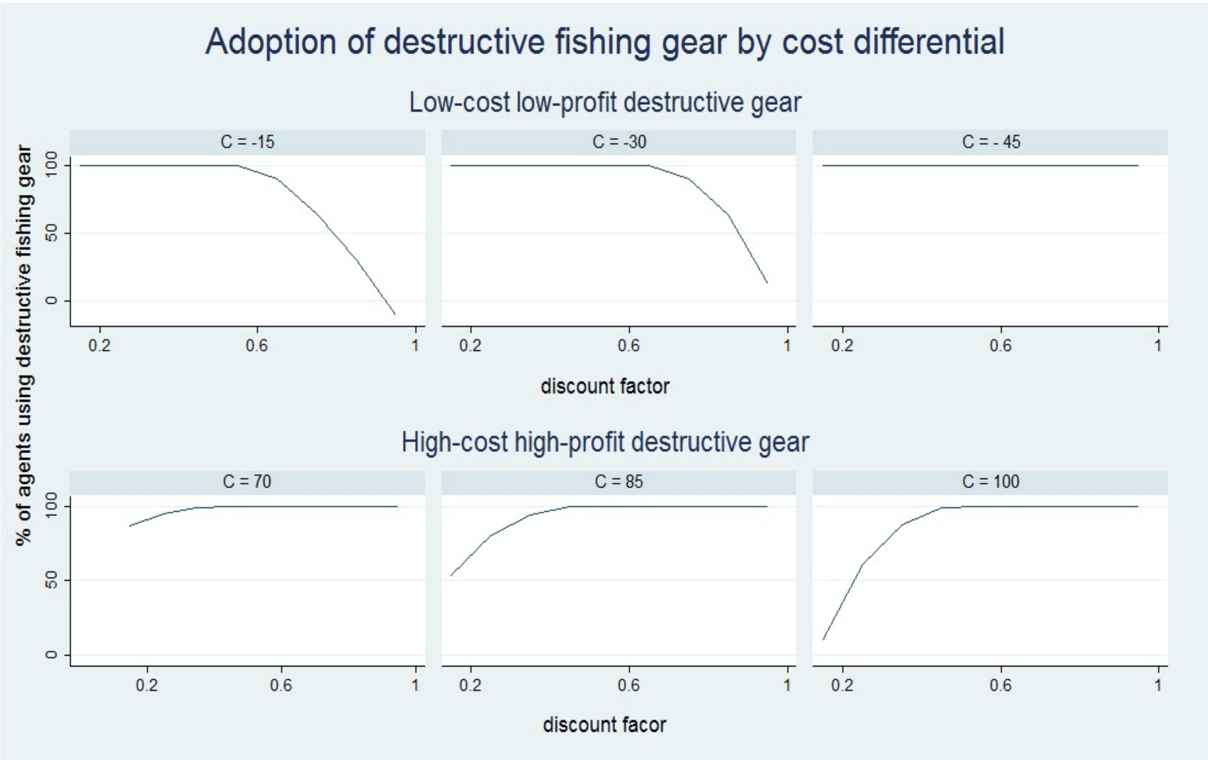
Before turning to the results, it is useful to bear in mind that qualitatively the difference between these two types of gears arise from the fact that disinvestment effect hypothesis is not as relevant to the first type of destructive gear since they require less capital than the traditional gears. For this reason when

[19] Results do not change qualitatively if we change these values.

discussing the first type of gear, we focus on the conditions under which even patient fishers end up switching to these low-cost low-profit destructive gears.

Figure 4.2 presents the difference between adoption process of prototype 1 (low-cost low-profit) and prototype 2 (high-cost high-profit) of destructive fishing gear, across different values of cost differential (C). Negative values of cost differential (C) indicate that the destructive fishing gear is cheaper than traditional gears and results in saving costs for the agents. Positive values of cost differential (C) indicate that the destructive fishing gear is costlier than the traditional gears and that agents´ have to bear these costs in order to switch to the destructive gear.

Figure 4.2: Relationship between time preferences and adoption of destructive fishing gear for different costs levels



Notes:

1) Negative fixed costs differential indicates that destructive fishing gear (gear2) is less expensive than traditional gear (gear1), positive fixed costs differential indicates that destructive fishing gear is more expensive than traditional gear. 2) Y-axis shows the percentage of agents using the more destructive gear at the end of the simulation, which is referred to as the adoption rate in the text. 3) Lower discount factor indicates impatience; higher discount factor indicates patience (such that agents with discount factor of 0 are extremely impatient while agents with discount factor of 1 are extremely patient).

Figure 4.2 indicates the adoption rate of destructive gear (represented by the percentage of destructive gear users) against different discount factor values (where lower values indicate impatience and higher values indicate greater patience). We find that conservation effect is dominant in the case of low-cost low-profit destructive gears. For low to mid-range values of negative cost differential (C = -15 or -30), we observe a negative relationship between discount factor and adoption rate of destructive fishing gear.

In these cases, low discount factors are associated with almost complete adoption of destructive gear. However, adoption rate decreases substantially for higher values of discount factor, indicating that patient agents are less likely to adopt the low-cost low-profit destructive gear.

We also find that, if low cost gear offers enough savings in terms of fixed costs (C = -45), the adoption rate of destructive gears becomes very high (close to 100%), even for very high values of discount factor indicating that even patient fishers switch to the destructive fishing gear. However, these conditions are such that impatient individuals adopt the destructive fishing gear as well.

For high-cost high-catch destructive gear, the disinvestment effect becomes more prominent as the cost differential increases. This can be seen by the difference in steepness of the curve between discount factor and adoption rate for different values of positive cost differential. Increasing cost differential results in lower adoption rates for low values of discount factor. This implies that, while patient agents can afford to invest in buying new gears, impatient agents, either cannot afford the high-cost destructive gear, or, are unwilling to invest in destructive gear due to their preference for immediate consumption.

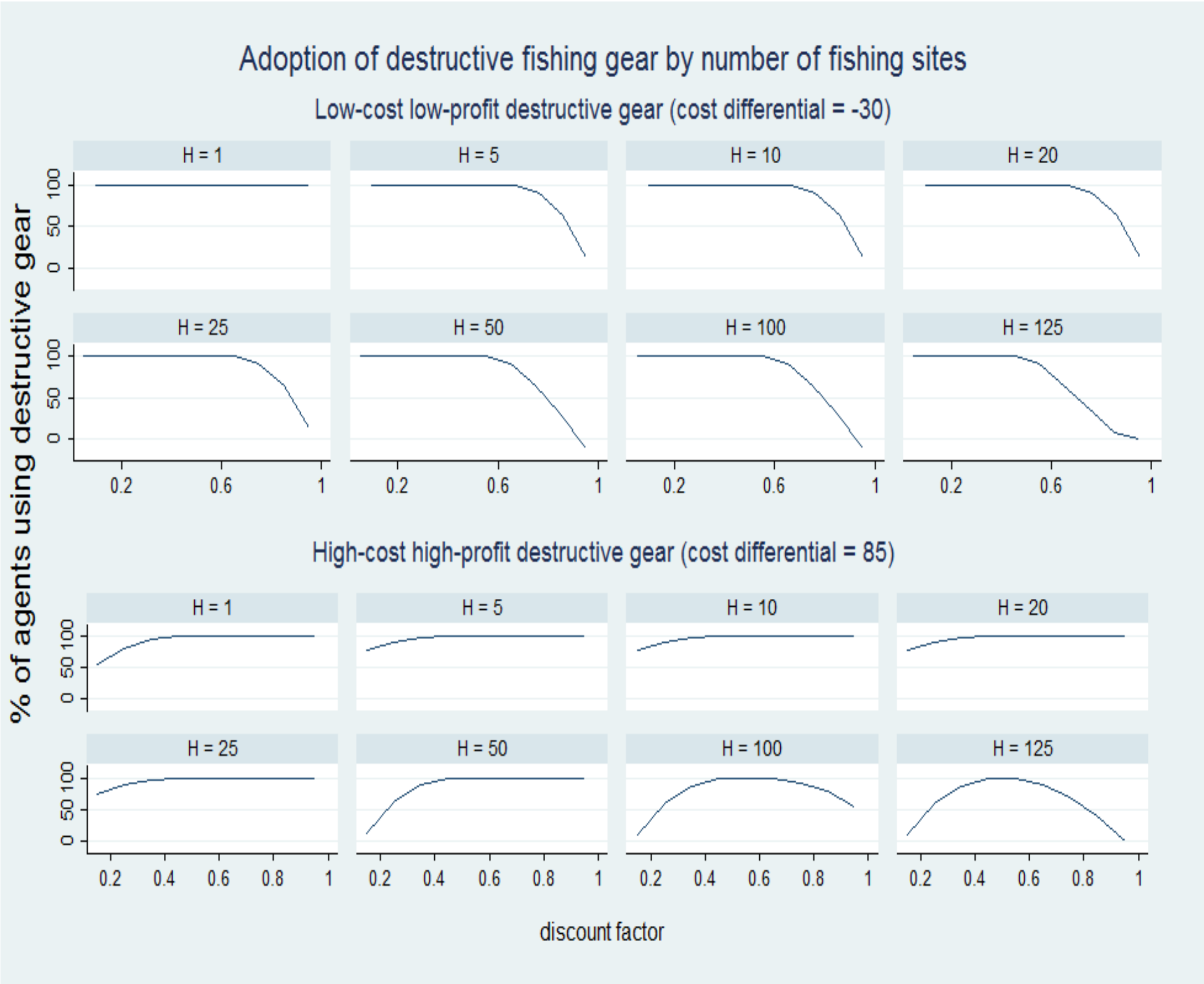
4.4.3 The role of social dilemma

In natural resource settings, social dilemma arises, as extraction from one user has a negative impact on the ability of others to use the same resource (Ostrom et al. 2002). In our baseline model, we start with a situation where all agents share the same resource. This can be understood as an open-access resource system. In real life, most small scale fisheries are shared between communities who restrict the number and identity of users fishing at specific sites. In order to capture this dynamic, we vary the level of social dilemma (externalities) by changing the number of fishing sites available (H = number of fishing sites), and therefore, the number of resource users (agents) sharing each fishing site (n, where n = N / H).

As suggested earlier, we start with one fishing site (H=1) where the total number of agent (N = 500) is equal to the number of agents sharing the resource (n), and consider this as the baseline scenario. Next, we increase the number of fishing site available to agents, thereby decreasing the number of agents per fishing site. In order to make sure that our results are not driven by resource dynamics of dividing the fishing site, we assume that fish stock is divided equally between all sites, and that each site has the same number of agents extracting resource from it. Furthermore, we assume that agents cannot move to another fishing site, even if her site is destroyed completely. So, for example, if H = 25, it means there are 25 fishing sites, where each fishing site has the same initial resource level and is shared between 20 agents (n=N/H = 20). In this case, each agent only makes assumptions about the behavior of 19 (n-1) other agents, who are sharing the resource with her. It should be noted that for all different values of H, the total population of agents (N) remains the same, only the number of agents sharing the resource with each other (n) changes.

Figure 4.3 presents the relationship between discount factor and adoption of destructive fishing gear for different levels of social dilemma.

Figure 4.3: Relationship between time preferences and adoption of destructive fishing gear for different levels of social dilemma



Notes: 1) Negative costs differential indicates that destructive fishing gear (gear2) is less expensive than traditional gear (gear1), positive costs differential indicates that destructive fishing gear is more expensive than traditional gear. 2) Higher values of H indicate low social dilemma situation, whereas lower values of H indicate higher social dilemma situation.

Looking at low-cost low profit gear, it is clear that decreasing the level of social dilemma results in dominance of conservation effect. Even under moderately low social dilemma conditions (H > 5), high discount factor results in very low adoption rates, meaning patient agents are less likely to adopt the low cost destructive fishing gear, whereas for impatient agents changing the level of social dilemma does not have any impact.

For high-cost high profit destructive gear, higher social dilemma (meaning few fishing sites; H < 50) results in disinvestment effect dominating the conservation effect. Under low social dilemma settings (H > 50), we observe an inverted-U shaped curve, where adoption rates are very low for low discount factors, then increase with increasing discount factors and finally start declining with higher discount factors after the mid-way point, leading to very low adoption rates for very high discount factors.

Low social dilemma situation implies that each agent's own actions have a much larger role in determining their current and future earnings as compared to high dilemma situation, since the number of other agents who can access the resource is lower. As a result, patient agents become less likely to adopt the destructive fishing gear. Additionally, low social dilemma, meaning higher number of fishing sites, implies that agents have more opportunities to learn from other agents´ actions and their impact on the resource level. Therefore, agents especially those who can only switch to destructive fishing gear late due to cost reasons (i.e. impatient agents), also become less likely to adopt the destructive gear, as they have a better idea of its negative consequences on the resource. The adoption rate is highest for middle values of discount factor, indicating that those who are neither extremely patient nor extremely impatient are more tempted to use destructive gear, even under very low social dilemma situations. This is due to the fact that: (i) they do not value the loss of future earnings due to the usage of destructive gear as highly as extremely patient agents, and (ii) unlike impatient agents they can afford to invest in high cost destructive gear in the very early stages.

4.4.4 The role of agent´s beliefs and expectations

A key feature of our modeling approach is that we test different scenarios regarding agent´s beliefs with respect to (i) future state of fisheries (g´), and (ii) other fisher´s actions (X'_{Jt}). For earlier sections we assumed that agents have perfect knowledge about the growth rate of the resource, and that they assume that other agents will continue repeating their past behavior. In this section, we relax both these assumptions, and see how this impacts the relationship between time preference and adoption of destructive fishing gear. This is motivated by the fact, that, fishers (in general) have to rely on incomplete and imperfect information about the resource and their fellow fishers. Indeed, predicting the condition of resource and how other agents are going to respond is one of the most difficult problems for any resource user.

Table 4.3 explains different assumptions which were used in our simulation experiments:

Table 4.3: agents´ assumptions about resource condition & other agent's actions

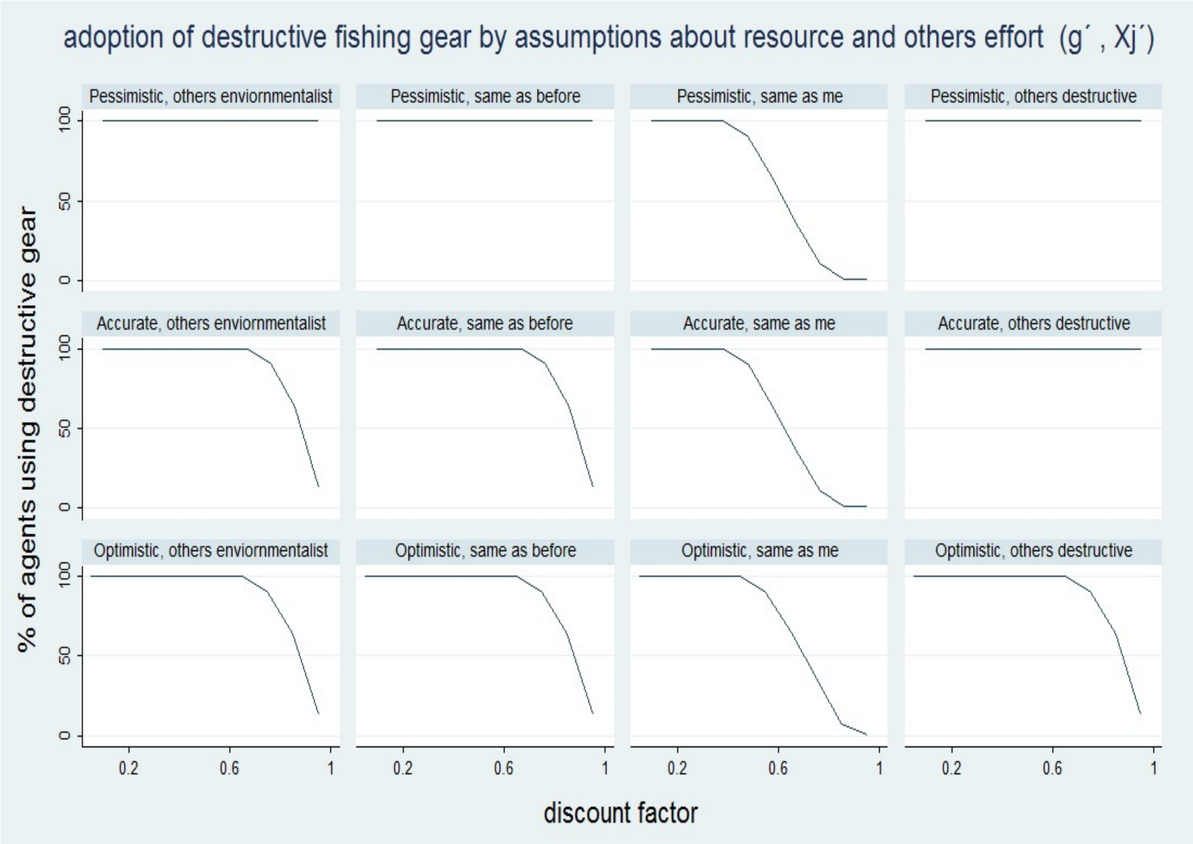
g'_i : perceived trend of Resource growth	*Accurate*	Accurate assessment of the resource stock
	Optimistic	Overly optimistic assessment by agents, meaning that agents believe that resource is growing at a much higher rate than reality
	Pessimistic	Overly pessimistic assessment by agents, meaning that agents believe that resource is decreasing at a much higher rate than reality
X'_{Jt}: perceived trend of fishing effort by other agents in T time periods	*Same-as-before*	Agent believes others are going to continue doing what they were doing before
	Same-as-me	Agent believes (all or at least a significant proportion of) other agents are conditional cooperator meaning if the agent uses destructive gear they are also going to do the same
	Destructive	Agent believes (all or at least a significant proportion of) other agents are going to start using the destructive gear in the near future
	Environmentalist	Agent believes (all or at least a significant proportion of) other agents are going to stick with the traditional gear

Below, we explain how these different assumptions impact the relationship between time preferences and adoption of destructive fishing gears. First, we explain our findings for the low-catch-low cost destructive gear, and then move to high-cost high-profit destructive gear.

4.4.4.1 Low cost destructive gear

For prototype 1 (low-cost low-profit gear), the results are simpler to explain. Under almost all conditions and assumptions, impatient individuals are either more or equally likely to adopt the low cost low profit destructive gear as compared to patient individuals. Figure 4.4 presents the relationship between discount factors and adoptions rate of low-cost low-profit destructive gear for different assumptions about resource level and other´s behavior.

Figure 4.4: Relationship between different assumptions and adoption of destructive fishing gears (low-cost low-catch gear)



Notes: H = 1; C = -30); lower discount factor indicates impatience, higher discount factor indicate patience (such that agent with discount factor of 0 is extremely impatient while agent with discount factor of 1 is extremely patient)

Overall, we find that for very high level of social dilemma (H=1) meaning virtually open access, even patient fishers can be tempted by the low-cost destructive fishing gear. This is especially true, if fishers underestimate the growth rate of resource and overestimate the extent of destructive fishing gear users (i.e. if g´ = *pessimistic* and/or X'_{Jt} = *others destructive*).

Basically, in this case we observe a self- fulfilling race-to-the-bottom phenomenon, where even patient fishers think that the resource is going down and others fishers are going to start using the destructive fishing gear. This results in them adopting destructive fishing gear to save costs and generate short-term profits, which in turn means that the resource actually starts decreasing and the number of fishers using destructive fishing gear starts increasing, motivating other patient fishers to start using the destructive fishing gear as well.

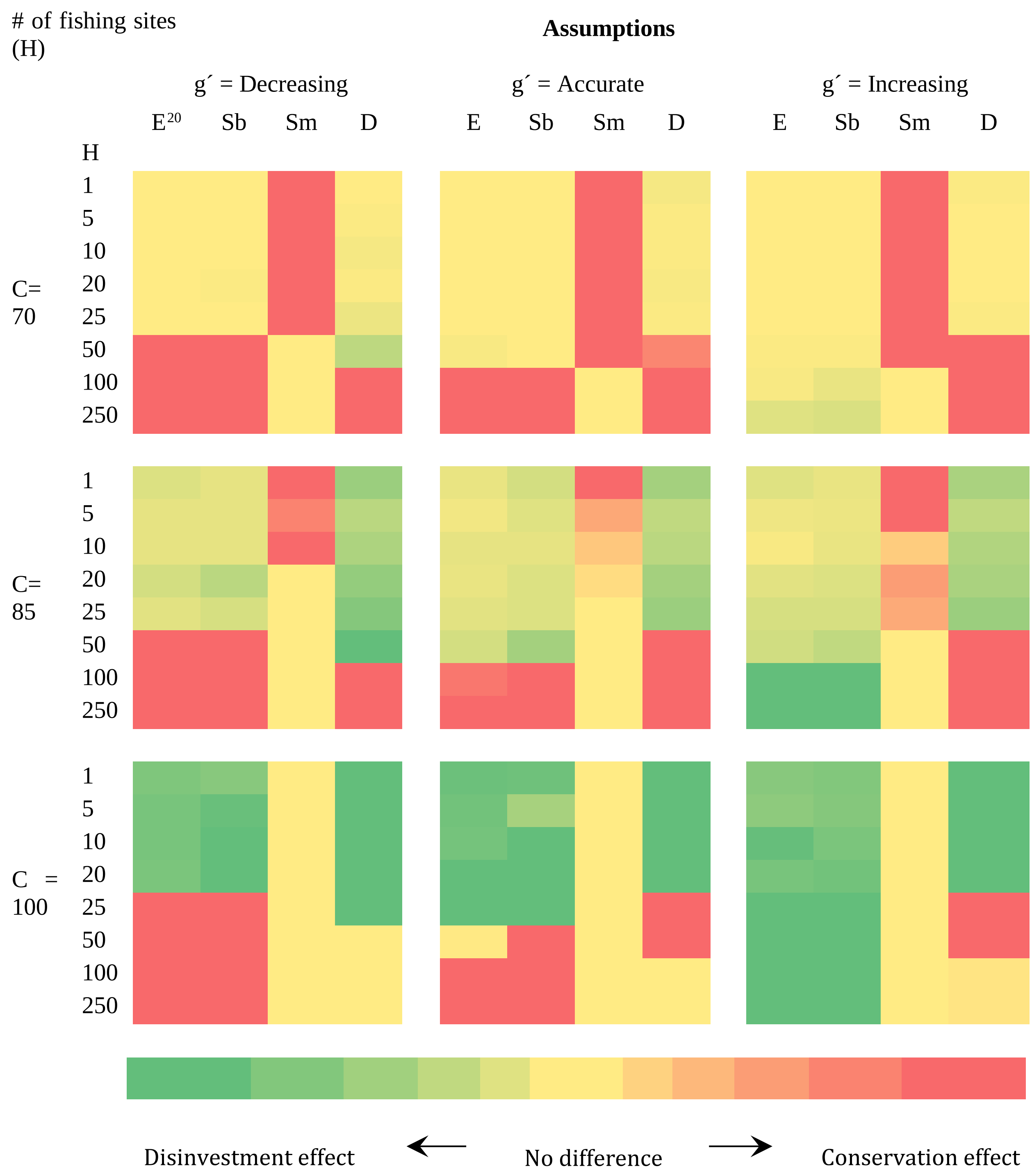
However, it should be noted that this happens in only a limited number of cases (for mid-range fixed costs values). For majority of the cases, either conservation effect is more dominant (for low fixed cost values) or there is no difference between patient and impatient agents across all different assumptions.

4.4.4.2 High cost high profit destructive gear

In this sub-section, we look at the findings from the high-cost high-profit gear. Figure 4.5 shows the heat map of conservation and disinvestment effects under different values of social dilemma and different assumptions, for particular discount factors (0.25 for impatient ones and 0.95 for patient ones), whereas figure 4.6 presents the average adoption level across different discount factors for different assumptions.

Both Figure 4.5 and figure 4.6 (a&b) have to considered together, as figure 4.5 looks at the intensity of differences in adoption between patient and impatient fishermen, therefore indicating the strength of conservation and disinvestment effects. However figure 4.5 does not show the extent of adoption or the differences across different discount factors. On the other hand, figure 4.6 (a&b) shows various patterns of adoption under different discount factors and assumption settings. However, figure 4.6 only consider two representative social dilemma settings, whereby figure 4.6 (a) looks at the high social dilemma situation (H = 1) and figure 4.6 (b) looks at the low social dilemma situations (H = 100).

Figure 4.5: Heat-map of conservation and disinvestment effect for different levels of social dilemma and cost differentials under different assumptions (high-cost high-catch gear)



[20] Xj´ = E = Environmentalist; Xj´ = Sb = Same as before; Xj´ = Sm = Same as me; conditional cooperation; Xj´ = D = Destructive

Figure 4.6: Relationship between different assumptions and adoption of destructive fishing gears (high-cost high-catch gear) (g´ , Xj´)

Fig. 4.6 (a) - (H = 1)

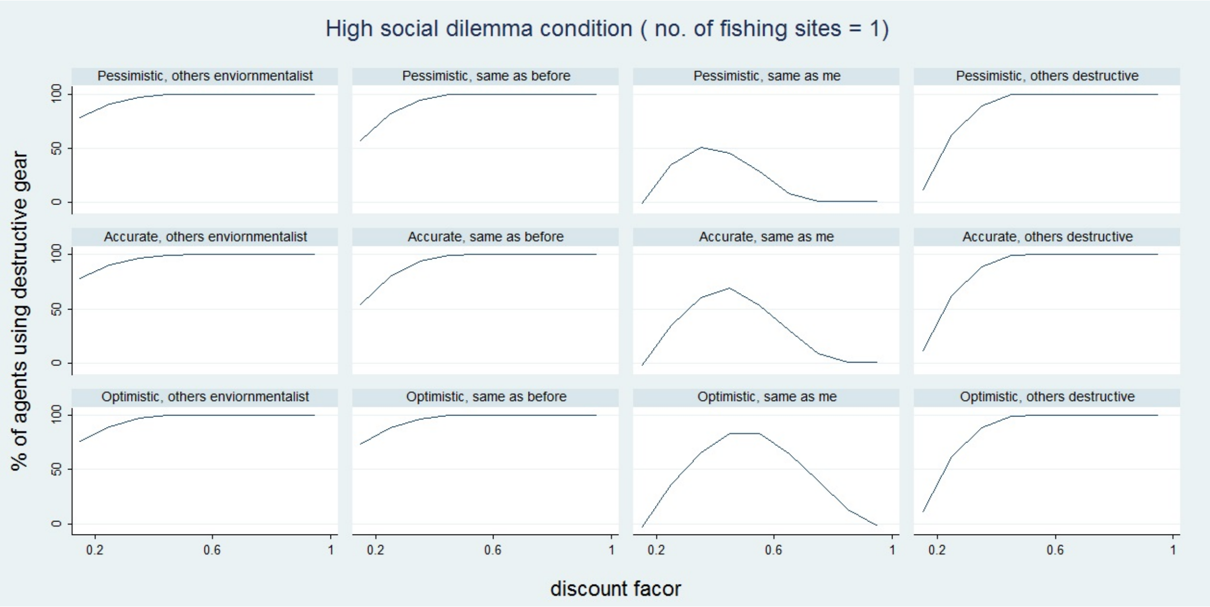
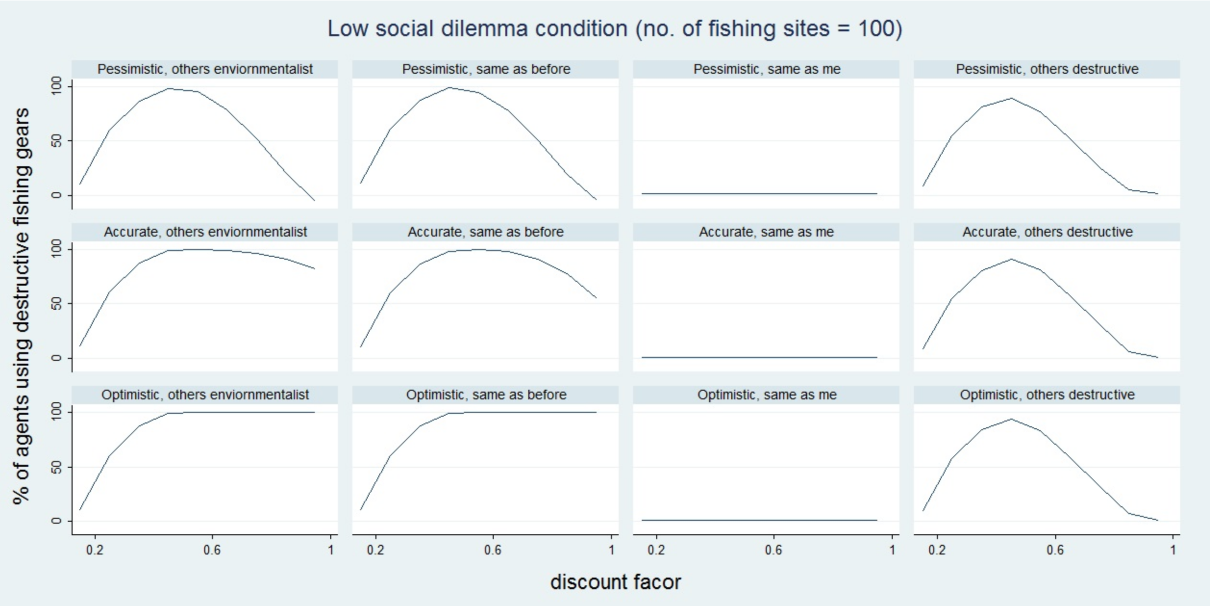


Fig. 4.6 (b) - (H = 100)



Notes:

1): fixed costs differential = 100 for both fig. 4.6(a) & 6(b). 2); lower discount factor indicates impatience, higher discount factor indicate patience (such that agent with discount factor of 0 is extremely impatient while agent with discount factor of 1 is extremely patient)

First, we note that, as expected, the disinvestment effect becomes more important as the costs of destructive fishing gear increases. This can be seen clearly from figure 4.5. The heat maps for lower cost values (C = 70) is mostly yellow or red, indicating that either there is not much difference between adoption levels or (in the case of red areas) conservation effect dominates. As the cost increases, we see more green areas (C = 85 or 100), indicating dominance of disinvestment effect. Second, as shown in the earlier section, we see an increase in the conservation effect as the level of social dilemma goes down, especially for H > 25. This is true for most assumptions/beliefs, but not all.

The most salient observation from our overall analysis is that conservation effect is dominant when agents´ assume that other agents are conditional cooperators (i.e., X'_{Jt} = *same as me)*, meaning that they will cooperate and use the traditional gear if the agent herself continues to use this gear, however they will switch to destructive gear (immediately or in brief time) if the agent starts using destructive gear. Both, impatient and patient agents are less likely to switch to destructive gear in these conditions. Looking at figure 4.6 (a & b) makes it clear, that, for almost all cases this leads to either very low adoption rates (for both patient and impatient agents), or an inverted U shaped curve where adoption rate is highest for low to mid-range values of discount factor and decreases sharply for high values of discount factor.

In addition to this, we also observe two other interesting findings. First, disinvestment effect is prevalent for over-optimistic agents under very low level of social dilemma (H > 50). This is especially true, if these over-optimistic agents also underestimate the adoption of destructive fishing gears by others who share the resource with them. So in fig. 4.5, when agents have over-optimist assumption about the growth rate of the resource (i.e. g´ = *optimistic*) and others´ action (i.e., X'_{Jt} = *E* or *Sb*), the area under low social dilemma situations (H > 25) is green, whereas for both accurate and overly pessimistic assumptions (i.e., g´ = *accurate* or *pessimistic*) the same area is red. This implies that over-optimistic patient agents are more likely to adopt the destructive gear than others. This is also illustrated in figure 4.6 (b). When looking at graph with g´ = *optimist*, and X'_{Jt} = *others environmentalist* or *same as before*, we have the typical disinvestment curve, where adoption rate increases sharply for mid-range discount factors and stays quite high even at very high values of discount factor. This is in contrast to the graphs for g´ = *accurate* or *pessimistic*, and X'_{Jt} = *others environmentalist* or *same as before*, where we observe the inverted U shaped curve. This happens, due to the fact that patient agents with over-optimistic assumptions about resource condition end up thinking that their investment in costly destructive fishing gear is going to bring them additional rewards in near future. Whereas patient agents with accurate or overly-pessimistic view about the resource tend to think that the investment in costly destructive gear is not going to be worthwhile. As a result, over-optimistic patient agents become more likely to adopt the costly destructive gear.

Second, in the case of high social dilemma settings (fig 4.6a), if agents believe that other agents are going switch to the destructive fishing gear (i.e. X'_{Jt} = *others destructive*), this results in impatient agents not investing in the high-cost destructive gear, as they don´t expect to recover the fixed costs in the immediate future. This is indicated by the steeper curve of extreme right column in figure 4.6 (a). On the other hand, patient individuals still consider their investment in destructive fishing gear worthwhile, resulting in the disinvestment effect strongly dominating the conservation effect.

4.5 Concluding remarks

Our study suggests that providing alternatives to destructive fishing gears and addressing social dilemma helps in minimizing the motivation for using destructive gear, by: (i) decreasing the potential benefits of using destructive gears, and (ii) via learning effects and weeding out unsuccessful fishers who destroy their resource (the link to own actions and destruction of resource is clearer).

However, they should not be seen as a guarantee against the adoption of destructive gear. We observe that the impact of social dilemma on the relationship between individual time preferences and the adoption of destructive gears is dictated by individual beliefs and expectations. In fact, we find that the possibility of patient (as well as impatient) individuals opting for destructive extraction gear remains, even under very low social dilemma situations. Addressing social dilemma may not work fully due to the fact that learning takes time, as there is a lag in using destructive gears and their negative impact on earnings. As a result, while agents may eventually learn from their counterpart, it still means that at least part of the resource suffers substantial damage. Additionally, learning is constrained by the availability of information. Agents do not possess perfect information. Incomplete and imperfect information can lead to agents´ taking wrong lessons from others.

Expectations play a key role in determining the adoption rate of destructive fishing gears. Over or under-estimating the resource growth and/or the effort level of other fishers, can lead to greater adoption rates. Indeed, the best mechanism to prevent the adoption of destructive fishing gear is to inculcate the belief, that, adopting the destructive gear would lead to a reaction by others, and that they would stop cooperating and start using the destructive gear as well. In such a scenario, patient individuals will be put-off by the potential reaction to their action. Overall, our model suggests that gear exchange programs or incentive to conserve programs have to address the issues related resource-users´ expectations and beliefs, in order to have greater chances of success.

While our model is one of the first to look at the relationship between individual time preferences and adoption of destructive fishing gears, it relies on related models of natural resource extraction. Due to this fact, there are several shortcomings and potential for future improvements. Firstly, we use the same discount factor to evaluate future outcomes both negative and positive. However, prospect theory suggests that this may not be the case in real-life (Hardisty et al. 2013). Secondly, we do not map the relationship between uncertainty and its impact on the relationship between time preferences and adoption of destructive gears (even though one of our sub models includes random variations in income from fishing activities). Ultimately, both of these issues require more empirical work.

Lastly, one of the major issues and possible extension of our model is to consider the possibility of endogenous preference formation. This may include co-evolution of technology and preferences based on changing resource and beliefs. This can also address the fact, that, our model is only concerned about the adoption process and doesn´t say anything about the conditions under which these innovations take place.

Appendix C: ODD protocol

Study purpose:

The purpose of the study is to look the relationship between fisher's individual time preferences and adoption of destructive gear. Theoretically there are two different point of views regarding the relationship between time preferences and adoption of destructive gears; (i) the conservation hypothesis which argues that high time preference (implying impatience) leads to greater adoption of destructive gears as impatient fishers care less about the loss of future productivity of resource as a result of use of these destructive gears, (ii) the disinvestment hypothesis which argues that for more expensive destructive gears, fishers with low time preference (implying higher patience) are more likely to adopt destructive fishing gear, as they have greater ability to invest in extraction capability.

Our main objective is to distinguish between scenarios where the conservation effect assumption is justified and where it is not justified, by providing a better understanding of fisher's motivation to adopt destructive gears and its relationship to individual time preferences.

State variables and scales

Social entity: fishers

Ecological entity: fish population

Technology: Fishing gears

Agents

Each agent represents a fisher.

Table 4.4: Summary of variables

Age (experience)	10-150	Agent´s age which signifies the level of fishing experience; initial values are assigned randomly
Wealth (W)	0-2000	Agent´s wealth; initial values are assigned randomly
savings-rate	0.3	Agent´s pure saving rate
X*i*		Effort is fixed such that in the initial time period $\sum X_i \approx$ pop-g
discount-rate (δ_i)	0-1	Agent´s discount factor used to evaluate future outcomes
a, b	0.45,0.375	Coefficients for return to effort, state of the resource. Used to generate a decreasing marginal return function.
Û	0.01	Utility threshold level for switching to destructive gear
ɤ	0.3	Proportion of wealth; ɤ*W is represents the maximum amount of wealth agent is willing to use for buying fishing equipment

State	[1,2,3]	State = 1 if agents are using gear 1 State = 2 if agents are susceptible to change State = 3 if agents are using gear 2

Agent's wealth is calculated as:

$$W_{it} = W_o + \sum_{j=1}^{t-1} \mathrm{Si} \, * \, p_{ij}$$

Where W_o is the initial wealth level which is determined randomly at the start of the simulation. p_{it} are the actual earnings in period t, S_i is the savings rate which is given as $S_i = f(\delta_i, s_i)$ where s_i is the individual specific saving rates, and δ_i is the individual discount factor representing an individual´s time preference.

Agents 'current earnings (p_{it}) are given as:

$$p_{it} = \left(\frac{X_{it}}{\left(\sum_{j=-\mathrm{i}}^{n} X_{j_t}\right)^{v}} \right)^{a} * \, (R_t)^b$$

$$= \left(\frac{x_i * \mathrm{L}_m}{\left(\sum_{j=-\mathrm{i}}^{n} X_{j_t}\right)^{v}} \right)^{a} * \, (R_t)^b \qquad (3)$$

Where v is the coefficient indicating congestion in terms of fishing effort[1], a & b are coefficients for earnings and resource level respectively which determine the total current earnings; a + b < 1 which depicts the decreasing marginal return of effort and resource level. So agent *i*´s earnings in time period *t* (p_{it}) are determined by the effective effort level (X_{it}), total effective effort level (in the same time period) of other agents sharing the common resource ($X_{Jt} = \sum_{j=-\mathrm{i}}^{n} X_{j_t}$), and the current resource level (R_t). Effective effort level is the product of effort level (x_i) and gear (G_m) used by the agent, where gear1 or G1 is the traditional/ environment-friendly gear and gear2 or G2 is the destructive gear. Since we are mainly interested in the gear adoption process, we assume that agent's´ effort level (x_i) is fixed over time.

Resource

Resource (fish stock) is defined by a logistic growth function:

$$\Delta R / \Delta t = g * R_t * (1 - R_t/K) \qquad (1)$$

Where Rt is the state of resource at time t, g is the intrinsic growth rate, K is the carrying capacity

Resource available to agent population for extraction in next period as[2]:

$$R_{t+1} = R_t + g \, * \, (R_t) * \left(1 - \frac{(R_t)}{K}\right) - V_t$$

The V_t is the damage done to the resource by all agents in current time period.

The damage done to the resource (V) by all agents in current time period depends on the effort level and gear being used:

$$\mathrm{V}_t = \left(\sum_{i=1}^{n} (\mathrm{Dm}_{it} * \mathrm{x}_i)\right)^{c} * (R_t)^d \qquad (5)$$

[1] This reflects the fact that if all fishers apply a lot of effort in the same time period their individual earnings in the current time period go down due to the congestion effect (Brown 1974).

[2] This form of equation 1 is equivalent to Gordon-Schaefer fisheries model for discrete time steps

Gears

There are two types of gear

(i) Traditional environmentally friendly gear
(ii) Destructive extraction gear

Agents (fishers) are able to choose between these two gears.

Additionally we experiment with different types of destructive gear and whether it impacts the relationship time preferences and adoption process. In particular we focus on two different types of destructive gears:

a. Low cost low profit destructive gears. Compared to traditional gear these destructive gears:
    - Lower capital investment
    - Lower to about the same level of Profit to effort ratio
    - Much higher destruction to profit ratio
b. High cost high profit destructive gears
    - Higher capital investment
    - Higher Profit to effort ratio
    - Much higher destruction to profit ratio

Process overview and scheduling

The agent based model can be briefly described as:

Step 1. "N" number of agents (or fishers) are generated, who are connected to each other via a social network. In this case we employ a **scale-free network.**

Step 2. The landscape is defined. This includes resource and the gears used for extraction.

- "n" number of agents share a resource whose initial value is user-defined. At each time step resource condition is calculated as:

$$R_{t+1} = R_t + g * (R_t) * \left(1 - \frac{(R_t)}{K}\right) - V_t$$

- There are two types of gear which can be chosen by the agents, gear1 and gear2. Gear1 is relatively environment-friendly gear, while gear2 is the destructive gear.

Step 3. Agents are assigned properties.

- At the start of simulation agents differ in terms their wealth level, fishing experience, time preference, effort level (which is fixed for both gears), utility threshold.

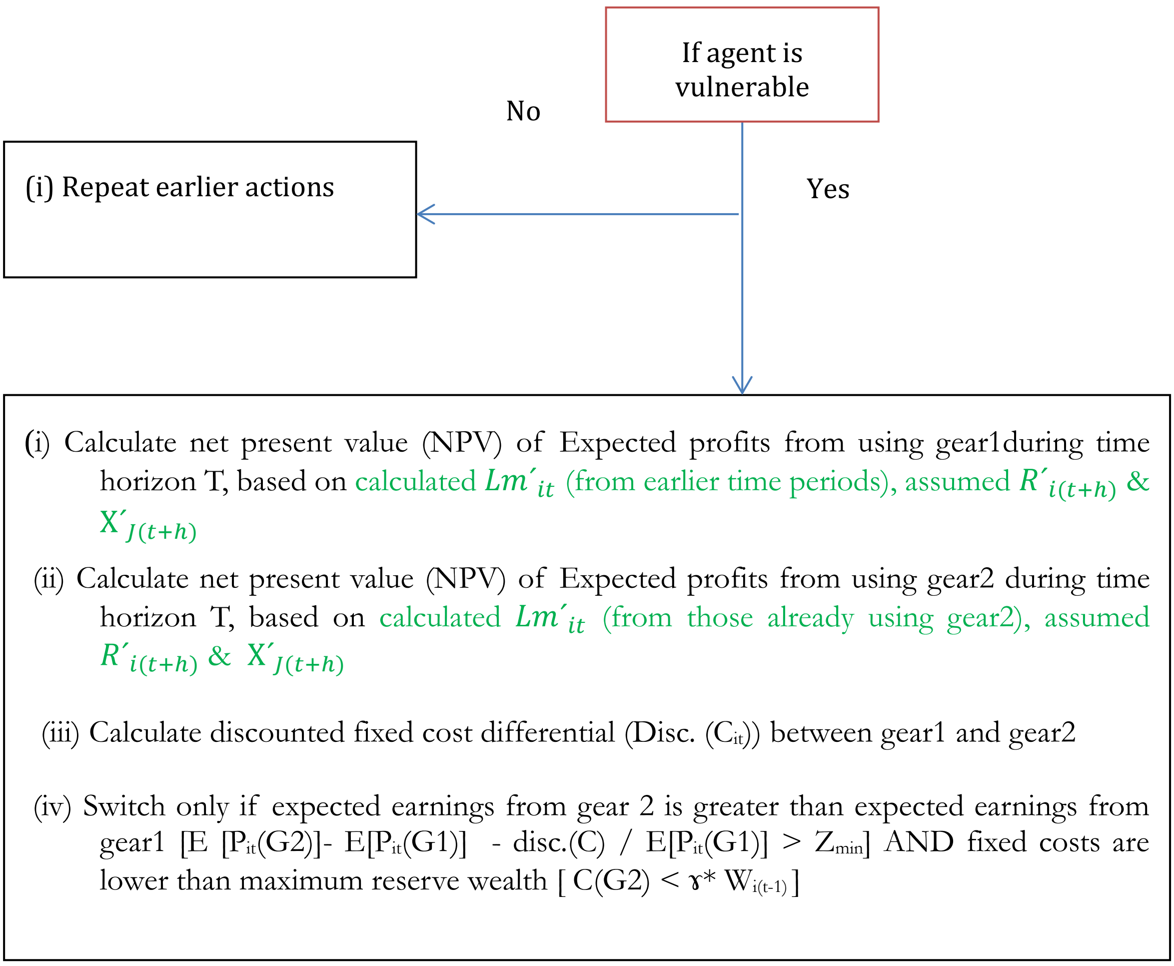
Step 4. After burn-in period (10 time steps), agents can decide which gear to choose

- A small number of agents (I = 1 % of total number of agents) are randomly chosen as innovators i.e. they start using gear2 while rest of the agents start with gear1.
- During each time step vulnerable agents (state = 2) calculate their expected utility from choosing different gears based on the current status of resource, relative number of people using different gears, and agent´s own characteristics
- At the end of time period agents actual utility from using their chosen gear is calculated

Step 5. The model stops if (i) the resource is completely extinguished, or (ii) all agents shift to the destructive gear (gear2).

Agent´s decision-making process[3]

During each time step agent´s decision making process can be described as:



<u>Expected earnings from gear 1</u>

$$E[P_{it}(G_1)] = E[p_{it}(G_1)] + PV(E[p_{iT}(G_1)])$$

$$= ([(x_i * L_{G1_{it}}{}') / (X'_{Jt})^v]^a * \; R_t{}^b) + \sum_{h=1}^{T} \delta_i{}^h \; * \; ([(x_i * L_{G1_{it}}{}') / (X'_{J(t+h)})^v]^a \quad (R'_{i(t+h)})^b)$$

Where δ is the individual discount factor; E[p_{iT}] is expected future earnings during "T" time periods

$R'_{i(t+h)}$ is the perceived trend of Resource in T time periods;

[3] Agent´s decision-making process can be defined as bounded rational; this is based on interviews and questionnaires of fishers in Zanzibar. Around 70% of the fishermen identified earnings and cost of gear as the two most important factors in deciding which gear to use. Additionally fishermen explained that while cost estimates are relatively easy, the exact productivity of the gear is not known to any them generally. Rather they base their opinion about gears based on their own experience or based on the opinion of others who are using these gears.

$X'_{J(t+h)}$ is the perceived trend of fishing effort by other agents in T time periods,

Expected earnings from gear 2

$$E[P_{it}(G_2)] = E[p_{it}(G_2)] + PV(E[p_{iT}(G_2)])$$

$$= ([(x_i * L_{G2_{it}}{}') \,/\, (X'_{Jt})^v]^a * \; R_t{}^b) + \sum_{h=1}^{T} \delta_i{}^h * ([(x_i * L_{G2_{it}}{}') \,/\, (X'_{J(t+h)})^v]^a \quad (R'_{i(t+h)})^b)$$

Where δ is the individual discount factor; $E[p_{iT}]$ is expected future earnings during "T" time periods

$R'_{i(t+h)}$ is the perceived trend of Resource in T time periods;

$X'_{J(t+h)}$ is the perceived trend of fishing effort by other agents in T time periods,

- It should be noted that $R'_{i(t+h)}$ and $X'_{J(t+h)}$ may change depending on the gear being used by the agent
- For gear being used by agents this Lm ratio is calculated by the agent based on her earlier experience
- For Gear not being used by the agent this Lm ratio is based on information from those currently using G_m

Discounted fixed costs Disc. C_{it}:

$$C = C(G2) - C(G1)$$

Where C(G1) and C(G2) are costs associated with gear1 and gear2 respectively

$$\text{Disc. } (C_{it}) = (C) \quad - (\delta_i{}^{Tc} \; * RV)$$

Where time period T_c refers to the nearest of either the agent's planning horizon (T) or the time period when the agent expects the resource to collapse. RV is the difference in resale value of gear 2 as compared to gear 1[4].

Benefits from switching $E[Z_{it}]$:

$$E[Z_{it}] = (E\,[P_{it}\,(G2) - E\,[P_{it}\,(G1)] - \text{disc.}[C_{it}]\,)\,/\,E\,[P_{it}(G1)]$$

Where $E[P_{it}(G2)]$ is the expected total earnings/profits from using gear 2, $E[P_{it}(G1)]$ is the expected total earnings from using gear 1, and disc. C_{it} are the costs associated with switching to gear2, all calculated in time period t.

Switching decision:

$$E[Z_{it}] = (E\,[P_{it}\,(G2) - E\,[P_{it}\,(G1)] - \text{disc.}[C_{it}]\,)\,/\,E\,[P_{it}(G1)] > Z_{min}$$

And

[4] We assume that the resale value of the gear at the end of its lifespan depends on its initial costs only, however it is possible to consider other possibilities in our model. If Tc < T, then resale value is calculated using Straight-line depreciation method.

$$C < \gamma * W_{it}$$

where Z_{min} is the minimum benefit threshold where agent decides to change from traditional gear to the destructive gear[5], W_{it} is agent´s total wealth and $\gamma * W_{it}$ is predefined fraction of agent´s total wealth which the agent is willing to use for investment in fisheries related capabilities.

Design Concepts

Emergence:

Gear frequency emerges from the interaction between agents

Interaction:

Agents exchange information about the productivity of destructive gear

Stochasticity:

Fitness:

In some sub-models agents measure their level of satisfaction and change their behavior based on this

Output:

Primary: Percentage of agents using the destructive fishing gear

Secondary: Speed of adoption AND Resource condition at the end of simulation

Initialization

Table 4.5: Initial values

n-of-fishers	500	Number of agents/fishers
n-of-innovators	0.01	Number of fishers who come up with the destructive gear
resource-size	40,000	Value of resource
growth-rate	1.7	Resource growth/reproduction rate
fishing-sites (H)	1	Number of fishing sites. In the baseline scenario all agents share one common resource.

Experiments

We are mainly interested in following three variables:

1. Nature of destructive gear
2. Level of social dilemma
3. Agents beliefs and assumptions

For each of these variables, we run simulations only varying the discount factor along with the variable in question to see how it impacts the relationship between discount factor and adoption of destructive gears. Note, in the baseline model we assume that all agents in the model have the same discount factor.

[5] Z_{min} is equal to one in our baseline model meaning agents switch even if G2 only provides marginally greater earnings. We experiment with different values of Z_{min} however it does not have any qualitative impact on the relationship between time preferences and adoption of destructive gears.

All experiments were conducted with the parameter values given in table 4.1. We have two variables which are determined randomly at the start of the simulation; agent's initial wealth level (W_o) and the innovative agents who start using destructive gear. In order to make sure that our results are not driven by the initial random assignment of these variables, we conduct 20 repetitions for each set of experiments.

Note for all experiments, we allow a 10 time step burn-in period, where agents do not make any decision regarding gear choice. At the end of 10th time step, “I” individuals are randomly selected as innovators. These innovative agents start using destructive fishing gear from the next time step. Since we are mainly interested in short to medium term effects, we stop each simulation run at 120th time step.

Gear types

With respect to different types of destructive gears we differentiate between two major prototypes of destructive gears:

> *Prototype 1:* Destructive gears having lower fixed costs, and lower profits as compared to environmentally-friendly traditional gear
>
> *Prototype 2:* Destructive gears having higher fixed costs and higher profits as compared to environmentally-friendly, traditional gear

We conduct experiment varying the following properties of both these types of gears.

Table 4.6: Gear properties

reward-effort-ratio (L_m)	Traditional gear	1	
	Low cost low profit	0.7-1	reward-effort-ratio describes the profits reaped from one unit of effort each gear
	High cost high profit	1.25-2.5	
destruction-effort-ratio (D_m)	Traditional gear	1	
	Low cost low profit	1.25-4.25	destruction-effort-ratio describes the damage done to the resource per unit of effort; differs for each gear
	High cost high profit	1.25-4.25	
fixed-costs(C2)	Low cost low profit	+ 15-50	Costs required to buy a new gear
	High cost high profit	50-150	

Externality variation

As stated earlier in the baseline model there is only one fishing site which is shared by all agents. However, we experiment with different number of fishing sites (1, 5, 10, 20, 25, 50, 100, and 250). In this way we are able to change the extraction externalities, while keeping other things the same. This allows us to look at the impact of different levels of social dilemma in determining the conservation effect of high discount factors.

Below we explain different values for this variable and what they mean;

Table 4.7: variation in social dilemma

No. of fishing sites (H)	Number of agents sharing one resource site (n)	
1	500	Only one fishing site means all agents are sharing the resource
5	100	5 fishing sites mean 100 agents are fishing in one site. Agents cannot move between sites.
25	40	25 fishing sites mean 40 agents are fishing in one site. Agents cannot move between sites. If the resource collapses in one site agents stop extracting
100	5	100 fishing sites mean 5 agents are fishing in one site. Agents cannot move between sites. If the resource collapses in one site agents stop extracting
125	4	250 fishing sites mean each agent has her own fishing site and one neighbor who share the resource with her. Agents cannot move between sites. If the resource collapses in her site agents stop extracting

Such that $\sum_{k=1}^{H} \mathrm{R}_k = R_w$; and $\sum_{k=1}^{H} \mathrm{n}_k = N$

Where R_w is the total amount of resource available for the whole agent population.

Agents beliefs and assumptions

As described earlier agents make assumptions about $\acute{R}_T$ and $\acute{Z}_{-jT}$. We experiment with the following different assumptions:

Table 4.8: Agent beliefs and assumptions

g'_i : perceived trend of Resource growth	*Accurate*	Accurate assessment of the resource stock
	Optimistic	Overly optimistic assessment by agents, meaning that agents believe that resource is growing at a much higher rate than reality
	Pessimistic	Overly pessimistic assessment by agents, meaning that agents believe that resource is decreasing at a much higher rate than reality
	Same-as-before	Agent believes others are going to continue doing what they were doing before

X'_{Jt}: perceived trend of fishing effort by other agents in T time periods	*Same-as-me*	Agent believes (all or at least a significant proportion of) other agents are conditional cooperator meaning if the agent uses destructive gear they are also going to do the same
	Destructive	Agent believes (all or at least a significant proportion of) other agents are going to start using the destructive gear in the near future
	Environmentalist	Agent believes (all or at least a significant proportion of) other agents are going to stick with the traditional gear

Sub-models

Vulnerability sub-models

These sub-models define how agents become vulnerable to change (state = 2)

I. **Rational:**
Rational agents start considering switching to the destructive gear as soon as someone else starts using it. When calculating expected utilities for switching decision agents use the Lm ratio for gear1 calculated based on their earlier experience and perceived Lm ratio for gear2 based on the experience of all others who are already using gear2.

II. **Social-influence:**
Socially influenced agents consider switching to gear2, if someone in their social network is using gear2. The Lm ratio used by the agent is based on the opinion of her neighbor (from the social network) who is already using the destructive gear.

III. **Satisfier:**
Satisfying agents only think about switching to new gear if their minimum needs are not satisfied. If not they start considering switching to gear2. The Lm ratio of gear2 is based on the first agent using destructive gear which they encounter.

IV. **Social satisfier:**
Social satisfiers only consider switching to new gear if their minimum needs are not satisfied or if they fall behind others in their social network (in terms of wealth standings). The Lm ratio of gear2 is only known to those who are using gear2, and only agents connected to those using gear2 know about gear2´s perceived productivity.

Switch back sub-model

In the baseline model agents do not consider switching back to using gear1 once they start using gear2. In this sub-model agents decide which gear to use once the gear they are currently using becomes redundant (life span of both gears is the same).Agents may decide to switch back to Gear1 if:

i. Their expected utility levels are below their expectations; OR
ii. The resource goes below their preferred minimum level (basically meaning that the resource is visibly degraded)

Heterogeneous beliefs and preferences sub-models

In baseline models all agents have the same beliefs and time preference. This allows us to do experiments with different values of beliefs and preferences. In these sub-models however, different agents have different beliefs as well as having different discount factors. The distribution of beliefs and time preferences is determined independently and randomly at the start of the simulation.

Assumptions

- No deterrence, no rules or regulations governing the use of different gears
- Agents are boundedly-rational in the sense that they try to maximize their utility given limited cognitive ability and incomplete/imperfect information
- Agents know how much resource they destroy and the condition of resource in the current time period
- Agents receive information from others in their social network
- Agents save a fraction of their earnings
- All gears have the same life span
- Agent´s planning horizon is the same as gear´s life span

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