Modelling and Testing Behavior in Applications to Climate Change

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Universiteit van Tilburg, op gezag van de rector magnificus, prof. dr. F. A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op

woensdag 15 februari 2006 om 10:15 uur

door

ROSSELLA BARGIACCHI

geboren op 20 juni 1974 te Pistoia, Italië

PROMOTOR: PROF. DR. AART DE ZEEUW

Acknowledgements

I would like to thank especially: Prof. Dr. Aart de Zeeuw who supervised and helped me throughout the research and in the writing of this dissertation, and who is co-author of chapter 5; Dr. Eline van der Heijden who supported and encouraged me, and who is co-author of chapters 2 and 3; Prof. Dr. Abdolkarim Sadrieh (University of Magdeburg, Germany) who helped me with his enthusiasm and competence and who also is co-author of chapter 3. I also would like to thank Prof. Dr. Jan Potters, Prof. Dr. Cees Withagen and Prof. Dr. Ekko van Ierland, members of the dissertation committee. Furthermore, I have had benefit from the anonymous referees who have helped improve the paper at the basis of chapter 1, and from all the colleagues who have given feedback on my work in several occasions.

Going back in time, I certainly owe a lot of my interest for research and for the field of environmental economics to Prof. Alessandro Vercelli and Prof. Nicola Dimitri, from the University of Siena (Italy), where I graduated in the summer of 2000. A person who strongly contributed to persuade me of the importance of climate change as an economic issue is Prof. Enzo Tiezzi, from the University of Siena, whose lessons I had the pleasure of attending during a specialization course in environmental modelling held in Siena (Italy) in the autumn 1997.

The present work would not have been possible without the support of my beautiful and beloved family, and of my friends, who all helped me through the tougher times and understood me even when the stress got the worst out of me. Special thanks are due to: mum, who has always believed in me and always encouraged me to do my best; dad, who reminded me to take care of myself also beside the work; Francesco, whose idealism and feel for poetic insights always inspired me; and Sara, my little sister, who manages to be close to my heart and present and never makes me feel alone, even from so far away according to geographic maps.

Among the friends I have met at Tilburg University, I owe special thanks to Edwin, Bas, Corrado and Emilia, Andrey, Anne, José, Simon, Federica and all the people who often took me out for dance, something that kept me alive during these long five years. Now that this work is finished, I hope I can bake all the pizzas I've promised you, guys. Besides this, there is the entire group from the GSS, and especially Steffan, Pierre-Carl, Anna, Man Wai, Youtha and Edwin, with whom I spent nice times in the managing board.

There are also many other people I've met in Tilburg and "surroundings", during my stay in Holland, especially Roel, the best artist currently alive and my personal guru; Bert, the first friend I've made here and also the most funny non-sense creative mind; and Josine, my eventual future partner in business, when both of us will figure out what we actually want to do as grown-ups. Finally, I have to thank the people from the ADI (Italian association of doctoral students) mailing lists, a source of helpful information and an excellent psychiatric-help first line in some of the most critical moments of my last three years as a Ph.D. student.

Contents

Introduction

The works that come to form the body of the present dissertation share an underlying motivation to investigate, criticize and redefine the normative background of policy making in the field of climate change. This choice is justified by the observation that climate change is currently a very hot political issue and that it has important ethical dimensions. The role of theories should in such circumstances go beyond explanation of the reality that we observe, and the scientist's effort should aim at offering a coherent and meaningful basis for planning our actions and for realizing changes in the real world. The leading question behind this research therefore is not so much why prevention does or does not occur, but to which extent, why, and how, it could and should be put in place.

It is possible to distinguish two economic approaches to climate change policy. A branch of the literature focuses on general equilibrium analysis and is concerned with the design of mechanisms for the implementation of abatement targets[1]. This issue is discarded in the present work, in which we have chosen a very abstract approach instead: we are here concerned with the general problem of defining the desirable abatement targets. The motivation for this choice is that we see in the current political debate at the international level the need for giving proper "rational" foundation to the choice of abatement targets and climate change prevention. Without such a foundation the political debate remains too much dichotomized, seeing the "environmentalists" on one side, and the industrial and financial lobbies on the other side. It is in such conditions impossible to find a common ground for further analysis and discussion, and even the implementation of cost-effective measures becomes impossible.

The definition of "optimal" abatement targets relies on two main streams of economic literature. On one side, there is a focus on decision making[2], which entails questions related to the value of preventing climate change. From an economic perspective, the value of prevention is a variable that depends on

[1] See for example the papers collected in Carraro (2000).

[2] See for instance Heal and Lin (1997)

several assumptions about preferences, damage, and the attitude towards uncertainty and towards discounting the future. On the other side, several studies address the issue of international environmental agreements[3]. This branch of literature is of a game-theoretical nature and stresses the role of strategic interaction: cooperation (or the lack of it) poses constraints to the extent and efficacy of prevention policies, in particular when prevention generates positive externalities.

The literature on decision making and the literature on game theory are deeply correlated: games are decision problems where two or more agents interact. Whereas game theory generally takes payoffs as given, a part of decision theory analyses how such payoffs are perceived in the minds of players, describing and circumscribing their utility-maximizing behavior. On the other hand, game theory is an instrument to decision theory, since it aims at identifying and predicting equilibrium patterns in multi-agent settings, and helps selecting strategic responses. In the case of climate change, the perceived value of prevention for one policy actor depends on the feasibility of its implementation and on the expected reduction in damage, which in turn depend on the degree of coordination at the international level. Similarly, the attractiveness of cooperation depends for each country on the perceived costs and benefits from prevention.

Despite such deep interrelation, the two disciplines have been following different paths in the past twenty years, for what concerns the methodologies and instruments used. This divergence especially holds for the applications to climate change, probably also because of the intrinsic complexity of the issue. For this reason the content of the dissertation suffers from some heterogeneity, and can therefore best be seen as split into two parts. Part one is made up by chapters 1 to 3 and it is dedicated to one-agent problems under uncertainty. Part two to is made up by chapters 4 and 5 and concentrates on multi-agents models useful for analyzing the issue of international cooperation.

In this introductory section I will outline the main points that are discussed more deeply in the rest of the book. Before that, I give a general introduction on

[3] See Finus (2003) for a review.

the scientific facts concerning climate change and on the relevance of climate as an economic factor.

Climate change: some background information

The basic scientific fact concerning climate change is that there is an unbalanced exchange of carbon between the atmosphere and other parts of the geophysical system of the Earth. This is an established fact that results in an increasing concentration of carbon dioxide (CO_2) and other "greenhouse gases" (GHG) in the atmosphere: Figure 1 shows the records of changes in atmospheric concentrations of CO_2, N_2O, and CH_4.

The most accredited explanation for this fact is that the use of fossil fuels, like coal and oil, for industrial use is disturbing the otherwise balanced cycle of carbon. As a matter of fact, fossil coal and oil reservoirs represent important sinks where huge quantities of carbon have stayed sequestrated for very long time periods. The industrial use of these materials consists of burning them as fuel, which means that their carbon component is suddenly liberated and ends up in the atmosphere, at such a fast pace that it cannot be reabsorbed or otherwise transformed and therefore cumulates in the atmosphere. Figure 2 shows an illustration of the main sources and sinks of carbon in the biosphere, and their exchange speed.

Carbon dioxide is normally present in the atmosphere where it represents one of the phases of the natural carbon cycle. Carbon is one of the main components of organic matter, similarly to water, and in a similar way it circulates among the several parts of the biosphere, which are therefore in a dynamic equilibrium of flows and processes involving carbon as a component. The natural equilibrium of the biosphere in the times when life as we know it has developed and where the current ecological equilibria have established has been based on a carbon cycle where the fossil sinks stayed more or less unchanged. Similar considerations hold for the other greenhouse gases: those gases that contribute to regulating the temperature on the surface of the Earth. Therefore, the temperature in the biosphere stabilized within levels favorable to the evolution of life.

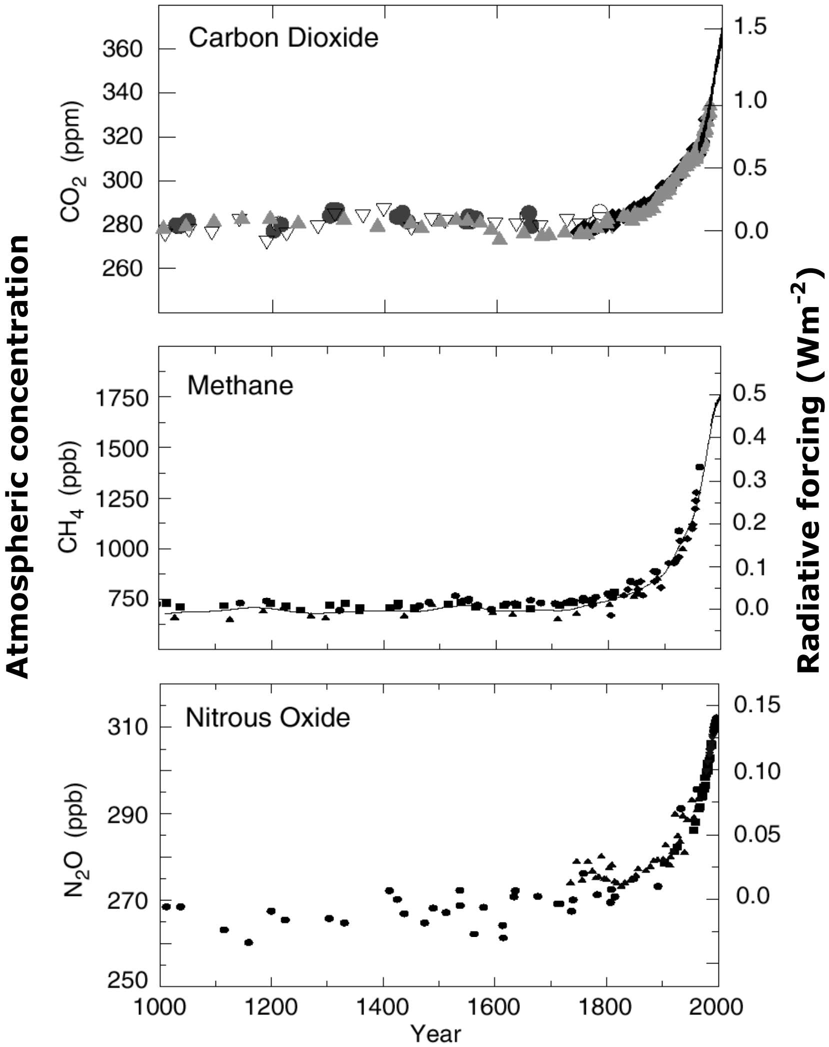


Figure 1 Records of changes in atmospheric composition[4].

[4] Source: IPCC (2001a) – p.36 of the Technical Summary

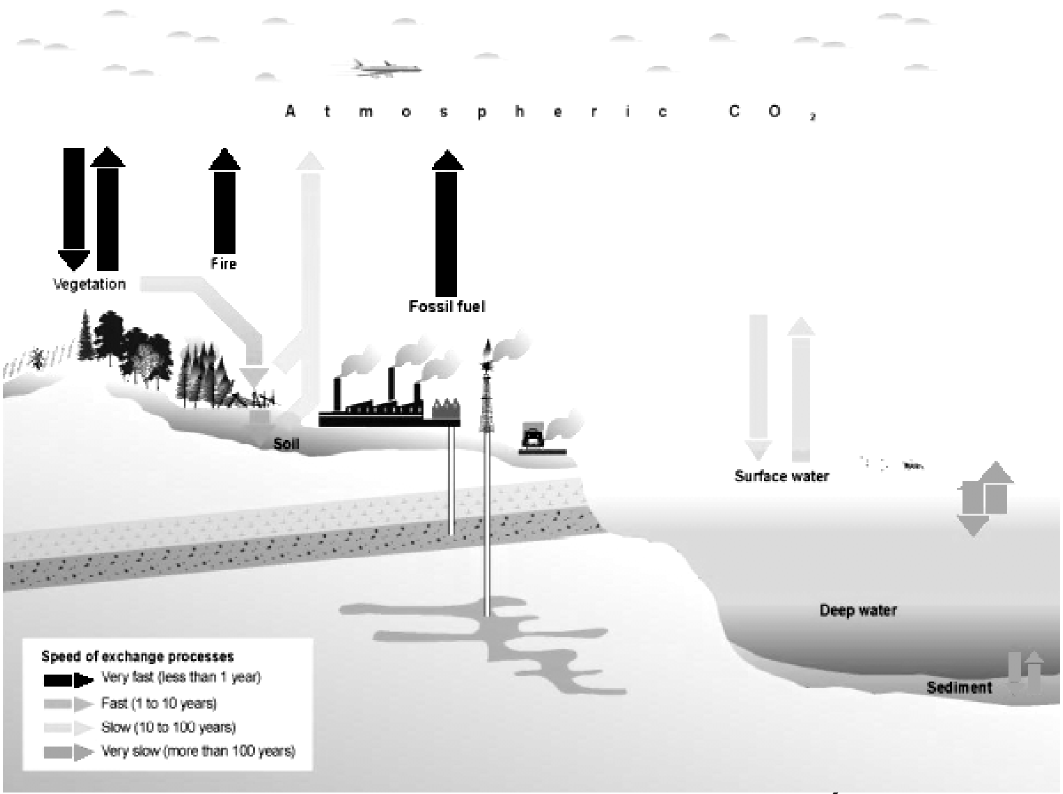


Figure 2 Fast and slow processes in the carbon cycle[5]

The industrial development of the last century, based largely on the exploitation of fossil fuels, is now threatening to change this old equilibrium. The rapid emission of carbon dioxide and other greenhouse gases results in increased concentrations of these gases in the atmosphere, leading to global warming. There is evidence that "most of the observed warming over the last 50 years is likely to have been due to the increase in greenhouse gas concentrations"[6]. When the average temperature increases too much, it is expected to generate reactions in the ecosystems, and eventually affect them to very high extent.

[5] Source: http://www.ipcc.ch/present/graphics.htm

[6] IPCC (2001a) – p. 61 of the Technical Summary

A lot of studies have been and are being conducted in order to try and understand the full concatenation of reactions that may follow as a consequence of global warming. In particular, it is not clear if there are self-regulation mechanisms that can lead the system to a new equilibrium compatible with life, or if the whole system risks to crash down completely. Even if a new equilibrium is reachable, it is not known with sufficient certainty how fast the reactions occur, what changes they may imply, and how those changes may affect life in general and human life in particular. There are reasons to be worried, if we consider that global warming is expected to affect more broadly the whole climate regime, on a global and local scale. For instance the incidence and distribution of extreme weather events, like tornados, frost, very high temperature peaks, lightnings and floods may change significantly. Besides, the sea level will rise as a consequence of higher water temperature and water dilatation, and because of ice melting at the polar caps. It is not difficult to think of reasons why these changes represent a threat to many human activities, including the most fundamental ones like agriculture and farming.

The relevance of climate change for economics

One can think of many paths through which climate does affect various sectors the economy: tourism, transportation, outdoor recreation, agriculture, and farming are obviously and directly affected by weather conditions. It is hard however to quantify the impact of weather as a productive factor. A few studies actually address the well-established correlation between average temperature and income: warmer countries perform worse according to economic indicators than cooler countries. Explanations for this evidence can partly be found in institutional and historical factors, but vector-borne diseases, which are much more present in hotter climates also prove to play a role in slowing down growth and development by affecting labor productivity and the efficiency of social institutions like health care[7]. Climate change, involving an increase in average temperature may lead to the spreading of vector-borne diseases and maybe other factors that already in the past have induced higher poverty in hotter countries. Besides, climate change

[7] Horowitz (2002); Gallup, Sachs and Mellinger (1999)

may affect income and growth also through capital accumulation, since expected damage may lead to lower investment rates, something for which developed countries might be even more sensitive than poorer ones[8].

This is enough to state that economic analysis, especially when finalized to policy making, should take the risk of climate change seriously into consideration. The costs of adaptation, the costs of prevention, and finally the costs and the risks posed by damage caused by climatic change should be accounted for when making economic predictions and when advising on economic and welfare policies. Also the financial sector, in particular insurance, investment, and credit, should be concerned, as climate change may affect the incidence of events like floodings or epidemics, which can involve large parts of the population at once.

The relevance of economics for climate change

Economics as a theoretical and applied science can help define the scope and means for climate change prevention and/or the most efficient paths to adaptation. Of course, it is not the economist's job to judge on the scientific background information regarding climate change itself, which has to be taken as a set of given "facts" and predictions, in the most neutral way. However, economics has the responsibility of producing tools that can be of help in: 1) understanding the possible impact of different natural events on the productive capability of human societies; 2) understanding and optimizing the cost structure of initiatives aimed at prevention, mitigation, and/or adaptation; 3) predicting the most likely responses that can be expected from the economic system and from society as a whole in different scenarios; 4) designing policy instruments to deal with the special challenges faced; 5) evaluating the welfare effects of proposed interventions.

It is one of the tasks of economic theory to judge the efficiency of policy instruments. This is quite an ambitious attitude in the framework of an issue like climate change: the challenge faced is unique for a number of reasons. First of all, climate change is an event for which there is no precedent in history, and this leaves us with little hard evidence to build and to test theories upon. One consequence of this is that part of the theoretical work involves some science-

[8] Frankhauser-Tol (2005)

fiction exercise: among others, thinking up catastrophic “worst-case scenarios” and dealing with a chance of facing unpredictable events. Secondly, the consequences of our actions today have effects lasting well beyond the duration of our own life. So we are in a difficult position when trying to judge their desirability: we take up the responsibility of defining priorities in the name of people who are not here to speak up for themselves, and whom we are not in state of compensating in case they turn out not to be happy about our choices. Finally, the global dimension of the decision processes involved implies that it is rather difficult to define a homogeneous set of values and priorities even for the present generations involved. The decision of bearing the costs of prevention and the choices needed to design the preferred kinds of intervention involve more or less all of the existing economic, cultural and political interest groups on Earth. This means a huge variety of different points of view on the matter, all with equal a-priori legitimacy. All these groups are not necessarily endowed with the same technical knowledge, political influence, and economic stability.

Economics as a discipline has the responsibility of finding ways to deal with those issues that do not immediately fit in the available trusted set of methods and assumptions: the situation is quite far from the ideal of a world where the subjects are rational and the property rights well defined. In other words, even though climate change is a real-life issue, and a topic for applied research, it poses some serious challenges of theoretical and methodological nature. This dissertation deals with a few of them, related to the attitude of decision makers towards uncertainty and to international cooperation.

Climate change and uncertainty

The first part of the dissertation, chapter 1 to 3, focuses on the behavioural aspects of dealing with uncertainty in the framework of climate change. The aim is to work towards the development of a satisfactory methodology for evaluating the uncertain benefits of prevention, on the one hand; and on the other hand, to investigate the consequences, in terms of emission targets, of using different theoretical approaches in the evaluation of the risks involved. This effort is justified by the underlying assumption that each policy should be evaluated by means of some cost-benefit analysis. Policies that aim at the prevention or mitigation of climate change pose some peculiar challenge to evaluation: among others, the very high degrees of uncertainty involved. These need to be taken into account in the definition of abatement targets.

Uncertainty is a very important aspect of climate change, as widely acknowledged in the literature[9]: as the climate affects and is affected by geological and biological systems, the sources of uncertainty are many and the understanding of their complexity requires the interdisciplinary contributions of many fields of science. The Intergovernmental Panel on Climate Change (IPCC) is the most authoritative official source for data and information, which publishes in not-too-technical terms in its Summaries for Policy Makers and Technical Summaries. In the most recent reports, the IPCC stresses that uncertainty about the quantitative and even the qualitative features of climate change in the near and further future is high. Moreover, given that the relationship between climate and economic systems is not well understood, this uncertainty in the climate projections translates into even higher uncertainty about future states of the economies of the world.

The evaluation of uncertain outcomes in economics is usually based on the assumption that agents wish to maximize their expected utility: individuals attach probabilities to states of the world that they believe possible, and then evaluate the utility of risky prospects by means of mathematical expectations.

In chapter 1 a discussion of this approach and of some alternative approaches is offered. The point of view that is adopted in that chapter is that it is important to define rationality with respect to the context in which it is applied. It can be argued that climate change presents features quite unusual for standard economic modelling; therefore it satisfies a necessary prerequisite for applying different definitions of rationality, in particular with respect to behavior under uncertainty. It is also arguable that alternative approaches to uncertainty need to be considered in order to account for ethical value systems that might be felt as compelling by the majority of the population[10] or because of ethical considerations that have been agreed upon in the political process. A famous example is the so-called

---

[9] Kriström-Heal (2002).

[10] Henry-Henry (2002).

Precautionary Principle: a principle stated by the United Nations[11], promoting the prevention of risks characterized by little scientific understanding.

From a policy perspective the attitude towards uncertainty makes a difference, as it usually affects the desirable level of prevention. Even though, as we discuss in chapter 1, from the economic literature it is not clear whether uncertainty about climate change should push in the direction of inducing higher or lower abatement levels, historically, one can argue that the prevention measures actually realized have been lower than optimal, if the United Nations felt compelled to produce a statement like the Precautionary Principle.

Chapter 1 of this dissertation contributes to this debate by developing a model of choice of optimal pollution levels where irreversibility and uncertainty are explicitly taken into account. The theoretical results are derived under different assumptions concerning the agents' attitude towards risk. The main conclusion reached is that prevention is likely to be more valuable if people give more importance to avoiding worse events rather than taking the chance of good events. However it is also shown that this result is not general, and that it can be reversed, especially if prevention is not likely to be successful and if the impact of climate change in utility terms is assumed to be not too high.

A question that is left open is therefore the determination of the real attitude of agents concerning uncertainty in a complex setting. Therefore chapter 2 and 3 turn to developing and testing a model of decision under risk that incorporates some attributes of complexity. In chapter 2 the theoretical framework is developed, while chapter 3 reports the results from an experiment conducted to test the model.

In order to keep the model tractable, and to make testing possible, we select only one essential feature of the climate change problem, namely the presence of thresholds in the payoff functions. Thresholds are a consequence of physical irreversibility: regenerating assets sometimes have the feature that an unknown critical level must be preserved in order to avoid extinction. The self-regulating capacity of the climate is an example where, if some critical level of pollution is surpassed, it may be the case that the equilibrium of the ecosystem is irrevocably

[11] UN (1993).

disturbed. As this critical level will usually not be known, this is a typical situation where uncertainty plays a role, together with the relative complexity of the payoff function.

As a consequence, the choices of environmental policy makers depend on their attitude towards risk. In chapter 2 the self-regulating capacity of the climate is modelled as a renewable resource, and atmospheric pollution as "harvesting", by analogy with livestock: the accumulation of greenhouse gases can be seen as subtracting from the renewable sink capacity of the atmosphere, which is not known with certainty. The chapter provides therefore models of different theoretical behavior rules and compares the consequences on the optimal harvesting rate from a renewable resource with unknown critical stock level. It is shown that the predictions of the models are qualitatively similar: according to all theories examined, when uncertainty increases, so does optimal harvesting; when the expected critical level becomes larger, then all the theories prescribe that harvesting should decrease. However, the optimal harvesting levels differ in their absolute magnitude; moreover, the attitude towards risk affects the likelihood of picking corner solutions, implying that either the resource is depleted for sure or no risk of depletion is tolerated.

The models are based on different decision-theoretical frameworks: expected value, expected utility and rank-dependent utility with convex or inverse-S shaped weights. Expected value and expected utility are the most widely used theories in the literature, and they are presented as benchmark models. Rank-dependent utility theory is chosen because it can be interpreted, as motivated extensively in chapter 1, as a possible way to implement ex-ante the precautionary principle. As discussed previously, somebody who shows ex-ante "prudent" attitudes towards risk does not necessarily take smaller risks: the reason for this counterintuitive behavior is simply that extremely high levels of resource extraction can in fact reduce total risk, because it pays more immediately and at the same time reduces uncertainty about future payoffs by making resource extinction a sure event.

Based on the theoretical models of chapter 2, chapter 3 presents an experimental study that is designed to provide an empirical assessment of the "rapid-consumption behavior" (eat it all before it is gone) in the presence of a stochastic extinction threshold. Also this chapter models the atmosphere as an available sink for greenhouse gases with a limited renewable capacity, taken as an unknown parameter. The experiment consists of confronting individuals with a choice for their level of pollution, facing a matrix of possible outcomes that depend on the level of pollution chosen and on the value of the parameter, which will be randomly selected in a second time. The aim of the experiment is to compare the predictive strength of the theoretical models presented in chapter 2.

In this experiment, a substantial subset of the observed decisions contradict standard expected utility theory (EUT) no matter which level of risk-aversion we assume, while the alternative model of rank-dependent utility (RDU) proves to be more successful in predicting actual choices. Rank-dependent utility is a theory of choice under risk that makes use of transformations on the probability distributions, rather than on the value function, to model the attitude of subjects towards risk. An interesting result is that in our specification convex transformations of the probability fit our data better than inverse S-shaped ones. A convex transformation function has the property of overweighting the probability of events leading to the worst outcomes; an inverse S-shaped transformation function, instead, has the property of overweighting the likelihood of both events leading to the best and events leading to the worst outcomes. The experimental observations presented in chapter 3 can therefore be interpreted by stating that our subjects show "prudent" (or also "pessimistic") behavior. Nevertheless, evidence for rapid consumption is found.

This result is in contrast to findings from earlier studies that generally found stronger evidence for inverse S-shaped than for convex probability weighting. However, this might be explained by the fact that while experiments in decision theory usually examine behavior in the choice among standard lotteries, the model presented in chapter 3 presents the subjects with a resource extraction situation with a stochastic extinction threshold, and this kind of task seems to invoke a much more prudent behavior than the standard tasks. This result seems therefore to speak in favour of those who think that decision criteria are context dependent and also to suggest that the calibrations of choice models that are based on the classical lottery-choice tasks may actually be inadequate for explaining behavior of subjects who face more complex choice problems.

From the analysis conducted in this first part of the thesis, the consequences for environmental policy making are not quite optimistic: although experimental tests do not reject the hypothesis that the behavior of subjects can be interpreted as "prudent" when the framework of choice is characterized by some of the complexities typical of climate change and other environmental issues, this is not sufficient to avoid rapid extraction behavior. On the contrary, both the theoretical models and the experimental observations show that the fact that decision-makers do take the risk of extinction into account, does not always lead to extracting less of the resource.

We can conclude that optimal prevention policy is a non-trivial issue when risk-preferences are taken into account and that all the models for decision-making that we have taken into consideration show a very high sensitivity to small changes in the unknown parameters. This conclusion has been reached under the assumption that the agent in charge of deciding is free to choose the optimal level of prevention, and does not have to take strategic considerations into account. However, in real life, climate change represents a global externality, where the choice of prevention cannot be taken by single agents independently: there is need for international coordination and cooperation in order to ensure that the preventive efforts put in place by one agent are not made useless by the strategic reactions of other agents. This is the topic of the second part of this dissertation.

Climate change and international cooperation

The literature on international environmental agreements makes use of game theoretic instruments to analyse the possibilities for cooperation on climate change issues. One can observe that cooperation is very hard to achieve in reality: very important countries, like the USA for instance, have not ratified the Kyoto Protocol on the reduction of greenhouse gases emissions; even if the abatement targets of Kyoto will be met, this is unlikely to be enough to prevent climate change. If the governments act rationally, the difficulty in achieving cooperation could be explained as an effect of strategic considerations. Each country anticipates the actions undertaken by others and hopes to "free ride": let the others do the prevention job and enjoy the benefits without bearing the costs. This situation is often described in terms of a "Prisoner's Dilemma", where cooperation would be valuable for everyone, but it cannot be reached because the incentives to free ride are too large.

A traditional way to induce cooperation in a Prisoner's Dilemma set up is introducing time and the possibility to repeat the game. In this extended framework, cooperation can be sustained by introducing "trigger strategies" in which a coalition falls apart completely if one of the countries defeats. It is an open question whether such a mechanism can work in the case of agreements involving greenhouse gases or other "stock pollutants" that have the property of accumulating over time. A problem here is that as a consequence of cooperation the structure of the game would change in such a way that the punishment threat is reduced due to first-period almost full-cooperative abatement[12].

The free-riding issue can also be overcome by introducing a possibility for countries to commit[13] to the coalition. In this case, the incentive to free ride still exists, but the committed countries can induce cooperation from the outsiders, for instance by means of monetary transfers. However, commitment in the presence of uncertainty can lead to inefficiency, and is less likely to take place. A trade-off between commitment and efficiency characterizes very often the choice of environmental policy strategies. This is one of the reasons why some authors feel that the central role of efficiency in evaluating policy instruments might have to be reconsidered[14].

The question is made even more complex by asymmetries among costs-benefits functions in different countries. With asymmetric countries, cooperation may be collectively rational (lead to better aggregate outcomes) but not individually rational if the distribution of efforts is such that some players end up bearing more costs and/or if some players get lower benefits from cooperation. A typical example is the difference in costs bearing and impact sensitivity between

[12] De Zeeuw (2005).

[13] Carraro-Siniscalco (1993).

[14] See for instance Endres-Ohl (2002).

developing and developed countries. Under some conditions, redistribution (transfer) schemes can be designed to deal with such situations[15]. However, things get more complicated in a dynamic framework, especially if an agreement can be renegotiated over time[16].

Moreover, the structure of the negotiation process can make a difference. Bauer (1992) for example shows that bilateral negotiation may be more successful in the presence of asymmetries among countries' costs-benefits functions. Two coalitions of two countries may then negotiate with each other and form a larger coalition, and so on. The difference here is made by the fact that in the process one country does not just negotiate for itself, but it negotiates a position conditional on participation of other countries as well. In such a way cooperation can be sustained on a larger scale and with better aggregate gains than if negotiations are unconditional.

Finally, the equilibrium concept that is used in modelling international agreements strongly affects the size of the coalition. In non-cooperative coalition games, the coalition forms as a Nash equilibrium of a two-stage game, where membership is decided in a first step and in a second step optimal abatement targets are set. In this game, a subset of countries ("insiders") plays as one player against the other countries ("outsiders") playing as singletons and the equilibrium is usually found by backward induction. In the equilibrium insider countries must not have an incentive to leave that coalition (internal-stability condition) and outsiders must not have an incentive to join that coalition (external-stability condition). Typically the size of the coalition that is both internally and externally stable is very small.

Cooperative coalition games, on the other hand, are based on different concepts of equilibrium. One of the most important ones is the γ-core concept[17]: A coalition is in the γ-core if no sub-coalition has an incentive to deviate, under the assumption that in that case the remaining coalition falls apart. This idea is similar to trigger strategies in repeated games: as mentioned, the assumption that

---

[15] An example using cooperative game theory is given in Chander-Tulkens (1997).

[16] See for instance Finus- Rundshagen (1998).

[17] Chander and Tulkens (1995).

the threat is credible is quite strong. Models with “farsightedness”[18] relax this assumption partially: deviations may trigger more deviations but not necessarily a complete break-up of the coalition. It can be shown that this model can also sustain large coalitions. A trade-off occurs between models with behavioural assumption that are less realistic but may lead to large coalitions and models with more realistic behavioural assumptions but only small coalitions.

Chapter 4 discusses the ability of countries involved in the negotiation process to commit in such way that they can play a trigger strategy leading to a larger coalition. As mentioned above, the γ-core concept is based on the assumption that countries in a coalition can commit to implement a punishment strategy in the case that a country unilaterally deviates. Most commonly the threat is that the whole coalition will break apart and that a fully non-cooperative Nash equilibrium will be played. As this usually leads to very bad outcomes, these models are able to more easily reach the conclusion that a full coalition is stable, and thus that cooperation is possible. However, when catastrophic consequences cannot be excluded, then we argue that it is not reasonable for the countries in the coalition to commit to a trigger strategy in response to deviations. This gives us reasons to believe that in the framework of climate change only the non-cooperative approach makes sense, and particularly if the players of the game do not control their decision variable perfectly and run therefore the risk of committing mistakes. In other words it is shown that a threat of this kind is not played in a “trembling-hand-perfect” equilibrium, where the agents attach a positive but small probability to the fact that the other agents might “miss” their optimal-strategy action.

It is clear that this kind of considerations, which are of some importance for any coalition game, are even more interesting in the framework of climate change, because of the complexity and uncertainty that characterize this issue, as discussed in the first part of the dissertation. Therefore, in modelling international agreements on climate change it is most recommendable to adopt a non-cooperative setting. As this leads to pessimistic conclusions about the possibility of reaching large consensus and effective abatement targets, it is necessary to look for mechanisms that can help improve the situation.

---

[18] Chwe (1994).

Therefore chapter 4 further investigates the role of investments as a form of commitment in a non-cooperative game. Investments, for instance in green electricity plants, constitute sunk-costs for the investor, and once they are undertaken they can change the structure of payoffs and reduce the incentives to free ride. Introducing the possibility of investing in green electricity plants in a game of international environmental agreements can therefore lead to more cooperation and to higher levels of CO_2 abatement. As the success and extent of such a positive correlation of events depends on the efficiency of the green technology, this model suggests that knowledge is the key to solve international negative externalities and that its value lies not only in the direct effects on production and growth but also incorporates the indirect effect on the cooperative attitude of countries.

These results are encouraging, but they are not built on standard assumptions. In particular, the payoff functions used in the model presented in chapter 4 are not derived from any optimization process, and are defined in a somewhat ad-hoc way. In chapter 5 we see therefore a model of coalition formation based on more standard settings.

Some of the positive feedbacks observed in the simpler model still hold true in this one: it is true in general that members of the coalition have a higher incentive to invest in green capital, and it is also true that larger coalitions induce higher overall investments in green capital, which in principle can sustain larger coalitions. However, outsiders to larger coalitions invest less in green capital, which lowers their investments costs. This is in fact another free-rider benefit that neutralizes the effect of the green capital, so that again small coalitions result in equilibrium. The model is anyway able to reach somewhat encouraging results, as it turns out that if the members of a coalition are allowed to share a relatively small positive externality, for example, the R&D costs of investment, the full coalition can be sustained.

This comes in accordance with the idea, already present in the literature[19], that cooperation in technology development is easier than cooperation on emission abatement. While this result has been previously stated on the basis of empirical

[19] Buchner and Carraro (2004).

observations, the present paper reaches the same conclusion following purely theoretical arguments. Thus this model provides an explanation and supports the thesis that the best way to reach effective international cooperation is an agreement based both on technology incentives and on abatement targets.

1. Climate change scenarios and the precautionary principle[20]

It is well known that uncertainty regarding climate change is particularly deep and extensive. Damage may occur in a totally uncontrollable and irreversible way, after exceeding unknown threshold levels of pollution. Moreover, most of the costs of prevention of climate change have to be borne by present generations, while damage is believed to mostly affect future generations. Clearly, determination of the "best" path of development would be controversial even if all future contingencies were known with certainty. It is therefore important that the ethical issues do not become obscured by the scientific difficulties.

The ethical guidelines for dealing with global warming and other problems related to development have been addressed by the United Nations Organization (UN). The precautionary principle, stated in the Rio '92 Declaration (UN 1993), may be read as a signal of dissatisfaction with current environmental policy practice, particularly in the face of uncertainty. Many reasons could be cited for such a failure, among them the fact that policy makers often fail in interpreting and representing the beliefs of individuals and (most of all) the scientific community.

This chapter proposes a model for the implementation of the precautionary principle in the climate change framework, a model therefore that aims at determining optimal abatement and prevention levels, explicitly assuming a special attitude towards uncertainty. Toward this end, I use a somewhat different approach from that used by most of the economic literature on this topic. Many authors (for example, Ulph and Ulph 1997, Nordhaus and Popp 1997, Gollier, Jullien and Treich 2000) identify the concept of prudence with conservative

---

[20] This chapter has been published in the book *Risk and Uncertainty in Environmental and Natural Resource Economics,* edited by J. Wesseler, H.P. Weikard, and R. Weaver, Cheltenham, UK: Edward Elgar, 2003.

behaviour ex post, and they analyse the emergence and “optimality” of conservative behavior in the presence of varying conditions of uncertainty, learning and irreversibility. The main result emerging from this literature is that—even when irreversible damage occurs—conservative behaviour (lower emission levels) arises only under specific assumptions on the utility functions and on the distribution of risk (Heal and Kriström 2002). Another flow of literature analyzes the emergence of conservative behavior as the result of deviation from expected utility behaviour on the part of authorities that have different objectives than the maximization of collective welfare. Bouglet, Lanzi and Vergnaud 2002, and Chevé and Congar 2000 and 2002, fall into this category. In these contributions, the precautionary principle is either explained by or identified with the minimization of future regret (limiting the risk of a sanction).

The essence of the precautionary principle, however, seems to be captured by neither of these classes of models. In my opinion, it lies in the fact that, given the special conditions that characterize the global warming issue, we should behave prudently ex-ante, while trying to maximize collective welfare. The approach followed in this paper, more in line with Vercelli (1995) and Henry and Henry (2002), is as follows: prudence is defined as a decision criterion, consisting in a deviation from expected utility. Given the adoption ex-ante of such a criterion, and given a description of uncertainty based on scenarios, I derive some conclusions on the predictability of the consequences on the desired level of emissions.

Typically, information regarding climate change is made available to policy makers in the form of scenarios. Scenarios describe possible future developments of a set of variables (demographic, economic, and environmental variables), given assumptions on actions that might be undertaken and/or states of the world that might occur. Decisions are based on such descriptions. The idea behind this paper is to treat scenarios as special states of the world, each representing some combination of hypotheses about interactions between climate and economy. Non-monotonic utility functions within scenarios reflect the risk of exceeding threshold levels of pollution, after which a sudden loss in utility occurs. Thus, scenarios differ from each other in the distribution of thresholds and their expected impact on utility.

The first question addressed is what the optimal choice of aggregate emissions and consumption is when uncertainty is represented by multiple scenarios and when the precautionary principle applies. A second question is: are actual decision makers likely to pursue such optimal policies? If not, are they instead likely to pollute more or less than the optimal amount? This depends on how we think governmental decision makers behave in the face of uncertainty. The literature on decision-making shows that individuals often deviate from standard definitions of rationality, even in situations where uncertainty is more straightforward than it is for climate change (Starmer 2000).

The paper is organized as follows. Chapter 2 introduces the analytical set-up. In section 2.1, I present a utility function characterized by thresholds whose location and impact are unknown and are described by probability densities. Uncertainty is the subject of section 2.2, where I characterize scenarios and give a simplified introduction of RDU theory. Section 2.3 builds the model for choice of consumption. I derive some analytical results and illustrate the features and outcomes of performed simulations in chapter 3. Finally chapter 4 draws some conclusions.

Irreversibility, uncertainty, and the precautionary principle

According to the precautionary principle, irreversibility is a sufficient pre-requisite for implementing prevention measures:

> "In order to protect the environment, the precautionary approach shall be widely applied by States according to their capabilities. Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation." (UN 1993)

Implementation of this principle depends clearly on the framework to which it is applied: in the case of Chlorofluorocarbons (CFCs), the international community agreed on banning their use (Montreal Protocol), since they were considered responsible for depleting the ozone layer of the stratosphere (with very dangerous consequences), and cheap substitutes could be introduced quickly. In the case of greenhouse gases (GHGs), a ban does not seem possible, since a fast and complete substitution of some sources of GHG, like fossil fuels, is not economically feasible. Therefore, balancing costs and benefits, some optimal positive level of emissions should be determined, even in the presence of strong uncertainties.

Precaution, according to the Longman Dictionary of Contemporary English, is "an action done to avoid possible danger". Being prudent means therefore to choose among different actions, paying particular attention to their worst consequences. Such behaviour can be represented analytically by means of rank-dependent utility (RDU) models under special hypotheses, as I will show later. Henry & Henry (2002) also make use of a similar model to discuss the precautionary principle: they argue that when the beliefs of individuals can be represented by means of non-additive probabilities, the choice of a regulator is sub optimal if it does not reflect this feature. Rank-dependent utility is a model based on non-additive beliefs, and therefore this normative argument applies.

One shortcoming of RDU is that it implies a violation of the independence axiom, which can lead to inconsistencies in choice (Machina 1989). However, more recently Ghirardato (2001) demonstrated that in the presence of unforeseen contingencies (that is, when the decision maker is aware that he cannot describe his problem in a complete way), nonadditive beliefs can be derived without relaxing the independence axiom, considering the possibility that acts be defined not as functions but as correspondences between states of the world and consequences. This result recalls the intuition behind Vercelli (1995), who suggests that nonadditive beliefs may legitimately drive choice when scientific understanding of a problem is incomplete. My personal view follows this line of reasoning, and my argument in favour of a normative use of RDU is that it reproduces prudence, and UNO recommends prudence in the face of irreversibility.

Finally, I choose to use RDU among all available models for two reasons. On the one hand, RDU is relatively tractable, since it consists of a simple transformation over cumulative probabilities, and can therefore easily be used in computer simulations just by adding few steps to the generation of usual random variables. On the other hand, RDU is mathematically very similar to Choquetexpected utility, and includes as a limit case the minimax principle. Therefore, even if formally this model is a model of choice under risk (since it assumes an underlying probability distribution), in practice it behaves very much like models of choice under uncertainty and can be easily put in relation to them. Ideally, one would like to use a model of choice under uncertainty for the case of climate change, but it is interesting to use RDU in this framework for its pragmatic advantages, which provide the possibility to analyze quite a flexible and general model and making use of (a large number of) computer simulations at the same time.

The following section introduces a way to represent the essential features of irreversibility in a static framework, by means of thresholds in the utility function.

Thresholds

The global climate is a complex system: when a change (like pollution) occurs in one part of the system, the chain of reactions can be very sensitive to small differences in the size of the initial shock. The relation between pollution and damage can consequently present threshold values where damage increases very steeply, or even jumps up in a discontinuous way. Carpenter, Ludwig and Brock 1999 give a relatively simple presentation of a pollution model with thresholds. The qualitative features of such a model can be considered similar to those of the climatic system.

Irreversibility in this framework means that once the threshold is crossed, a structural change in the model occurs which cannot be repaired—even if the emission level is brought back to lower levels afterwards. In other words, the choice to cross the threshold is made only once. This means that learning may not be a valuable option (Aalbers 1999), which makes a static model the most appropriate. This paper refers indeed to a static model of utility maximization in the presence of thresholds, developed by Aalbers (1999). In such framework, two independent probability densities are assumed: 1) $\pi(B)$, defined over the interval $[B_{\min}; B_{\max}]$, describes the location of a threshold B for GHG emissions; 2) $\theta(\alpha)$, defined on the interval $[0;1]$, describes the fraction $(1-\alpha)$ of consumption lost due to environmental damage, once the threshold is crossed.

If the consumption level is c, and assuming one-to-one correspondence between consumption and pollution, then the probability of crossing the threshold is $\Pr\{B \leq c\} = \Pi(c)$, where $\Pi(B)$ is the distribution function for $\pi(B)$.

Since we assume that the two variables B and α are independent of each other, their joint distribution is given by $\Omega(B,\alpha) = \Pi(B) \times \Theta(\alpha)$. Suppose the decision maker derives utility deriving both from consumption, c, and from amenity, $a \equiv B - c$, in this way: $U(c) = u(c) + v(a)$, where $v(a) = 0$ if $a \leq 0$ (assuming that no utility is derived from the environment if the threshold has been crossed). Once c has been chosen and when the true state of nature is $(\tilde{B}, \tilde{\alpha})$, utility is given by:

$$U\left(c \mid \left(\tilde{B}, \tilde{\alpha}\right)\right) = \begin{cases} u(c) + v\left(\tilde{B} - c\right) & \text{if } c < \tilde{B} \\ u(\tilde{\alpha} c) & \text{if } c \geq \tilde{B} \end{cases}$$

Therefore, a priori expected utility for each level of consumption is:

$$EU(c) = \int_{c}^{B_{\max}} [u(c) + v(B - c)]\pi(B) dB + \int_{B_{\min}}^{c} \left[\int_{0}^{1} u(\alpha c)\theta(\alpha) d\alpha \right] \pi(B) dB \quad .$$

To simplify the analysis, we can assume that $u(0) = v(0) = 0$, and that $u(\alpha c) = u(\alpha) u(c)$. Substituting, the expression for expected utility becomes:

$$EU(c) = u(c) + \int_{c}^{B_{\max}} v(B - c)\pi(B) dB - l(u,\theta) u(c) \Pi(c),$$

where $l(u,\theta) = 1 - E[u(a)]$ denotes the expected value in utility units of the percentage loss in consumption.

In reality, the two probability densities $\pi(B)$ and $\theta(\alpha)$ are not known, and even the most accurate analyses do not provide reliable and complete predictions about threshold values for pollution and their impact on the economy. The scientific community prefers to make use of scenario analyses, which provide projections of possible future developments for the main subsystems of interest (socio-economic, political, and ecological systems), based on different probability assessments that correspond to a variety of hypotheses regarding how these systems work and how they relate to each other.

Uncertainty and the scenario approach

> "Projected climate changes during the 21st century have the potential to lead to future large-scale and possibly irreversible changes in Earth systems resulting in impacts at continental and global scales. These possibilities are very climate scenario-dependent and a full range of plausible scenarios has not yet been evaluated." (IPCC 2001b).

The Intergovernmental Panel on Climate Change (IPCC) works on the development of climate scenarios. Such scenarios include assumptions and predictions on both geophysical and socio-economic factors. In particular, the latter are meant to depict possible developments for the future and to provide directions for the choice of structured sets of policies that complement each other, dealing with all dimensions of the problem. However, it is quite reasonable to think that not all these policies can be implemented simultaneously and in a coordinated way: from the point of view of one single decision unit (say, the ministry for environment of one specific country) some socio-economic conditions are exogenously determined, beyond its own control, and substantially independent of its current decision. Therefore there is uncertainty, not only within scenarios, but also across scenarios.

Geophysical uncertainty must also be taken into account: the climate system is chaotic, which means that predictions are affected by both model uncertainty and initial conditions. To increase reliability, probability forecasts are obtained on basis of "multi-model, multi-initial-condition ensembles" (IPCC 2001a). Yet, the report of Working Group I of the IPCC stresses that "an important question is whether a multi-model ensemble made by pooling the world climate community's stock of global models adequately spans the uncertainty in our ability to represent faithfully the evolution of climate". (IPCC2001a).

As a result, a plurality of scenarios can be considered, which differ in their assumptions on both socio-economic and physical parameters. Such scenarios can be treated as states of the world in a traditional decision-making problem, because they are exogenously given, while a subset of variables (here only emissions) can be considered decision variables. This is the approach taken in this paper. Even though I use the word "scenario" basically as a synonym for "state of the world", I maintain the lexical distinction, since one distinctive feature of scenarios is that they constitute a sample of possible states of the world, while decision theory requires that the set of states of the world be exhaustive and exclusive (one and only one state of the set realizes).

Characterization of scenarios.

The warming effect of GHGs may be reduced by some reactions in parts of the system, which are therefore called "negative feedbacks." "Negative" refers to the sign of the relative effect on the temperature, whereas it may be increased by other kinds of reactions; these are therefore called "positive feedbacks". The sign of a feedback is not always known—for instance, the aggregate impact of aerosols on temperature, as reported by IPCC (2001a). We can therefore talk about several scenarios that differ in the underlying assumptions about the sign of groups of feedbacks. As already suggested, among the uncertain feedbacks we might want to include also the possible actions of parts of the human social and economic system. This is possible as long as such actions can be considered independent from the present action. Considering all possible combinations of positive/negative signs for all uncertain feedbacks, we obtain a complete and exclusive state space.

Within a scenario $s = 1,...,S$, I assume that an assessment for the probability densities $\pi_s(B)$ and $\theta_s(\alpha)$ is given. Let us say that $s = 1$ denotes the most favourable case where all uncertain feedbacks are negative, $s = 2$ denotes a less favourable case in which some of the uncertain feedbacks are positive (and so on), until $s = S$ denotes the worst scenario in which all uncertain feedbacks are positive.

I assume that the support of the density function is the same in each scenario ($\left[B_{\min}^{s};B_{\max}^{s}\right]=\left[B_{\min};B_{\max}\right],\ \forall s=1,...,S$). Therefore the following expected utility function represents how expected utility varies over consumption in each scenario:

$$EU_s(c)=u(c)+\int_{c}^{B_{\max}}v(B-c)\pi_s(B)dB-l_s(u,\theta_s)u(c)\Pi_s(c)$$

for $s=1,...,S$.

The vector $(EU_1(c),...,EU_S(c))$ of expected utility values reached in each state when consumption level *c* is chosen can be interpreted as a "lottery" in which one gets $EU_1(c)$ if state 1 occurs, $EU_2(c)$ if state 2 occurs, and so on.

Choice and uncertainty

Consider the lottery $(EU_1(c),...,EU_S(c))$, and denote $EU(c)$ as its expected utility:

$$EU(c)=\sum_{s=1}^{S}p_sEU_s(c).$$

According to traditional decision theory, individuals should choose among lotteries as if they were maximizing expected utility, for some probability distribution $(p_1,...,p_S)$. Actual decision makers however, in real and experimental frameworks, do not always seem to follow such a criterion. Evidence from experimental and field observations clearly show that individuals deviate from expected utility maximization on many occasions, and many theories have been developed with the purpose of clarifying and predicting the patterns of actual choice in the presence of uncertainty (Starmer, 2000). One possible explanation is that people transform probabilities in some systematic way, just like they do with outcomes in their utility function. We are familiar with the idea that individuals may have concave utility functions, which reflects the fact that they value differently the same change in consumption from different starting points. In the same way, they might apply a transformation on probabilities. This is the intuition behind the rank-dependent utility theory (RDU), of which I give a short presentation hereafter. This presentation draws much from Wakker (1989), to which I refer the reader for a more precise and complete, but still intuitive, presentation of RDU theory.

For given consumption c, let us consider a permutation over the set of scenarios $(\rho_1,...,\rho_S)$, such that $EU_{\rho 1}(c) \geq ... \geq EU_{\rho S}(c)$. For each scenario we can compute decumulative probabilities: $P_{\rho s} = p_{\rho 1} + ... + p_{\rho s}$. Let now $\varphi(P)$ be a nondecreasing transformation function such that $\varphi(0) = 0$ and $\varphi(1) = 1$. The RDU-value of our lottery is defined as:

$$RDU(c) = \sum_{s=1}^{S} EU_{\rho_s}(c)\left[\varphi(\mathrm{P}_{\rho_s}) - \varphi(\mathrm{P}_{\rho_{s-1}})\right]$$

where I abuse notation defining $P_{\rho 0} = 0$.

To understand the difference between $RDU(c)$ and $EU(c)$, first notice that we can rewrite $EU(c)$ as follows:

$$\mathrm{EU(c)} = \sum_{s=1}^{S} EU_{\rho s}(c)\left[P_{\rho s} - P_{\rho s-1}\right].$$

Therefore, we can consider expected utility (EU) as a special case of RDU, where the transformation function is linear: $\varphi(P) = P$. Defining the decision weights $dw_{\rho s} \equiv \lfloor P_{\rho s} - P_{\rho s-1} \rfloor$ and $dw'_{\rho s} \equiv \lfloor \varphi(P_{\rho s}) - \varphi(P_{\rho s-1}) \rfloor$, we see in Figure 3 that $dw_s \geq dw'_s$ whenever $\varphi(P_{\rho s})$ has slope not larger than 1, and $dw'_s \geq dw_s$ whenever $\varphi(P_{\rho s})$ has slope not smaller than 1. In particular, in Figure 3 we see that for a convex transformation function the decision weights of RDU are smaller for better outcomes and larger for worse outcomes than the decision weights for EU (remember that P, reported on the horizontal axis, are decumulative probabilities).

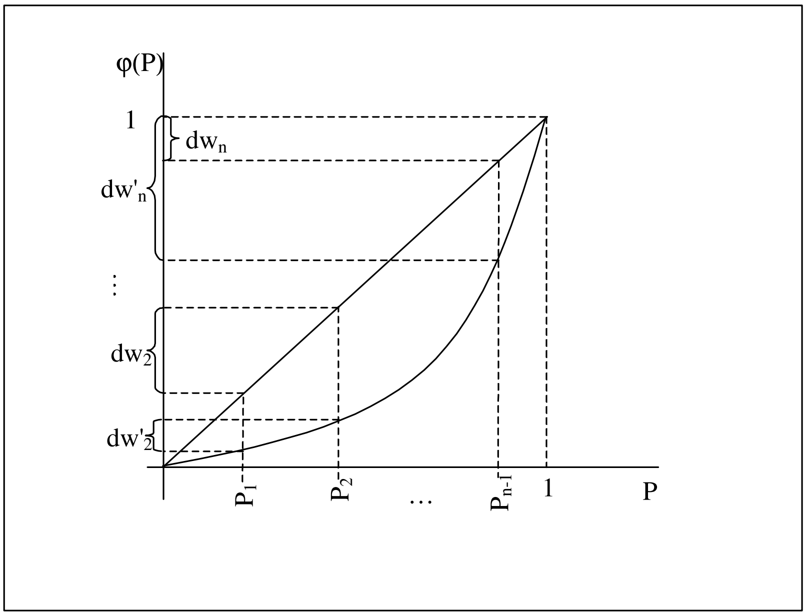


Figure 3 Convex transformation function and relative decision weights.

RDU has been tested in experiments of choice under uncertainty, and empirical evidence (Tversky and Wakker 1995) suggests that actual weighting functions are inversely S-shaped, as is shown in Figure 4. The inverse-S shaped weighting functions have a very nice interpretation in terms of sensitivity to probabilistic estimates: if the weighting function is approximately linear for decumulative probabilities bounded away from the extreme values zero and one, then the slope of the linear portion of the graph represents an index of deviation from expected utility: it is one for EU-maximizers, and smaller than one for RDU-maximizers, as illustrated in the diagram by the dotted line with slope σ. This means that observed deviations from EU could be interpreted in terms of sensitivity to probabilistic information. The smaller σ, the more an individual deviates from EU, and the less he pays attention to those probabilities that are bounded away from the certainty values zero and one. Accordingly, he focuses more attention on the best and the worst outcomes.

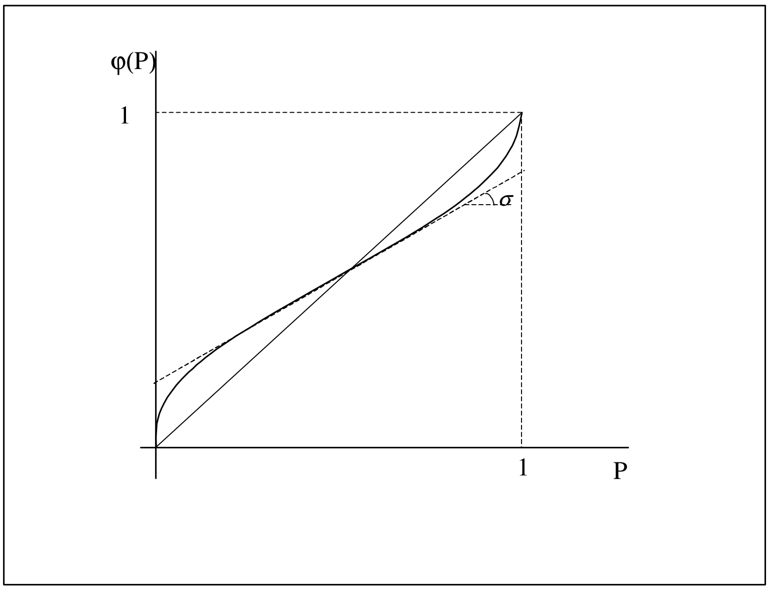


Figure 4. Inverse-S shaped transformation function

Implementing the precautionary principle

Discussing RDU gave us two insights. First, individuals do not always maximize expected utility, but RDU models with inversely S-shaped transformation functions are sometimes more adapt at explaining their behaviour. This does not necessarily imply that also governments behave like that, but it raises two questions: whether they do behave in this way, and what impact this might have on their policies about climate change. Second, a hypothetical individual who maximizes RDU with a convex transformation function systematically attaches more weight to the worse outcomes, and less to the better outcomes, than an individual that maximizes EU. This may sound appealing from a normative point of view, since this kind of model seems intuitively to reproduce what we call a prudent behaviour.

It is interesting to see what would be the consequences on consumption levels if a government chose this way to implement the precautionary principle, and compare it to the two "more realistic" situations in which the government either maximizes EU, or RDU with an inversely S-shaped transformation function. I will refer to the last two models as the "benchmark 1" and "benchmark 2" respectively, and I will refer to the RDU model with convex transformation function as the "precautionary model".

Results

Both benchmark 2 and the precautionary model are derived from maximization of (6), where only the assumptions about $\varphi(P)$ change. Both models are quite complex to deal with analytically. Some results can be derived for given location densities (that is, when only expected damage varies across scenarios). In this case it is possible to prove that a convex-weight-RDU-maximizer always chooses a consumption (emission) level lower or equal to the level chosen by a EU-maximizer. Such a result is reported in section 3.1. For more general situations, in which both the density for the location of the threshold and the expected impact of crossing the threshold vary across scenarios, I report the results of a number of numerical simulations in section 3.2. The experiments show that even under these more general conditions a convex-weight-RDU-maximizer (precautionary model) only rarely chooses higher levels of consumptions than benchmark 1. For inverse-S shaped weights (benchmark 2) no general results can be derived; simulations show, however, that optimal consumption for this model is quite often higher than for benchmark model 1.

Analytical results

Some analytical results can be stated for the cases in which scenarios differ only in the expected impact of crossing the threshold. In this case an individual that maximizes convex-weighted RDU, which is a "prudent" individual in my definition, will never choose a higher level of emissions when compared to a EU-maximizer. This result is stated in Proposition 1, which is preceded by two preliminary results in Lemmas 1 and 2.

Lemma 1 For given $\pi(B)$, $EU_s(c) \geq EU_{s'}(c)$ $\forall c \in [0;1]$ iff $l_s(u,\theta_s) \leq l_{s'}(u,\theta_{s'})$.

> **Proof.** Suppose $\pi_s(B) = \pi_{s'}(B) = \pi(B)$, and $l_s(u,\theta_s) \leq l_{s'}(u,\theta_{s'})$, then $EU_s(c) - EU_{s'}(c) = u(c)\Pi(c)[l_{s'}(u,\theta_{s'}) - l_s(u,\theta_s)] \geq 0$ $\forall c$.

Lemma 2 For given $\pi(B)$, either $RDU\,(c) \geq EU\,(c)\ \forall c \in [0;1]$, or $RDU(c) \leq EU(c)\ \forall c \in [0;1]$, depending on the probabilities attached to the scenarios and on the transforming function. In particular, for convex weights, $RDU(c) \leq EU(c)\ \forall c \in [0;1]$.

Proof. Lemma 1 ensures that the rank ordering of scenarios does not change over *c*. Therefore an individual that maximizes RDU applies the same weights dw_s, $s = 1,...,S$ for every *c*. Thus:

$$\sum_s dw_s EU_s(c) \geq \sum_s p_s EU_s(c) \Leftrightarrow \sum_s dw_s EU_s(c') \geq \sum_s p_s EU_s(c'),\ c, c' \in [0;1]$$

which proves the first statement. The second statement follows straightforwardly, since for convex weighting functions more weight is assigned to those states of the world for which expected utility is lower.

Proposition 1 For given $\pi(B)$, and for convex weighting functions, an individual that maximizes RDU always chooses a level of consumption non-larger than an individual that maximizes EU.

Proof. It holds true that:

$$\frac{dEU_s(c)}{dc} \geq \frac{dEU_{s'}(c)}{dc} \Leftrightarrow [\Pi(c)u'(c) + \pi(c)u(c)][l_{s'}(u, \theta_{s'}) - l_s(u, \theta_s)] \geq 0$$

that is, by Lemma 1:

$$\frac{dEU_s(c)}{dc} \geq \frac{dEU_{s'}(c)}{dc} \Leftrightarrow EU_s(c) \geq EU_{s'}(c).$$

The function that lies below has a smaller first derivative. Moreover, as already noticed, it has relatively larger decisions weights in RDU than in EU. Thus it holds:

$$\frac{dRDU(c)}{dc} = \sum_s dw_s \frac{dEU_s(c)}{dc} \leq \sum_s p_s \frac{dEU_s(c)}{dc} = \frac{dEU(c)}{dc}, \forall \mathrm{c} \in [0;1].$$

The first derivative of *RDU*(*c*) is always smaller than that of *EU*(*c*). Therefore: (i) if there is an interior global optimum both for *EU*(c) and for *RDU*(*c*), the latter must lie to the left of the former; (ii) if *EU*(*c*) has global optimum in $c=1$, then *RDU*(*c*) has either an interior global optimum, or an optimum in $c=0$, or in $c=1$; (iii) if *EU*(*c*) has a global optimum in $c=0$, then *RDU*(*c*) also has a global optimum in $c=0$, since by lemma 2 it always lies below, and for $c=0$ $RDU(c)=EU(c)=EU_s(c)\ \forall s$.

The intuition behind this result is that if the location of the threshold has the same distribution in all scenarios, the only thing that matters is the assessed impact of crossing the threshold. Within scenarios it is always true that the higher this impact, the lower the utility and its first derivative for every level of consumption. Therefore, for convex weights, *RDU*(*c*) has everywhere a smaller derivative than *EU*(*c*), and it must reach the optimum at a lower or equal level of consumption.

This reasoning does not apply when scenarios differ also in the density that describes the location of the threshold, $\pi_s(B)$. In this case all sorts of situations can arise, and in some cases convex-weighted RDU leads to higher emission levels than EU. To understand the intuition behind this, consider that when consumption increases, so does the probability of crossing the threshold. But this happens at a different rate for different densities. In some "bad" scenarios, the threshold is probably already crossed at low levels of consumption: a further increase does not lead to a big increase in the probability of crossing the threshold. In such circumstances it is better to increase consumption, in order to compensate for the environmental loss that has already occurred: the worst outcome would arise from crossing the threshold and not exploiting consumption possibilities. Depending on the other parameters of the problem, such an effect can prevail, leading a ”prudent” decision maker to choose even higher levels of consumption than a “traditional” decision maker.

Simulation results

In order to better understand how the model works and whether more general results can be found besides those stated in Proposition 1, I have run several simulations. To do so, I had to give some specification to the model:

- *probability densities for the location of the threshold* ($\pi(B)$): since the support is finite, and since I want to control the skewedness and variability of the density in order to generate various kinds of hypothetical scenarios, I used beta densities (the assumption of unimodal distributions is maintained overall in what follows); the parameters *A* and *B* for the beta distributions have been pseudo-randomly generated from a computer-based log-normal generator, so that the interval $[0;\infty]$ has been screened concentrating on more “plausible values” for the parameters;

- *probability densities for the impact of crossing the threshold* ($\theta(\alpha)$): this density does not appear in the model but through the expected damage $l(u,\theta)$; I therefore used pseudo-random uniformly distributed values on the interval $[0;1]$ to represent such expectations;

- *utility function*: I use a utility function of the shape $u(c)=c^b+(B-c)^a$. In simulations I always assume that $b=1$, $a=\frac{1}{2}$;

- *probability of a scenario*: for most simulations I assumed two scenarios; the probability of one scenario was driven from a pseudo-random number generator that simulates a uniform distribution over $[0;1]$; the probability for the second scenario was of course derived by imposing $p_1+p_2=1$;

- *RDU transformation functions*: I used two types of weighting functions, one that was introduced in the decision-theory literature by Tversky and Kahneman (and that has the typically observed inverse-S shape), $\varphi(P)=P^\gamma\Big/\left[P^\gamma+(1-P)^\gamma\right]^{1/\gamma}$, and a strictly convex one, $\varphi(P)=P^{1/\gamma}$; both functions are defined for $\gamma\in(0;1]$, in the simulations I tried ten values of γ (γ=0.1,0.2,…,1) for each combination of all other parameters.

Figure 5(a) shows an example where $S=3$ and $A^1=2$, $B^1=3$, $l^1=0.5$, $A^2=7$, $B^2=6$, $l^2=0.2$, $A^3=10$, $B^3=10$, $l^3=0.3$. In Figure 5(b) the continuous line represents the expected utility function across scenarios, $EU(c)$, and c^* is the optimal choice of consumption when $p_1 = 0.3$, $p_2 = 0.5$, $p_3 = 0.2$. The dashed line instead represents the RDU-expected utility function, $RDU(c)$, and c^{**} is the optimal choice of consumption when $\varphi(P) = P^{1/\gamma}$ and $\gamma = 0.4$.

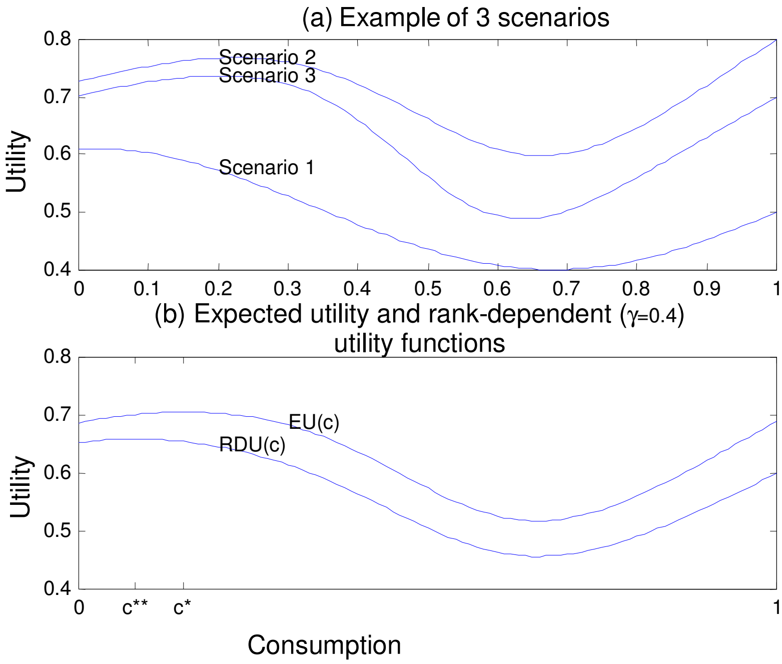


Figure 5. Example of three scenarios and relative cross-scenario RDU and EU functions**.**

In this first case $c^* > c^{**}$. Figure 6 shows a case in which the opposite occurs.[21] This illustrates the result that no general relation between c^* and c^{**} can be easily found. To explore this topic in more detail, I ran a number of simulations, limiting the analysis to the simple case of two scenarios. In these simulations, pseudo-random and independent values of the parameters *A*, *B*, and *l* were drawn, and for each combination c^* and c^{**} were compared for $\gamma = 0.1, 0.2, \ldots, 1$. One hundred combinations were analysed in this way for Tversky-Kahneman weighting functions and another one hundred for convex weighting functions.

[21] In this example S=2 and A^1=2 B^1=10 l^1=0.05, A^2=3 B^2=2 l^2=0.4, p_1=0.2, p_2=0.8, and the weighting function is convex with γ=0.4.

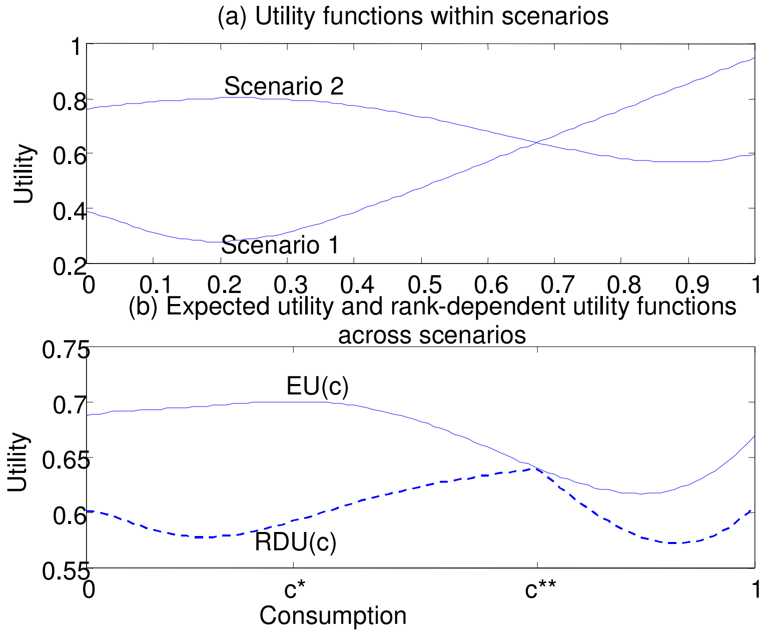


Figure 6

In the case of convex weighting functions $c^{**} > c^{*}$ for 12% of randomly drawn parameter combinations, while in the case of Tversky-Kahneman weighting functions, this percentage is 31%, so that we can conclude that in general it is really difficult to predict the direction of deviations from expected utility optimal values if an individual maximizes RDU. However, one can state that convex-weight-RDU-maximizers only rarely choose higher levels of consumption than EU-maximizers, while this is more likely for inverse-S shaped weights.

Conclusions

The model in this paper aims at defining optimal choice of emission levels under special circumstances, such as thresholds in the utility function and lack of scientific knowledge about relevant aspects of the problem. The approach of the paper has been to adopt a special decision criterion *ex-ante* in order to account for the fact that the precautionary principle applies in the circumstances mentioned. I have shown that for this model results are not unequivocal, since in some cases imposing “prudent” behaviour leads to higher levels of pollution. The reason for this result is that some model specifications make it very likely to cross threshold levels of pollution already for low consumption; in these cases, if the assessed impact of climate change is not too high it is possible that the most prudent decision is indeed to compensate the loss of environmental utility with more consumption. Though the high degree of unpredictability of the results of this model is common to other models that analyse the same problem, the interpretation here is somewhat different, since it implies that a conservative use of resources is not necessarily optimal *even applying the precautionary principle ex-ante*. However, it is also clear that for most parameters combinations, convex-weighted RDU (prudence) determines a lower level of emissions than the benchmark EU model, and this is always the case when scenarios differ only in the assessed impact of crossing the threshold.

Normatively, these results stress one feature of RDU: since more weight is given to the worse outcomes, a big issue becomes how the worst scenario is designed. Making the precautionary principle operational translates then in a problem of identifying the appropriate state space, as suggested also by Henry & Henry (2002). Such a high sensitivity to the specification of the state space leaves a large degree of freedom in implementation, and it might be regarded as a shortcoming of this theory. However, it is interesting that this way of modeling actually forces the debate between economists and (climate) scientists deep into ontological aspects and away from modelling issues (such as the shape of the utility function). What really matters here is the value of the physical parameter l (expected damage from crossing the threshold) and the distribution π (describing the location of the threshold). Indeed, there exists a tension between scientists and economists about the problem of climate change. Such a tension is obviously sharpened by some communication problems between two different disciplines, but is probably more deeply rooted in diverging perceptions of “how bad can bad be?”, with respect to the consequences of climate change. If this model correctly reflects such a tension, this may turn the negative aspect of sensitivity into a positive aspect of identification of a relevant content that too often remains hidden behind sophisticated mathematics.

Finally, simulations show that there is a relevant difference between convex-weighted-RDU maximizers and inverse-S shaped RDU maximizers; the latter are namely “more likely” to choose higher levels of emissions than the former. This observation becomes particularly interesting if we believe that actual decision makers are inverse-S shaped RDU maximizers, as appears to be the case in experiments on individual choice under uncertainty. On the other hand, nothing can ensure that policy makers behave in the face of uncertainty in the same way as single individuals do, and the circumstances of choice about climate change have never, to my knowledge, been reproduced in laboratory experiments. This work therefore stresses the importance of testing such a hypothesis.

2. Resource depletion facing the risk of unknown thresholds: theoretical models of choice

In this chapter we present a model of resource depletion with thresholds. As already done in chapter 1, we assume that when harvesting pushes the stock of a renewable resource underneath a critical level, the resource looses its regenerative properties and is not able to renew itself anymore. If this critical level is unknown, an agent engaged in the harvesting of the resource faces a problem of choice under risk[22]. In real life similar situations can be faced when managing a renewable resource like a fishery, or the atmospheric and climatic equilibrium.

We are interested in the decision-making problem faced by the agent when the only limits to harvesting are given by the initial stock of the resource and the uncertainty about the critical level. For reasons of tractability the model is kept very simple in its building blocks: we have linear payoff functions and uniform probability distributions, and we completely disregard the value of leisure and the costs of harvesting. This is functional to our purpose of focussing on the effects of perceived risk on harvesting. As discussed already in chapter 1, different theories can be used to predict and explain behavior under risk and uncertainty. In this chapter we present a model similar to the model in chapter 1, but much

[22] Discussions of renewable resource management under uncertainty and with thresholds can be found in Van Kooten and Bulte (2000), although they do not discuss the case where both characteristics occur. Aalbers (1999) discusses uncertainty regarding the location and impact of the threshold in the context of climate change.

more simple, and use it to analyze and compare three major theories of decision under risk: expected value maximization, risk-aversion, and rank-dependency[23].

The comparison of the theories should help us draw conclusions on the qualitative and quantitative differences among these theories, concerning the predicted levels of optimal harvesting. If we interpret harvesting broadly as "use" of a resource, we can see how these conclusions can be of interest in the framework of climate change, where we can see the atmosphere as a pollution sink of given, renewable, capacity, and pollution as the use of such capacity.

Compared to the analysis in chapter 1, this chapter offers a more limited analysis, focussing only on the risk represented by the unknown location of the threshold, while we assume that the impact of crossing the threshold is known. The advantage of this focus is that we can derive more results analytically, and also that we can use the models in this section as a theoretical basis for an experimental analysis, which will be the subject of chapter 3.

For each theory we derive the consequences on harvesting decisions when the parameters of the probability distribution for the critical stock level vary: in particular we look at how optimal harvesting varies across theories when the range and the mean of the distribution change.

The decision problem

One agent chooses the amount d of harvesting from a renewable resource, having the initial stock R_0. The growth function of the resource is such that if the agent extracts a lot and depletes the resource, reducing it to a level lower than a threshold R^{CRIT}, the system collapses and nothing will be left for future generations.

Assume that R^{CRIT} is unknown, and all what the agent knows is that the threshold can vary over a compact range, $A = \left[\underline{R}; \overline{R}\right]$, with some probability density function, $f(R)$. Let $g(d)$ be the payoff function derived from direct consumption, and $\hat{\pi}(d)$ the utility function derived from leaving $R_0 - d$ of the resource for use to future generations. Harvesting is sustainable if d is such that the remaining

[23] For an overview of these theories with special attention to rank-dependent utility see Diecidue and Wakker (2001).

stock exceeds the critical level necessary for the resource to "survive": $R^0 - d \geq R^{CRIT}$. If harvesting is sustainable in period one we assume that $\hat{\pi}(d) > 0$, otherwise $\hat{\pi}(d) = 0$. Thus the total payoff for the agent at time one is given by:

$$\pi(d) = \begin{cases} g(d) + \hat{\pi}(d) & \text{if } R^{CRIT} \leq R^0 - d \\ g(d) & \text{otherwise} \end{cases}.$$

Therefore the expected payoff for the agent when he/she chooses a level *d* of consumption in period one is:

$$E(\pi(d)) = g(d) + \hat{\pi}(d)F(R^0 - d)$$

where *F*(*R*) is the cumulative density for the threshold. If the agent is risk neutral he/she maximizes this expression.

If instead the agent is risk averse and has utility function $u(\cdot)$, with $u' > 0$ and $u'' < 0$, then he/she maximizes expected utility:

$$EU(d) = u(g(d) + \hat{\pi}(d))F(R^0 - d) + u(g(d))[1 - F(R^0 - d)].$$

Currently EV and EU are the most common ways of modelling preferences under uncertainty in the environmental economics literature[24]. However, decision theorists have shown that in many experimental situations individuals behave inconsistently with these theories (see the discussion in chapter 1 for more details).

Among the alternative models that are used in the literature for descriptive purposes, rank-dependent utility is one of the most successful[25]: if we assume for simplicity that utility is linear ($u(x) = x$), and that all payoffs are non-negative, then the rank-dependent utility model predicts that an agent maximizes the following expression[26]:

[24] See for instance an application in Armantier and Treich (2004).

[25] See Starmer (2000) for a review.

[26] See appendix A1.

$$RDU(d) = g(d) + \hat{\pi}(d) \cdot w(F(R_o - d))$$

where $w(.)$ is a probability transformation function, defined on the interval [0;1], where it is assumed to be monotonically increasing, and such that $w(0) = 0$ and $w(1) = 1$. The transformation function is usually assumed to be inverse-S shaped, however for our purposes it is more interesting to consider convex transformation functions. An agent maximizing RDU with convex transformation functions attaches more weight to worse outcomes, compared to an agent maximizing expected payoffs, and therefore modelling choices in this way induces a kind of behaviour that can be interpreted as "prudent" (see also the discussion and the description of the theory in chapter 1). We think this particular feature of the model might play a role in a setting with thresholds: in most cases crossing the threshold would be the worst possible outcome, and agents might well experience some fear and explicitly try to avoid it.

In the following sections we derive analytically the first-order and second-order conditions for the special case when the payoffs are linearly increasing in the use of the resource d, and the probability density of the threshold value for the resource stock R^{CRIT} is uniform over a given range. To be more specific it is assumed that both the "present" payoff, $g(d)$, and the "future" payoff, $\hat{\pi}(d)$, are linear, i.e. $g(d) = kd$ and $\hat{\pi}(d) = \alpha d$, where k and α are given coefficients for the first and the second period respectively. This is done for different models: (1) assuming that agents maximize expected value (i.e. are risk neutral), (2) assuming that agents maximize expected utility (i.e. are risk averse) and (3) assuming that agents maximize rank dependent utility with convex weights.

Risk neutral agents

When we assume that the agents maximize the expected value it is possible to derive the optimum harvesting amount explicitly. Expected payoff is given by:

$$EV[\pi(d)] = \begin{cases} kd + \alpha d & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ kd + \alpha d\left[\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right] & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

If there is an interior optimum, it must thus be found solving:

$$\max_{R_0 - \overline{R} \le d \le R_0 - \underline{R}} \quad kd + \alpha d\left[\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right]$$

which can easily be shown to give:

$$d^* = \frac{k\left(\overline{R} - \underline{R}\right) + \alpha\left(R_0 - \underline{R}\right)}{2\alpha}$$

Such interior optimum is indeed a global optimum if the following two conditions hold:

1. *Condition EV1:* $kR_0 \le kd^* + \alpha d^*\left[\dfrac{R_0 - d^* - \underline{R}}{\overline{R} - \underline{R}}\right]$

   That is:

   $$\left(k\left(\overline{R} - \underline{R}\right) + \alpha\left(R_0 - \underline{R}\right)\right)^2 \ge 4\alpha k R_0\left(\overline{R} - \underline{R}\right)$$

2. *Condition EV2:* $(k + \alpha)\left(R_0 - \overline{R}\right) \le kd^* + \alpha d^*\left[\dfrac{R_0 - d^* - \underline{R}}{\overline{R} - \underline{R}}\right]$

   That is:

   $$\left(\overline{R} - \underline{R}\right)^2 (k^2 + 2\alpha k) + \left(\overline{R} - \underline{R}\right)\left(\overline{R} - R_0\right)\left(2k\alpha + 4\alpha^2\right) + \alpha^2\left(R_0 - \underline{R}\right)^2 \ge 0$$

We can rewrite the internal optimum in terms of the mean and range of the distribution as follows, defining $M = \dfrac{\overline{R} + \underline{R}}{2}$, $r = \overline{R} - \underline{R}$:

$$d^* = \left(\frac{k}{2\alpha} + \frac{1}{4}\right)r + \frac{1}{2}\left(R_0 - M\right)$$

From which it follows that

$\dfrac{\partial d^*}{\partial r} = \dfrac{k}{2\alpha} + \dfrac{1}{4} > 0$, and

$$\frac{\partial d^*}{\partial M} = -\frac{1}{2} < 0$$

This means that as the range of the distribution increases, implying more uncertainty, harvesting increases. When the mean of the distribution increases, meaning that on expectation more of the stock is needed to keep the resource productive, harvesting decreases.

Risk-adverse agents

Next we look at the case when risk averse agents maximize expected utility, which is given by:

$$EU[\pi(d)] = \begin{cases} u(kd+\alpha d) & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ u(kd+\alpha d)\left[\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right] + u(kd)\left[\dfrac{\overline{R} - R_0 + d}{\overline{R} - \underline{R}}\right] & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

Assuming a (constant relative risk aversion) utility function of type $u(x) = x^a$, with $0 < a < 1$, if there is an interior optimum it can be found solving:

$$\max_{R_0 - \overline{R} \le d \le R_0 - \underline{R}} \quad ((k+\alpha)d)^a \left[\frac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right] + (kd)^a \left[\frac{\overline{R} - R_0 + d}{\overline{R} - \underline{R}}\right]$$

Which gives the optimal extraction level:

$$d^* = \frac{a}{a+1} \frac{(k+\alpha)^a (R_0 - \underline{R}) + k^a (\overline{R} - R_0)}{(k+\alpha)^a - k^a}$$

Such an interior optimum is a global optimum if the following two conditions hold:

1. *Condition CRRA1:*

$$(kR_0)^a \le [(k+\alpha)d^*]^a \frac{R_0 - d^* - \underline{R}}{\overline{R} - \underline{R}} + (kd^*)^a \frac{\overline{R} - R_0 + d^*}{\overline{R} - \underline{R}}$$

2. *Condition CRRA2:*

$$\left[(k+\alpha)\left(R_0-\overline{R}\right)\right]^a \leq \left[(k+\alpha)d^*\right]^a \frac{R_0-d^*-\underline{R}}{\overline{R}-\underline{R}}+\left(kd^*\right)^a \frac{\overline{R}-R_0+d^*}{\overline{R}-\underline{R}}$$

In this case, the optimum can be expressed in terms of the mean and range of the distribution of R^{CRIT} as follows:

$$d^* = \frac{a}{a+1}\left[\frac{(k+\alpha)^a+k^a}{2(k+\alpha)^a-2k^a}r+R_0-M\right]$$

From which it follows that

$$\frac{\partial d^*}{\partial r} = \frac{a}{a+1}\left[\frac{(k+\alpha)^a+k^a}{2(k+\alpha)^a-2k^a}\right] > 0$$

and

$$\frac{\partial d^*}{\partial M} = -\frac{a}{a+1} < 0$$

This means that qualitatively the predictions of this model are the same as the EV predictions: when uncertainty increases, harvesting increases, and when the expected R^{CRIT} increases, harvesting decreases, thus leaving more of the resource stock intact.

Note that this also holds for other models like CARA etc.

Rank-dependent utility

As a third model we assume that an agent chooses harvesting as to maximize rank-dependent utility, which is defined as follows[27]:

[27] See Appendix A1

$$RDU[\pi(d)] = \begin{cases} kd + \alpha d & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ kd + \alpha d \cdot w\left(\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right) & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

therefore the interior optimum is the solution to:

$$\max_{R_0 - \overline{R} \le d \le R_0 - \underline{R}} \quad kd + \alpha d \cdot w\left(\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right)$$

which implies the first-order condition:

$$k + \alpha \cdot w\left(\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right) - \frac{\alpha d}{\overline{R} - \underline{R}} \cdot w'\left(\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right) = 0 .$$

Because we want to use a convex weighting function, we will assume that $w(x) = x^{1/\gamma}, 0 < \gamma < 1$. Thus the first-order condition becomes:

$$k + \alpha\left(\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right)^{\frac{1}{\gamma}} - \frac{\alpha d}{\overline{R} - \underline{R}} \frac{1}{\gamma}\left(\frac{(R_0 - d) - \underline{R}}{\overline{R} - \underline{R}}\right)^{\frac{1}{\gamma}-1} = 0 ,$$

or, in terms of mean and range:

$$k + \alpha\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}} - \frac{\alpha d}{r} \frac{1}{\gamma}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1} = 0$$

It is not possible in this case to derive the optimal extraction level explicitly. However we can show that this model has the same qualitative implications compared to EV and CRRA: the internal optimum is increasing in *r* and decreasing in *M*. We prove this result in the following sections.

Optimal harvesting under RDU when the range of possible R^{CRIT} varies

To see how the optimum varies when the range increases, one can study the sign of the derivative of the first-order condition with respect to *d* and with respect to *r*, and then apply the implicit function theorem.

We define:

$$L \equiv k + \alpha\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}} - \frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1},$$

and we know that when the first-order condition holds, $L = 0$, and if both $\frac{\partial L}{\partial d}$ and $\frac{\partial L}{\partial r}$ are positive or both are negative, then the implicit function theorem ensures us that $\frac{\partial d^*}{\partial r} < 0$. On the contrary, when the sign of the two derivatives $\frac{\partial L}{\partial d}$ and $\frac{\partial L}{\partial r}$ is the opposite, then the theorem implies that $\frac{\partial d^*}{\partial r} > 0$.

1) Derivative with respect to d

It is straightforward to derive that

$$\frac{\partial L}{\partial d} = -2\frac{\alpha}{\gamma r}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1} + \frac{\alpha d}{r^2\gamma^2}(1-\gamma)\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-2}$$

is smaller than zero if and only if[28]:

$$d < \frac{\gamma}{\gamma+1}\left[2(R_0 - M) + r\right]$$

This condition is also the second-order condition that we need to impose because we are only searching for a maximum. Thus we know that no internal optimum can be found for $d > \frac{\gamma}{\gamma+1}\left[2(R_0 - M) + r\right]$. We also know that the

[28] See Appendix A2.

internal optimum has to be searched in the interval $J \equiv \left[R_0 - \overline{R}; R_0 - \underline{R}\right]$. If we express it in terms of mean and range of the distribution of R^{CRIT}, the interval becomes $J = \left[R_0 - M - \frac{1}{2}r; R_0 - M + \frac{1}{2}r\right]$. If there is an internal optimum, it therefore has to be found in the intersection between J and $I \equiv \left[0; \frac{\gamma}{\gamma+1}\left[2(R_0 - M) + r\right]\right]$. This is stated more precisely in Lemma 1 below.

Lemma 1

If $R_0 - M > \frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$, then there exists no internal optimum.

If $R_0 - M \leq \frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$ and if there exists an internal optimum d^*_{RDUCW}, then it holds true:

$$d^*_{RDUCW} \in \left[R_0 - M - \frac{1}{2}r; \frac{\gamma}{\gamma+1}\left[2(R_0 - M) + r\right]\right]$$

Proof: see Appendix B.

It is now trivial to notice that the sign of $\frac{\partial L}{\partial d}$ is always negative in the range of admissible values for the internal optimum, which implies that the sign of $\frac{\partial d^*_{RDUCW}}{\partial r}$ is entirely determined by $\frac{\partial L}{\partial r}$.

2) First derivative with respect to r

We can show[29] that $\frac{\partial L}{\partial r}$ is positive for:

$$d \in [d_1; d_2]$$

---

[29] See Appendix A2.

with:

$$d_1 = \frac{(R_0-M)(2\gamma+1)+\gamma r-\sqrt{(R_0-M)^2+2\gamma^2 r(R_0-M)+\gamma^2 r^2}}{2(\gamma+1)}$$
$$d_2 = \frac{(R_0-M)(2\gamma+1)+\gamma r+\sqrt{(R_0-M)^2+2\gamma^2 r(R_0-M)+\gamma^2 r^2}}{2(\gamma+1)}$$

and negative elsewhere.

Furthermore, we can prove that any internal optimum is such that $d^*_{RDUCW} > d_1$. To see this, call L_0 the left-hand side of the first order condition when $k = 0$:

$$L_0 \equiv \alpha\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}} - \frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}$$

Denote with d_0^* the solution to $L_0 = 0$. This can easily be derived analytically:

$$d_0^* = \frac{\gamma}{2(\gamma+1)}\left[2(R_0-M)+r\right]$$

and it can be proven[30] to always be larger than d_1.

It also is a straightforward consideration to notice that the second-order condition implies $\frac{\partial L_0}{\partial d} < 0$, since the parameter *k* does not play a role here. This means that L_0 varies in the opposite direction as d. If we now set $k = \tilde{k} > 0$, we can deduce that $\tilde{k} + L_0 > 0$. To satisfy the first-order condition we thus have to reduce L_0, that is, increase d. Thus we can conclude that:

[30] See Appendix C.

Lemma 2 For all admissible parameter values, if there is an internal optimum d^*_{RDUCW}, it holds true that $d^*_{RDUCW} > d^*_0 > d_1$.

Imposing the second order condition, we notice[31] finally that $d_2 > \frac{\gamma}{\gamma+1}[2(R_0 - M) + r]$. Because $\frac{\partial L}{\partial r}$ is always positive between d_1 and d_2, lemma 1 and lemma 2 together imply:

Proposition 1 If the problem admits an internal optimum, d^*_{RDUCW}, it holds true that:

$$d^*_{RDUCW} \in \left[d_1 ; \frac{\gamma}{\gamma+1}[2(R_0 - M) + r] \right]$$

$$\frac{\partial d^*_{RDUCW}}{\partial r} > 0$$

Thus when the range of possible values for the unknown threshold varies, we have the same result for RDUCW as it holds for EV and EU. This means that when uncertainty increases, then the optimal harvesting also increases. This result does not take corner solutions into account. We will discuss corner solutions later on.

Optimal harvesting under RDU when the mean of R^{CRIT} varies

We proceed here similarly as in the previous section in order to determine the sign of $\frac{\partial L}{\partial M}$ and then use some of the results in the previous section in order to derive the sign of $\frac{\partial d^*}{\partial M}$.

The first derivative of L with respect to M is:

[31] See Appendix C.

$$\frac{\alpha}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}\frac{-2}{2r}-\frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1}{\gamma}-1\right)\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-2}\frac{-2}{2r}$$

This derivative is non-negative if and only if[32]

$$-\left(\frac{2(R_0-d)-2M+r}{2r}\right)-\frac{d}{r\gamma}(1-\gamma)\geq 0$$

which leads to the condition:

$$d\geq\gamma\left(R_0-M+\frac{1}{2}r\right)$$

In order to have an internal optimum, we need to impose that $L=0$ and we need to check that this local maximum is a global one, that is, it has to be larger in value than the corner solutions. This implies that the following two conditions need to be met simultaneously:

$$\begin{cases} k=-\alpha\left[\frac{2(R_0-d)-2M+r}{2r}\right]^{\frac{1}{\gamma}}+\frac{\alpha d}{r}\frac{1}{\gamma}\left[\frac{2(R_0-d)-2M+r}{2r}\right]^{\frac{1}{\gamma}-1} \\ kR_0\leq kd+\alpha d\left[\frac{2(R_0-d)-2M+r}{2r}\right]^{\frac{1}{\gamma}} \end{cases}$$

Substituting the RHS of the first expression for k in the second expression, we obtain:

$$2d^2-2R_0(\gamma+1)d+\gamma R_0(2R_0-2M+r)\geq 0$$

It is straightforward to see that:

$$\Delta=4R_0^2(\gamma+1)^2-8\gamma R_0[2(R_0-M)+r]=4\left[R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)\right]\geq 0$$

[32] See appendix A2.

if $M \geq \frac{r}{2}$, and because $\underline{R} = M - \frac{r}{2}$ is the lower limit of the distribution of R^{CRIT} then it has to be non-negative, implying that $\Delta \geq 0$.

Thus we can find two values, $d_5 \leq d_6$ such that an internal optimum exists only if $d \leq d_5$ or $d \geq d_6$:

$$d_5, d_6 = \frac{R_0(\gamma+1) \pm \sqrt{R_0^2(\gamma-1)^2 + 2\gamma R_0(2M - r)}}{2}$$

However, the second order condition requires $d < \frac{\gamma}{\gamma+1}\left(2(R_0 - M) + r\right)$ and we can prove[33] that $d_6 \geq \frac{\gamma}{\gamma+1}\left(2(R_0 - M) + r\right)$, and thus there exists no internal global optimum such that $d^* \geq d_6$.

Besides, we can show[34] that $d_5 \leq \gamma\left(R_0 - M + \frac{r}{2}\right)$, and thus for all global optima such that $d^* \leq d_5$ it holds true that $\frac{\partial L}{\partial M} < 0$. This implies that if there is an internal global optimum, then it is such that: $\frac{\partial d^*}{\partial M} < 0$. Thus we can state the following:

Proposition 2 For all admissible parameters, it holds true that, if there exists an internal optimum d^*_{RDUCW}, then:

1. $d_1 \leq d^* \leq d_5$;
2. $\frac{\partial d^*}{\partial M} < 0$.

[33] See Appendix C

[34] See Appendix C.

Combining propositions 1 and 2, and noticing that $d_5 \leq \frac{\gamma}{\gamma+1}\left[2\left(R_0 - M\right)+r\right]$[35] it follows:

Proposition 3 For all admissible parameters, it holds true that, if there exists an internal optimum d^*_{RDUCW} , then:

1. $d_1 \leq d^*_{RDUCW} \leq d_5$;
2. $\frac{\partial d^*_{RDUCW}}{\partial r} > 0$;
3. $\frac{\partial d^*_{RDUCW}}{\partial M} < 0$.

Proposition 3 states that the same results hold for RDUCW as for EV and EU: if the spread of the distribution of R^{CRIT} , *r*, becomes larger, then for all these theories the optimal harvesting increases; if the average of the distribution, *M*, becomes higher, then the optimal harvesting decreases.

In the next section we show some examples to illustrate the behavior of the internal optimum when the parameters *r* and *M* vary, and compare the outcomes across the different theories. We also look at some examples where we get corner solutions.

Comparison of the theories

It is easy to verify that for internal optima it always holds true that:

$$\left|\frac{\partial d^*_{EU}}{\partial M}\right| > \left|\frac{\partial d^*_{CRRA}}{\partial M}\right|$$

Observations derived by 400 numerical examples typically suggest that:

[35] See Appendix C.

$$\left|\frac{\partial d^*_{EU}}{\partial M}\right| > \left|\frac{\partial d^*_{RDUCW}}{\partial M}\right| > \left|\frac{\partial d^*_{CRRA}}{\partial M}\right| \quad \text{for high } \gamma \text{ or low } \alpha$$

$$\left|\frac{\partial d^*_{EU}}{\partial M}\right| > \left|\frac{\partial d^*_{CRRA}}{\partial M}\right| > \left|\frac{\partial d^*_{RDUCW}}{\partial M}\right| \quad \text{for low } \gamma \text{ or high } \alpha$$

The way the optimum varies in r is more difficult to predict and in general it is not possible to say which theory predicts sharper reactions, and examples can be found for all possible situations. We will show hereafter a few examples to illustrate this observation. In designing the examples we use parameters close to the ones used in the experiment described in chapter 3.

Example 1

We set here:

$$R_0 = 12 \;\; M = 6 \;\; r = 12 \;\; \alpha = 6 \;\; k = 1$$

And obtain:

$$d^*_{EV} = \left(\frac{k}{2\alpha} + \frac{1}{4}\right) r + \frac{1}{2}(R_0 - M) = 7$$

$$d^*_{CRRA} = \frac{a}{a+1}\left[\frac{(k+\alpha)^a + k^a}{2(k+\alpha)^a - 2k^a} r + R_0 - M\right] = \begin{cases} 6.17 & \textit{if} \quad a = 0.1 \\ 6.26 & \textit{if} \quad a = 0.3 \\ 6.43 & \textit{if} \quad a = 0.5 \\ 6.64 & \textit{if} \quad a = 0.7 \\ 6.88 & \textit{if} \quad a = 0.9 \end{cases}$$

$$d^*_{RDUCW} = \begin{cases} 12 & \textit{if} \quad \gamma = 0.1 \\ 12 & \textit{if} \quad \gamma = 0.3 \\ 5.17 & \textit{if} \quad \gamma = 0.5 \\ 6.05 & \textit{if} \quad \gamma = 0.7 \\ 6.72 & \textit{if} \quad \gamma = 0.9 \end{cases}$$

This example illustrates a feature that we have observed in simulations, that is, it is relatively easy to get corner solutions when computing the optimal harvesting according to RDUCW, compared to the other theories: 88% of the parameter combinations used in the simulations lead to corner solutions for RDUCW, compared to 62.5% for CRRA and 78% for EV. This means that giving more importance to worse outcomes leads more easily to the decision of crossing the threshold for sure or stay safe for sure. One could say that RDUCW theory triggers more extreme decisions. In this particular case the upper corner solution prevails, because the spread of the distribution here is so large that crossing the threshold is an event that cannot be avoided for sure.

Figure 7 to Figure 9 illustrate the utility functions according to expected value, expected utility, and rank-dependent utility theory, respectively.

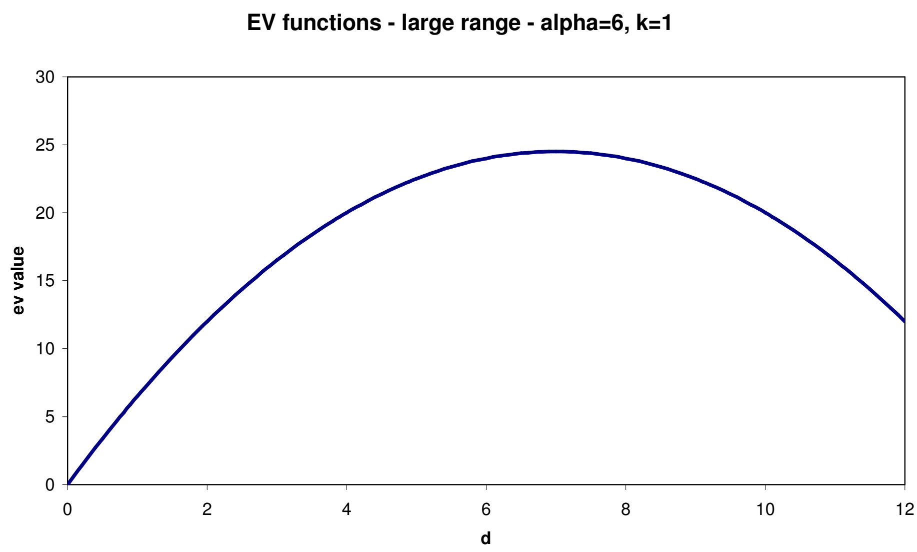


Figure 7

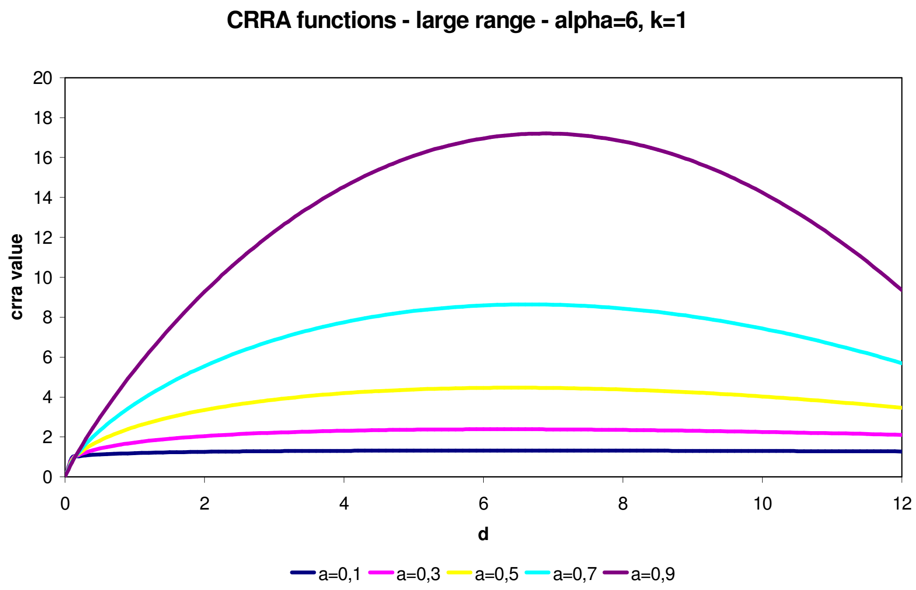


Figure 8

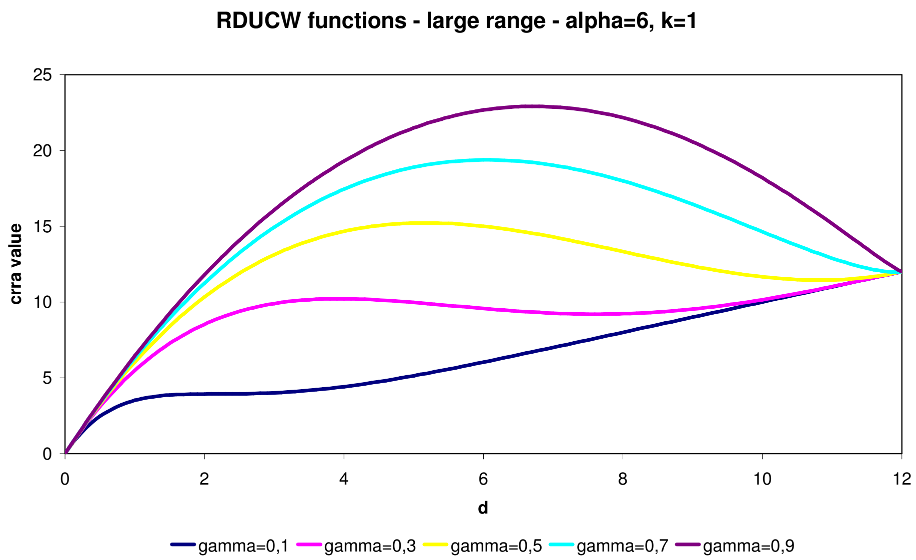


Figure 9

Example 2

In this example we use the same parameters, but we reduce the range of the possible unknown values for R^{CRIT}. We set:

$$R_0 = 12 \;\; M = 6 \;\; r = 6 \;\; \alpha = 6 \;\; k = 1$$

and observe that:

$$d^*_{EV} = \left(\frac{k}{2\alpha} + \frac{1}{4}\right) r + \frac{1}{2}(R_0 - M) = 5$$

$$d^*_{CRRA} = \frac{a}{a+1}\left[\frac{(k+\alpha)^a + k^a}{2(k+\alpha)^a - 2k^a} r + R_0 - M\right] = \begin{cases} 3.36 & \textit{if} \quad a = 0.1 \\ 3.82 & \textit{if} \quad a = 0.3 \\ 4.22 & \textit{if} \quad a = 0.5 \\ 4.56 & \textit{if} \quad a = 0.7 \\ 4.86 & \textit{if} \quad a = 0.9 \end{cases}$$

$$d^*_{RDUCW} = \begin{cases} 3 & \textit{if} \quad \gamma = 0.1 \\ 3 & \textit{if} \quad \gamma = 0.3 \\ 3.35 & \textit{if} \quad \gamma = 0.5 \\ 4.16 & \textit{if} \quad \gamma = 0.7 \\ 4.76 & \textit{if} \quad \gamma = 0.9 \end{cases}$$

From our simulations we see that, just like in this example, CRRA often reacts more sharply to a variation in the range *r* of the probability distribution, compared to the other two theories: for small variations of *r* this happens in the 84% ca. of the simulated examples where all theories present an internal optimum.

Also notice that in this case, RDUCW is the only one to predict corner solutions, even though in this case the preferences are attracted more towards the lower corner rather than the upper corner as observed in example 1. What has happened? Reducing the range of the distribution means that there is less doubts where the actual R^{CRIT} may be located. As a result, all the utility functions are now more skewed to the left. The RDUCW function, especially for very low values of γ, especially evaluates the advantage of securing a safe outcome, and picks the lower corner solution. This option was not available in example 1. Figures 4 to 6 show the shape of the functions in this case.

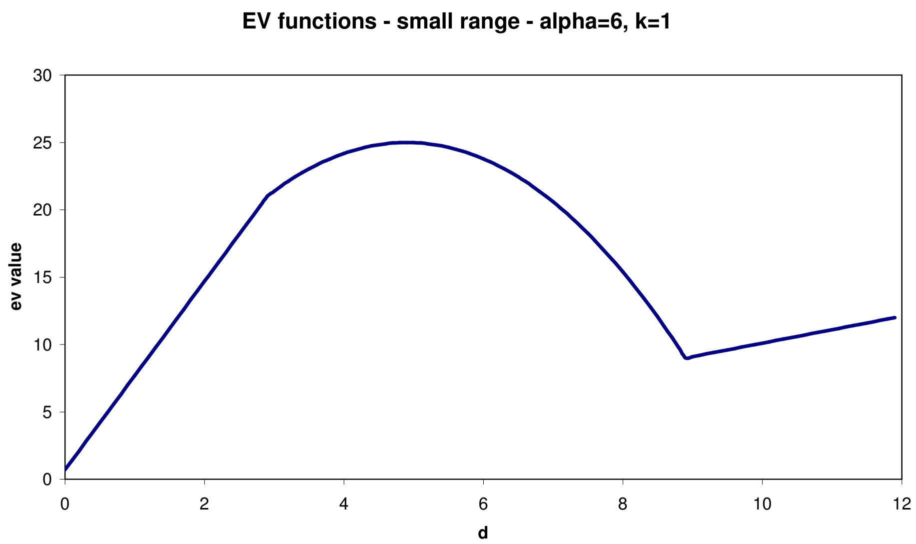


Figure 10

CRRA functions - small range - alpha=6, k=1

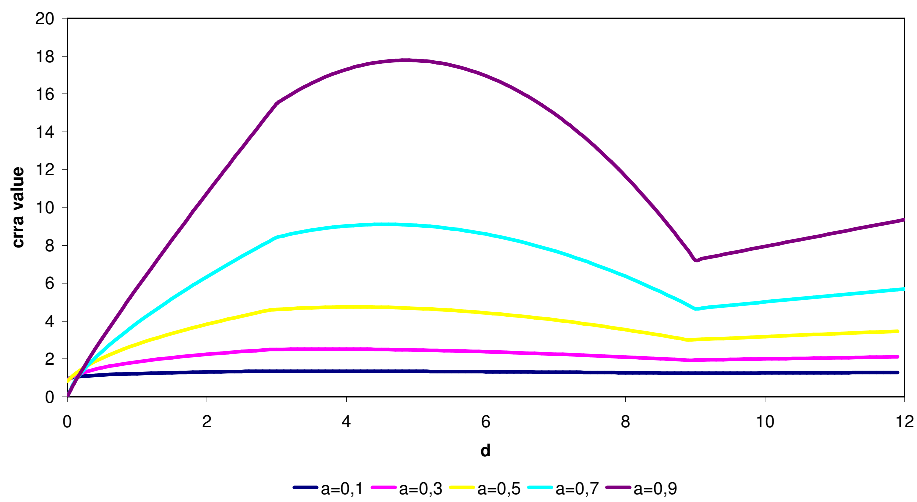


Figure 11

RDUCW functions - small range - alpha=6, k=1

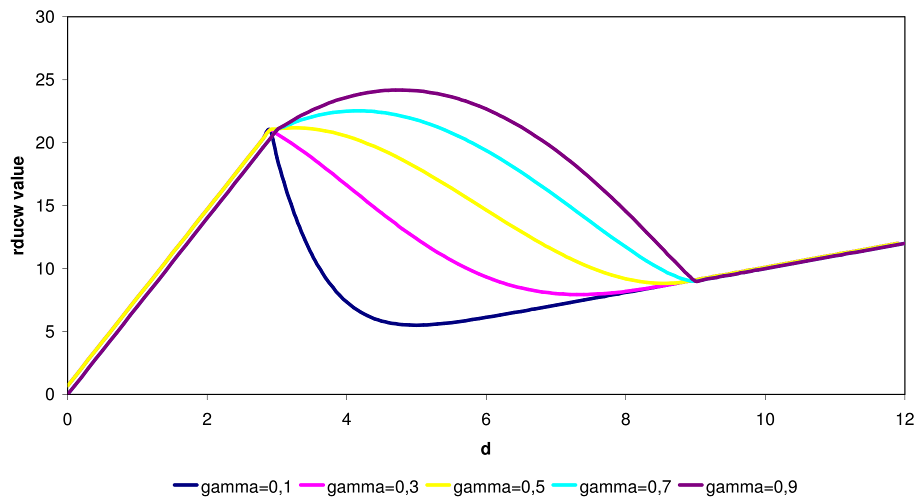


Figure 12

Example 3

We now look at what happens if we increase the mean of the distribution. We set:

$$R_0 = 12 \;\; M = 7 \;\; r = 6 \;\; \alpha = 7 \;\; k = 5$$

Figures 7 to 9 show that all functions are now skewed even more to the left, and thus the optimal choices are also lower in most cases. As the optimal values are close to the ones obtained in example 2, we do not report them here.

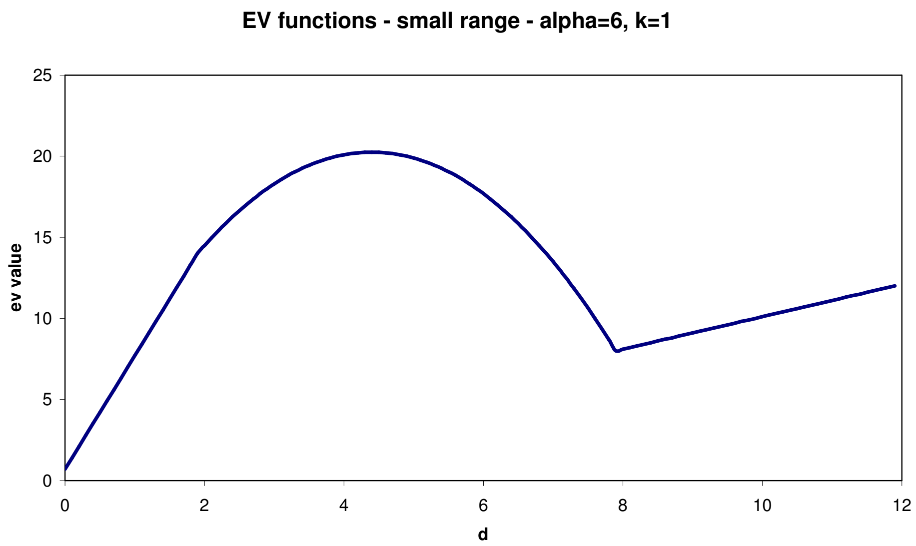


Figure 13

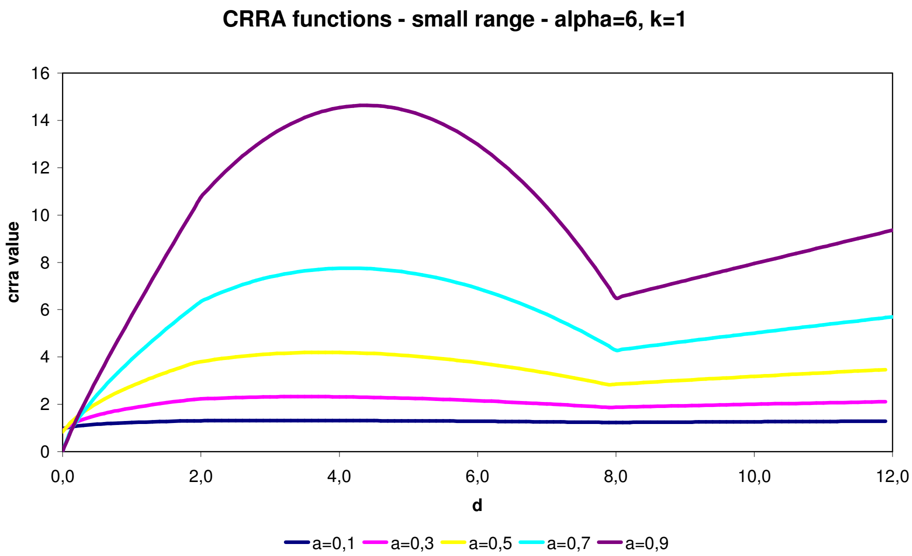


Figure 14

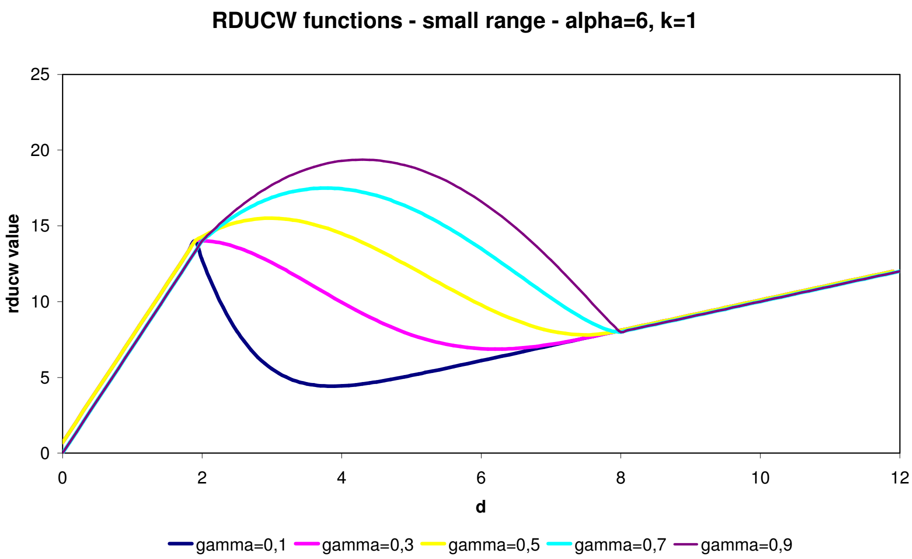


Figure 15

Example 4

We now give an example where all theories express an optimum at the upper corner solution. We set:

$$R_0 = 12 \quad M = 6 \quad r = 6 \quad \alpha = 7 \quad k = 5$$

The result is clearly illustrated in figures 10 to 12.

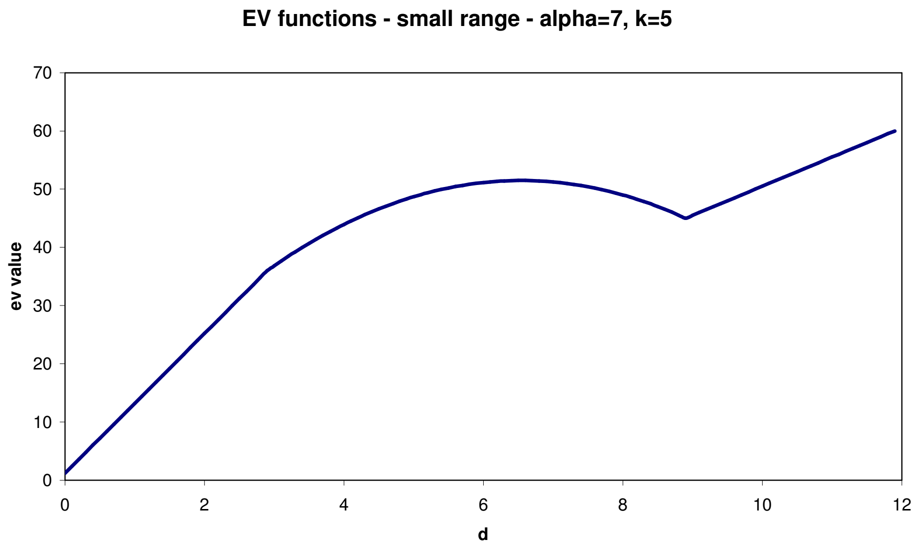


Figure 16

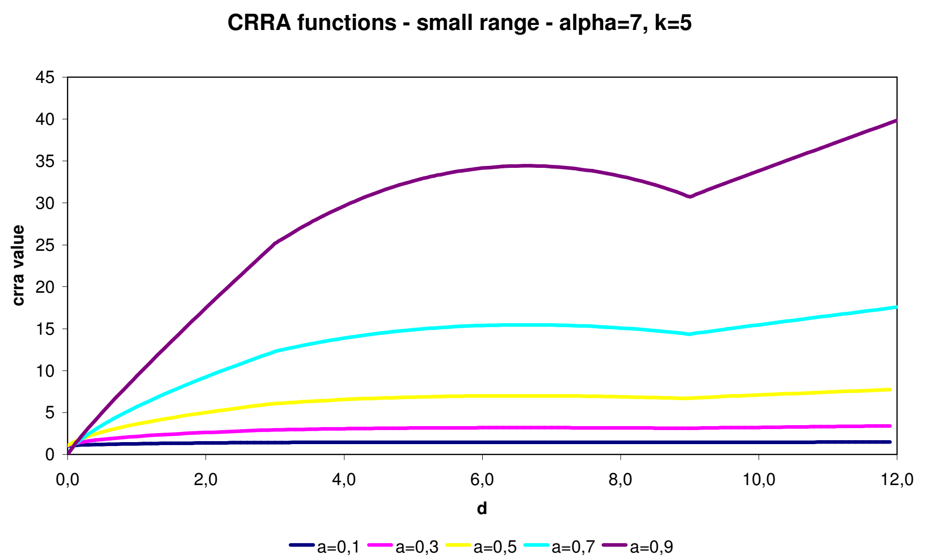


Figure 17

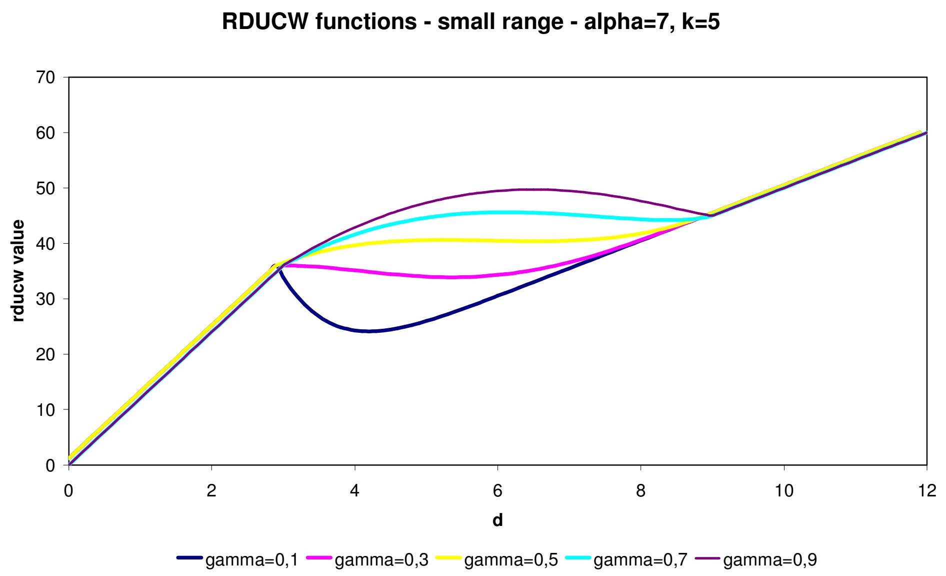


Figure 18

Conclusions

We have used three different theoretical frameworks to describe the behavior of an agent that wants to manage a renewable resource and faces the risk of crossing an unknown threshold. If harvesting is such that the remaining stock of the resource is below a critical level, the resource will not be productive in the future. Our models analyze the choice of the agent when we assume that the agent is risk-neutral, risk-adverse, or when we assume that the agent wishes to avoid bad outcomes. In all these situations, if the optimal harvesting is not a corner solution, the models predict the same qualitative behavior when the range and the mean of the distribution of the unknown parameter change: if the range of the distribution increases, meaning more uncertainty, then it is optimal to harvest more; if the mean of the distribution increase, meaning that it is easier to cross the threshold, then it is optimal to harvest less. However, often the theories predict corner solutions, in which case usually no reaction is expected when a slight change in the range and mean of the distribution occurs, and very sharp reactions are observed when the range or the mean of the distribution change more substantially. For agent maximizing a utility function of the CRRA or RDUCW type, these results also depend on the parameter of the utility function, α and γ respectively. Usually lower values of the parameters induce stronger variations in harvesting: this is not surprising, as these parameters are inversely related to the sensitivity of the agent to risk and to bad outcomes.

Appendices

Appendix A1: The rank-dependent utility function

When $d = \tilde{d}$, we have a state-space made of two events:

$$E_1 : R_0 - \tilde{d} \geq R^{CRIT}$$

and

$$E_2 : R_0 - \tilde{d} < R^{CRIT}$$

If event E_1 occurs, then the payoff is given by $g(\tilde{d}) + \hat{\pi}(\tilde{d})$. If event E_2 occurs, then the payoff is given by $g(\tilde{d})$, with $g(\cdot) \geq 0, \hat{\pi}(\cdot) \geq 0$. One and only one of the two events occurs.

The probability that E_1 occurs is:

$$p_1 = \Pr\{R^{CRIT} \leq R_0 - \tilde{d}\} = F(R_0 - \tilde{d})$$

and the probability that E_2 occurs is:

$$p_2 = 1 - F(R_0 - \tilde{d})$$

E_1 is the best outcome, so its decision weight is given by:

$$dw_1 = w(p_1) = w(F(R_0 - \tilde{d}))$$

and consequently the decision weight for E_2 is:

$$dw_2 = 1 - w(F(R_0 - \tilde{d}))$$

Meaning that the RDU value for $\tilde{d}$ is:

$$RDU(\tilde{d}) = \left[g(\tilde{d}) + \hat{\pi}(\tilde{d})\right] \cdot w(F(R_o - \tilde{d})) + g(\tilde{d}) \cdot \left[1 - w(F(R_o - \tilde{d}))\right]$$

It takes straightforward calculations to see that

$$RDU\left(\tilde{d}\right) = g\left(\tilde{d}\right) + \hat{\pi}\left(\tilde{d}\right) \cdot w\left(F\left(R_o - \tilde{d}\right)\right)$$

Thus the RDU function has the form:

$$RDU(d) = g(d) + \hat{\pi}(d) \cdot w(F(R_o - d))$$

Appendix A2: Derivation of the signs of the derivatives with respect to *d*, *r*, and *M*

1) Derivation of the derivative with respect to d and its sign

$$-\frac{\alpha}{\gamma}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1}\frac{2}{2r} - \frac{\alpha}{r}\frac{1}{\gamma}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1} +$$

$$+\frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1}{\gamma} - 1\right)\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-2}\frac{2}{2r} =$$

$$-2\frac{\alpha}{\gamma r}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1} + \frac{\alpha d}{r^2\gamma^2}(1-\gamma)\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-2}$$

Dividing by $\frac{\alpha}{\gamma r}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-2} > 0$ gives

$$-2\left(\frac{2(R_0 - d) - 2M + r}{2r}\right) + \frac{d(1-\gamma)}{r\gamma}$$

This is larger than or equal to zero iff:

$$-\left(2(R_0 - d) - 2M + r\right) + d\frac{1-\gamma}{\gamma} \geq 0$$

or:

$$d \geq \frac{\gamma}{\gamma+1}\left[2\left(R_0 - M\right)+r\right]$$

2) Derivation of the derivative with respect to r and its sign

$$\frac{\alpha}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}\frac{2r-(2(R_0-d)-2M+r)2}{4r^2}+\frac{\alpha d}{r^2}\frac{1}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}+$$
$$-\frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1}{\gamma}-1\right)\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-2}\frac{2r-(2(R_0-d)-2M+r)}{4r^2}=$$

$$\frac{\alpha}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}\frac{M-(R_0-d)}{r^2}+\frac{\alpha d}{r^2}\frac{1}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}+$$
$$-\frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1-\gamma}{\gamma}\right)\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-2}\frac{M-(R_0-d)}{r^2}$$

This is larger than or equal to zero if (dividing by $\left[\frac{2(R_0-d)-2M+r}{2r}\right]^{\frac{1}{\gamma}-2}>0$):

$$\frac{\alpha}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)\frac{M-(R_0-d)}{r^2}+\frac{\alpha d}{r^2}\frac{1}{\gamma}\left(\frac{2(R_0-d)-2M+r}{2r}\right)+$$
$$-\frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1-\gamma}{\gamma}\right)\frac{M-(R_0-d)}{r^2}\geq 0$$

which is equivalent to (multiplying by $2\gamma^2 r^3>0$):

$$\alpha\gamma\left(2(R_0-d)-2M+r\right)\left[M-(R_0-d)\right]+\alpha\gamma d\left(2(R_0-d)-2M+r\right)$$
$$-2\alpha d(1-\gamma)\left[M-(R_0-d)\right]\geq 0$$

Thus the first derivative of the equilibrium condition with respect to r is positive if and only if:

$$-2(1+\gamma)d^2 + 2d\big((R_0 - M)(2\gamma+1) + \gamma r\big) - \gamma(R_0 - M)\big(2(R_0 - M) + r\big) \geq 0$$

This, in turn is equivalent to:

$$2(1+\gamma)d^2 - 2d\big((R_0 - M)(2\gamma+1) + \gamma r\big) + \gamma(R_0 - M)\big(2(R_0 - M) + r\big) \leq 0$$

Define: $\Delta = 4\left[(R_0 - M)(2\gamma+1) + \gamma r\right]^2 - 8\gamma(1+\gamma)(R_0 - M)\big(2(R_0 - M) + r\big)$.
Then it holds true that $\Delta \geq 0$ for all admissible parameter combinations:

Proof:

$$\Delta = 4\left[(R_0 - M)^2(2\gamma+1)^2 + \gamma^2 r^2 + 2\gamma r(R_0 - M)(2\gamma+1)\right] - 8\gamma(1+\gamma)\left[2(R_0 - M)^2 + r(R_0 - M)\right] \geq 0$$

$$\Leftrightarrow$$

$$(R_0 - M)^2 + 2(R_0 - M)\gamma^2 r + \gamma^2 r^2 \geq 0$$

Which is always true given our assumptions on the parameters.

Thus, $\dfrac{\partial L}{\partial r}$ is positive for:

$$d \in I \equiv [d_1; d_2] = \left[\frac{(R_0 - M)(2\gamma+1) + \gamma r - \sqrt{(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2}}{2(\gamma+1)};\ \frac{(R_0 - M)(2\gamma+1) + \gamma r + \sqrt{(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2}}{2(\gamma+1)}\right]$$

3) Derivation of the derivative with respect to M

$$\frac{\alpha}{\gamma}\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-1}\frac{-2}{2r} - \frac{\alpha d}{r}\frac{1}{\gamma}\left(\frac{1}{\gamma} - 1\right)\left(\frac{2(R_0 - d) - 2M + r}{2r}\right)^{\frac{1}{\gamma}-2}\frac{-2}{2r} =$$

$$-\frac{\alpha}{\gamma r}\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-1}+\frac{\alpha d}{r^2\gamma^2}(1-\gamma)\left(\frac{2(R_0-d)-2M+r}{2r}\right)^{\frac{1}{\gamma}-2}$$

This is larger than or equal to zero if (dividing by $\frac{\alpha}{\gamma r}\left[\frac{2(R_0-d)-2M+r}{2r}\right]^{\frac{1}{\gamma}-2}>0$)

$$-\left(\frac{2(R_0-d)-2M+r}{2r}\right)+\frac{d}{r\gamma}(1-\gamma)\geq 0$$

$$-(R_0-d)+M-\frac{1}{2}r+d\frac{1-\gamma}{\gamma}\geq 0$$

$$-\gamma R_0+\gamma d+\gamma M-\frac{1}{2}\gamma r+d(1-\gamma)\geq 0$$

$$d\geq \gamma R_0-\gamma M+\frac{1}{2}\gamma r$$

$$d\geq \gamma\left(R_0-M+\frac{1}{2}r\right)$$

Appendix B: Proof of lemma 1

Proof of lemma 1

1) $\frac{\gamma}{\gamma+1}\left[2(R_0-M)+r\right]\geq R_0-M-\frac{1}{2}r$ if and only if $R_0-M\leq\frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$.

$$R_0-M-\frac{1}{2}r\leq\frac{\gamma}{\gamma+1}\left[2(R_0-M)+r\right]$$

implies by straightforward computations:

$$R_0-M\leq\frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$$

2) $\frac{\gamma}{\gamma+1}\left[2(R_0-M)+r\right]\leq R_0-M+\frac{1}{2}r$ for all admissible parameter values:

$$\frac{\gamma}{\gamma+1}\left[2(R_0-M)+r\right]\leq R_0-M+\frac{1}{2}r$$

$$\gamma\left[2(R_0-M)+r\right]\leq\gamma\left[(R_0-M)+\frac{1}{2}r\right]+R_0-M+\frac{1}{2}r$$

$$\gamma\left[(R_0-M)+\frac{1}{2}r\right]\leq R_0-M+\frac{1}{2}r$$

This is always true as $0<\gamma<1$.

Thus from 1) and 2) it follows that:

$$J\cap I=\varnothing \quad \text{if} \quad R_0-M>\frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$$

$$J\cap I=\left[R_0-M-\frac{1}{2}r;\frac{\gamma}{\gamma+1}\left[2(R_0-M)+r\right]\right] \quad \text{if} \quad R_0-M>\frac{1}{2}r\frac{3\gamma+1}{1-\gamma}$$

Appendix C

1) $d_0^* > d_1$

$$d_0^* = \frac{\gamma}{2(\gamma+1)}[2(R_0 - M) + r]$$

$$d_1 = \frac{(R_0 - M)(2\gamma+1) + \gamma r - \sqrt{\Delta}}{2(\gamma+1)}$$

$$\frac{\gamma}{2(\gamma+1)}[2(R_0 - M) + r] > \frac{(R_0 - M)(2\gamma+1) + \gamma r - \sqrt{\Delta}}{2(\gamma+1)}$$

$$\gamma[2(R_0 - M) + r] > (R_0 - M)(2\gamma+1) + \gamma r - \sqrt{\Delta}$$

$$0 > (R_0 - M) - \sqrt{\Delta}$$

$$\sqrt{\Delta} > (R_0 - M)$$

$$(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2 > (R_0 - M)^2$$

$2\gamma^2 r(R_0 - M) + \gamma^2 r^2 > 0$ which is always true.

2) $d_2 > \frac{\gamma}{\gamma+1}[2(R_0 - M) + r]$

$$\frac{(R_0 - M)(2\gamma+1) + \gamma r + \sqrt{\Delta}}{2(\gamma+1)} > \frac{\gamma}{\gamma+1}[2(R_0 - M) + r]$$

$$(R_0 - M)(2\gamma+1) + \gamma r + \sqrt{\Delta} > 2\gamma[2(R_0 - M) + r]$$

$$\sqrt{\Delta} > (2\gamma - 1)(R_0 - M) + \gamma r$$

$$\sqrt{(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2} > (2\gamma - 1)(R_0 - M) + \gamma r$$

$$(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2 > [(2\gamma - 1)(R_0 - M) + \gamma r]^2$$

$$(R_0 - M)^2 + 2\gamma^2 r(R_0 - M) + \gamma^2 r^2 > (2\gamma - 1)^2 (R_0 - M)^2 + \gamma^2 r^2 + 2\gamma(2\gamma - 1)(R_0 - M)$$

$$0 > (4\gamma^2 - 4\gamma)(R_0 - M) + (4\gamma^2 - 2\gamma) - 2\gamma^2 r$$

$$0 > 4\gamma(\gamma - 1)(R_0 - M) + 2\gamma^2 (2 - r) - 2\gamma \quad \text{always true for } r \geq 2 .$$

3) $d_6 \geq \dfrac{\gamma}{\gamma + 1}(2(R_0 - M) + r)$:

$$\frac{R_0(\gamma + 1) + \sqrt{R_0^2(\gamma - 1)^2 + 2\gamma R_0(2M - r)}}{2} \geq \frac{\gamma}{\gamma + 1}(2(R_0 - M) + r)$$

$$(\gamma + 1)\sqrt{R_0^2(\gamma - 1)^2 + 2\gamma R_0(2M - r)} \geq -R_0(\gamma + 1)^2 + 2\gamma(2(R_0 - M) + r)$$

$$(\gamma + 1)\sqrt{R_0^2(\gamma - 1)^2 + 2\gamma R_0(2M - r)} \geq -R_0(\gamma + 1)^2 + 4\gamma(R_0 - M) + 2\gamma r$$

which is always true because:

$$-R_0(\gamma + 1)^2 + 4\gamma(R_0 - M) + 2\gamma r < 0$$

$$-R_0(\gamma^2 + 2\gamma + 1) + 4\gamma R_0 - 4\gamma M + 2\gamma r < 0$$

$$-R_0(\gamma^2 - 2\gamma + 1) - 4\gamma M + 2\gamma r < 0$$

$$-R_0(\gamma - 1)^2 - 2\gamma(2M - r) < 0 \quad \text{always.}$$

4) $d_5 \leq \gamma\left(R_0 - M + \dfrac{r}{2}\right)$:

$$\frac{R_0(\gamma+1)-\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}}{2} \leq \gamma\left(R_0-M+\frac{r}{2}\right)$$

$$R_0(\gamma+1)-\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)} \leq 2\gamma\left(R_0-M+\frac{r}{2}\right)$$

$$R_0(\gamma+1)-2\gamma\left(R_0-M+\frac{r}{2}\right) \leq \sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}$$

$$R_0(1-\gamma)+\gamma(2M-r) \leq \sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}$$

$$[R_0(1-\gamma)+\gamma(2M-r)]^2 \leq R_0^2(1-\gamma)^2+2\gamma R_0(2M-r)$$

$$R_0^2(1-\gamma)^2+\gamma^2(2M-r)^2+2\gamma(1-\gamma)R_0(2M-r) \leq R_0^2(1-\gamma)^2+2\gamma R_0(2M-r)$$

$$R_0-M+\frac{r}{2} \geq 0$$

5) $d_5 \leq \frac{\gamma}{\gamma+1}[2(R_0-M)+r]$

$$\frac{R_0(\gamma+1)-\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}}{2} \leq \frac{\gamma}{\gamma+1}[2(R_0-M)+r]$$

$$R_0(\gamma+1)^2-2\gamma[2(R_0-M)+r] \leq (\gamma+1)\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}$$

$$R_0(\gamma^2+1+2\gamma)-4\gamma R_0+4\gamma M-2\gamma r \leq (\gamma+1)\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}$$

$$R_0(\gamma-1)^2+2\gamma(2M-r) \leq (\gamma+1)\sqrt{R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)}$$

$$\left[R_0(\gamma-1)^2+2\gamma(2M-r)\right]^2 \leq (\gamma+1)^2\left[R_0^2(\gamma-1)^2+2\gamma R_0(2M-r)\right]$$

$$\left[R_0(\gamma-1)^2+2\gamma(2M-r)\right]^2 \leq (\gamma+1)^2 R_0\left[R_0(\gamma-1)^2+2\gamma(2M-r)\right]$$

$$R_0(\gamma-1)^2+2\gamma(2M-r)\leq(\gamma+1)^2R_0$$

$$-4\gamma R_0+2\gamma(2M-r)\leq 0$$

$-2\gamma[2(R_0-M)+r]\leq 0$, which is true by assumption.

3. Can fear of extinction foster extinction?

Regenerating assets sometimes have the feature that an unknown critical level must be preserved in order to avoid extinction. In case of livestock, for example, it is well known that a critical minimum stock size (or minimum gene pool) is necessary to allow a sustainable rate of reproduction. Similar scenarios with different critical thresholds are possible. It may be the case, for example, that the equilibrium of an ecosystem is irrevocably disturbed, if some critical level of pollution is surpassed. In most of these settings, however, neither exact theoretical values nor exact empirical measurements of the critical threshold variables are available. Hence, such resources can be modelled as having a *stochastic extinction threshold*, i.e. there is a positive probability of extinction that increases in the level of extraction.[36]

The management of a renewable resource with a stochastic extinction threshold, obviously, involves making risky choices, because any choice of the current consumption level corresponds to some level of extinction risk. In the classical Expected Utility (EU) choice model as well as in most Non-Expected Utility (Non-EU) models, the manager of such a resource weighs off the benefit of a higher consumption today against the benefit of risky future consumption of the resource. Thus, the optimal choices of resource managers will obviously depend on their attitude towards risk.

From an environmental economics point of view, the somewhat surprising outcome of the optimization in most choice models is that resource managers, who prefer to avoid risk, tend to choose much higher extraction levels than those, who are risk seeking (Bargiacchi 2003; see also chapter 2 of the present

[36] The details of the models may differ. For example, ex-ante there may be a lower threshold, below which the probability of extinction is known to be zero, and an upper threshold, above which the probability of extinction is known to be one. This corresponds to knowing the lower and upper bounds of the distribution of the (ex-post) stochastic extinction threshold.

dissertation). The surprising element here is that more "fearful"[37] resource managers take on a much greater risk of resource extinction than "fearless" managers. The reason for this counterintuitive behavior is simply that extremely high levels of resource extraction actually entail less payoff risk, because today's instantaneous and risk-free consumption is increased in exchange for uncertain future resource consumption. In other words, maximizing current consumption may in fact reduce total risk, because it pays more immediately and at the same time reduces uncertainty about future payoffs by making resource extinction a sure thing. Hence, theory suggests that sustainable usage of resources with stochastic extinction thresholds is more likely to be achieved with a fearless resource manager than with a fearful one.

The *rapid-consumption behavior* (i.e. "eat it up quickly, before it's gone" behavior) by fearful managers is a theoretical result, with different choice models predicting widely varying degrees of the effect.[38] Since the literature on risky choice is still far from having identified a single most appropriate model for all decision situations (Starmer 2000), assessing the actual behavior of resource managers when faced with a stochastic extinction threshold remains an empirically relevant, but scientifically open question.

In this chapter, we present an experimental study that is designed to provide an empirical assessment of the rapid-consumption behavior in the presence of a

---

[37] Note that we are avoiding the term "risk-averse", because there is no general consensus yet on how risk-aversion is to be defined in the domain of Non-EU models, even though the discussion by Schmidt and Zank (2002) has made important progress on the issue. Following a similar definition as Schmidt and Zank (2002), chapter 2 of this dissertation examines the behavior of resource managers in our setting, when it is assumed that they like to avoid outcome dispersion as measured by a mean-preserving spread.

[38] Note that non-ecological assets with stochastic extinction thresholds may also lead to a rapid consumption behavior of managers. If, for example, a risk-averse manager recognizes that the survival of his firm depends on an unknown (i.e. stochastic) minimum level of financial resources, he may prefer a rapid extraction of the firms resources to a prudent behavior that may nevertheless end with the firm's total collapse. The financial extractions initiated by ENRON managers in the pre-collapse phase were perhaps due to such a rapid extraction behavior.

stochastic extinction threshold. We run an experiment on a simple one-player, two-period resource extraction game, the same game that has been analyzed theoretically in chapter 2. First, the resource manager chooses an initial extraction from the resource. If the amount of resource left after the initial extraction is less than a randomly drawn and ex-ante unknown extinction threshold, the game ends. Otherwise, the resource manager chooses the extraction level for the second period, after which the game ends. Since the random distribution of the extinction threshold variable is ex-ante known to the resource manager, but not its realization, the manager faces a risky choice.

The purpose of the experiment is to test agents' behaviour when uncertainty and thresholds are present. This chapter relates thus to the previous two chapters in that it looks for evidence in support or against the theories presented until now.

We find that a substantial subset of the observed decisions contradict standard expected utility theory (EUT) no matter which level of risk-aversion we assume. Hence, we compare our results also with two versions of the rank-dependent utility (RDU) model, which is the most widely accepted non-expected utility model (Camerer 1995, Starmer 2000, Decidue and Walker 2001). One version (RDUTK) is based on the parameterization suggested by Tversky and Kahneman (1992) and entails an inverse S-shaped probability weighting function, which implies that the probability of "undesired" outcomes and that of very good outcome are given more weight than in a linear weighting. Since the assumption that the risk of the very good events is "over-weighted" by resource managers seems rather unintuitive in our context, we also compare our results with a version of the RDU-model in which the probability weighting function is convex in outcomes (RDUCW). This parameterization of the RDU model is based on Bargiacchi (2003) and leads to an "over-weighting" of only the undesired outcomes in comparison to linear weights. Hence, resource managers, whose behavior is of the RDUCW-type, will tend to be more "prudent" concerning any catastrophic outcome, obviously including the worst-case scenario of resource extinction.

From the four decision models that we consider – risk-neutral expected utility (EV), constant relative risk-aversion expected utility (CRRA), rank-dependent utility with a Tversky and Kahneman (1992) probability weighting function

(RDUTK), and rank-dependent utility with a convex probability weighting function (RDUCW) – only the first is parameter-free. All other three have a single parameter that must be estimated empirically. While out-of-sample estimates of the parameters are available and occasionally used in the literature, assuming a single value for all decision-makers (or all experimental subjects) would be ignoring the fact that these parameters describe individual risk-attitudes that may be distributed over a wide range due to individual differences. On the other hand, when the parameters' value ranges are taken into consideration, a comparison of competing models becomes more involved, because the sets of outcomes that are predicted by different models may diverge greatly in size.

We deal with these issues by comparing our observations to the theoretical models in two ways. First, we compare the experimental outcomes to the point-predictions of each model for parameter values that cover the feasible range.[39] Using this method, we not only find that our in-sample-estimates of the model parameters come astonishing close to the values reported in the literature[40]. We also find that when applying the best-fit parameters, the two rank-dependent models do much better in explaining the data than the two expected utility models. This result is inline with numerous other studies on risky choice behavior.[41]

The second method we use to assess the explanatory power of the alternative models is to compare the predictive success of the models using Selten's (1991) *measure of predictive success*. This measure compares each model's "prediction area" (i.e. the entire set of outcomes that is predicted over the admissible range of parameters) to its "hit rate" (i.e. the number of observations within the prediction area). The rank-dependent utility model with convex weights (RDUCW) turns out to be the model with the highest measure of predictive success, i.e. the model

---

[39] Obviously, EV always makes a unique point prediction, because it is parameter-free. CRRA entails a parameter of risk-aversion that is generally restricted to lie between 0 and 1. RDUTK and RDUCW each require a parameter that controls the shape (curvature) of the probability weighting function. Both of these parameters are also assumed to be in the range from 0 to 1.

[40] See for instance Donkers, Melenberg, and Van Soest (2001).

[41] E.g. Lattimore, Baker, and Witte (1992); Tversky and Kahneman (1992); Abdelaoui (1998); Gonzalez and Wu (1999). For an overview see Starmer (2000).

exhibiting the best relationship between the range of feasible outcomes and the rate of model-compliant observations. This result is in contrast to findings from earlier studies (see footnote 5) that generally found stronger evidence for inverse S-shaped than for convex probability weighting.

There is an important difference, however, between the decisions typically examined and those in our experimental setup. While standard lottery choice problems are examined in all the other cited studies, we model a resource extraction situation with a stochastic extinction threshold. This type of task seems to invoke a much more prudent behavior of subjects than the standard tasks, which would explain why the behavior we observe is better explained by the prudent (or "pessimistic" as Starmer (2000) puts it) version of the rank-dependent decision model with a convex probability weighting function.

Note that subjects in other experiments involving an extinction risk have also been reported to exhibit an "overly" prudent behavior. Hey, Neugebauer, and Sadrieh (2005), for example, observe substantially higher levels of "under-extraction" (harvesting less than the optimal amount) in the treatments with incomplete information on the resource extinction threshold than in the treatments with perfect information.[42] Although the experimental setup was very different from ours and did not allow a clear comparison with the theoretical decision-making models, the result does support the general notion that resource managers facing the danger of resource extinction maybe much more cautious in their extraction behavior than subjects performing simple lottery-choice tasks. This in turn suggests that the calibrations of choice models that are based on the classical

[42] It is well-known that the management of renewable resources, in general, is not optimally preformed by human subjects (Sterman 1989; Moxnes 1998). Most of the experimental studies in the area, however, are concerned with extremely complicated decision situations that do not allow clear comparisons of the observed behavior with theoretical decision-making models of the type that we consider here. One difficulty arises from the fact that subjects make wrong judgments on the dynamics of growth, usually underestimating the exponential dynamics. Hence, when stochastic and dynamic elements enter the decision situation – as is the case in many of the studies so far – then it is difficult to distinguish the behavioral effects separately. We focus on the risky choice aspect, by using a design that totally avoids the confounding effect of growth dynamics.

lottery-choice tasks may actually be inadequate for explaining behavior of subjects who face more complicated risky choices that involve extreme low-probability negative outcomes such as total loss in the case of resource extinction.

Theoretical Framework

Our experiment is based on a theoretical model[43] where one agent chooses the amount d of harvesting from a renewable resource, having the initial stock R_0. The renewal capacity of the resource is such that if the agent extracts a lot and depletes the resource, reducing it to a level lower than a threshold R^{CRIT}, the system collapses and nothing will be left for future generations. R^{CRIT} is assumed unknown, and it can fall in a compact range of values, $A = \lfloor \underline{R}; \overline{R} \rfloor$, with uniform probability $f(R) = \frac{R - \underline{R}}{\overline{R} - \underline{R}}$. Function $g(d) = kd$ is the payoff derived from direct consumption, and $\hat{\pi}(d) = \alpha d$ is the payoff derived from leaving $R_0 - d$ of the resource for use to future generations. Harvesting is sustainable if d is such that the remaining stock exceeds the critical level necessary for the resource to "survive": $R^0 - d \geq R^{CRIT}$. If harvesting is sustainable in period one we assume that $\hat{\pi}(d) > 0$, otherwise $\hat{\pi}(d) = 0$, so that the total payoff is given by:

$$\pi(d) = \begin{cases} (k + \alpha)d & \text{if } \quad R^0 - d \geq R^{CRIT} \\ kd & \text{otherwise} \end{cases}$$

Therefore the expected payoff for the agent when he/she chooses a level d of consumption in period one is:

[43] See Chapter 2 for a full description of the model and of its theoretical implications.

$$EV[\pi(d)] = \begin{cases} kd + \alpha d & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ kd + \alpha d\left[\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right] & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

If the agent is risk neutral he/she maximizes this expression.

If instead the agent is risk averse and has utility function $u(x) = x^a$, then he/she maximizes expected utility:

$$EU[\pi(d)] = \begin{cases} (k+\alpha)^a d^a & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ (k+\alpha)^a d^a\left[\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right] & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

Finally, if we assume for simplicity that utility is linear ($u(x) = x$), and that all payoffs are non-negative, then the rank-dependent utility model predicts that an agent maximizes the following expression:

$$RDU[\pi(d)] = \begin{cases} kd + \alpha d & \text{if} \quad 0 \le d < R_0 - \overline{R} \\ kd + \alpha d \cdot w\left(\dfrac{R_0 - d - \underline{R}}{\overline{R} - \underline{R}}\right) & \text{if} \quad R_0 - \overline{R} \le d \le R_0 - \underline{R} \\ kd & \text{if} \quad d > R_0 - \underline{R} \end{cases}$$

where $w(.)$ is a probability transformation function, defined on the interval [0;1], where it is assumed to be monotonically increasing, and such that $w(0) = 0$ and $w(1) = 1$. We will test RDU with two possible weighting functions:

1. a convex function: $w(x) = x^{1/\gamma}, 0 < \gamma < 1$
2. an inverse-S-shaped function: $w(x) = \dfrac{x^\gamma}{\left[x^\gamma + (1-x)^\gamma\right]^{1/\gamma}}, 0 < \gamma < 1$

These are not the only weighting functions proposed in the literature. In particular for inverse-S-shaped weights there have been a number of functions tested in previous experiments. We choose simple weighting functions with only one parameter because we want to fairly judge their performance in comparison to "plain" expected utility, which also only has one parameter. It has been shown that functions with two parameters can better explain behavior in experiments, and also that a combination of risk-aversion and probability weighting can reach better performances. These questions have been left out from the present work, because we focus on an applied setting, and wish therefore to keep the theoretical and methodological aspects relatively simple.

The models presented have similar qualitative implications on the optimal choice of harvesting, but they present different degrees of sensitivity to changes in the probability distribution of the uncertain threshold. In particular, rank dependent utility is more likely to select corner solutions, and therefore solutions that are more stable with respect to small changes in the probability distribution, but more unstable with respect to substantial changes in the probability distribution. Furthermore in this setting, rank-dependent utility is more likely to select "eager" solutions, that is, corner solutions at which the resource is depleted completely.

Experimental design and hypotheses

Experimental design

The main aim of this paper is to examine the decisions individuals make in situations with thresholds and with varying conditions of uncertainty. To that end we have set up an experiment, in which the subjects have to deal with a special two-period decision problem, based on the theoretical framework described in section 2. In the first period they will actually have to make a choice about their desired level of "extraction" from a virtual resource. The resource needs a critical amount to be able to renew itself and thus to ensure future income. The critical amount is a threshold, and it is unknown. The only thing subjects know is that the threshold has a certain distribution within a given range.

If a subject extracts too much, that is, if the left over is smaller than the threshold value of the resource, the payoff in the second period will be zero, so he will only have a positive payoff in the first period. If a subject extracts less than the (unknown) critical value, he will gain a given payoff in the second period in addition to the positive payoff in the first period. The second-period payoff is increasing in the level that has been chosen in the first period (the explanation here is that part of the harvesting in the first period increases the harvesting capacity in the second period).

Note that in the experiment, the subjects do not actually have to make a choice in the second period, and can concentrate exclusively on their first-period choice, but their payoffs reflect the theoretical structure of the problem. In the experiment only linear payoffs and uniform distributions are used.

To see the relationship between the theoretical framework from section 2 and the decisions tasks in the experiment consider the following example (task 5 in the experiment). The following tables show the linear payoffs for $R^0 = 12$, $k = 1$ and $\alpha = 6$. Table 1 simply shows for each choice of the extraction d in the first period the total payoff conditional on the choice being "sustainable", i.e. if $12 - d \geq R^{CRIT}$. In this case total payoffs are the sum of the payoffs in the two periods. Table 2 shows for each choice of d in the first period the total payoff conditional on the choice being "not sustainable", i.e if $12 - d < R^{CRIT}$. In this case, total payoff only consists of the payoff obtained in the first period. Table 3 shows the total payoff conditional on the threshold level of the resource. This table is a combination of Table 1 and Table 2. In Table 3 the range of possible threshold levels is 13 ($R^{CRIT} = 0,\ldots,12$), which will be referred to as a large spread.

D	k*d	α*d	Total payoff
0	0	0	0
1	1	6	7
2	2	12	14
3	3	18	21
4	4	24	28
5	5	30	35
6	6	36	42
7	7	42	49
8	8	48	56
9	9	54	63

10	10	60	70
11	11	66	77
12	12	72	84

Table 1 Payoffs if first-period choice is sustainable.

D	*K**d	Total payoff
0	0	0
1	1	1
2	2	2
3	3	3
4	4	4
5	5	5
6	6	6
7	7	7
8	8	8
9	9	9
10	10	10
11	11	11
12	12	12

Table 2 Payoffs if first-period choice is not sustainable.

Note that in the experiment we have only used tables like Table 3[44] to show outcomes to subjects, using different specifications of the parameters k, α, and of the range of possible critical values for the resource stock, always assuming a uniform distribution over the range (see below). An interesting extension for future research would be to investigate experimentally whether subjects make the same decisions if they get to see the first two tables instead of the third one.

Let us now look at the decisions people have to make and the theoretical predictions for this example. Consider first the first two tables. Obviously,

[44] The booklet with the instructions of the experiment and the tasks is attached in the appendix.

choosing a higher value of d implies higher payoffs if the choice is sustainable, and also if it is not sustainable. The point is that a higher d increases the probability that the threshold will be passed, i.e. it increases the chance that the subject ends up in the Table 2, which has lower payoffs than Table 1. This feature is also present and visible in table 3. For instance, if a subject would choose $d = 4$ he has a relatively high probability of getting a payoff of 28 (if $12 - d \geq R^{CRIT}$, or $12 - R^{CRIT} \geq 4$), and a small probability of getting 4 (if $12 - d < R^{CRIT}$, or $12 - R^{CRIT} < 4$). Note that the payoff of 28 corresponds to the outcome in Table 1 for $d = 4$, and the payoff of 4 corresponds to the outcome in Table 2 for $d = 4$. On the other hand, if a subject would choose $d = 9$, he has a relative high probability of getting a payoff of 9. However there is also a small probability of getting a payoff as high as 63. It is precisely this trade-off that causes various theories to have different predictions, as we will see below.

d \ 12-R^{crit}	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	7	7	7	7	7	7	7	7	7	7	7	7
2	2	2	14	14	14	14	14	14	14	14	14	14	14
3	3	3	3	21	21	21	21	21	21	21	21	21	21
4	4	4	4	4	28	28	28	28	28	28	28	28	28
5	5	5	5	5	5	35	35	35	35	35	35	35	35
6	6	6	6	6	6	6	42	42	42	42	42	42	42
7	7	7	7	7	7	7	7	49	49	49	49	49	49
8	8	8	8	8	8	8	8	8	56	56	56	56	56
9	9	9	9	9	9	9	9	9	9	63	63	63	63
10	10	10	10	10	10	10	10	10	10	10	70	70	70
11	11	11	11	11	11	11	11	11	11	11	11	77	77
12	12	12	12	12	12	12	12	12	12	12	12	12	84

Table 3 Total payoffs conditional on the threshold level of the resource.

In the experiment the subjects were confronted with a booklet containing eight tasks. The eight tasks, which form eight treatments, are the result of a 2x2x2 factorial design, with treatment variables α ($\alpha = 6$ and $\alpha = 7$), k (k=1 and k=3) and the range of the possible critical amounts (small spread with 7 possible values and large spread with 13 possible values).[45] Table 4 gives an overview of the treatments:

Task	K	α	Spread
1	1	7	Large
2	1	6	Small
3	3	7	Small
4	3	6	Large
5	1	6	Large
6	3	7	Large
7	3	6	Small
8	1	7	Small

Table 4 Overview of the eight treatments.

The hypotheses

The hypotheses we want to test follow directly from the theoretical framework described in section 2, where we use the uniform distribution and linear payoffs. We consider four models, which lead to the following four hypotheses:

H_0: the choices are consistent with EV maximization

$$\max_{d \in \{0,\ldots,12\}} kd + \alpha d \Pr\left\{12 - d \geq R^{CRIT}\right\};$$

H_1: the choices are consistent with CRRA utility maximization with risk-aversion equal to a

$$\max_{d \in \{0,\ldots,12\}} \left[(k + \alpha)d\right]^a \Pr\left\{12 - d \geq R^{CRIT}\right\} + (kd)^a \left[1 - \Pr\left\{12 - d \geq R^{CRIT}\right\}\right]$$

[45] The tasks in the booklet have been designed in the attempt to maximize the power of the hypothesis testing. That is, the combinations of α and k are chosen such that the different theories lead to different predictions, and the distance between the predictions is as large as possible, in order to make it easier to discriminate among the theories and to make the distinction more reliable.

H$_2$: the choices are consistent with RDU maximization with inverse-S shaped weights and convexity parameter γ_{TK}

$$\max_{d \in \{0,\dots,12\}} kd + \alpha d \cdot w\left[\Pr\left\{12 - d \geq R^{CRIT}\right\}\right]$$

$$\text{where } w(x) = \frac{x^{\gamma_{TK}}}{\left[x^{\gamma_{TK}} + (1-x)^{\gamma_{TK}}\right]^{1/\gamma_{TK}}}.$$

H$_3$: the choices are consistent with RDU maximization with convex weights (prudent behavior) with convexity parameter γ_{CW}

$$\max_{d \in \{0,\dots,12\}} kd + \alpha d\left[\Pr\left\{12 - d \geq R^{CRIT}\right\}\right]^{1/\gamma_{CW}}$$

where:

$$\Pr\left\{12 - d \geq R^{CRIT}\right\} = \begin{cases} 1 & \text{if} \quad 0 \leq d \leq 12 - \overline{R} \\ \dfrac{12 - d - \underline{R}}{\overline{R} - \underline{R}} & \text{if} \quad 12 - \overline{R} \leq d \leq 12 - \underline{R} \\ 0 & \text{if} \quad 12 - \underline{R} \leq d \leq 12 \end{cases}$$

For each of the eight tasks, Table 5 shows the optimal choices for all parameter values and for each theory separately. The second row displays whether the spread is small (range 3-9) or large (range 0-12). Parameter values yielding the same optimal choice have been combined. For instance if we assume that people maximize their utility using a CRRA utility function in task 1 the choice d = 6 would be consistent with parameter values between 0.1 and 0.3, whereas the choice d = 7 would be optimal for parameter values equal to or larger than 0.4.

	Task	1	2	3	4	5	6	7	8
	Range	**0-12**	**3-9**	**3-9**	**0-12**	**0-12**	**0-12**	**3-9**	**3–9**
EV		7	6	6 & 7	10	8	9	7	5 & 6
CRRA	$0.1 \leq a \leq 0.3$	6	4	6	11	7	10	12	4
	$a = 0.4$	7	5	6	10	7	10	12	4
	$a = 0.5$	7	5	6	10	7	10	7	5
	$0.6 \leq a \leq 0.9$	7	5	6	10	7	9	7	5
RDUTK	$0.1 \leq \gamma_{TK} \leq 0.3$	12	3	12	12	12	12	12	3
	$\gamma_{TK} = 0.4$	12	3	9	12	12	12	9	3
	$\gamma_{TK} = 0.5$	11	8	9	12	11	12	9	3
	$\gamma_{TK} = 0.6$	10	7	8	11	10	11	9	7
	$\gamma_{TK} = 0.7$	9	7	8	11	9	11	8	7
	$\gamma_{TK} = 0.8$	8	6	7	11	9	10	8	6
	$\gamma_{TK} = 0.9$	8	6	6	10	8	10	7	6
RDUCW	$0.1 \leq \gamma_{CW} \leq 0.2$	12	3	12	12	12	12	12	3
	$\gamma_{CW} = 0.3$	4	3	12	12	12	12	12	3
	$\gamma_{CW} = 0.4$	5	3	12	12	5	12	12	3
	$\gamma_{CW} = 0.5$	5	4	12	12	6	12	12	4
	$\gamma_{CW} = 0.6$	6	4	12	12	6	12	12	4
	$\gamma_{CW} = 0.7$	6	5	6	12	7	9	12	5
	$\gamma_{CW} = 0.8$	7	5	6	10	7	9	12	5
	$\gamma_{CW} = 0.9$	7	5	6	10	7	9	7	5

Table 5 Optimal choices according to the theory.

The experimental procedure

The experiment was run with students of first-year microeconomics classes at Tilburg University in December 2003.[46] At the beginning of the class the lecturer told the students that they could participate in a decision-making experiment, to be run during the break. After the first hour of class the experimenters came into the classrooms and asked who wanted to participate. The students who volunteered to participate received a booklet containing the eight one-shot decisions tasks (see Appendix). It was explained that subjects had to make a series of decisions, one in each task. One task would be played for real money and subjects would receive the payoffs from the experiment immediately after the second hour of the class. Students could fill in their booklets at their own pace. It took them on average almost fifteen minutes to do so.

The experimenters re-entered the class after the second hour. First it was determined which task would be paid by a random draw from a covered deck of eight cards. Then the level of the threshold was determined by a random draw from a covered deck of cards that contained 13 (7) cards in case the selected task had a large (small) spread.

A total of 45 students have taken part in the experiment, and each of them responded to all eight tasks, i.e. they were involved in eight treatments. This gives us a total of 360 observations. The subjects earned on average 3,50 euro.

Results

Our observations present quite a high variation in choices across individuals and across tasks. Figure 19 shows for each task the recurrence of each possible choice in our observations. The highest concentration is observed in task 4 where more than 1/3 of the subjects choose $d = 12$

[46] Before running the experiment in class, a pilot experiment was conducted. The main purpose of this pilot experiment, in which 10 Graduate students participated, was to check whether the instructions were clear and how long it took to make the eight decisions. Although the subjects were also paid, we do not include the observations in the analyses in this paper.

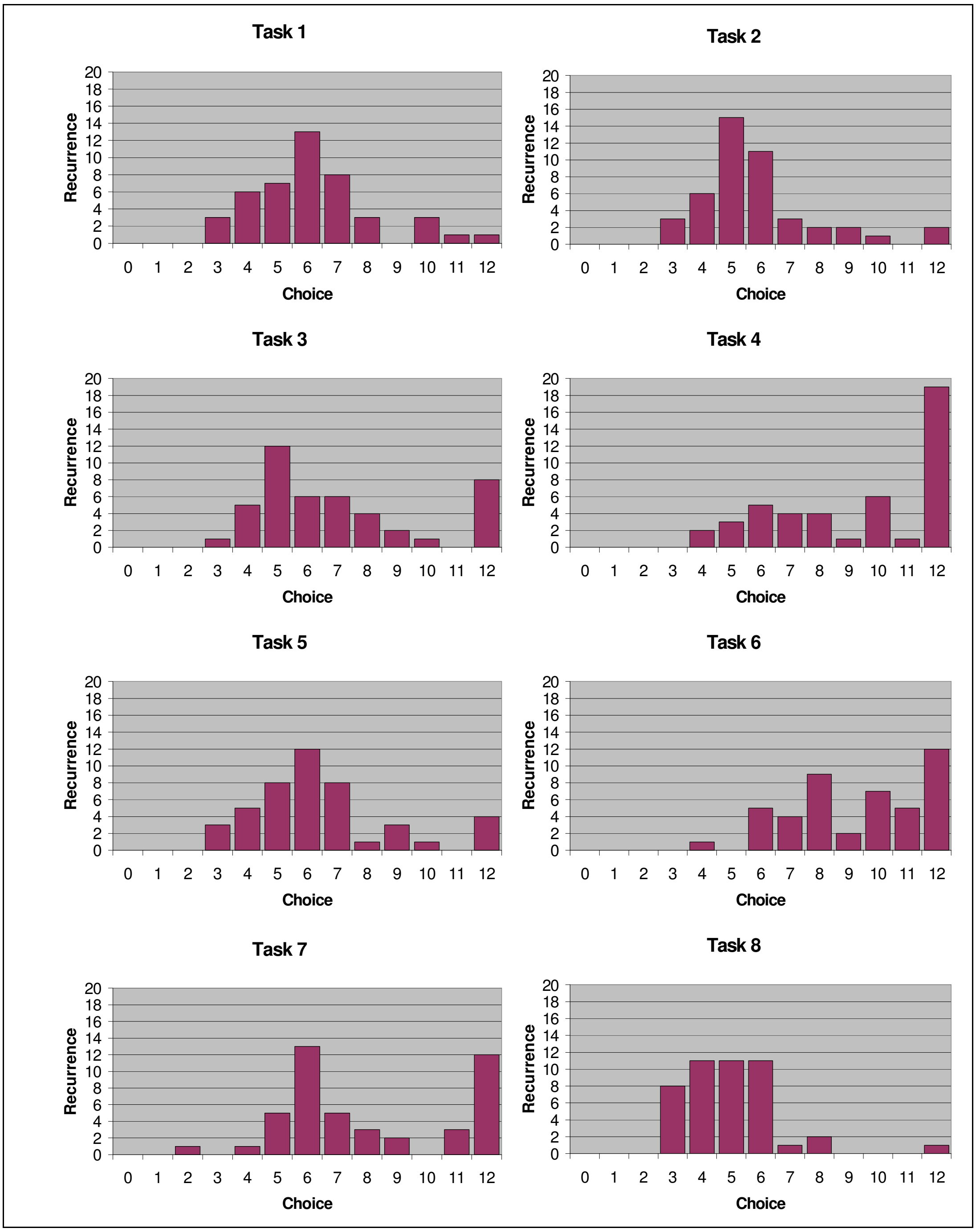


Figure 19 Distribution of observed choices per task.

A couple of tasks, namely tasks 6, 7, and 8, exhibit double or even triple modal value for d. In the other four tasks the observations are nicely dispersed around one single mode. More precisely, task 3 presents something like a "prevailing" mode, with most of the observations dispersed around d = 5, and a "secondary" mode in d = 12. The variation observed in our data is a reassuring aspect, a sign that central number bias and the experimental setting did not too strongly affect our subjects. Random answers on the other hand seem also not too likely since we observe quite different distributions corresponding to different tasks, as you would expect when subjects actually react to changing conditions. Also reassuring is the fact that only 11 observations out of 360, meaning ca. 3%, violate stochastic dominance.

In the following paragraphs we will compare our observations to the predictions that can be derived by each one of the theories described in section 3.

Comparing choices to Expected Value maximization

No subject behaves perfectly in accordance to EV theory. The two subjects who come closest, choose the EV maximizing value of d in 4 out of 8 tasks. On average, subjects choose a value of d that does *not* maximize EV in 6,5 tasks out of 8.

The choices that instead are compatible with EV maximization (also called "hits") are distributed as shown in Table 6. In total they make ca. 19% of the observations.

TASK	HITS	relative frequency
1	8	.18
2	11	.24
3	12	.27
4	6	.13
5	1	.02
6	2	.04
7	5	.11
8	22	.49
OVERALL	67	.19

Table 6 Distribution of EV hits across tasks.

Figure 20 compares the observed choices to the EV predictions. The light bubbles represent the experimental observations: the larger the bubble, the more often the choice was observed. The dark points represent the EV theoretical point predictions. From the graph it seems that EV does not represent the data very correctly, in particular it seems to miss the very clear mode of task 4, and also performs not so good in tasks 3 and 5.

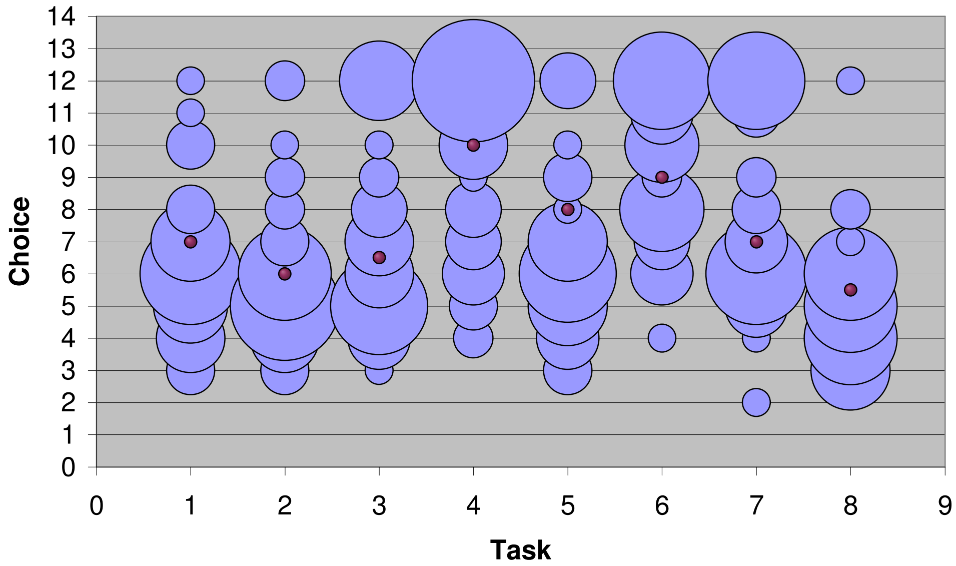


Figure 20 Comparison between the theoretical EV predictions and the experimental observations.

Comparing choices to Constant Relative Risk Aversion utility maximization

Also in the case of CRRA, no subject behaves perfectly in accordance to the theory. The 5 subjects, who come closest, have 4 out of 8 choices consistent with the theoretical predictions for an arbitrary but given parameter. On average, subjects choose a value of *d* that does *not* maximize CRRA for any arbitrary but given parameter in 5,8 tasks out of 8. Besides, on average, subjects choose in ca. 69% of the observations a value of *d* that does not maximize CRRA for *any* value of the parameter *at all*. In other words, these observations contradict the theory.

In order to estimate the best fit of the CRRA parameter *a*, we had to drop all these theory violating observations. This left us with 111 valid observations for estimation. Table 7 below summarizes the distribution of valid observations per task.

TASK	HITS	relative frequency
1	21	.47
2	21	.47
3	6	.13
4	7	.16
5	8	.18
6	9	.20
7	17	.38
8	22	.49
OVERALL	111	.31

Table 7 Summary of valid CRRA observations per task.

Using the valid observations, we estimate the parameter as follows. Per each individual we compute the sum over all tasks of the squared distances from the theoretical optimum in utility terms. We do this for 9 parameter values distributed over a regular grid covering the whole parameter domain. Minimizing such sum of squared errors, we assign to each individual an estimated parameter. We then count how many times each parameter appears as the best fit for an individual. Figure 21 compares the recurrences of each parameter over all observations.

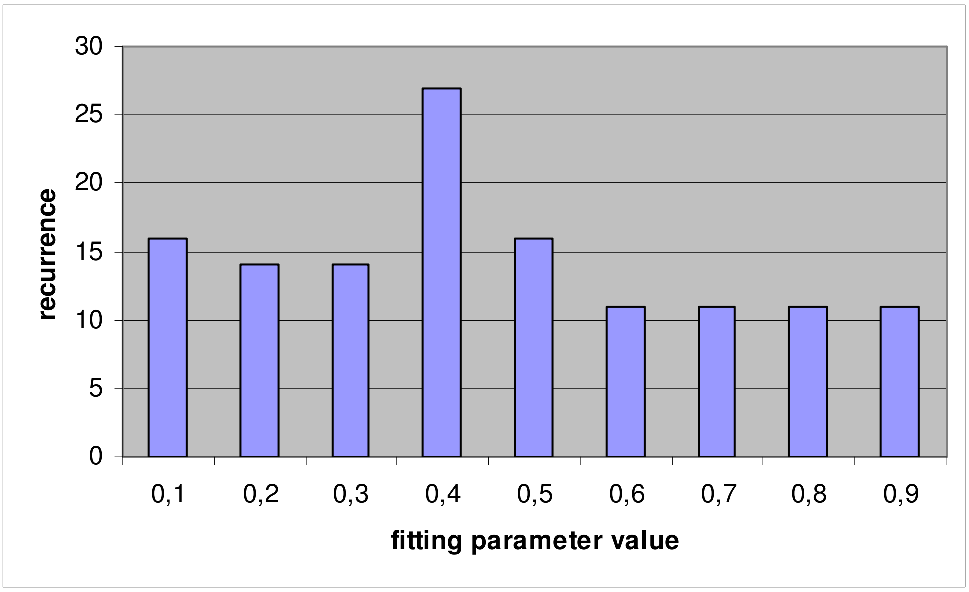


Figure 21 Recurrence of best-fitting parameter values for CRRA theory across individuals.

Our best overall estimate is the one that exhibits the highest recurrence, in this case $a = 0.4$. Using this value of the parameter, we compare in Figure 22 the theoretical point predictions to the observations, as done for EV in Figure 19. From the picture it is clear that CRRA gives a better representation of the data than EV. In particular it does quite well in tasks 2, 5 and 8. Like EV, however, it still does not represent very well the observed choices in task 4.

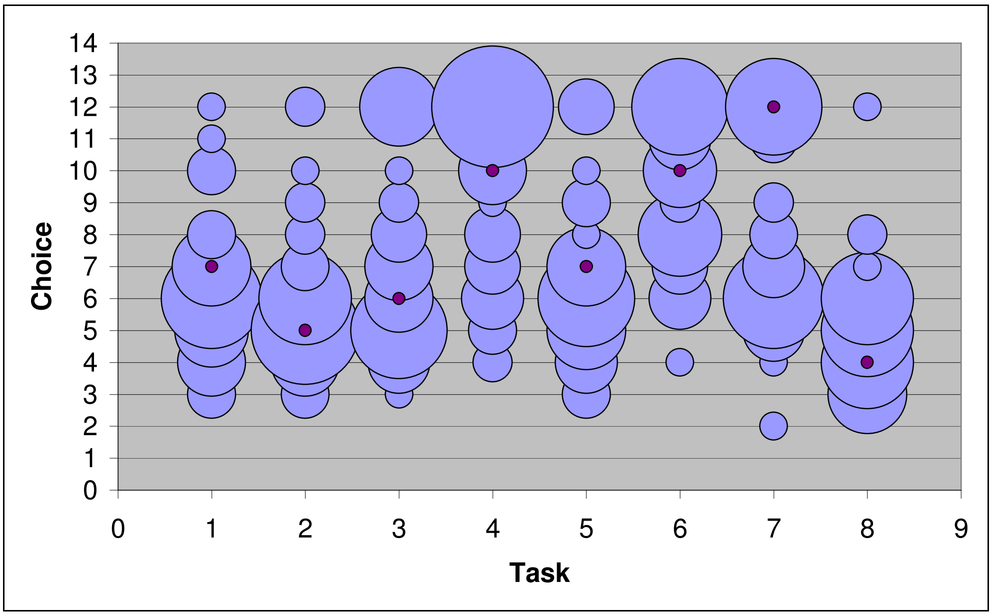


Figure 22 Comparison of theoretical CRRA predictions for a=0.4 and experimental observations.

Comparing choices to Rank Dependent Utility maximization with Tversky-Kahneman Weights

No subject behaves perfectly in accordance to RDUTK theory. Only 8 subjects exhibit choices consistent to theoretical predictions for an arbitrary but given parameter in at least 4 tasks; of these, 1 subject is consistent with the theory in 6 tasks. On average, subjects choose a value of *d* that does *not* maximize RDUTK for any arbitrary but given parameter in 5,8 tasks out of 8. Besides, on average, subjects choose a value of *d* that does not maximize RDUTK for *any* value of the parameter *at all* in ca. 59% of the observations. In order to proceed with estimation of the parameter, we dropped the theory violating observations. This left us with 148 valid observations useful to estimate the parameter. Table 8 below summarizes the valid observations per task.

TASK	HITS	relative frequency
1	8	.18
2	19	.42
3	20	.44
4	26	.58
5	9	.20
6	24	.53
7	22	.49
8	20	.44
OVERALL	148	.41

Table 8 Summary of valid RDUTK observations per task.

Using the valid observations, we estimate the RDUTK parameter as we did for CRRA. Figure 23 displays the recurrence with which each parameter value resulted as the best fit for a subject.

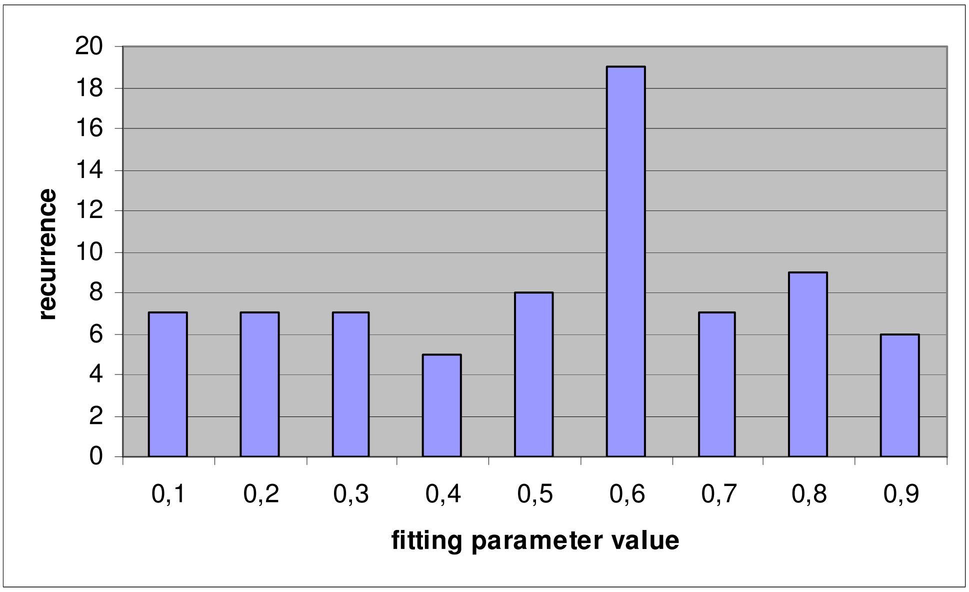


Figure 23 Recurrence of best-fitting parameter values for RDUTK theory across individuals.

Our best estimate for an overall RDUTK parameter is therefore $\gamma_{TK} = 0.6$. Using this parameter value, we compare the theoretical point predictions to the observations in Figure 24. RDUTK does not predict correctly the behaviour of subjects in tasks 1 to 3 and in tasks 5 and 7. It does come the closest to the prevailing mode in task 6, which is missed by all other theories.

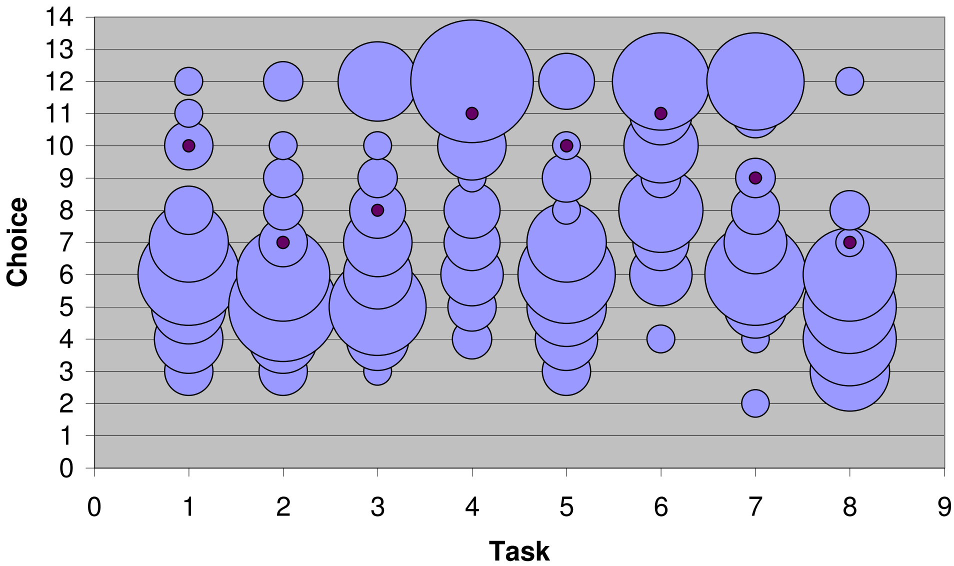


Figure 24 Comparison of theoetrical RDUTK predictions for γ_{TK}=0.6 and experimental observations.

Comparing choices to Rank Dependent Utility maximization with Convex Weights

No subject behaves perfectly in accordance to RDUCW theory. The 3 subjects that come closest to theoretically predicted behaviour, make choices that are consistent with the theory in 6 out of 8 tasks. Another 7 subjects make at least 4 choices that are consistent with the theoretical predictions for an arbitrary but given parameter. On average, subjects choose a value of *d* that does *not* maximize RDUCW for any arbitrary but given parameter in 5,1 tasks out of 8. Besides, on average, subjects choose a value of *d* that does not maximize RDUCW for *any* value of the parameter *at all* in ca. 47% of the observations. This left us with 191 valid observations for estimating the parameter, which we did following the same procedure as done for CRRA. Table 9 below summarizes the valid observations per task.

TASK	HITS	relative frequency
1	35	.78
2	24	.53
3	14	.31
4	25	.56
5	32	.71
6	14	.31
7	17	.38
8	30	.67
SUM	191	.53

Table 9 Summary of valid RDUCW observations per task.

Figure 25 shows the recurrence of best fitting parameters across individuals.

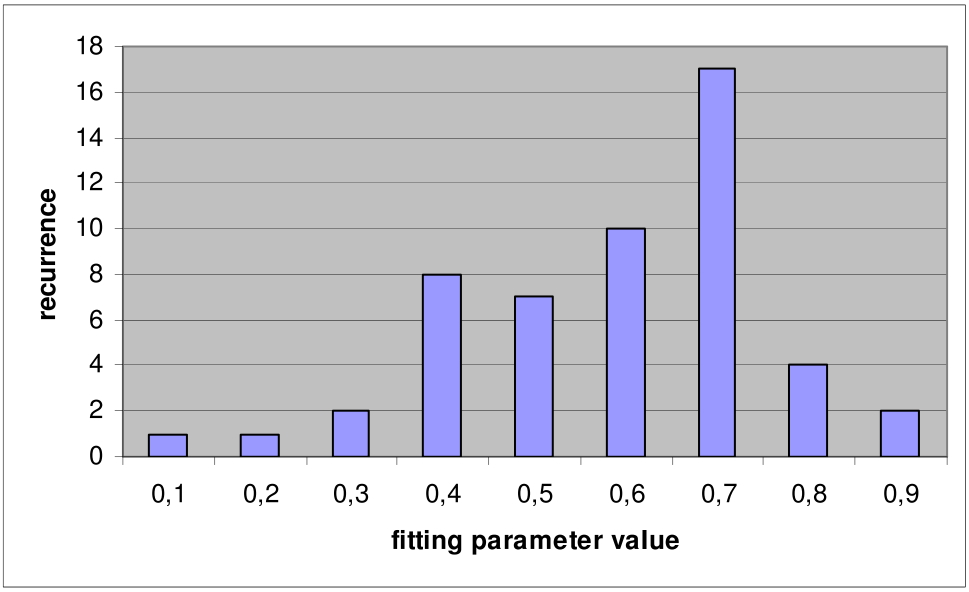


Figure 25 Recurrence of best-fitting parameter values for RDUCW theory across individuals.

Our best overall estimate for the RDUCW parameter value is $\gamma_{CW} = 0.7$. Using this value, we can compare the theoretical point predictions to the observations in

Figure 26. RDUCW improves on the EV predictions in tasks 1 to 5. It predicts the same in task 6. In tasks 7 and 8, the RDUCW point prediction is not much better, but surely not worse than in the EV case. Compared to CRRA, it performs better in tasks 1 and 4, but worse in task 8. It also performs better than RDUTK in task 4 and 8.

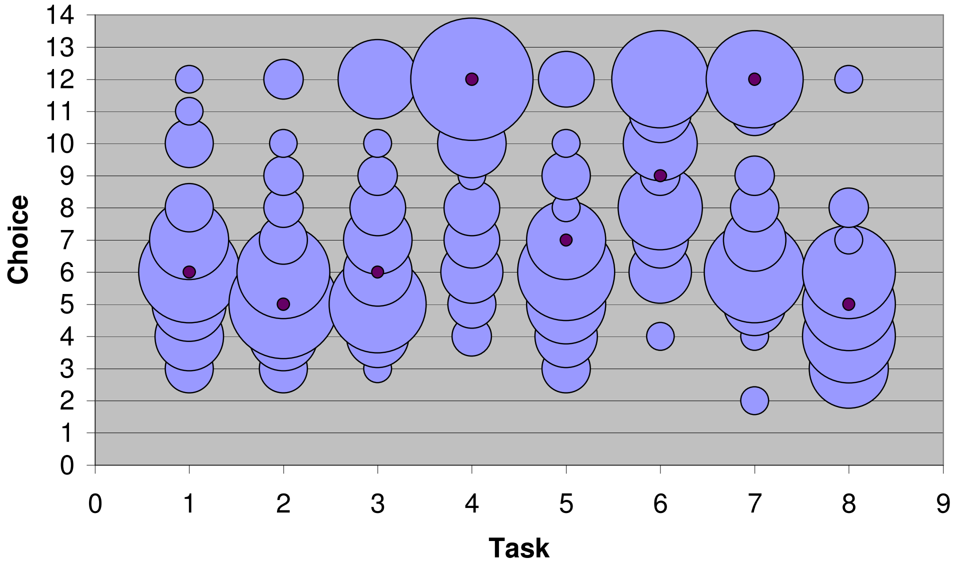


Figure 26 Comparison of theoretical RDUCW predictions for γ_{CW}=0.7 and experimental observations.

Measuring the predictive success of the theories

In the previous section we have used part of our data to calibrate the parameters of each theoretical model. The estimates that we have obtained come close to other estimates previously found in the literature on decision making. We turn now to comparing the predictive success of the theories, using the parameter values that we have estimated.

In order to compare the relative performance of the theories, we can make use of Selten's "Measure of Predictive Success" (Selten, 1991). This measure is computed by subtracting the prediction "area" of a theory from its "hit rate". The area is defined as the number of choices that can be predicted by one theory (varying the parameter), divided by the number of available choices. The hit rate is the number of observations that fall in the prediction of the theory, divided by the number of observations. The higher the measure, the better the performance of the theory. The indexes so computed are shown in Table 10, per task and over the total set of observations. Bold numbers indicate the highest value per row.

Task	EV	CRRA	RDUTK	RDUCW
1	0,100855	0,312821	-0,206838	**0,393162**
2	0,184982	**0,346154**	0,144689	0,340659
3	0,125224	0,062612	0,157424	**0,171735**
4	0,062612	0,008945	0,373882	**0,427549**
5	-0,0547	0,100855	-0,184615	**0,403419**
6	-0,03248	0,046154	**0,302564**	0,157265
7	0,042125	**0,250916**	0,216117	**0,250916**
8	0,346154	0,346154	0,223776	**0,451049**
TOTAL	0,095823	0,183436	0,125992	**0,326124**

Table 10 The theories compared on basis of Selten's Measure of Success.

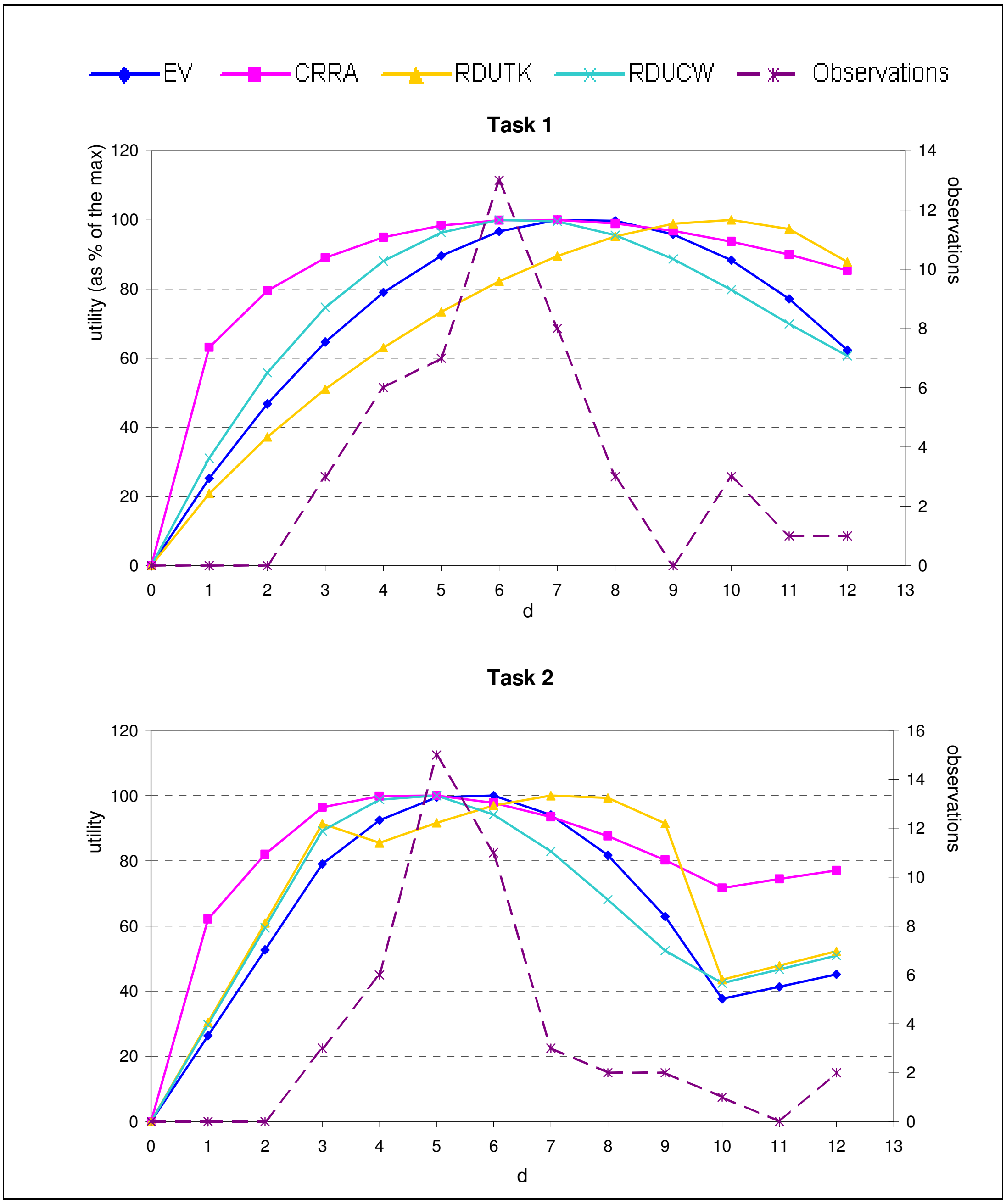
In Table 10, the total index is derived subtracting the total area for each theory (= the total number of predictions / total number of possibilities) from the total hit rate (= total number of hits / total number of observations).[47]

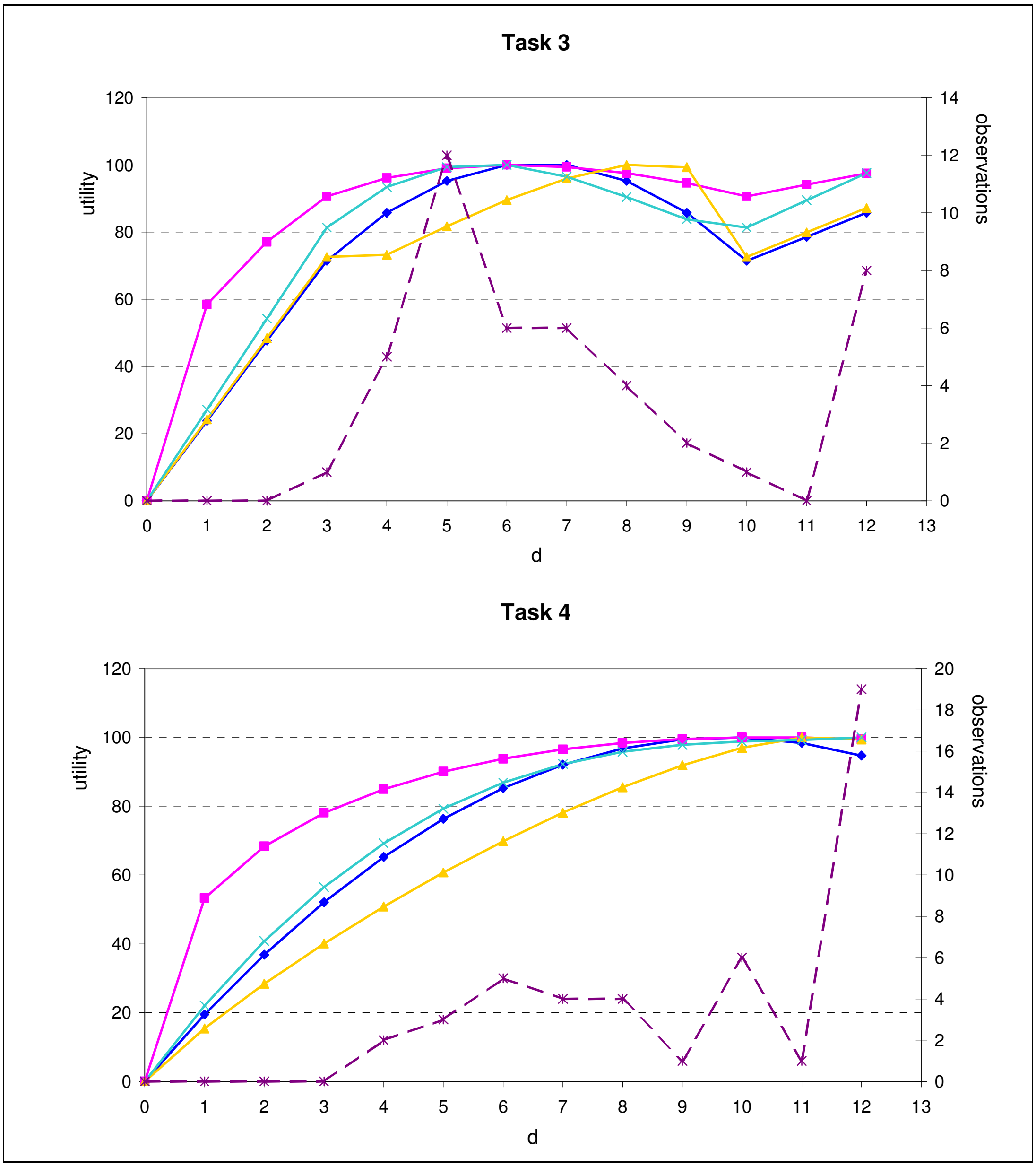
The numbers indicate quite clearly that RDUCW performs best in most occasions, and always close to the best. Task 6 deserves some special attention, as most theories are unable to predict the behaviour displayed by our subjects. It is perhaps important to mention that this task was the one with the highest payoffs at stake, meaning that choosing d = 12 the subjects would get a low chance to earn quite a substantially high payoff. Our observations seem to suggest that in such circumstances individuals tend to behave in a different way than usual. In fact, only RDUTK has a relatively high predictive success rate for this task. But note that at the same time this theory performs rather poorly on all other tasks.

[47] Net of the observations discarded because they violate dominance.

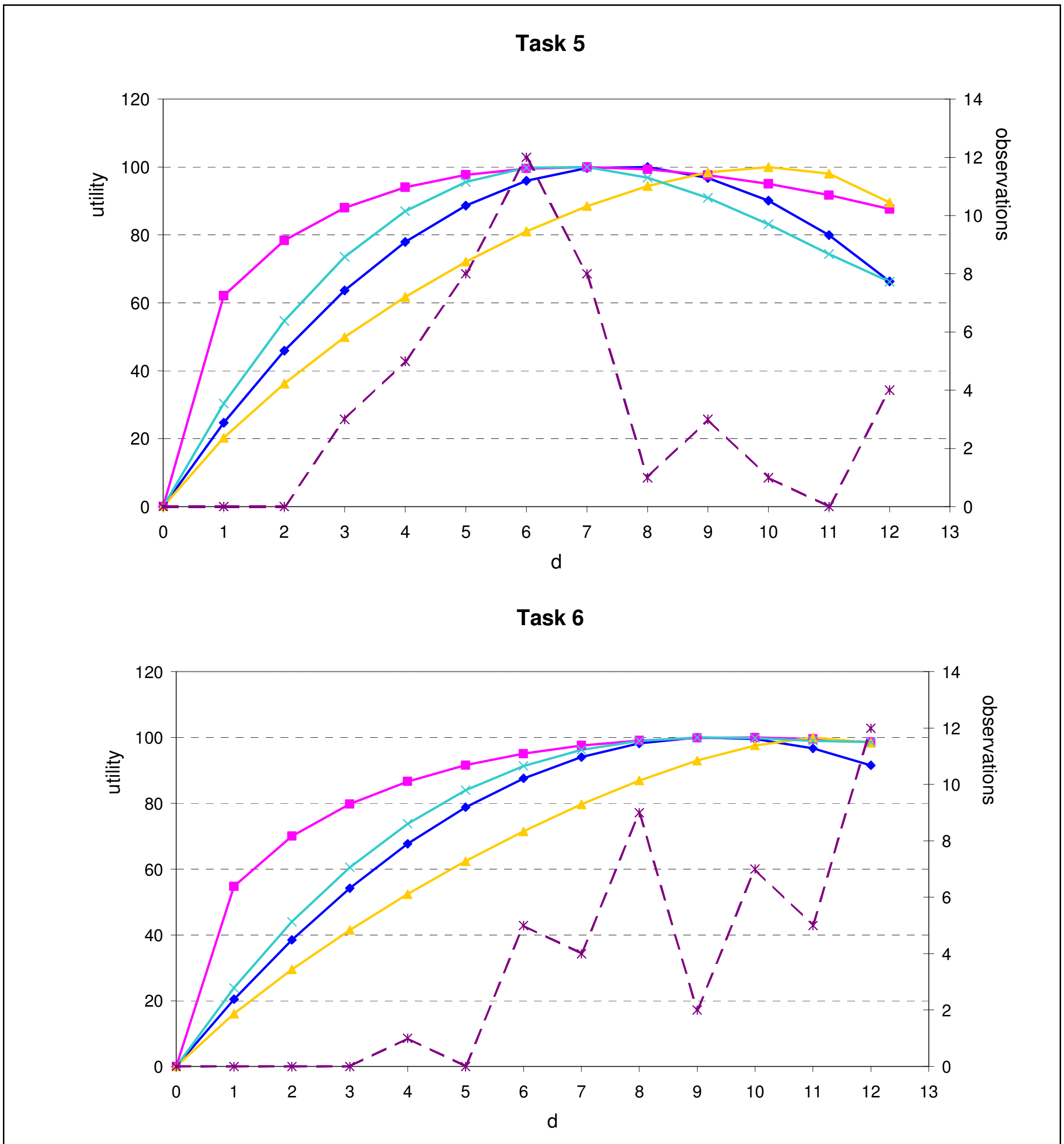
Each of the theories we have presented leads to point predictions regarding choices. However, when a utility function is smooth, the difference in terms of utility between the optimum and some other points nearby might be so small that subjects consider it irrelevant. The resulting observations would reflect a spread of choices around the optimum.

We will use a number of graphs to compare theoretical utility levels to observed choices. This method does not provide us with a synthetic measure of the relative success of theories, but it enables us to have a look at what happens beside the maximum-point prediction. In Figure 27 the theoretical utility functions per each task are plotted on the same plot area as a scatter of the empirical observations. The scales of the functions are not comparable, but the relative positions of each point of one function, can be compared to the relative positions of each point of the other functions. In this way it is possible to visually compare peaks and lows in the frequency of observed choices to their relative utility level according to each theory.


EV
CRRA
RDUTK
RDUCW
Observations
Task 1
utility (as % of the max)
observations
d
Task 2
utility
observations
d



Task 3
utility
observations
d
0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 20 40 60 80 100 120
0 2 4 6 8 10 12 14
Task 4
utility
observations
d
0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 20 40 60 80 100 120
0 2 4 6 8 10 12 14 16 18 20


Task 5
utility
observations
d
0
1
2
3
4
5
6
7
8
9
10
11
12
13
0
20
40
60
80
100
120
0
2
4
6
8
10
12
14
Task 6
utility
observations
d
0
1
2
3
4
5
6
7
8
9
10
11
12
13
0
20
40
60
80
100
120
0
2
4
6
8
10
12
14

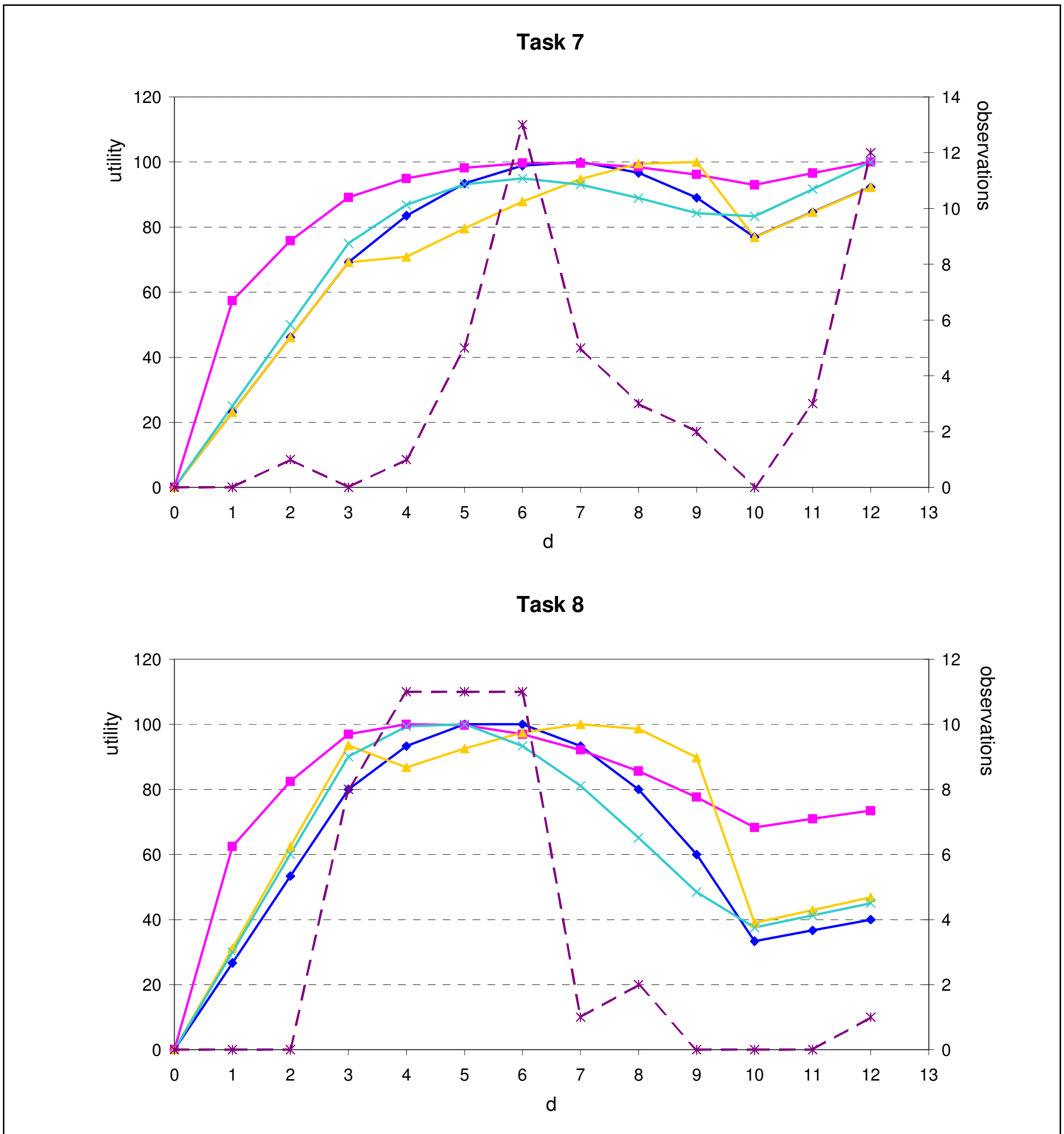


Figure 27 Utility functions derived from the theories compared to the empirical frequencies.

From the graphs it seems that the same observations apply as discussed until now: in general no theory is able to precisely reproduce all of the peaks and lows; however RDUCW often follows the shape of the empirical distributions more sharply and more precisely than the other functions do, and thus appears better in explaining the frequencies also of values of *d* that differ from the optimal ones.

Conclusions

An extremely important, but yet open question in the assessment of environmental policies is how people deal with decision situations in which they can trade-off immediate consumption against decreasing the probability of a very large scale (future) loss. The management of renewable resources with stochastic extinction thresholds is such a decision situation, because as extraction levels are increased, the probability of resource extinction increases. Applying the results of the standard experimental work on risky choice to this type of decision setting yields a counterintuitive result, because risk avoidance – both in expected and in most non-expected utility models – leads to a rapid extraction behavior, i.e. the resource is extracted as quickly as possible in order to avoid the risk associated with future consumption. In terms of environmental policy this result basically implies that installing a risk-seeking resource manager reduces the risk of resource extinction.

To which extent rapid extraction behavior is to be expected, however, strongly depends on the specific risky choice model and the calibration of its parameters. The classical expected utility model with relative risk-aversion (CRRA) predicts a high degree of rapid extraction at any level of risk aversion in the range of parameter values reported in the literature. The most popular non-expected utility model, the rank-dependent utility model with an inverse S-shaped probability weighting function (RDUTK) as suggested by Tversky and Kahneman (1992), in many cases leads to an even higher degree of rapid extraction than CRRA, when standard parameter estimates are used for both models. The same result holds for the rank-dependent utility model with a convex probability weighting function (RDUCW), which also often predicts a higher level of rapid extraction than CRRA.[48]

The experimental research in this paper is concerned with the question how well each of the different models of risky choice can capture extraction behavior in the presence of a stochastic extinction threshold. Given the results of other experiments in resource management, we started out with the hypothesis that

[48] For a detailed theoretical comparison of the model predictions see chapter 2.

subjects will be more prudent in the resource extraction than predicted by CRRA and RDUTK (i.e. exhibit rapid extraction behavior to a lower degree). In fact, using Selten's (1991) measure of predictive success, we find that the RDUCW, which is the most "prudent" of the models suggested, provides the best fit for our observations. This holds even when we allow for heterogeneity of the parameters of the model across individuals. Hence, our experiment shows that subjects facing extraction decisions in a setting with stochastic extinction threshold are best modelled as a population of rank-dependent utility maximizers with convex probability weighting functions and heterogeneous weighting parameters.

On first sight, the result of our experiment seems at odds with results obtained in earlier experiments comparing different risky choice models, because most other papers conclude that the inverse S-shaped probability weighting function provides the best overall fit. Those papers, however, have in general used very specific types of risky choice situations (mostly simple lottery choice tasks) to assess behavior. Hence, one conclusion from our study is that which risky choice model fits best will strongly depend on the type of decision task that is used. Obviously, tasks – such as ours – that resemble renewable resource management invoke a more prudent behavior than simple lottery choice tasks.

From an environmental policy point of view our results are not as good news as it might seem. Although we can interpret the behavior of our subject as "prudent" in the sense that they appear to weight bad outcomes heavier than good ones, rapid extraction behavior is present. Our experiment, which was specifically designed to test the behavior in such situations, shows that a large majority of decision-makers do take the risk of extinction into account, but that does not always lead to extracting less of the resource.

Appendix

Participant code: A1

Welcome to our choice experiment!

Instructions

This booklet contains eight tasks.

In each task, you will see a "payoff table" that describes all possible scores resulting from your choice (the row) and from a random draw (the column).

In all tasks, the payoff table contains 13 rows that are numbered from 0 to 12.

In each task, you must choose one of the 13 rows of the payoff table.

Please, make your choice by writing the number of the row that you prefer most on the blank under the table. Write one of the numbers 0 to 12 under each of the eight tables.

Once you have made all your eight choices, you will draw two cards from two different decks. The first card draw is from a covered deck with 8 cards. The number written on the card that you draw specifies which task will actually be played for money. Only one task will be played for money.

If the task to be played out for money has a "large" payoff table with 13 columns, your second draw will be from a covered deck with 13 cards.

If the task to be played out for money has a "small" payoff table with 7 columns, your second draw will be from a covered deck with 7 cards.

In either case, the drawn card specifies the column of the table that is relevant for your final payoff. By matching this number with the number of the row that you have chosen, you will find the cell in the payoff table that contains your final payoff in points.

Each point is exchanged with 10 Cents and paid out to you privately in cash.

You find an example in the next page.

Example

Random Draw of the Card

Your Choice	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	2	7	7	7	7	7	7	7	7	7	7	7	7
2	4	4	14	14	14	14	14	14	14	14	14	14	14
3	6	6	6	21	21	21	21	21	21	21	21	21	21
4	8	8	8	8	28	28	28	28	28	28	28	28	28
5	10	10	10	10	10	35	35	35	35	35	35	35	35
6	12	12	12	12	12	12	42	42	42	42	42	42	42
7	14	14	14	14	14	14	14	49	49	49	49	49	49
8	16	16	16	16	16	16	16	16	56	56	56	56	56
9	18	18	18	18	18	18	18	18	18	63	63	63	63
10	20	20	20	20	20	20	20	20	20	20	70	70	70
11	22	22	22	22	22	22	22	22	22	22	22	77	77
12	24	24	24	24	24	24	24	24	24	24	24	24	84

Suppose that the payoff table above belongs to the task that will be played out for money.

Suppose that you have chosen the row “9” in this task.

Since this is a “large” payoff table with 13 columns, you will draw from a deck of 13 cards.

Suppose that you draw the card with the number “2”.

Your payoff is displayed in the cell where row “9” and column “2” intersect: 18 points.

You will be paid (18 x 10 Cents =) Euro 1.80 for your participation.

TASK 1

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	8	8	8	8	8	8	8	8	8	8	8	8
2	2	2	16	16	16	16	16	16	16	16	16	16	16
3	3	3	3	24	24	24	24	24	24	24	24	24	24
4	4	4	4	4	32	32	32	32	32	32	32	32	32
5	5	5	5	5	5	40	40	40	40	40	40	40	40
6	6	6	6	6	6	6	48	48	48	48	48	48	48
7	7	7	7	7	7	7	7	56	56	56	56	56	56
8	8	8	8	8	8	8	8	8	64	64	64	64	64
9	9	9	9	9	9	9	9	9	9	72	72	72	72
10	10	10	10	10	10	10	10	10	10	10	80	80	80
11	11	11	11	11	11	11	11	11	11	11	11	88	88
12	12	12	12	12	12	12	12	12	12	12	12	12	96

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 2

	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0
1	7	7	7	7	7	7	7
2	14	14	14	14	14	14	14
3	21	21	21	21	21	21	21
4	4	28	28	28	28	28	28
5	5	5	35	35	35	35	35
6	6	6	6	42	42	42	42
7	7	7	7	7	49	49	49
8	8	8	8	8	8	56	56
9	9	9	9	9	9	9	63
10	10	10	10	10	10	10	10
11	11	11	11	11	11	11	11
12	12	12	12	12	12	12	12

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 3

	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0
1	10	10	10	10	10	10	10
2	20	20	20	20	20	20	20
3	30	30	30	30	30	30	30
4	12	40	40	40	40	40	40
5	15	15	50	50	50	50	50
6	18	18	18	60	60	60	60
7	21	21	21	21	70	70	70
8	24	24	24	24	24	80	80
9	27	27	27	27	27	27	90
10	30	30	30	30	30	30	30
11	33	33	33	33	33	33	33
12	36	36	36	36	36	36	36

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 4

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	3	9	9	9	9	9	9	9	9	9	9	9	9
2	6	6	18	18	18	18	18	18	18	18	18	18	18
3	9	9	9	27	27	27	27	27	27	27	27	27	27
4	12	12	12	12	36	36	36	36	36	36	36	36	36
5	15	15	15	15	15	45	45	45	45	45	45	45	45
6	18	18	18	18	18	18	54	54	54	54	54	54	54
7	21	21	21	21	21	21	21	63	63	63	63	63	63
8	24	24	24	24	24	24	24	24	72	72	72	72	72
9	27	27	27	27	27	27	27	27	27	81	81	81	81
10	30	30	30	30	30	30	30	30	30	30	90	90	90
11	33	33	33	33	33	33	33	33	33	33	33	99	99
12	36	36	36	36	36	36	36	36	36	36	36	36	108

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 5

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	7	7	7	7	7	7	7	7	7	7	7	7
2	2	2	14	14	14	14	14	14	14	14	14	14	14
3	3	3	3	21	21	21	21	21	21	21	21	21	21
4	4	4	4	4	28	28	28	28	28	28	28	28	28
5	5	5	5	5	5	35	35	35	35	35	35	35	35
6	6	6	6	6	6	6	42	42	42	42	42	42	42
7	7	7	7	7	7	7	7	49	49	49	49	49	49
8	8	8	8	8	8	8	8	8	56	56	56	56	56
9	9	9	9	9	9	9	9	9	9	63	63	63	63
10	10	10	10	10	10	10	10	10	10	10	70	70	70
11	11	11	11	11	11	11	11	11	11	11	11	77	77
12	12	12	12	12	12	12	12	12	12	12	12	12	84

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 6

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	3	10	10	10	10	10	10	10	10	10	10	10	10
2	6	6	20	20	20	20	20	20	20	20	20	20	20
3	9	9	9	30	30	30	30	30	30	30	30	30	30
4	12	12	12	12	40	40	40	40	40	40	40	40	40
5	15	15	15	15	15	50	50	50	50	50	50	50	50
6	18	18	18	18	18	18	60	60	60	60	60	60	60
7	21	21	21	21	21	21	21	70	70	70	70	70	70
8	24	24	24	24	24	24	24	24	80	80	80	80	80
9	27	27	27	27	27	27	27	27	27	90	90	90	90
10	30	30	30	30	30	30	30	30	30	30	100	100	100
11	33	33	33	33	33	33	33	33	33	33	33	110	110
12	36	36	36	36	36	36	36	36	36	36	36	36	120

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 7

	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0
1	9	9	9	9	9	9	9
2	18	18	18	18	18	18	18
3	27	27	27	27	27	27	27
4	12	36	36	36	36	36	36
5	15	15	45	45	45	45	45
6	18	18	18	54	54	54	54
7	21	21	21	21	63	63	63
8	24	24	24	24	24	72	72
9	27	27	27	27	27	27	81
10	30	30	30	30	30	30	30
11	33	33	33	33	33	33	33
12	36	36	36	36	36	36	36

Which row do you choose? __________ (Please, write a number between 0 and 12.)

TASK 8

	3	4	5	6	7	8	9
0	0	0	0	0	0	0	0
1	8	8	8	8	8	8	8
2	16	16	16	16	16	16	16
3	24	24	24	24	24	24	24
4	4	32	32	32	32	32	32
5	5	5	40	40	40	40	40
6	6	6	6	48	48	48	48
7	7	7	7	7	56	56	56
8	8	8	8	8	8	64	64
9	9	9	9	9	9	9	72
10	10	10	10	10	10	10	10
11	11	11	11	11	11	11	11
12	12	12	12	12	12	12	12

Which row do you choose? __________ (Please, write a number between 0 and 12.)

Additional questions

O Male O Female

1. How much time did it take to fill in the questionnaire?

2. Were the instructions clear enough?

3. Were the examples clear enough?

4. Can you shortly describe how you made your choices?

Please add any comments

Score sheet

Participant code: ____________________

Question drawn d card value Score

____________ _______ _________

____

Payment: ____________________

Signature:

____

4. Modelling negotiations for an international agreement on climate change

In part one we have approached climate change from the perspective of one unique decision agent that we can see as a global benevolent dictator trying to maximize an aggregated measure of global welfare. In that framework we have shown that optimal policy is a non-trivial issue when risk-preferences are taken into account and that all existing models for decision-making show a very high sensitivity to small changes in the unknown parameters. Moreover, we have shown that none of the existing models represents to a satisfactory extent the actual risk-preferences of real agents.

In that framework we have abstracted completely from strategic issues that arise when decisions have to be made by more than one agent at the same time. Since climate change is a global pollution problem, we know that such issues play a central role in the current debate. Even though there is at this point in time a fairly wide consensus about the need for climate policies, it still proves very hard for political leaders to find an agreement on an international scheme of abatement of greenhouse gases emissions. The negotiations about the Kyoto protocol have recently seen important countries like the USA and China withdraw with the argument that they want to implement other ways out of the climate change problem. In particular, these countries do not want to impose abatement targets at the expenses of economic growth and they state that it is more efficient to incentivate the development of green technology. This argument is not convincing, though: of course it is true that developing green technology is needed to prevent climate change and at the same time ensure economic welfare, but it is not in contradiction with the goal of setting transparent abatement targets;

on the contrary, setting the targets is a way of credibly committing to give sufficient incentives for the development of green technology.

As we will discuss in the following two chapters, investments in technology may play an important role in the negotiations. However, they can be seen as an alternative way to reach the common goal of emission abatement. This goal can be fixed taking technological change into account, and the one does not preclude the other. On the contrary, we will show that under some conditions on the structure of costs and benefits, investments in green technology should be expected to foster cooperation. In particular we can show that if part of the costs can be shared by a coalition, thereby creating a positive externality, then full cooperation can be reached. One can think here for example of shared sunk investments in research and development.

Climate change as a prisoner's dilemma

In the economic literature on international agreement, climate change like other environmental externalities are usually represented as games of the "prisoner's dilemma" type. In these games, the social optimum is not reached because when all other players play the socially optimal strategy, there are incentives for each player to deviate. In the assumptions of the game, if all other countries abate their greenhouse gas emissions, it is better for my country to maintain the same emission level as usual, or even emit more, as it allows economic growth without costs of abatement, while climate change is prevented thanks to the efforts spent by other countries.

It is not clear, as a matter of fact, that just reducing emissions can prevent climate change, thus the causal relationship and the logical structure of a traditional "prisoner's dilemma" does not necessarily fit our problem in reality. As already discussed in the first part of this thesis, there is high uncertainty as for what the true outcomes of current actions will be in the future. There are also time lags to be accounted for, and the measurements we do today are only able to evaluate our actions in the past, meaning that we do not know if our current actions are actually capable of implementing the desired outcomes. We cannot exclude the possibility of very pessimistic scenarios, according to which any action today would not be sufficient to prevent climate change or even mitigate it. If such a scenario was true, then we would not have the need to undertake any action: the outcome of the game would not depend on our actions. There would in fact be no game to play and no cake to share. In such a scenario it would as well be reasonable to pollute as much as we like, since it would make no difference at all. On the other hand, it is also not possible to exclude that the only efficient strategy would be to abate 100% emissions as quickly as possible. This might be true if the actual payoff structure was dichotomised: either emissions stop or a catastrophic event will occur and everyone will be worse off. In this case we would not be facing a prisoner's dilemma, but rather a coordination issue: either we all abate 100%, or we do not need to undertake any other action, since that would not make any difference. Such a situation could be represented in the following game where a generic country (i) plays "against" the rest of the world (*ROW*):

		ROW abate	*ROW* not abate
i	abate	10;10	0;0
i	not abate	0;0	0;0

This game has two Nash equilibria: either everybody abates or nobody does. It is a matter of coordination to pick the best outcome, and it may not be a very interesting problem from a game-theoretical point of view. It is nevertheless a scenario that should be kept in mind when one thinks about policy recommendations, and it does pose a couple of interesting questions for economists to answer: how can we reach 100% abatement in the fastest and least costly way? And could it be economically efficient to help poorer countries face the costs of abatement so that we can make sure that the only meaningful outcome can be reached?

These are important considerations from a political and economical point of view, but as we have discussed, they are not of a game-theoretical nature, and they do not explain why current negotiations are failing[49].

Because we want to investigate the game theoretical aspects of the problem, we need therefore to assume that these rather extreme scenarios are not true, and that there is room for negotiation: there is a cake to share. No matter whether this situation is real or not, the perceived payoff structure is what matters in a game, and if some of the political agents think that other countries' effort will be enough to ensure some economic benefits, then the prisoner's dilemma may represent appropriately the way that the climate negotiation game is played.

For this reason we continue in this tradition and deal with a model of coalition formation where the payoffs are such that the incentives to quit the agreement increase faster than the benefits from joining, so that the full coalition, where all countries in the game join the agreement, is not sustained. In this framework we want to look for conditions and policy instruments that are capable to induce better cooperation.

Cooperative vs. non-cooperative behavior

Global environmental problems such as climate change require cooperation between sovereign states to overcome welfare losses that occur if these states only focus on the effects of their own emission reductions on their own level of welfare. International cooperation, however, is vulnerable to free-rider behaviour so that one is confronted with the classical dilemma between the benefits of cooperation and the incentives to free ride. The dominant strand in the literature is

[49] They might however give some extra insight also into cooperation issues. For instance they may help explain the apparently irrational behaviour of countries, like Europe, that keeps cooperating even in the face of important defections on part of other big countries. One might think that Europe perceives the payoff structure underlying the negotiations for a climate protocol as a coordination game. If that is the case it might be a rational strategy to try and give signals in the hope to be followed by the rest of the world, so that the good outcome can be selected.

based on an equilibrium concept for these two aspects. The idea is that a coalition forms with the property that countries neither have an incentive to leave that coalition (in order to enjoy free-rider benefits) nor to join that coalition (in order to enjoy the benefits of cooperation). Usually this is referred to as internal and external stability (Hoel, 1992, Carraro and Siniscalco, 1993, Barrett, 1994, Finus, 2003). This equilibrium is a Nash equilibrium of the so-called open-membership game where countries first decide whether they want to be part of the coalition or not and then decide on their emission reduction, either as a member of the coalition or as an outsider.

Typically the size of the coalition that is both internally and externally stable is very small. This result has been challenged by approaches that are based on different game theoretic models. One is based on the γ-core concept in cooperative games (Chander and Tulkens, 1995). A coalition is in the γ-core if no sub-coalition has an incentive to deviate (under the assumption that in that case the remaining coalition falls apart). It can be shown that transfers between countries exist such that the grand coalition is in the γ-core and in that sense stable. This idea is similar to trigger strategies in repeated games where cooperation can also be sustained by assuming that in case some country deviates cooperation falls apart. The behavioural assumptions in these approaches are quite strong, however. These assumptions can be relaxed somewhat by introducing the idea of farsightedness (Chwe, 1994). In this approach deviations may trigger more deviations but not necessarily a complete break-up of the coalition. It can be shown that this model can also sustain large coalitions. A trade-off occurs between models with behavioural assumption that are less realistic but may lead to large coalitions and models with more realistic behavioural assumptions but only small coalitions.

In this chapter we discuss an important aspect of the negotiation process, namely the ability to commit in such a way to implement a trigger strategy that can lead to larger coalitions. As mentioned above, the γ-core theoretical framework is based on the assumption that countries in a coalition can commit to implement a punishment strategy in the case that a country unilaterally deviates from the agreement. Most commonly the threat is that the whole coalition will break apart and that the fully non-cooperative Nash equilibrium will be played.

We will designate this as a "γ-strategy". As this usually leads to very bad outcomes, these models are able to more easily reach the conclusion that a full coalition is stable, and thus that cooperation is possible. The non-cooperative models instead are based on the assumption that when one country does not join the coalition, the others will play their best-response strategy, which might well be to form a smaller coalition. In other words, they are not able to commit to playing punishment strategies. As a result of this assumption, the equilibrium will be a "PANE" (Partial Agreement Nash Equilibrium) where a coalition formed by a subset of the countries (insiders) play as one player a Nash game against the other countries, each playing on their own (outsiders).

In what follows we show why we think that the γ-strategy is not a credible one, considering the consequences in case the negotiation game is played as a simultaneous move game or a sequential move game where the coalition moves second.

Suppose N countries are negotiating a coalition and consider the choice of country i that is playing against a coalition formed by j countries. Carraro and Siniscalco (1997) define two payoff functions $P(j)$ and $Q(j)$, respectively for insiders and outsiders of a coalition of size j, and they assume that when the number of countries in the coalition increases then both insiders and outsiders earn higher payoffs. Furthermore, the outsider payoff function $Q(j)$ is assumed to increase faster in the size of the coalition, j, than the insider payoff function $P(j)$, because the countries in the coalition have to internalize more damage and therefore abate more as more countries join in. The following set of conditions are used to model the game when s is the equilibrium size of the coalition:

1. $P(j+1) \geq P(j)$;
2. $Q(j+1) \geq Q(j)$;
3. $P(j+1) \geq Q(j)$ for $j = 1,\ldots,s-1$;
4. $P(j+1) \leq Q(j)$ for $j = s,\ldots,n$.

Since the countries in the coalition have already found a cooperation agreement, their strategy space consists of the choice between γ (the coalition does not form unless country i participates) and δ (the coalition forms anyway).

		Coalition γ	Coalition δ
Country i	C	$P(s+1); P(s+1)$	$P(s+1); P(s+1)$
	NC	$P^0; P^0$	$Q(s); P(s)$

where $P(1) = Q(1) \equiv P^0$. For this game, whenever $Q(s) > P(s+1)$, and for any $s \geq 2$, there are two Nash equilibria: $(C;\gamma)$, and $(NC;\delta)$. In the first case the coalition threatens country i playing a γ-strategy and therefore i is induced to cooperate. In the second case the coalition does not use its threatening power and therefore i does not cooperate. In the latter equilibrium, the coalition is worse off and country i is better off than in the former.

There are some reasons to argue however that this "worse" (from the standpoint of the coalition) equilibrium is more likely to occur.

Except for the special case where $s = 1$, one can see that δ is a weakly dominating strategy for the coalition, in this one-shot game. This implies (in a two-players game like this) that $(NC;\delta)$ is the only trembling-hand perfect Nash equilibrium. That is, this equilibrium is robust to the possibility that some player makes a mistake. In this sense, caution precludes players from playing weakly dominated strategies (see Mas-Colell, Winston and Green, 1995, section 8.F).

To prove this, notice that the Nash equilibrium $(C;\gamma)$ cannot be trembling-hand perfect: if a vector of (randomized) strategies representing a Nash equilibrium of a game is trembling-hand perfect it cannot involve playing a weakly dominated strategy with positive probability. One can therefore focus on the only other Nash equilibrium. To show that $(NC;\delta)$ is indeed a trembling-hand perfect Nash equilibrium, consider first the sequence of totally mixed strategies $\left(\frac{1}{k_i+1};1-\frac{1}{k_i+1}\right)$ for country *i*, where *i* plays *C* with probability $0<\frac{1}{k_i+1}<1$, and *NC* with probability $1-\frac{1}{k_i+1}$. As $k_i \to \infty$ such a sequence approaches the pure strategy *NC*. Furthermore, best response of the coalition to each element of the sequence is *δ*, since:

$$EU(\delta)=\frac{1}{k_i+1}P(s+1)+\left(1-\frac{1}{k_i+1}\right)P(s)>$$

$$>\frac{1}{k_i+1}P(s+1)+\left(1-\frac{1}{k_i+1}\right)P^0=EU(\gamma)$$

for any natural number $k_i \geq 1$. In the same way, one can consider the sequence of totally mixed strategies $(p(k);1-p(k))$, where the coalition plays *γ* with probability $0<p(k)=\frac{Q(s)-P(s+1)}{(Q(s)-P^0)k}<1$ and *δ* with probability $1-p(k)$. As $k\to\infty$ such sequence approaches the pure strategy *δ*, since $p(k)\to 0$. Besides, the best response of country *i* to each element of the sequence is *NC*, since:

$$EU(NC)-EU(C)=-\frac{Q(s)-P(s+1)}{(Q(s)-P^0)k}\left[Q(s)-P^0\right]+\left[Q(s)-P(s+1)\right]\geq 0$$

for any natural number $k\geq 1$. Therefore, $(NC;\delta)$ is the trembling-hand perfect Nash equilibrium.

Moreover, it can be argued that since P^0 is a worse outcome than $P(s+1)$, country *i* should be careful in avoiding such outcome. However, this has some cost, and in real-life situations emissions cannot be controlled perfectly, so that a positive probability has to be assigned to country *i* playing *NC* even if it expects the coalition to play *γ*. This creates a cost to the coalition in case they decide to threaten playing *γ*. Such a cost, c_1, is given by the difference in expectations when playing *δ* and when playing *γ*, given that country *i* plays *NC* with positive probability p: $c_1=p\left[P(s)-P^0\right]$. But, avoiding the threat and playing *δ* straightforward also has a cost, c_2, given by the difference in the best outcomes that are reachable by playing such strategies if players behave rationally (that is, if they make no mistakes). Such outcomes are obviously those obtained in the Nash equilibria and therefore the cost for the coalition of playing δ is $c_2 = P(s+1) - P(s)$. One can thus expect the coalition to play δ when this cost is smaller than the cost of playing γ:

$$c_1 - c_2 = p\left[P(s) - P^0\right] - P(s+1) + P(s) \geq 0 .$$

This implies that the coalition should choose to play δ when the probability that country i plays NC exceeds the threshold $\overline{p} = \dfrac{P(s+1) - P(s)}{P(s) - P^0}$. Notice that the threshold decreases with P^0, and tends to zero when P^0 becomes infinitely negative. This shows that when non-cooperation leads to a catastrophic event, the coalition prefers playing δ, even if this practically prevents the enlargement of the coalition. This is another argument in favour of considering $(NC;\delta)$ a more likely outcome of the game, rather than $(C;\gamma)$.

We can find more arguments if we now turn to consider an extensive-form game. If the coalition is able to commit, it can be considered as the first mover. For a generic starting coalition size j, the game is then illustrated by Figure 28.

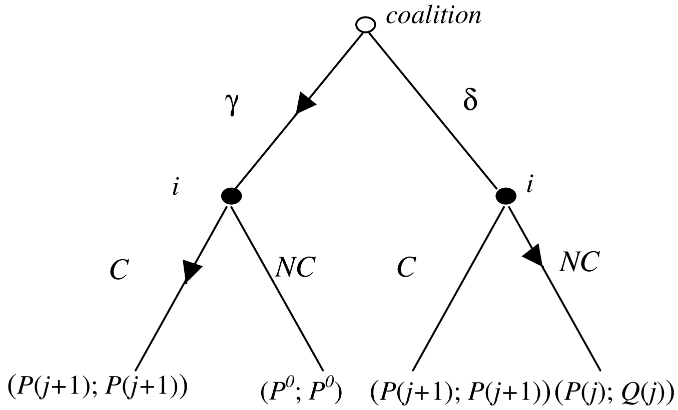


Figure 28 Extended form of the game if the coalition can commit to a strategy

The sub-game perfect game equilibrium leads to $(C;\gamma)$ with certainty for all $j>1$. In other words, if the coalition can announce credibly to be playing γ, then country i will certainly cooperate. The ability to commit is not a common feature of international agreements, as there is no super-national institution capable of enforcing agreements. Therefore, if the coalition is unable to commit, the choice whether to play γ or δ can be thought of as a choice made after player i has decided about cooperation. This situation is illustrated in Figure 29, from which it is apparent that the outcome reached is $(NC;\delta)$.

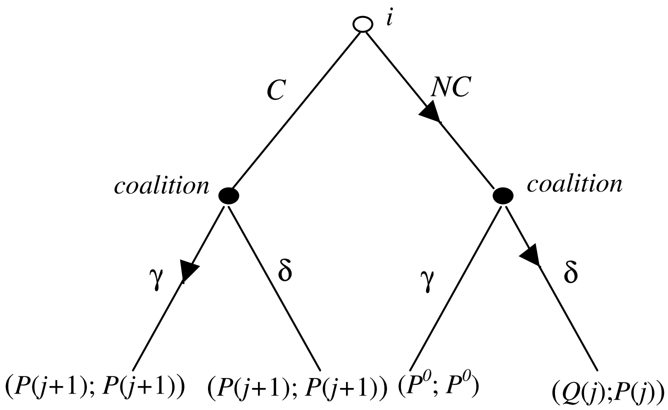


Figure 29 Extended form of the game if the coalition cannot commit

Green investments to foster cooperation in a non-cooperative setting

From what is discussed above, it is clear that there are good reasons for analysing the international agreements on climate change in a non-cooperative framework. This is "bad news": as we have seen, it often implies that only small coalitions can be sustained. In what follows we propose a model that incorporates green investments as a way to foster cooperation and make larger coalitions possible.

As we have mentioned, it is often argued that technological change is the best answer to the global warming challenge. In the long run, if "green" (or greener) technology will be available and cheap enough, we would expect that emissions should drop, while not much negatively affecting other variables, such as income. We are here interested in looking at the effects of green technology on international cooperation. Nowadays, green technology is not yet widespread and cheap enough to completely substitute the dirty one. However, several countries use renewable resources like water, wind, sun, or biogas, to produce at least part of their energy supply in sustainable ways. Does the availability of green technology affect the cooperative attitude of a country? Endres and Ohl (2002) use the term "cooperative-push" to designate an intrinsic feature of a political or economic measure that is able to induce cooperative behaviour, by changing the payoff structure of the negotiation game[50].

Is it possible to apply a similar concept in the climate change setting? We think that investments in green technology, besides being an important factor needed to ensure sustainable growth, also might have the property of changing the payoff structure of the international negotiation game on climate change: if the costs of abatement are reduced, then the incentives to free-ride might decrease, and it might result easier to achieve self-enforcing cooperation agreements.

To analyse this issue, we expand on the Carraro-Siniscalco (1997) approach. We assume, to simplify, that $P(j)$ and $Q(j)$ are continuous and monotonic functions, and thus use the following set of assumptions, which is equivalent to the set of assumptions originally used in the discrete framework:

1. $P'(j) > 0$;

[50] Endres and Ohl mention here as an example the implementation of unleaded fuel policy in Germany. This failed at the European Union level, because some countries, like Italy, did not want to cooperate. After Germany unilaterally introduced catalytic converters, though, the Italians were induced to provide unleaded fuels in order to keep attracting German car-tourists, and eventually this led to the spreading of catalytic cars in Italy as well.

2. $Q'(j) > 0$;

3. $Q(0) < P(0)$;

4. $Q(n) > P(n)$.

Consider that when the marginal country *i* does not join the coalition, then its realized gain, $Q(j) - P(j+1)$, can be decomposed as follows:

$$Q(j) - P(j+1) = [Q(j) - P(j)] - [P(j+1) - P(j)] \equiv H_j - D_j$$

where $H_j = Q(j) - P(j)$ represents the gain from being outside the coalition instead than inside of it (that is, the free-riding incentive), and $D_j = P(j+1) - P(j)$ represents the (social) loss from foregone extra reductions in emissions that could have occurred if country *i* had joined the coalition.

For our modelling purposes, we introduce one more variable, *K*, representing a sunk-cost investment in a green technology. A green technology has the property of producing clean goods, for instance renewable energy, thereby reducing the cost of ex-post abatement. An example of such an activity could be a source of "alternative energy", like solar energy or wind energy. Building more plants for the production of alternative energy represents a sunk investment and implies that H_j is reduced: even if the country does not cooperate, it will now cost less to reduce emissions, and therefore the advantage of free-riding is reduced by the sunk investment. We can therefore introduce it in our setting, assuming that it increases the payoffs (gross of the sunk cost) for any country. Moreover, if abatement costs are convex, it increases the insiders' payoff more than the outsiders' because the former have to abate more.

To see this, assume that abatement costs are given by a function $c(a)$, with $c' > 0$ and $c'' > 0$. Furthermore, assume that investing a sum *K* in the clean technology provides with a costless abatement rate $b(K)$. Therefore, if a represents total abatement, its cost equals $c(a - b(K))$. If the insiders of the coalition have to abate a' and the outsiders a'', with $a' > a''$, it follows that the gains from investing a given sum *K* in the renewable energy are higher for the insiders since convexity implies: $c(a') - c(a' - b(K)) > c(a'') - c(a'' - b(K))\ \forall K > 0$.

We can model this by assuming that $P(j)$ and $Q(j)$ are a function of *K*, such that $P_K(j,K) > Q_K(j,K)$. As a result, $H_j = H_j(K)$ is decreasing in *K*. We do not need to assume that *K* affects D_j: for instance if *K* only induces a shift in the functions, it will not affect this component.

If the initial equilibrium size of the coalition was *j*, after investments have taken place to an amount *K*, it may result $H_j(K) < D_j$ and therefore country *i* now wants to join the coalition as well. The system has a new equilibrium at a new situation where the coalition is formed by $j' \geq j$ countries. In Figure 30, one can see a graphic representation of the incentive curves $P_j(K)$ and $Q_j(K)$ for a low and high value of *K* respectively, and the way in which the relative equilibrium coalition changes.

The reasoning that we have followed does not include any consideration about the fact that a forward-looking player will take into account the consequences of investments in green technology on the final equilibrium. We can call this a "myopic" model.

If we now want to allow the countries to be more forward-looking, we need to formalize the relation between investments and the size of the coalition. Each country faces a two-step decision: in the first step they chose the level of investment in the alternative energy, in the second step they chose whether to join the coalition or not, and thereby determine the equilibrium size of the coalition.

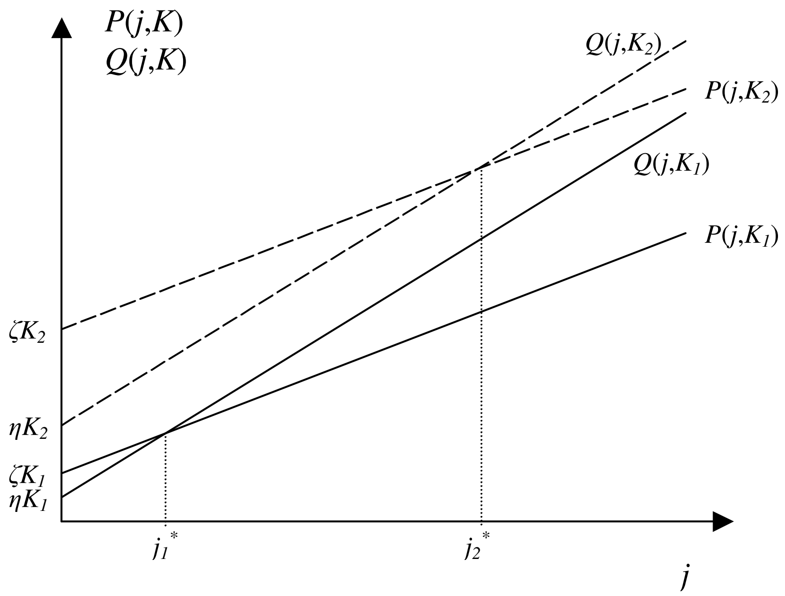


Figure 30

Let K be the level of investment chosen in the first step and assume that the payoff functions are of the type:

$$P(j,K) = \zeta K + \alpha j$$

$$Q(j,K) = \eta K + \gamma j$$

with $0 < \alpha < \gamma$ so that there are incentives to free ride as j becomes larger, and with $0 < \eta < \zeta$, so that investing in K is less attracting if you are out of the coalition.

Then, for given K, the incentive to free ride is decreasing in K, whereas the gains from cooperation are constant:

$$H(j,K) = Q(j,K) - P(j,K) = (\gamma - \alpha)j - (\zeta - \eta)K$$

$$H_K(j,K) = -(\zeta - \eta) < 0$$

$$D(j,K) = P(j+1,K) - P(j,K) = \alpha \, .$$

Notice that in these assumptions it holds $H_j(K) \leq H_{j+1}(K)$, meaning that for given technology the advantage of free riding is higher when the coalition is larger[51]. This is not necessarily implied by the standard assumptions on $P(j)$ and $Q(j)$, and it is a consequence of using linear functions.

In this model, investments foster cooperation, as shown in figure Figure 31 below.

The picture shows that for higher values of *K* the coalition size becomes larger in equilibrium. As payoffs are always increasing in the size of the coalition, both insiders and outsiders are better off with a positive level of investments in the green technology. The optimal amount of investment depends on the investment cost relative to the other parameters, in particular η and ζ, which represent the efficiency of the green technology.

The model can be solved per backward induction: first the equilibrium size of the coalition in the second stage of the game is derived as a function of the level of investments, and then such function is used to determine the optimal investment strategy in the first stage.

---

[51] This is not an innocent assumption: it implies that insiders' (outsiders') abatements are always non-decreasing (non-increasing) in *j*. Let us denote with a_I the insiders' abatement, with a_O the outsiders', and with a the total abatement when the coalition has size *j*. Let us define a function $b(a)$, denoting the benefits from abatement and assume that both insiders and outsiders benefit in the same way from abatement. Then we can write:

$$H_j = Q(j) - P(j) = b(a) - c(a_O) - b(a) + c(a_I) = c(a_I) - c(a_O)$$

(where we have assumed *K* constant) meaning that:

$$H_{j+1} \geq H_j \Leftrightarrow c(a'_I) - c(a_I) + c(a_O) - c(a'_O) \geq 0 \Leftrightarrow a'_I \geq a_I \text{ and } a_O \geq a'_O$$

where we denote with a'_I the insiders' abatement, and with a'_O the outsiders', when the coalition has size $j+1$.

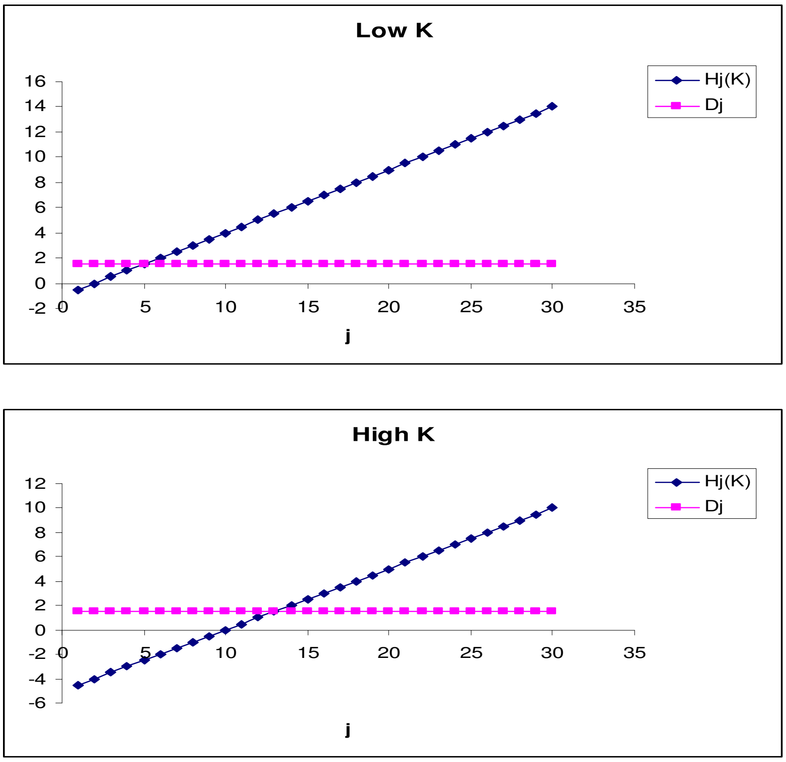


Figure 31

We can make several assumptions regarding the negotiation process in the second stage. In particular, we can assume either that countries are unable to know whether they will be insiders or outsiders (for instance because the negotiation process will happen in random order), or that they are able to foresee perfectly their role inside or outside the coalition. We will distinguish these two cases in the following presentation and derive the equilibrium size of the coalition and the level of investment for both cases separately.

Random negotiation process

2nd STAGE: Coalition size

Given K, the equilibrium size of the coalition is that value of j such that $Q(j,K)=P(j+1,K)$. Notice that our assumptions are such that the two functions cross once and only once.

So in the equilibrium it must hold:

$$j^*(K) = \frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha}.$$

1st STAGE: Optimal investment

The optimal investment is at the level where expected payoffs are maximum, given the probabilities that a country is an insider or an outsider. Such probabilities coincide with the relative numbers of insiders and outsiders respectively:

$$\max_K \left[N - \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \right] \left[\eta K + \gamma \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \right] +$$
$$+ \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \left[\zeta K + \alpha \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \right] - K$$

The first derivative of this objective function is constant and it equals:

$$D = N\eta + N\gamma \frac{\zeta - \eta}{\gamma - \alpha} - \frac{\gamma\eta}{\gamma - \alpha} - \frac{2\eta(\zeta - \eta)}{\gamma - \alpha} K - 2\gamma \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \left(\frac{\zeta - \eta}{\gamma - \alpha} \right) +$$
$$+ \frac{\gamma\zeta}{\gamma - \alpha} + \frac{2\zeta(\zeta - \eta)}{\gamma - \alpha} K + 2\alpha \left(\frac{\gamma + (\zeta - \eta)K}{\gamma - \alpha} \right) \left(\frac{\zeta - \eta}{\gamma - \alpha} \right) - 1 =$$
$$= (N\eta - 1) + (N - 1)\gamma \frac{\zeta - \eta}{\gamma - \alpha}$$

There is thus no internal optimum for this problem. Each country desires to invest as much as possible in the clean technology if D is positive, and nothing at all if it is negative. Assuming for simplicity that K expresses the percentage conversion from current technology to clean technology we can impose $0 \leq K \leq 1$. Therefore we can state the following result:

Proposition 1

If $(N\eta-1)+(N-1)\gamma\dfrac{\zeta-\eta}{\gamma-\alpha}>0$, then:

$$K^*=1$$
$$j^*=\frac{\gamma+(\zeta-\eta)}{\gamma-\alpha}$$

If $(N\eta-1)+(N-1)\gamma\dfrac{\zeta-\eta}{\gamma-\alpha}<0$, then:

$$K^*=0$$

$$j^*=\frac{\gamma}{\gamma-\alpha}.$$

Besides we can see with straightforward computations that the following holds:

Corollary 1

$$\eta>\frac{1}{N}\ \Rightarrow (N\eta-1)+(N-1)\gamma\frac{\zeta-\eta}{\gamma-\alpha}>0.$$

Which offers a clear intuition for our result: when the productivity of green investments is sufficiently high, then it is worth for all countries to invest[52].

From Proposition 1 it is clear that the equilibrium size of the coalition is increasing in α and in ζ, and decreasing in η and γ when $D>0$. Instead, the

[52] Notice that in our model we have set *N* as a given number and *not* as a parameter, hence we cannot make any statement about its influence on the other variables of this model. Our payoff functions do not depend on this value, which is of course not true in real life. So it is meaningless to make comparative-static analysis regarding this parameter. In particular, we cannot state that the productivity of green investments required by condition 1 increases or decreases in the total number of countries: *N* is here just a given number without any meaning and corollary 1 simply means that green-investment productivity has to reach a positive lower limit in order for investments to be non-zero.

coalition size does not depend on the productivity of green investments when $D < 0$: this makes sense because in this latter case sunk-investments are absent.

Non-random negotiation process

Let us now assume that the negotiation process is structured in such a way that already in the first stage countries are able to anticipate whether they will be insiders or outsiders. The optimal level of investment in the green technology does not need to be the same for an insider as for an outsider. Denoting with K_I investments for an insider and with K_O investments for an outsider, we can use the same simple model as in the previous section, where:

$$P(j, K_I) = \zeta K_I + \alpha j$$

$$Q(j, K_O) = \eta K_O + \gamma j$$

2nd STAGE: coalition size

In equilibrium it holds that:

$$P(j^*, K_I) = Q(j^* - 1, K_O)$$

that is:

$$\zeta K_I + \alpha j^* = \eta K_O + \gamma (j^* - 1)$$

which implies:

$$j^* = \frac{\gamma + \zeta K_I - \eta K_O}{\gamma - \alpha}$$

1st STAGE: optimal investments

In the first stage, insiders solve:

$$\max_{K_I} \zeta K_I + \alpha \left(\frac{\gamma + \zeta K_I - \eta K_O}{\gamma - \alpha} \right) - K_I$$

and outsiders solve:

$$\max_{K_O} \eta K_O + \gamma\left(\frac{\gamma + \zeta K_I - \eta K_O}{\gamma - \alpha}\right) - K_O$$

As the objective functions are linear and separable in the two control variables, we have that K_I and K_O are chosen independently from each other and that there are no internal solutions. Thus we can state:

Proposition 2

If $\zeta + \frac{\alpha}{\gamma} > 1$ then:

$$K_O^* = 0$$

$$K_I^* = 1$$

$$j^* = \frac{\gamma + \zeta}{\gamma - \alpha}$$

If $\zeta + \frac{\alpha}{\gamma} < 1$ then:

$$K_O^* = 0$$

$$K_I^* = 0$$

$$j^* = \frac{\gamma}{\gamma - \alpha}$$

Also this result has a clear intuition: when $\zeta + \frac{\alpha}{\gamma} > 1$, it means that the marginal benefits of green investments, plus a correction term that can be interpreted as the cooperative gain induced by the new technology, are larger than its marginal costs. In this case therefore, it is convenient for insiders to replace the old technology with the green one.

We can compare the outcome of this version of the model with the outcome of the model with non-random negotiations and see that with random negotiations the predicted size of the coalition is smaller. This observation is consistent with our intuition: when the negotiations are conducted randomly and each country has a chance to end up as an outsider, then the expected gain from green investments is lower than it is in the non-random model for those countries that already know they will be insiders. Thus the incentive to invest is lower and so is the cooperative push of green investments.

Conclusions

Our model is oversimplified but it shows that when our hypotheses on the shape of the payoff functions for members of a given coalition and outsiders hold true, then investments in green technology and the participation in international environmental agreements are strategically interconnected in a positive way. The intuition for this is that investments in green technologies reduce the incentives to free ride and induce larger participation rates in the agreement. Since in our assumptions higher participation rates require more abatement effort, it then becomes more convenient to invest in green technologies. This leads to a virtuous circle where technological change and cooperation enhance each other.

As the success and extent of such a positive correlation of events depends on the technological parameters η and ζ, which in turn depend on the efficiency of the green technology, it can be concluded that, under our assumptions, knowledge is the key to solve international negative externalities. From a policy perspective this implies that research in the field of green technologies should be encouraged and facilitated, as its value lies not only in the direct effects on green technology but also incorporates the indirect effect on the cooperative attitude of countries.

It has to be noticed, however, that the assumptions of our model are non-standard ones. In particular, we make assumptions on the shape of the payoff functions, which are not derived from any optimization process. In chapter 5 we therefore turn to analyzing a model in the standard setting, and find the conditions under which green investments can foster cooperation.

5. Stable coalitions with green investments

Introduction

In this chapter we go deeper into the question of analysing the role of investment in green capital in models with internal and external stability. We look for micro-foundations for the model described in Chapter 4, where investments in green capital are shown to foster cooperation. In that framework we made assumptions on the shape of the payoff functions and showed that it was possible to sustain full cooperation. In this chapter we analyze a model based on maximization of net benefits of abatement, so that we can derive the payoff functions as a result of the optimal choice of abatement levels, on part of the members of the coalition and the outsiders. Our analysis shows that in this kind of models full cooperation cannot be reached under general conditions.

In what follows we show that it is true in general that members of the coalition have a higher incentive to invest in green capital. It is also true that larger coalitions induce higher overall investments in green capital, which in principle can sustain larger coalitions. However, outsiders to larger coalitions invest less in green capital, which lowers their investments costs. This is in fact another free-rider benefit that neutralizes the effect of the green capital, so that again small coalitions result in equilibrium. The only way larger coalitions can result is by noting that the members of a coalition may share, for example, the R&D costs of investment. To put it differently, only some extra positive externality of cooperation can boost the size of the coalition.

The idea that cooperation in technology development is easier than cooperation on emission abatement is not new in the literature. Buchner and Carraro (2004) discuss the possibility of substituting international agreements based only on abatement targets, like the Kyoto protocol, with agreements based only on R&D funds and the introduction of technology standards. In their paper they show with calibrated simulations that the latter kind of agreements, while self-enforcing, is not likely to produce the desired effect of reducing emissions, because R&D on the one hand induces cooperation, but it also stimulates growth on the other hand. The authors claim that probably better results could be reached by an agreement based both on technology incentives and on abatement targets. The present paper seems to reach the same conclusion, based on purely theoretical arguments.

We first present the simplest abatement model that shows that coalitions are small when internal and external stability are required. Then the option of investment in green capital, with the purpose to lower the cost of abatement, is introduced. It is shown that the low-size property is quite robust. Different ways to introduce this cost reduction and extensions to more standard types of models all have the property that the size of the coalition remains small, if the green capital stocks are given. However, if countries know that they will be members of the coalition and will abate together, they will also jointly decide on investments. This implies that a larger coalition will induce higher investments and in this way a larger coalition may be sustained. This requires a model with three stages. In the first stage countries decide on membership, in the second stage coalition and outsiders decide on investments in green capital, and in the third stage they decide on abatement. It will be shown that when the coalition shares the fixed costs of investments, large coalitions can be sustained.

Internal and external stability without green investments

The simplest abatement model that shows why coalitions are small, when internal and external stability are required, is formulated as follows. Each country *i*, for $i = 1,2,...,n$, with *n* the total number of countries, can abate a_i with benefit a_i and cost $\frac{1}{2}a_i^2$. Each individual country maximizes:

$$\sum_{i=1}^{n} a_i - \frac{1}{2}a_i^2$$

and the members of a coalition of size *m* jointly maximize:

$$m\sum_{i=1}^{n} a_i - \frac{1}{2}a_1^2 - ... - \frac{1}{2}a_m^2$$

This implies that each member of the coalition will abate $a_i = m$ and each individual country will abate $a_i = 1$. It follows that the members of the coalition have a net benefit:

$$P(m) = \frac{1}{2}m^2 + n - m$$

and the outsiders have a net benefit:

$$Q(m) = m^2 + n - m - \frac{1}{2}$$

Internal stability requires that the following condition is met:

$$P(m) \geq Q(m-1)$$

and external stability requires:

$$P(m+1) \leq Q(m)$$

This is only satisfied for $m = 2$ and $m = 3$. Note that this is independent of the total number of countries n. Whether a coalition of size *2* or *3* results depends on what we assume in case of indifference.

Internal and external stability with green investments

Suppose now that the countries can invest in green capital k_i, which changes their decision problem on abatement. For example, it affects the parameter in their cost function in the following way:

$$\frac{1}{2}e^{-k_i}a_i^2$$

or it assures a certain level of abatement so that they only have to pay for additional abatement in the following way:

$$\frac{1}{2}(a_i - k_i)^2$$

In the first case the members of the coalition abate $e^k m$ and the outsiders abate e^k, and the expressions for net benefits become

$$P_i(m) = m\sum_{j=1}^{m} e^{k_j} + \sum_{j=m+1}^{n} e^{k_j} - \frac{1}{2}e^{k_i}m^2$$

$$Q_i(m) = m\sum_{j=1}^{m} e^{k_j} + \sum_{j=m+1}^{n} e^{k_j} - \frac{1}{2}e^{k_i}$$

and in the second case the countries abate $m + k_i$ and $1 + k_i$ respectively, and here the expressions become

$$P(m) = \frac{1}{2}m^2 + n - m + \sum_{i=1}^{n} k_i$$

$$Q(m) = m^2 + n - m - \frac{1}{2} + \sum_{i=1}^{n} k_i$$

In the second case it is immediately clear that the results on the size of the coalition do not change, because the capital terms cancel out, but the first case needs a bit more analysis. Internal stability requires:

$$(m-1)\sum_{j\neq i}^{m} e^{k_j} + e^{k_i} + \sum_{j=m+1}^{n} e^{k_j} - \frac{1}{2}e^{k_i} \leq m\sum_{j=1}^{m} e^{k_j} + \sum_{j=m+1}^{n} e^{k_j} - \frac{1}{2}e^{k_i}m^2$$

for $i = 1,...,m$. That is equivalent to:

$$-\sum_{j\neq i}^{m} e^{k_j} + \frac{1}{2}e^{k_i} \leq me^{k_i} - \frac{1}{2}e^{k_i}m^2$$

or

$$(\frac{1}{2}m^2 - m + \frac{1}{2})e^{k_i} \le \sum_{j \ne i}^{m} e^{k_j}$$

It follows that:

$$(\frac{1}{2}m^2 - m + \frac{1}{2})\sum_{j=1}^{m} e^{k_j} \le (m-1)\sum_{j=1}^{m} e^{k_j}$$

or

$$\frac{1}{2}(m-1)^2 \le (m-1)$$

And thus we can conclude that:

$$m \le 3$$

Again the conclusion holds that the size of the coalition that is internally and externally stable is small, regardless of the total number of countries. This means that if the levels of green capital are given, the story remains the same. It also means that asymmetries in costs do not change the general conclusion. The result seems very robust.

The basic model above is simple but misses one aspect that may be important. The interaction is rather weak: outsiders, for example, will always abate the same amount, regardless of what the coalition does. One would expect, however, that outsiders should abate less, if the coalition is large and abates more. This is the idea of carbon leakage. We now extend our model in order to capture this phenomenon. To keep the analysis tractable, the effect of green capital will be modelled in the simple way (see above): not as an effect on the parameter of the cost function but as a shift of the cost function.

Assume that for a given level of investment k_i, the net benefits of country i are given by

$$\beta a-\frac{1}{2}a^2-\frac{1}{2}\alpha(a_i-k_i)^2$$

If a coalition of size $1\leq m<n$ forms, member countries within the coalition internalize the benefits of abatement of all other members as well, thus they optimize:

$$\max_{a_1,\ldots,a_m} m\left(\beta a-\frac{1}{2}a^2\right)-\frac{1}{2}\alpha(a_i-k_i)^2$$

leading to the FOCs:

$$m\beta-ma-\alpha(a_i-k_i)=0\ \ ,i=1,\ldots,m$$

while outsider maximize their own net benefits:

$$\max_{a_i} \beta a-\frac{1}{2}a^2-\frac{1}{2}\alpha(a_i-k_i)^2,\ \ i=m+1,\ldots,n$$

leading to the FOCs:

$$\beta-a-\alpha(a_i-k_i)=0,\ \ i=m+1,\ldots,n$$

It follows that:

$$(m^2+n-m)(\beta-a)-\alpha a+\alpha k=0$$

where $a=\sum a_i$, $k=\sum k_i$.

$$a=\frac{(m^2+n-m)\beta+\alpha k}{m^2+n-m+\alpha}$$

$$\beta-a=\frac{\alpha\beta-\alpha k}{m^2+n-m+\alpha}$$

$$a_i=\frac{m(\beta-k)}{m^2+n-m+\alpha}+k_i,\ \ i=1,\ldots,m$$

$$a_i = \frac{\beta - k}{m^2 + n - m + \alpha} + k_i, \quad i = m+1,...,n$$

Note that the Nash equilibrium without coalition formation results for $m = 1$, and that the abatement levels for the full coalition are given by the first expression with $m = n$. Note also that for this model only total green capital k affects the behaviour in the last stage of the game.

Optimal investments

The expressions for net benefits become

$$P(m,k) = \frac{(\frac{1}{2}(m^2 + n - m)\beta + \alpha(\beta - \frac{1}{2}k))((m^2 + n - m)\beta + \alpha k) - \frac{1}{2}\alpha m^2(\beta - k)^2}{(m^2 + n - m + \alpha)^2}$$

$$Q(m,k) = \frac{(\frac{1}{2}(m^2 + n - m)\beta + \alpha(\beta - \frac{1}{2}k))((m^2 + n - m)\beta + \alpha k) - 0.5\alpha(\beta - k)^2}{(m^2 + n - m + \alpha)^2}$$

The general analysis is complicated so that we use an example to show what happens. A more general full analytical discussion will be presented in the next section.

Example

Suppose that the total number of countries $n = 4$ and the parameters and $\alpha = 20$. In case a coalition of size $m = 3$ forms, it follows from the previous section that

$$a = \frac{5 + 2k}{3}$$

$$a_i = 3\frac{5 - k}{30} + k_i, \quad i = 1,2,3$$

$$a_i = \frac{5 - k}{30} + k_i, \quad i = 4$$

so that

$$P(3,k) = \frac{400 - 29k^2 + 290k}{90}$$

$$Q(3,k) = \frac{600 - 21k^2 + 210k}{90}$$

In case a coalition of size $m = 2$ forms, it follows that

$$a = \frac{30 + 20k}{26}$$

$$a_i = 2\frac{5-k}{26} + k_i,\ i = 1,2$$

$$a_i = \frac{5-k}{26} + k_i,\ i = 3,4$$

so that

$$P(2,k) = \frac{2450 - 240k^2 + 2400k}{676}$$

$$Q(2,k) = \frac{3200 - 210k^2 + 2100k}{676}$$

Note that $P(3,5) = Q(3,5) = P(2,5) = Q(2,5)$: the reason is that $k = 5$ means that the green capital is equal to β, which can be interpreted as the initial level of emissions or the maximum level of abatement. In this case the investment in green capital is so high that abatement is not needed any more in the last stage of the game.

Note also that $Q(2,k) > P(3,k)$ for $k < 5$ which means that for a given level of green capital, the coalition of size 3 is not internally stable. This is in accordance with what was found for the preliminary models in the previous section. However, if a coalition of size 3 triggers a higher investment in green capital $k(3)$ than a coalition of size 2, it may happen that $Q(2,k(2)) < P(3,k(3))$, so that a coalition of size 3 becomes internally stable: for any level $k(2) < 5$, there exists a k' such that for $k' < k(2) < 5$ it holds that $Q(2,k(2)) < P(2,k(3))$. Furthermore, if countries decide on membership first, before they decide on investment, it is reasonable to assume that they decide on investment together. This may drive up the level of green capital sufficiently high to sustain the larger coalition.

It will be shown that total investment in green capital will indeed be higher if more countries first decide to join the coalition, but this does not necessarily sustain a larger coalition. The reason is that total investment increases but the investment of outsiders decreases. Outsiders therefore have lower investment costs: in fact another free-rider benefit. If we now look at the total net benefit for the investment stage and the abatement stage together, internal stability for the larger coalition is lost again.

Consider the case each country has the same convex investment costs $\frac{1}{2}\gamma k_i^2$, with $\gamma = 20$.

If a coalition of size $m = 3$ forms, the optimality conditions for investment are:

$$\frac{3}{90}(-58k + 290) - 20k_i, \quad i = 1,2,3$$

$$\frac{1}{90}(-42k + 210) - 20k_i = 0, \quad i = 4$$

It follows that

$$k = 1.1929, \; k_1 = k_2 = k_3 = 0.368, \; k_4 = 0.0888$$

If a coalition of size $m = 2$ forms, the optimality conditions for investment are:

$$\frac{2}{676}(-480k + 2400) - 20k_i = 0, \; i = 1,2$$

$$\frac{1}{676}(-420k + 2100) - 20k_i = 0, \; i = 3,4$$

It follows that

$$k = 0.8477,\ k_1 = k_2 = 0.2948,\ k_3 = k_4 = 0.129$$

Note that $k(3) = 1.1929 > k(2 = 0.8477)$, so that a larger coalition indeed triggers a higher total investment in green capital.

Note also that $Q(2, k(2)) = 7.1439 < P(3, k(3)) = 7.8297$, so that a coalition of size 3 seems to become internally stable. However, this conclusion is not correct because in this case membership is decided before investment and abatement and net benefit for these two stages together satisfies

$$P(3, k(3)) - 10k_1^2 = 6.4755 < Q(2, k(2)) - 10k_4^2 = 6.9775$$

Outsiders to a larger coalition invest less and therefore also have free-rider benefits in the investment stage, so that we have the same old story again.

R&D spillovers foster cooperation

We have shown that green investments are not sufficient to foster cooperation. In this section we will show that the larger coalitions can be achieved if the members of the coalition have lower average investment costs than the outsiders: for example, when the members of the coalition share the costs of R&D[53].

In order to show this we introduce a fixed cost of investment δ. The members of the coalition share this cost or have a lower fixed cost because of a knowledge spillover between them. In this way the optimality conditions, the resulting investments and $P(3, k(3))$ and $Q(2, k(2))$ are the same. If for example $\delta = 1$, then the net benefits of an outsider always decrease by 1, but the net benefits of a member of the coalition with size 3 only decrease by $1/3$. It follows that:

$$P(3, k(3)) - 10k_1^2 - 0.33 = 6.1422 > Q(2, k(2)) - 10k_4^2 - 1 = 5.9775$$

so that the coalition of size 3 is stable.

The conclusion is that just introducing an investment stage is not sufficient to sustain larger coalitions. Some positive externality of cooperation is needed to get

[53] See also Carraro and Siniscalco (1997), and Katsoulacos (1997)

this result. This can also be achieved by introducing a positive externality of cooperation directly into the abatement stage, but we prefer to model investments explicitly.

The question remains how large the internally and externally stable coalition can be, and for which level of δ. In order to investigate this question, we need a full analysis of the model in section 3.

The full model

In the investment stage, the coalition of size m maximizes

$$mP(m,k) - \delta - \frac{1}{2}\gamma k_1{}^2 - ... - \frac{1}{2}\gamma k_m{}^2$$

and the outsiders maximize

$$Q(m,k) - \delta - \frac{1}{2}\gamma k_i{}^2, \quad i = m+1,...,n$$

From the optimality conditions (see appendix A) we can derive total investment in green capital:

$$k = \alpha\beta \frac{(m^4 + n - m) + \alpha(m^2 + n - m)}{\alpha(m^4 + n - m) + \alpha^2(m^2 + n - m) + \gamma(m^2 + n - m + \alpha)^2}$$

where the members of the coalition each invest:

$$k_i = \alpha\beta \frac{\alpha m + m^3}{\alpha(m^4 + n - m) + \alpha^2(m^2 + n - m) + \gamma(m^2 + n - m + \alpha)^2}, \quad i = 1,2,...,m$$

and the outsiders invest:

$$k_i = \alpha\beta \frac{\alpha + 1}{\alpha(m^4 + n - m) + \alpha^2(m^2 + n - m) + \gamma(m^2 + n - m + \alpha)^2}, \quad i = m+1,...,n$$

The expressions for net benefits become:

$$P(m,k) - \frac{\delta}{m} - 0.5\gamma k_i^{\,2}, \quad i = 1,2,...,m$$

$$Q(m,k) - \delta - 0.5\gamma k_i^{\,2}, \quad i = m+1,...,n$$

At this point the expressions become too difficult to continue analytically. It is easy, however, to programme these equations and to test for internal and external stability numerically. We know from the example in section 4 that for $\delta = 0$ we still have the old grim story of small stable coalitions, but for $\delta > 0$ we may be able to enlarge the size of the stable coalition. Two values of δ are interesting: the minimum value of δ needed to enlarge the coalition with one country, which we call δ_1 hence after, and the minimum value of δ needed to get the full coalition, which we call δ_f. We will analyze numerically how these two values depend on the value of the parameters: the initial level of emissions β, the cost parameters α and γ, and the total number of countries n.

We fix the parameter $\beta = 5$ and equate the cost parameters α and γ so that we can look at the value of δ as a function of the cost parameter $\alpha = \gamma$ and the total number of countries n. First we state, as a benchmark, the precise result for $\delta = 0$.

Proposition 1

For $\delta = 0$ the size of the stable coalition is either 1 or 2. For any n, a value α' exists, such that for $\alpha < \alpha'$ the size of the stable coalition is 1 and for $\alpha > \alpha'$ the size of the stable coalition is 2. The value of α' is increasing in n.

This confirms the standard result that the size of the stable coalition is small. For high values of the cost parameter the size is 2, but even this small coalition breaks down for low values of the cost parameter, and this happens sooner in case the total number of countries is large. Next we introduce a positive δ, representing a positive externality of joint R&D for the coalition, and calculate the minimum value needed to enlarge the coalition with one country. Figure 32 presents the typical result that can be stated as follows.

Proposition 2

For $\delta \geq \delta_1$ the size of the stable coalition is enlarged with at least one country. As a function of the cost parameter *α*, the minimum value δ_1 first increases, then decreases down to zero at $\alpha = \alpha'$, and then jumps up and decreases asymptotically to zero.

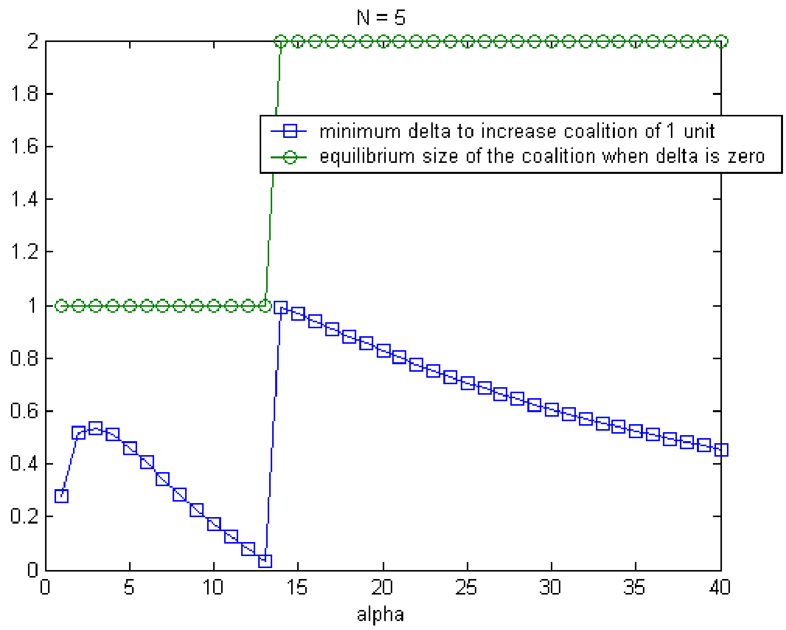


Figure 32 Typical behavior of δ_1

It is clear that $\delta_1 = 0$ at $\alpha = \alpha'$ because at that point, according to Proposition 1, the stable coalition is already enlarged from size 1 to size 2 without introducing any δ. It is also intuitively clear that beyond that point δ_1 decreases because a higher value of the cost parameter *α* makes it easier to enlarge the size of the stable coalition, and the same applies for the decrease just before α'. The initial increase in δ_1 for low values of α is due to the effect of the relative size of δ_1 and α: it can be shown that $\frac{\delta_1}{\alpha}$ is always decreasing. In Proposition 1 it was shown that α' increases in *n*. This implies for the pattern in Proposition 2 that the picture is stretched out to the right: Figure 33 and Figure 34 give examples for larger values of *n*.

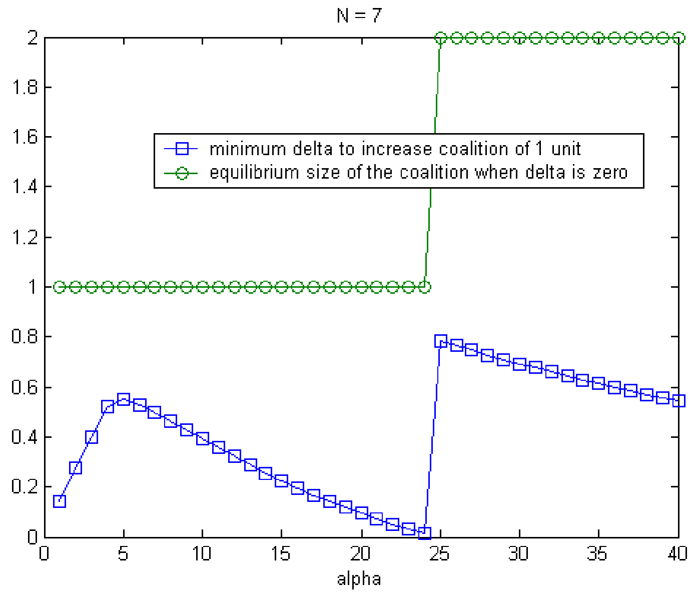


Figure 33

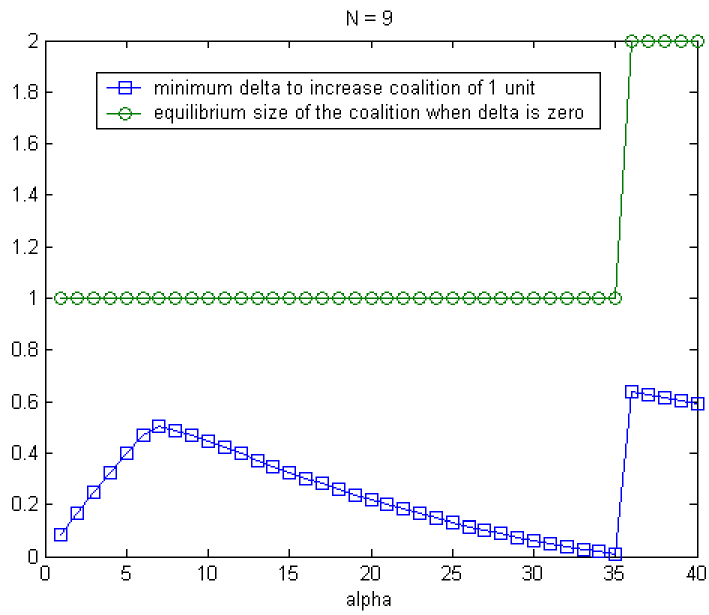


Figure 34

The important conclusion is that some positive externality of cooperation opens up the possibility of a larger stable coalition. In the standard model a higher value of the cost parameter α increases the size of the stable coalition from 1 to 2 but then it stops. This result is very robust for variations in the standard model. However, with the positive externality it is possible to increase the size of the stable coalition further. Moreover, for high values of the cost parameter α only a little bit is needed: for any small $\delta > 0$, a value α'' exists, such for $\alpha > \alpha''$ the size of the stable coalition is 3.

Finally, it is interesting to see if the full coalition can also result as a stable coalition and therefore we define δ_f as the minimum value of δ needed to get the full coalition. Figure 4 shows that δ_f also first increases and then decreases in α, just as the general tendency for δ_1. However, δ_f is not forced to zero at $\alpha = \alpha'$ because the focus is now on the stability of the full coalition and not on the stability of the coalition of size 2. Furthermore, δ_f is everywhere larger than δ_1, as is to be expected of course. Again it can be shown that $\frac{\delta_f}{\alpha}$ is always decreasing, so that the initial increase is due to the effect of the relative size of δ_f and α.

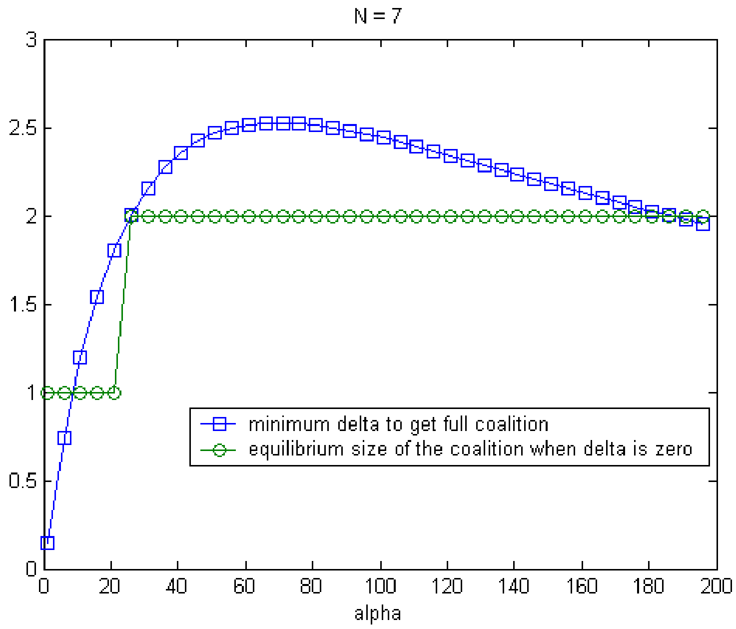


Figure 35

If we fix the cost parameter α and plot δ_f as a function of the total number of countries *n*, Figure 36 results. First note that the benchmark case now shows a stable coalition of size 2 in the beginning, followed by a stable coalition of size 1. The reason is that for a fixed α, we need a small *n* to get a stable coalition of size 2 (compare with figures 1 and 2): in this picture it holds that for any α there exists a value n' such that for $n > n'$ the size of the stable coalition is 1. The pattern of δ_f is interesting. Initially, when the stable coalition has size 2 in the benchmark case, δ_f is increasing in *n*. However, when the coalition of size 2 breaks down in the benchmark case, δ_f becomes decreasing in *n*. It means that for a large total number of countries, only a small positive externality is needed to get the full coalition.

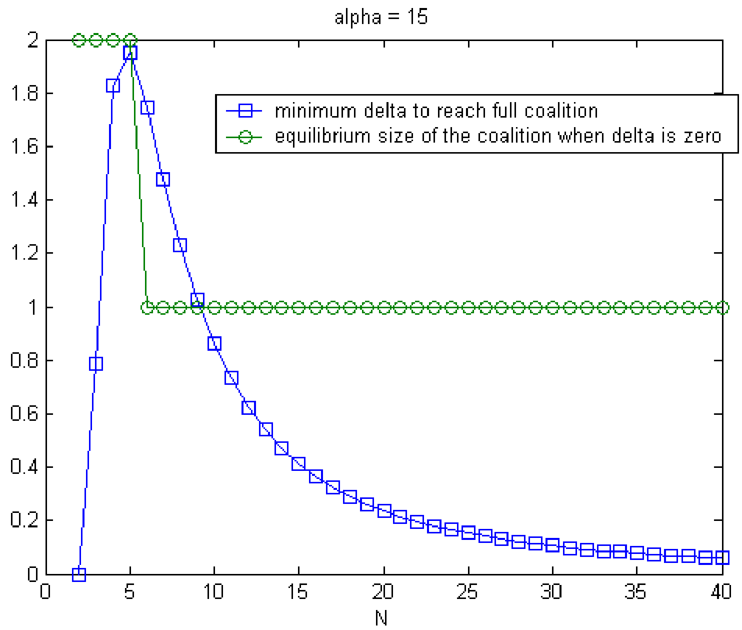


Figure 36

A possible explanation for this observation is that when *n* is large, the relative value of sharing the fixed-cost investment increases, as its cost can be shared among more participants. At the same time, for large *n*, the difference $Q(n-1,k_{n-1})-P(n,k_n)$[54] tends to decrease, and converges asymptotically to zero, thus implying that less and less of the positive externality is needed to achieve full cooperation. This is shown in Figure 37.

[54] With k_n and k_{n-1} we denote here the optimal investments when the size of the coalition is *n* and *n-1* respectively.

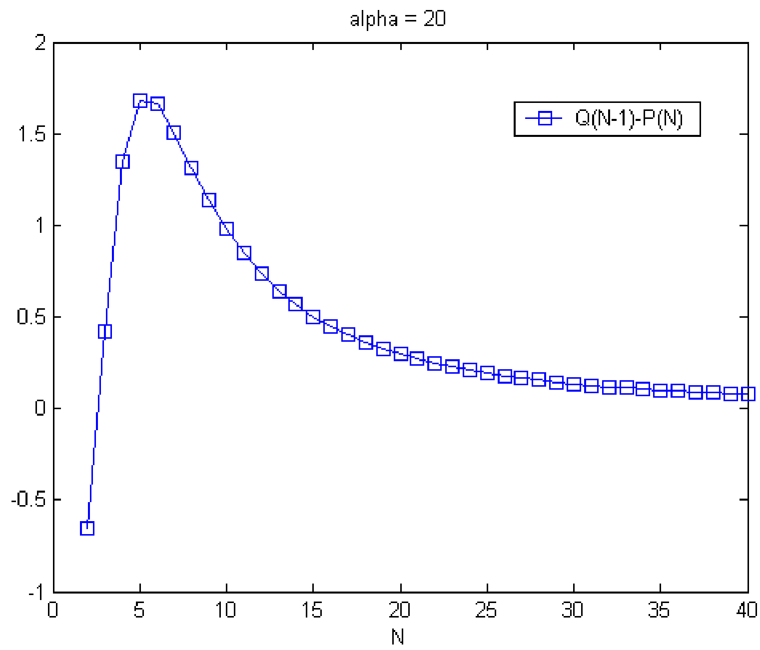


Figure 37

Conclusions

The simulations prove that in a model where the payoff functions are derived by the optimization of the costs and benefits of abatement, the introduction of green investments does not suffice to induce a larger coalition size in the game. To obtain larger coalitions, we need to assume that the countries that choose to cooperate have the opportunity to share some fixed costs of the investment. Such fixed costs could be for example the costs of R&D.

This result seems in line with what other authors claim in the current debate on international agreements on climate change. In particular, our model provides theoretical basis to the argument that probably the best way to reach effective international cooperation is an agreement based both on technology incentives and on abatement targets.

The relative magnitude of the R&D investment that is needed to induce larger coalitions seems in general to be quite small and decreasing both in the number of countries and in the absolute magnitude of the costs of abatement. This happens because the properties of the benchmark model without fixed-costs sharing are such that the incentives to free-ride always decrease in the two parameters α and N, due to the fact that abatement per country is reduced when more countries participate in the game and when the costs of abatement are higher. Because the incentives remain positive, there is a need for a counterbalancing positive externality, but its relative magnitude decreases as the incentives to free-ride decrease in the benchmark model.

Appendices

Appendix A: Optimal investment

We assume that the objective function for a coalition of size m is given by the net benefits from abatement given investments, minus the investment costs which are made up of a fixed-costs part that can be shared by the members, (δ), plus a varying part depending on the size of the investment on part of member countries, $\frac{1}{2}\gamma\sum_{j=1}^{m}k_j^2$:

$$m\left\{\beta\frac{\left(m^2+n-m\right)\beta+\alpha k}{m^2+n-m+\alpha}-\frac{1}{2}\left(\frac{\left(m^2+n-m\right)\beta+\alpha k}{m^2+n-m+\alpha}\right)^2-\frac{1}{2}\alpha\left(m\frac{\beta-k}{m^2+n-m+\alpha}\right)^2\right\}+$$
$$-\delta-\frac{1}{2}\gamma\sum_{j=1}^{m}k_j^2$$

Maximization of this objective function leads to the system of FOCs:

$$\frac{m\beta\alpha}{m^2+n-m+\alpha}-m\alpha\frac{\left(m^2+n-m\right)\beta+\alpha k}{\left(m^2+n-m+\alpha\right)^2}+m^2\alpha\frac{\beta-k}{\left(m^2+n-m+\alpha\right)^2}-\gamma k_i=0,$$
$$i=1,\ldots,m$$

The outsider countries maximize instead their own net benefits from abatement given investments, minus the investment costs, which in this case is borne entirely by one country:

$$\beta\frac{\left(m^2+n-m\right)\beta+\alpha k}{m^2+n-m+\alpha}-\frac{1}{2}\left(\frac{\left(m^2+n-m\right)\beta+\alpha k}{m^2+n-m+\alpha}\right)^2-\frac{1}{2}\alpha\left(\frac{\beta-k}{m^2+n-m+\alpha}\right)^2+$$
$$-\delta-\frac{1}{2}\gamma k_i^2,\quad i=m+1,\ldots,n$$

leading to the system of FOCs:

$$\frac{\beta\alpha}{m^2+n-m+\alpha}-\alpha\frac{\left(m^2+n-m\right)\beta+\alpha k}{\left(m^2+n-m+\alpha\right)^2}+\alpha\frac{\beta-k}{\left(m^2+n-m+\alpha\right)^2}-\gamma k_i=0,$$
$$i=m+1,\ldots,n$$

Adding up all the FOCs for insiders and outsiders we get one equation in *k*:

$$m\left[\frac{m\beta\alpha}{m^2+n-m+\alpha}-m\alpha\frac{\left(m^2+n-m\right)\beta+\alpha k}{\left(m^2+n-m+\alpha\right)^2}+\alpha m^2\frac{\beta-k}{\left(m^2+n-m+\alpha\right)^2}\right]+$$
$$+\left(n-m\right)\left[\frac{\beta\alpha}{m^2+n-m+\alpha}-\alpha\frac{\left(m^2+n-m\right)\beta+\alpha k}{\left(m^2+n-m+\alpha\right)^2}+\alpha\frac{\beta-k}{\left(m^2+n-m+\alpha\right)^2}\right]-\gamma k=0$$

that is:

$$k=\alpha\beta\frac{\left(m^4+n-m\right)+\alpha\left(m^2+n-m\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2}.$$

Substituting in the original system, we can reduce it to a system of two equations in two variables:

$$\begin{cases}
\dfrac{m\beta\alpha}{m^2+n-m+\alpha}-m\alpha\dfrac{\left(m^2+n-m\right)\beta+\alpha^2\beta\frac{\left(m^4+n-m\right)+\alpha\left(m^2+n-m\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2}}{\left(m^2+n-m+\alpha\right)^2}+ \\
\qquad +m^2\alpha\dfrac{\beta-\alpha\beta\frac{\left(m^4+n-m\right)+\alpha\left(m^2+n-m\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2}}{\left(m^2+n-m+\alpha\right)^2}-\gamma k_I=0 \\
\dfrac{\beta\alpha}{m^2+n-m+\alpha}-\alpha\dfrac{\left(m^2+n-m\right)\beta+\alpha^2\beta\frac{\left(m^4+n-m\right)+\alpha\left(m^2+n-m\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2}}{\left(m^2+n-m+\alpha\right)^2}+ \\
\qquad +\alpha\dfrac{\beta-\alpha\beta\frac{\left(m^4+n-m\right)+\alpha\left(m^2+n-m\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2}}{\left(m^2+n-m+\alpha\right)^2}-\gamma k_O=0
\end{cases}$$

with solution:

$$\begin{cases} k_I = \alpha\beta \dfrac{m\alpha + m^3}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ k_O = \alpha\beta \dfrac{1 + \alpha}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \end{cases}$$

It is easy to check that the full-coalition and the Nash-equilibrium solutions are special cases of the PANE solutions and can be derived directly form the PANE solutions.

Appendix B: deriving the payoff functions

From the solution of the first order conditions we get the following system of expressions:

$$\begin{cases} k_I = \alpha\beta \dfrac{m\alpha + m^3}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ k_O = \alpha\beta \dfrac{1 + \alpha}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ k = \alpha\beta \dfrac{\left(m^4 + n - m\right) + \alpha\left(m^2 + n - m\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a_I = m \dfrac{\beta - k}{m^2 + n - m + \alpha} + k_I \\ a_O = \dfrac{\beta - k}{m^2 + n - m + \alpha} + k_O \\ a = \dfrac{\left(m^2 + n - m\right)\beta + \alpha k}{m^2 + n - m + \alpha} \end{cases}$$

that can be rewritten as:

$$\begin{cases} k_I = \alpha\beta \dfrac{m\alpha + m^3}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ k_O = \alpha\beta \dfrac{1 + \alpha}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ k = \alpha\beta \dfrac{\left(m^4 + n - m\right) + \alpha\left(m^2 + n - m\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a_I = \beta \dfrac{\gamma m\left(m^2 + n - m\right) + \alpha m\left(\gamma + \alpha + m^2\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a_O = \beta \dfrac{\gamma\left(m^2 + n - m\right) + \alpha\left(1 + \alpha + \gamma\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a = \beta \dfrac{\alpha\left(m^4 + n - m\right) + \left(m^2 + n - m\right)\left[\gamma\left(m^2 + n - m\right) + \alpha\left(\gamma + \alpha\right)\right]}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \end{cases}$$

We can then substitute these results into the expressions for the payoff function for insiders and for outsiders:

$$\text{I:} \quad \begin{cases} k_I = \alpha\beta \dfrac{m\alpha + m^3}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a = \beta \dfrac{\alpha\left(m^4 + n - m\right) + \left(m^2 + n - m\right)\left(m^2\gamma + n\gamma - m\gamma + \alpha\gamma + \alpha^2\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ a_I = \beta \dfrac{\gamma m\left(m^2 + n - m\right) + \alpha m\left(\alpha + \gamma + m^2\right)}{\alpha\left(m^4 + n - m\right) + \alpha^2\left(m^2 + n - m\right) + \gamma\left(m^2 + n - m + \alpha\right)^2} \\ P_m = \beta a - \dfrac{1}{2}a^2 - \dfrac{1}{2}\alpha\left(a_I - k_I\right)^2 - \dfrac{\delta}{m} - \dfrac{1}{2}\gamma k_I^2 \end{cases}$$

$$
\text{O:}\begin{cases}
k_O = \alpha\beta \dfrac{1+\alpha}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2} \\
a = \beta \dfrac{\alpha\left(m^4+n-m\right)+\left(m^2+n-m\right)\left(m^2\gamma+n\gamma-m\gamma+\alpha\gamma+\alpha^2\right)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2} \\
a_O = \beta \dfrac{\gamma\left(m^2+n-m\right)+\alpha(\alpha+\gamma+1)}{\alpha\left(m^4+n-m\right)+\alpha^2\left(m^2+n-m\right)+\gamma\left(m^2+n-m+\alpha\right)^2} \\
Q_m = \beta a - \dfrac{1}{2}a^2 - \dfrac{1}{2}\alpha\left(a_O-k_O\right)^2 - \delta - \dfrac{1}{2}\gamma k_O^2
\end{cases}
$$

Conclusions

It has been our choice in this work to investigate from an economic perspective the question of the optimal extent of climate change prevention. We have therefore chosen an abstract approach to analyze the problem of giving proper "rational" foundation to the choice of abatement targets, taking into account relevant cognitive and cooperative issues that characterize the climate change problem.

The definition of "optimal" abatement targets involves two conceptually different kinds of economic issues: determining the value of prevention on one side; and implementing international environmental agreements on the other hand. These two issues are deeply correlated: in the case of climate change, the perceived value of prevention for one policy actor depends among other things also on the degree of coordination expected at the international level; similarly, the attractiveness of cooperation depends crucially on the perceived costs and benefits from prevention.

Methodologically, however, determining the value of prevention involves the use of very different instruments and concepts than the discussion on international cooperation. For this reason the content of the dissertation can be divided into two parts. Part one is made up by chapters 1 to 3 and it is dedicated to one-agent problems under uncertainty. Part two to is made up by chapters 4 and 5 and concentrates on multi-agents models useful for analyzing the issue of international cooperation.

In the first chapter, we have described some features of the climate change problem that we consider relevant from a cognitive point of view. In particular, we introduced thresholds in the utility function and assumed that scientific knowledge about relevant aspects of the problem was incomplete. We have then given an interpretation of the precautionary principle as a special decision criterion, described by means of rank-dependent utility theory with convex weights. This mathematical representation of the preferences of agents concerning risky outcomes has the property of reproducing what we call a "prudent" attitude, that is, an attitude where more attention is paid to worse chances rather than better ones. The (meta-) choice of implementing such a criterion *ex-ante* has consequences on the level of optimal prevention, and in this respect results are not unequivocal, since in some cases imposing "prudent" behaviour leads to higher levels of pollution. The reason for this result is that given some parameter specifications it is very likely to cross threshold levels of pollution already for low consumption; in these cases, if the assessed impact of climate change is not too high it is possible that the most prudent decision is indeed to compensate the loss of environmental utility with more consumption. This is in contrast with many other approaches that tend to interpret the precautionary principle straight as a request for more prevention: our results imply that a conservative use of resources is not necessarily optimal *when applying the precautionary principle ex-ante.* However, it is also clear from our simulations that for most parametric combinations, a "prudent attitude" determines a lower level of emissions than the benchmark expected utility model, and this is always the case when scenarios differ only in the assessed impact of crossing the threshold.

Normatively, these results stress one feature of convex-weighted rank-dependent utility: since more importance is given to the worse outcomes, a big issue becomes how the worst scenario is designed. Making the precautionary principle operational translates then in a problem of identifying the appropriate state space, as suggested also by Henry and Henry (2002). This stresses the major importance of geophysical parameters, such as l (expected damage from crossing the threshold) and π (describing the location of the threshold), and suggests that modelling issues (such as the shape of the utility function) are relatively less important.

Our results also show that agents maximizing convex-weighted rank-dependent utility more often choose lower levels of emissions than inverse-S-shaped rank-dependent utility maximizing agents. This is an important observation if we consider that actual decision makers show behaviour of the latter type in most experimental studies on individual choice under uncertainty. If we believe that the precautionary principle should be put in place, implementing rank-dependent utility with convex-weights, and if we believe that in real life most people behave as inverse-S-shaped rank-dependent utility maximizing agents, then we can conclude that most likely we observe too low levels of prevention in reality.

We have thus proceeded in chapter two and three to, respectively, build a testable model, and test the behaviour of real agents. To this purpose, we have included in these tests assumptions that reproduce two salient features of the climate issue, namely the presence of thresholds in the outcomes and uncertainty regarding the location of the thresholds. We have then tested four different theories: expected utility, expected value, rank-dependent utility with convex weights, and rank-dependent utility with inverse-S shaped weights.

The model we have used is based on a simple model of harvesting choice without labour costs. The link to climate change can be seen if we interpret the atmosphere as a pollution sink with a given (renewable) capacity: “harvesting” is then the act of using some of this capacity. Thresholds are present in the outcome function because if harvesting is such that the remaining stock of the resource is below a critical level, the resource will not be productive in the future.

In chapter two, we build up models to analyze the choice of the agent when we assume that the agent is risk-neutral, risk-adverse, or when we assume that the agent wishes to avoid bad outcomes. In all these situations, if the optimal harvesting is not a corner solution, the models predict the same qualitative behavior when the range and the mean of the distribution of the unknown parameter change: if the range of the distribution increases, meaning more uncertainty, then it is optimal to harvest (= pollute) more; if the mean of the distribution increases, meaning that it is easier to cross the threshold, then it is optimal to harvest less. However, often the theories predict corner solutions: harvest all (= deplete the atmospheric regeneration capacity) or eliminate all risks (= use less of the resource than the minimum possible threshold value). In these cases usually no reaction is expected when a slight change in the range and mean of the distribution occurs, and very sharp reactions are observed when the range or the mean of the distribution change more substantially. If we believe that people behave in real life like these theories predict, then this conclusions mean that we can expect extreme reactions of people when facing outcome functions with thresholds. We also can expect these reactions to show little sensitivity to nuanced changes and high sensitivity to substantial changes in the perceived outcomes.

In chapter three we actually have tested each of the models of extraction behavior in the presence of a stochastic extinction threshold that were presented in chapter two, plus one, namely rank-dependent utility with inverse-S shaped probability weighting. Using Selten's (1991) measure of predictive success, we have found that rank-dependent utility with convex weights (RDUCW), which is the most "prudent" of the models suggested, provides the best fit for our observations. This holds even when we allow for heterogeneity of the parameters of the model across individuals. Hence, our experiment shows that subjects facing extraction decisions in a setting with stochastic extinction threshold are best modelled as a population of rank-dependent utility maximizers with convex probability weighting functions and heterogeneous weighting parameters.

The result of our experiment is different from what observed in earlier experiments designed to compare different risky choice models: most other papers conclude that the inverse S-shaped probability weighting function provides the best overall fit. A way to explain this difference is found noticing that previous experiments used very specific types of risky choice situations: mostly simple lottery choice tasks. In order to assess behaviour in the face of climate change we choose instead to present our subjects with tasks that reproduce more closely a problem of renewable resource management. In particular, subjects have more choices, and the outcome functions present thresholds. We have introduced thresholds in a payoff matrix, so that our subjects can understand in an intuitive way the role the threshold plays in determining the uncertain outcome of their decisions. The fact that our subjects give reasonable solutions to the tasks, while at the same time act differently from what normally subjects do in other types of experiments suggests that the type of decision task affects behaviour and this is reflected in the theoretical model that best fits observed choices.

From an environmental policy point of view our results are not as good news as it might seem. Although we can interpret the behavior of our subject as "prudent" in the sense that they appear to weigh bad outcomes heavier than good ones, rapid extraction behavior is present. Our experiment, which was specifically designed to test behavior in situations with risk of extinction of a resource, shows that a large majority of decision-makers do take the risk of extinction into account, but that does not always lead to extracting less of the resource.

In this first part we have shown that optimal policy depends on risk-preferences, on the perceived state-space (the set of all possible events), and on the structure of the decision task. These observations all concerned one-agent decision tasks, that is, tasks where only one individual or institution is responsible for choice. The issue of prevention becomes even more complex if we consider that climate change is a global pollution problem, and thus several governments have to coordinate their action in order to successfully reduce emissions of greenhouse gases and realize prevention goals. In the second part of the dissertation, including chapters four and five, we have therefore focussed on this kind of issues, concerning international cooperation, and for reasons of tractability have had to leave aside uncertainty and thresholds. We have kept these issues in the back of our mind, though, and this has led us to make some considerations of a methodological nature. First of all, a high level of uncertainty means that different countries may have a different perception of the very structure of the game: we have argued that this might explain why Europe and USA follow different strategies, without implying either position to be necessarily "irrational". Secondly, we have pointed out that the level of uncertainty could affect the cooperation game in such a way that a cooperative approach to coalition formation becomes impossible. When a country withdraws from a coalition, the rest of the members have no interest in breaking apart and implementing a trigger strategy leading to complete lack of cooperation, as this would leave the chance of catastrophic outcomes open. The possibility of committing to a trigger strategy is the founding element for the (γ-core) cooperative approach to coalition formation, and therefore given the lack of such possibility, this approach is not very appropriate in the framework of climate change. This is very bad news, as we have argued in chapter four, because it implies that typically only a very small coalition of two or three countries forms in the end. We have thus looked for mechanisms that can lead to enlargement of the coalition in a non-cooperative setting.

The first model we have looked at is one that introduces the possibility of investing in green-energy plants. If a coalition forms, and if the countries in the coalition are allowed to share some of the costs of green investments, this can even lead to full cooperation. The model in chapter four is very simple and based on somehow ad-hoc hypotheses on the shape of the payoff functions for the members and outsiders of a given coalition. This simple representation, however, shows that investments in green technology and the participation in international environmental agreements are strategically interconnected in a positive way. The intuition for this is that investments in green technologies reduce the incentives to free ride and induce larger participation rates in the agreement. Since in our assumptions higher participation rates require more abatement effort, it then becomes more convenient to invest in green technologies. This leads to a virtuous circle where technological change and cooperation enhance each other.

As the success and extent of such a positive correlation of events depends on the parameters that define the efficiency of the green technology, it can be concluded that, under our assumptions, knowledge is the key to solve international negative externalities. From a policy perspective this implies that research in the field of green technologies should be encouraged and facilitated, as its value lies not only in the direct effects on green technology but also incorporates the indirect effect on the cooperative attitude of countries. The assumptions that lead to our results in this model, however, are not derived from any optimization process. This makes the intuitive process clearer, but might cut out important relations among the variables of the model. In chapter five we therefore turn to analyzing a model in a more standard optimizing setting, and find the conditions under which green investments can foster cooperation.

The model in chapter five is based on the maximization of net benefits of abatement, and the payoff functions are derived as a result of the optimal choice of abatement levels. We have run simulations and have observed that in this kind of model allowing for green investments is not sufficient to induce a larger coalition size in the game. More positive results have been obtained though, once we have assumed that the countries that choose to cooperate also have the opportunity to share some fixed costs of the investment. Such fixed costs could be for example interpreted as the costs of R&D. With this respect, our model provides theoretical basis to the idea (until now only present in the empirical literature) that probably the best way to reach effective international cooperation concerning climate change prevention is an agreement based both on technology incentives and on abatement targets.

The relative magnitude of the R&D investment that is needed to induce larger coalitions seems in general to be quite small and it is decreasing both in the number of countries and in the absolute magnitude of the costs of abatement. This happens because abatement per country is reduced when more countries participate in the game and when the costs of abatement are higher. This implies that as the costs of abatement are higher, or the number of countries increases, then the incentives to free ride decrease, always remaining positive but tending to zero. Because the incentives remain positive, there is always a need for a counterbalancing positive externality, but its relative magnitude decreases as the incentives to free-ride decrease in the benchmark model, meaning that less and less of the fixed costs need to be shared in order to foster cooperation. From a policy perspective this suggests that an agreement based on abatement targets and including a sufficient number of countries can be reached if the participating countries are allowed to share the costs of research in green technology while the non-participating countries are not.

References

Aalbers R. (1999), *On the Implications of Thresholds for Economic Science and Environmental Policy*, CentER dissertation, n. 51, CentER for Economic Research, Tilburg: Tilburg University.

Abdellaoui, M. (1998), Parameter-Free Eliciting of Utilities and Probability Weighting Functions, mimeo, GRID, ENS Cachan.

Armantier O. and N. Treich (2004), Social willingness to pay, mortality risks, and contingent valuation, *The Journal of Risk and Uncertainty*, 29, 1, pp. 7-19.

Bargiacchi R., 2003. Climate change scenarios and the precautionary principle, *Risk and Uncertainty in Environmental and Natural Resource Economics,* J. Wesseler, H.P. Weikard, and R. Weaver (eds.), Cheltenham, UK: Edward Elgar, pp. 113-130.

Barrett S. (1994), Self-enforcing international environmental agreements, *Oxford Economic Papers*, 46, pp. 878-894.

Bauer A. (1992), International cooperation over environmental goods. De Münchener Wirtschaftswissenschaftlichen Beiträge, Volkswirtshaftliche Fakultät Ludwig-Maximilians-Universität München.

Bouglet T., T. Lanzi and J-C. Vergnaud (2002), The Precautionary Principle: an announcement of circumstance? *Proceedings of the conference on Risk and Uncertainty in Environmental and Resource Economics*, E.C. van Ierland, H.P. Weikard and J. Wesseler (eds.), Wageningen: Environmental Economics and Natural Resources Group of Wageningen University.

Buchner B., and C. Carraro (2004), Economics and Environmental Effectiveness of a Technology-based Climate Protocol, Nota di lavoro 61.2004, Venice: Fondazione Eni Enrico Mattei.

Camerer, C.F. (1995), Individual Decision Making, *Handbook of Experimental Economics*, J. Kagel and A.E. Roth (eds.), Princeton: Princeton University Press.

Carpenter S.R., D. Ludwig and W.A. Brock (1999), Management of eutrophication for lakes subject to potentially irreversible change, *Ecological Applications,* 9, pp. 751-771.

Carraro, C. (ed.) (2000), Efficiency and Equity of Climate Change Policy, Dordrecht: Kluwer Academic Publishers.

Carraro C. and D. Siniscalco (1993), Strategies for the international protection of the environment*, Journal of Public Economics*, 52, pp. 309-328.

Carraro, C. and D. Siniscalco (1997), R&D cooperation and the stability of international environmental cooperation, *International Environmental Agreements: Strategic Policy Issues*, C. Carraro (ed.), Cheltenham: Edward Elgar.

Chander, P. and H. Tulkens (1995), A core-theoretic solution for the design of cooperative agreements on transfrontier pollution, *International Tax and Public Finance*, 2, pp. 279-293.

Chander P. and H. Tulkens (1997), The core of an economy with multilateral environmental externalities, *International Journal of Game Theory*, 26, pp. 379-401.

Chevé M. and R. Congar (2002), Optimal pollution control under imprecise environmental risk and irreversibility, *Risk, Decision and Policy,* 5, pp. 151-164.

Chevé M. and R. Congar (2002), Managing environmental risks under scientific uncertainty and controversy*, Proceedings of the conference on Risk and Uncertainty in Environmental and Resource Economics*, E.C. van Ierland, H.P. Weikard and J. Wesseler (eds.), Wageningen: Environmental Economics and Natural Resources Group of Wageningen University.

Chwe, M. (1994), Farsighted coalitional stability, *Journal of Economic Theory*, 63, pp. 299-325.

De Zeeuw, A.J. (2005), Dynamic Effects on the Stability of International Agreements, Nota di Lavoro 41.2005, Venice: Fondazione Eni Enrico Mattei.

Diecidue, E. and P.P. Wakker (2001), On the Intuition of Rank-Dependent Expected Utility, *Journal of Risk and Uncertainty*, 23, pp. 281-298.

Donkers B., B. Melenberg and A. Van Soest (2001), Estimating Risk Attitudes using Lotteries: A Large Sample Approach, *The Journal of Risk and Uncertainty*, 22, 2, pp. 165-195.

Ellsberg D. (1961), Risk, ambiguity, and the Savage axioms, *Quarterly Journal of Economics*, 75 [4], pp. 643-669.

Endres A. and C. Ohl (2002), Introducing 'cooperative push': How inefficient environmental policy (sometimes!) protects the global commons better, *Public Choice*, 111, pp. 285-302.

Finus M. (2003), Stability and design of international environmental agreements: the case of transboundary pollution, H. Folmer and T. Tietenberg (eds.), *The International Yearbook of Environmental and Resource Economics 2003/2004*, Cheltenham, UK: Edward Elgar, pp. 82-158

Finus M. and B. Rundshagen (1998), Renegotiation-Proof Equilibria in a Global Emission Game When Players Are Impatient, *Environmental and Resource Economics*, 12, pp. 275-306.

Frankhauser S. and R.S.J. Tol (2005), On climate change and economic growth, *Resource and Energy Economics*, 27, pp. 1-17.

Gallup, J.L., J.D. Sachs and A. Mellinger (1999), Geography and Economic Development, CID Working Paper 1, Harvard Center for International Development, Cambridge.

Ghirardato P. (2001), Coping with ignorance: unforeseen contingencies and non-additive uncertainty, *Economic Theory,* 17, pp. 247-276.

Gollier C., B. Jullien and N. Treich (2000), Scientific progress and irreversibility: an economic interpretation of the "Precautionary Principle", *Journal of Public Economics,* 75, pp. 229-253.

Gonzales R. and G. Wu (1999), On the Shape of the Probability Weighting Function, *Cognitive Psychology*, 38, pp. 129-166.

Heal G. and B. Kriström (2002), Uncertainty and Climate Change, *Environmental and Resource Economics,* 22, pp. 3-39.

Heal G. and Y. Lin (1997), The Value of Avoiding Climate Change, Papers 97-10, Columbia - Graduate School of Business.

Henry C. and M. Henry (2002), Formalization and applications of the precautionary principle, *Cahier du Laboratoire d'Econometrie* 2002-008, Paris: Ecole Polytechnique.

Hey, J. D., T. Neugebauer and A. Sadrieh (2005): An Experimental Analysis of Optimal Renewable Resource Management: The Fishery; mimeo, Universities of York, Bari, Hannover, and Magdeburg.

Hoel, M. (1992), International environmental conventions: the case of uniform reductions of emissions, *Environmental & Resource Economics*, 2, pp. 141-159.

Horowitz J.K. (2001), The income-temperature relationship in a cross-section of countries and its implications for global warming, U. of Maryland Working Paper 01-02.

IPCC (2001a), *Climate Change 2001: The Scientific Basis. Contribution of Working Group I To The Third Assessment Report of The Intergovernmental Panel on Climate Change*, New York: Cambridge University Press.

IPCC (2001b), *Climate Change 2001: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, New York: Cambridge University Press.

Katsoulacos, Y. (1997), R&D spillovers, R&D cooperation, innovation and international environmental agreements, *International Environmental Agreements: Strategic Policy Issues*, C. Carraro (ed.), Cheltenham, UK: Edward Elgar.

Lattimore, P.K., J.R. Baker and A.D. Witte (1992), The Influence of Probability on Risky Choice: A Parametric Examination, *Journal of Economic Behavior and Organization*, 17, pp. 377-400.

Machina M. (1989), Dynamic consistency and non-expected utility models of choice under uncertainty, *Journal of Economic Literature,* 27, pp. 1622-1668.

MacCrimmon K. & S. Larsson, 1979. Utility Theory: Axioms versus 'Paradoxes', *Expected Utility and the Allais Paradox,* Maurice Allais & Ole Hagen (eds.), D. Reidel Publishing Company, pp. 333-409.

Mas-Colell A., M.D. Whinston and J.R. Green (1995), *Microeconomic Theory*, New York: Oxford University Press.

Moxnes, E. (1998), Not Only the Tragedy of the Commons: Misperceptions of Bioeconomics, *Management Science*, 44, pp. 1234-1248.

Nordhaus W.D. and D. Popp (1997), What is the value of scientific knowledge? An application to global warming using the PRICE model, *The Energy Journal*, 18, pp. 1-45.

Selten, R. (1991), Properties of a Measure of Predictive Success, *Mathematical Social Sciences*, 21, pp. 153-167.

Sterman, J. D. (1989), Modelling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment, *Management Science*, 35 (3), pp. 321-339.

Starmer, C. (2000): Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk, *Journal of Economic Literature*, 38 (2), pp. 332-382.

Schmidt, U. and H. Zank (2002), Risk Aversion in Cumulative Prospect Theory, mimeo, Universities of Hannover and Manchester.

Starmer C. (2000), Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk, *Journal of Economic Literature,* 38, pp. 332-382.

Tversky, A. and D. Kahneman (1992), Advances in Prospect Theory: Cumulative Representation of Uncertainty, *Journal of Risk and Uncertainty*, 5, pp. 297-323.

Tversky A. and P. Wakker (1995), Risk attitudes and decision weights, *Econometrica*, 63, pp. 1255-1280.

Ulph A. and D. Ulph (1997), Global warming, irreversibility and learning, *The Economic Journal,* 107, pp. 636-650.

UN (1993), *Agenda 21: programme of action for sustainable development. Rio declaration on environment and development. Statement of forest principles: the final text of agreements negotiated by governments at the United Nations Conference on Environment and Development (UNCED)*, *3-14 June 1992, Rio de Janeiro, Brazil*, New York: United Nations Department of Public Information.

Van Kooten G. C. and E. H. Bulte (2000), *The Economics of Nature – Managing Biological Assets*, Oxford: Blackwell Publishers.

Vercelli A. (1995), From Soft Uncertainty to Hard Environmental Uncertainty, *Economie Appliquee: archives de l'Institut de Science Economique Appliquee*, 48, pp. 251-270.

Wakker P. (1989), Transforming probabilities without violating stochastic dominance, *Mathematical psychology in progress*, E.E. Roskam (ed.), Berlin: Springer.

Samenvatting

Dit proefschrift behandelt de optimale mate van preventie van klimaatverandering vanuit economisch perspectief. Er is gekozen voor een abstracte benadering om een rationele verklaring voor de keuze van emissie reductiedoelstellingen te geven. Hierbij wordt rekening gehouden met relevante cognitieve en coöperatieve problemen die karakteristiek zijn voor het probleem van klimaatverandering.

De definitie van optimale emissie reductiedoelstellingen raakt aan twee conceptueel verschillende economische onderwerpen: aan de ene kant het bepalen van de waarde van preventie en aan de andere kant het implementeren van internationale milieuverdragen.

Deze twee onderwerpen hangen sterk met elkaar samen: in het geval van klimaatverandering is de verwachte waarde van preventie voor één beleidsactor onder meer afhankelijk van de verwachte mate van coördinatie op internationaal niveau; tegelijkertijd is de aantrekkingskracht van samenwerking uitermate afhankelijk van de verwachte kosten en baten van preventie.

In methodologisch opzicht vraagt het bepalen van de waarde van preventie het gebruik van geheel andere instrumenten en concepten dan de discussie over internationale samenwerking. De inhoud van deze dissertatie is daarom in tweeën te delen. Het eerste deel bestaat uit de hoofdstukken 1 tot en met 3 en behandelt problemen bij onzekerheid in modellen met één agent. Deel twee bestaat uit hoofdstuk 4 en 5. Dit deel concentreert zich op modellen met meerdere agenten om het onderwerp van internationale samenwerking te analyseren.

In het eerste hoofstuk worden enkele vanuit congnitief oogpunt relevante kenmerken beschreven van het probleem van klimaatverandering beschreven. In het bijzonder worden drempels (thresholds) in de nutsfunctie geïntroduceerd en wordt aangenomen dat de wetenschappelijke kennis van relevante aspecten van het probleem niet volledig is. Vervolgens wordt een interpretatie gegeven van het voorzorgsprincipe als een bijzonder besliscriterium, beschreven door middel van de rang-afhankelijke nutstheorie (rank-dependent utility theory) met convexe waarschijnlijkheidsgewichten. Deze wiskundige weergave van de voorkeuren van agenten met betrekking tot risicovolle uitkomsten heeft de eigenschap om een behoedzame houding te reproduceren. Anders gezegd, een houding van agenten waarbij meer aandacht uitgaat naar slechtere uitkomsten dan naar de betere. De (meta) keuze om een criterium ex-ante te implementeren heeft gevolgen voor het niveau van optimale preventie. In dit opzicht zijn de resultaten van dit hoofdstuk niet ondubbelzinnig, aangezien in sommige gevallen behoedzaam gedrag tot een hogere mate van vervuiling leidt. De reden voor dit resultaat is dat voor sommige specificaties van parameters de drempelniveaus van vervuiling gemakkelijk overschreden kunnen worden. In deze gevallen is het mogelijk dat het meest behoedzame besluit inderdaad is om het verlies aan nut uit milieu te compenseren met een hogere consumptie. In tegenstelling tot de vele andere benaderingen die ertoe neigen om het voorzorgsprincipe te interpreteren als een rechtstreekse vraag naar meer preventie, zeggen de resultaten in dit onderzoek dat een spaarzaam gebruik van bronnen niet noodzakelijk de meest optimale is wanneer het voorzorgsprincipe ex-ante toegepast wordt. Daarentegen is uit de tests ook duidelijk geworden dat bij de meeste parameterwaarden de behoedzame houding een lager niveau van uitstoot geeft dan het standaard model van verwacht nut. Dit is altijd het geval wanneer de scenario's alleen van elkaar verschillen in de vastgestelde gevolgen van het overschrijden van een drempel.

Normatief gezien, benadrukken deze resultaten één kenmerk van rang-afhankelijke nutstheorie met convexe waarschijnlijkheidsgewichten: aangezien meer waarde wordt gehecht aan de slechtste uitkomsten wordt de vraag hoe het ontwerp van het 'worst case scenario' er uitziet van belang. Wanneer het voorzorgsprincipe vervolgens in werking gesteld wordt, vertaalt dit zich in het probleem van de identificatie van de juiste toestandsruimte, zoals dit al werd voorgesteld door Henry & Henry (2002). Dit benadrukt het enorme belang van geofysische parameters, zoals de verwachte schade bij het overschrijden van een drempel en de beschrijving van de locatie van de drempel, en laat zien dat het vraagstuk van modellen (zoals de vorm van de nutsfunctie) relatief minder belangrijk is.

De resultaten laten ook zien dat agenten die rang-afhankelijk nut met convexe gewichten maximaliseren vaker voor lagere niveaus van uitstoot kiezen dan de agenten die rang-afhankelijk nut met omgekeerde-S gewichten maximaliseren. Dit is een belangrijke observatie indien verondersteld wordt dat de eigenlijke besluitvormers zich in de meeste experimentele studies gedragen volgens het laatste type. Als aangenomen wordt dat het voorzorgsprincipe gebruikt zou moeten worden, door het implementeren van rang-afhankelijke nutstheorie met convexe waarschijnlijkheidsgewichten, en als er vanuit gegaan wordt dat in werkelijkheid de meeste mensen rang-afhankelijk nut met omgekeerde-S gewichten maximaliseren, dan worden er hoogstwaarschijnlijk in werkelijkheid te lage preventie niveaus gehanteerd.

In aansluiting hierop wordt in hoofstuk twee en drie een testmodel ontwikkeld om het gedrag van echte agenten te testen. In de test zijn aannamen meegenomen die twee opvallende kenmerken van het klimaatprobleem reproduceren, namelijk de aanwezigheid van drempels in de resultaten, en de onduidelijkheid over de locatie van die drempels. Er zijn vervolgens vier verschillende theorieën getest: verwacht nut, verwachte waarde, rang-afhankelijke nutstheorie met convexe waarschijnlijkheidsgewichten, en rang-afhankelijke nutstheorie met omgekeerde-S waarschijnlijkheidsgewichten.

Het gebruikte model is gebaseerd op een eenvoudig model van een hernieuwbare hulpbron zonder arbeidskosten. Het verband met klimaatverandering kan gezien worden als een interpretatie van de atmosfeer als een stortplaats voor vervuiling met een beperkte (vernieuwbare) capaciteit: de oogst is dan het gebruik van een deel van deze capaciteit. Drempels zijn aanwezig in de oorzaak-gevolg relatie, want als na de oogst de overblijvende voorraad van de bron onder een bepaald kritisch niveau komt, dan zal de bron in de toekomst niet productief zijn.

In hoofdstuk twee worden modellen ontwikkeld om de keuze van een agent te analyseren indien wordt aangenomen dat een bepaalde agent risico-neutraal of risico-avers is, of indien aangenomen wordt dat de agent slechte uitkomsten wil vermijden. In alle gevallen geldt dat als de optimale oogst geen hoekoplossing is, de modellen dan hetzelfde kwalitatieve gedrag voorspellen wanneer de onbekende parameters veranderen: als de onzekerheid hoger is, dan is het beter om meer te vervuilen; als het makkelijker wordt om een drempel te overschrijden, dan is het beter om minder te vervuilen. Daarentegen voorspellen de theorieën vaak extreme keuzes: de uitputting van het herstelvermogen van de atmosfeer of de eliminatie van alle risico's. In deze gevallen wordt gewoonlijk geen reactie verwacht wanneer een kleine verandering in het aantal mogelijke uitkomsten plaatsvindt en zeer duidelijke reacties worden waargenomen wanneer het aantal mogelijke uitkomsten en het gemiddelde van de distributie substantieel veranderen. Als ervan uitgegaan wordt dat mensen zich in werkelijkheid zullen gedragen zoals deze theorieën beweren, dan betekenen deze conclusies dat extreme reacties verwacht kunnen worden als deze mensen geconfronteerd worden met een oorzaak-gevolg relatie met drempels. Er kan ook verwacht worden dat bij kleine veranderingen in deze relatie er weinig reacties zullen plaatsvinden en dat er veel reacties bij substantiële veranderingen plaatsvinden.

In hoofdstuk drie wordt door middel van een experiment ieder model van het gebruik van een hernieuwbare hulpbron uit hoofdstuk twee, plus de rang-afhankelijke nutstheorie met omgekeerde-S gewichten getest. Gebruik makend van Selten's (1991) maatstaf van voorspellend vermogen, is gebleken dat de rang-afhankelijke nutstheorie met convexe gewichten, welke het meest "behoedzame" van de onderzochte modellen is, het beste past bij de bevindingen in dit onderzoek. Dit houdt zelfs stand wanneer individuen heterogeen zijn in de modelparameters. Het experiment laat zien dat proefpersonen het beste gemodelleerd kunnen worden als een populatie van agenten die heterogeen zijn in de waarschijnlijkheidsgewichten en hun rang-afhankelijke nut met convexe gewichtsfuncties maximaliseren.

Het resultaat van dit experiment is anders dan de resultaten uit eerdere experimenten die ook verschillende modellen van keuzen onder risico wilden vergelijken: in het grootste deel van de literatuur wordt geconcludeerd dat de omgekeerde-S gewichtsfunctie het beste past. Een verklaring hiervoor is dat in eerdere experimenten zeer specifieke soorten problemen van keuzen onder risico werden gebruikt, meestal waren dit simpele loterij opdrachten. Om te bestuderen hoe agenten omgaan met de risico's van klimaatverandering is er in hoofdstuk drie voor gekozen om de proefpersonen taken aan te bieden die meer lijken op het probleem van het beheersen van een hernieuwbare hulpbron. De proefpersonen hebben vooral meer keuzemogelijkheden en de oorzaak-gevolg relaties bevatten een drempel. Via een beloningsmatrix beseffen proefpersonen op een intuïtieve manier welke rol de drempel speelt bij het bepalen van de onzekere uitkomst van hun beslissingen. De proefpersonen geven redelijke oplossingen voor de opdrachten, maar tegelijkertijd anders dan normaalgesproken proefpersonen doen in andere soorten experimenten: dit laat zien dat de vorm van de opdracht het gedrag beïnvloedt en dit is terug te zien in het theoretische model dat deze keuzes het beste beschrijft.

Vanuit het standpunt van milieubeleid zijn deze resultaten enigszins teleurstellend. Hoewel het gedrag van een proefpersoon als "behoedzaam" geïnterpreteerd kan worden, wordt te snel geëxtraheerd. Het experiment is specifiek ontwikkeld om gedrag te testen in situaties die het risico van leegvallen van een bron met zich meebrengen, en het laat zien dat een groot deel van de besluitnemers wel rekening houdt met dit risico, maar dat het niet altijd leidt tot een verminderd gebruik van de bron.

In het eerste deel van dit proefschrift wordt aangetoond dat optimaal beleid afhankelijk is van risico-voorkeuren, de verzameling van alle mogelijkheden en de structuur van de opdracht. De waarnemingen richten zich op taken waar alleen een individu of instelling verantwoordelijk is voor de keuze. Het probleem van preventie is nog complexer als bedacht wordt dat klimaatverandering een probleem is van internationale omvang, en regeringen moeten dus samenwerken om er in te slagen het broeikaseffect te verminderen en preventieve doelen te stellen. Het tweede deel van deze dissertatie, hoofdstuk vier en vijf, concentreert zich op internationale samenwerking, en laat onzekerheid en drempels buiten beschouwing. Deze issues blijven op de achtergrond wel aanwezig, en dit leidt tot enige methodologische overwegingen. Ten eerste, een hoog niveau van onzekerheid betekent dat verschillende landen een andere kijk kunnen hebben op de structuur van het spel: in hoofdstuk vier wordt beargumenteerd dat dit een verklaring kan zijn voor de verschillende strategiën van Europa en de VS. Ten tweede wordt aangetoond dat het niveau van onzekerheid effect kan hebben op het samenwerkingsspel zodat een coöperatieve benadering om een coalitie te verkrijgen onmogelijk wordt. Als een land de coalitie verlaat, hebben de andere landen geen interesse om uit elkaar te gaan, omdat dit het risico van catastrofale gevolgen vergroot. De mogelijkheid om de coalitie te breken als straf voor overtreders is de fundamentele aanname van de (g-core) coöperatieve benadering om een coalitie te verkrijgen, en als deze mogelijkheid ontbreekt, dan is de coöperatieve benadering dus niet goed van toepassing. Als gevolg daarvan kunnen alleen heel kleine coalities van twee of drie landen ontstaan. Hoofdstuk vier onderzoekt dan een manier om de coalitie te verbreden in de context van een niet-coöperatieve benadering.

Het model in hoofdstuk vier introduceert de mogelijkheid om te investeren in de productie van groene stroom. Als een coalitie ontstaat, en als de samenwerkende landen een deel van de investeringskosten kunnen delen, dan kan dit leiden tot wereldwijde samenwerking. Het model in hoofdstuk vier is heel simpel en gebaseerd op ad-hoc aannamen omtrent de vorm van de beloningsfuncties voor de deelnemers aan de coalitie en voor de buitenstanders. Deze simpele weergave laat zien dat investeren in groene technologie en internationale samenwerking op een positieve manier aan elkaar gekoppeld zijn. De intuïtie hierachter is dat investeringen in groene technologie de prikkel tot liftersgedrag verminderen en leiden tot bredere samenwerking. Omdat er in dit model van uit gegaan wordt dat bredere samenwerking ook meer preventie inhoudt, worden investeringen in groene technologie nog waardevoller. In dat geval ondersteunen technische ontwikkeling en internationale samenwerking elkaar.

Indien aangenomen wordt dat de koppeling van technologie en samenwerking afhankelijk is van de efficiëntie van de groene technologie, kan kennis de sleutel tot oplossing van internationale negatieve externaliteiten zijn. Vanuit het oogpunt van beleid betekent dit dat onderzoek in het veld van groene technologie moet worden ondersteund, omdat de waarde daarvan niet alleen in de directe effecten op de kosten van groene technologie ligt, maar ook in de indirecte effecten op de houding van landen in het proces van samenwerking. De aannamen die ten grondslag liggen van het model in hoofdstuk vier leiden tot intuitief duidelijke resultaten, maar hebben als nadeel dat belangrijke relaties tussen variabelen van het model misschien onderbelicht worden.

In hoofdstuk vijf wordt de ad-hoc benadering van hoofdstuk vier losgelaten en wordt de relatie tussen groene investerinen en samenwerking met een meer standaard benadering geanalyseerd. Dit laatste model is gebaseerd op de maximalisering van de netto baten van preventie. De beloningsfuncties worden bepaald als gevolg van een optimale keuze van emissie reductiedoelstellingen. Door middel van simulaties wordt geconstateerd dat in dit soort modellen de mogelijkheid om te investeren in groene technologie niet toereikend is om bredere coalities te laten ontstaan. Echter, de samenwerking kan worden verbeterd als wordt aangenomen dat landen in de coalitie ook de mogelijkheid krijgen om vaste investeringskosten te delen. De vaste kosten zijn mogelijk te interpreteren als kosten van onderzoek en ontwikkeling. Op deze wijze geeft dit model theoretische steun aan het idee (tot nu alleen aanwezig in de empirische literatuur) dat de beste manier om internationale samenwerking voor klimaatbeleid te bereiken een verdrag is dat gebaseerd is op zowel prikkels voor technologie als emissie reductiedoelen.