The Strategic Relevance of Adaptation in International Climate Change Policy

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Chapter 1

Introduction

To mitigate or to adapt? Policymakers concerned with climate change face a highly complex risk management problem. The ultimate objective of climate risk management is to avert climate-induced loss of livelihood and economic damage. This objective can be achieved by two major strategies: one is mitigation, aimed at reducing the probability of climate damage; the other is adaptation, aimed at reducing the severity of climate damage. It is recognized that "effective climate policy [...] involves a portfolio of diverse adaptation and mitigation actions" (Klein et al., 2007, p. 747). It is, however, often overlooked that the optimal composition of this portfolio not only depends on immediate costs and benefits, but also on the strategic interdependencies between mitigation and adaptation.

My dissertation seeks to shed light on the strategic relevance of adaptation in an international policy context. The key finding is that the possibility to adapt to climate change aggravates the social dilemma associated with reducing greenhouse gas emissions. The dissertation consists of three single-authored papers. The first paper proposes a game-theoretic model of the climate risk management problem, based on the particular economic characteristics of mitigation and adaptation. The model reveals that the possibility to adapt can cause a negative strategic effect on welfare. The size of this effect depends on the number of countries involved, the relative marginal cost of adaptation, and the severity of climate damage. The second and third paper are empirical works. In two economic computer lab experiments, I collected data to test the validity of the theory and to estimate the size of the strategic effect. The empirical results support the model-based theoretical predictions. All three papers are closely connected; yet every single one is fully self-contained and can be read on its own. This introduction defines the key concepts and provides the technical foundations and economic premises upon which the model is based. It concludes with an overview that shortly summarizes the three papers and relates them to each other.

Risk and risk management are concepts covered by various disciplines; accordingly, numerous definitions refer to the respective context -e.g. economics, finance, engineering, health, ecology- and sometimes collide, which causes "Babylonian Confusion" (Thywissen, 2006). In the context of this work, climate risk is defined as the combination of an extreme weather event -occurring with a certain probability- and a system that is susceptible to damage caused by this impact. The degree to which a system is susceptible to damage depends on the exposure of the system to the impact, its vulnerability, and its resilience.

Extreme weather events have occurred at all ages, as historical and paleoclimatological record establishes. At least since biblical times, people's livelihoods have time and again been severely affected by floods, droughts, storms, heat waves and cold spells. In the recent past, however, the climate is changing. It is generally acknowledged that the main driver of climate change is the high concentration of greenhouse gases in the atmosphere, caused by anthropogenic greenhouse gas emissions (IPCC, 2007b; Rogner et al., 2007), and that continued emissions at or above the current rates will further accelerate climate change (Hegerl et al., 2007). Climate is a stochastic concept; thus, climate phenomena are inherently associated with probabilities and risk. Climate risk, however, does not manifest itself in averages such as the often-quoted global mean temperature. Instead, climate change is potentially hazardous because it incurs changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather events (IPCC, 2012). Since the mid-20th century, these changes have become evident in several observations: heat waves and heavy precipitation events have occurred more often, droughts have become heavier and more frequent, the tropical cyclone activity has increased, and sea level extremes have risen. (IPCC, 2007c; Trenberth et al., 2007; IPCC, 2012). Model-based projections of future climate change indicate that these trends are likely to continue. In particular, even if the changes in temperature and precipitation means are relatively small, climate scientists expect considerable changes in the tails of the climatic distributions, which will most likely lead to more and unprecedented extreme weather events (Meehl et al., 2007; IPCC, 2012, p. 783).

An extreme weather event, e.g. the persisting absence of rain, is not *per se* good or bad, nor does it necessarily trigger risk. "Nature is neutral, and [..] the environmental event becomes hazardous only when it intersects with man" (Burton 1993, p. 232). A system is potentially at risk only if it is *exposed* to the physical impact. Exposure is defined as the "presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected." (IPCC, 2012, p. 5). For example, a storm surge that floods an uninhabited island, no matter how frequently, does not create risk. In a different place, however, the same event hits an urban area and thus leads to risk. Exposure is first and foremost a matter of geographical location; however, it is also influenced by land use and by the built environment, e.g., the distribution of urban areas in low elevation coastal zones

(Martine, 2013).

Exposure is necessary but not sufficient to put a system at risk. The second important constituent of climate risk is the system's *vulnerability*, denoted as the "propensity of exposed elements such as human beings, their livelihoods, and assets to suffer adverse effects when impacted by hazard events" (Cardona et al., 2012, p. 69). The vulnerability of an element depends on its characteristics, which can be immanent features of the element or external conditions. Consider crop farming as an example: on the one hand, vulnerability can refer to the robustness of plants, such as natural pest resistance and drought tolerance. On the other hand, vulnerability depends on external conditions such as pesticide use and irrigation technology. The internal and external conditions that make a system vulnerable are manifold; thus, vulnerability can be viewed as "a result of diverse historical, social, economic, political, cultural, institutional, natural resource, and environmental conditions and processes" (Lavell et al., 2012, p. 32).

The third critical factor for a system's susceptibility to damage is *resilience*, defined as "the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a potentially hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions." (Lavell et al., 2012, p. 34). While vulnerability relates to loss prevention, resilience describes an entity's capability to recover *after* it has experienced a harmful event and suffered a loss. Yet, the determinants of resilience are similar to those of vulnerability. In particular, resilience depends on economic resources, e.g. the amount and type of wealth and income; social resources, e.g. nature and extent of social networks, gender, culture, caste, and class; and institutional characteristics, e.g. stability of the political and legal system, market liquidity, access to insurance, and coverage of social security.

To sum up, climate risk arises if a probabilistic climate impact hits a system that is susceptible to climate-induced damage. According to the two main constituents of risk, there exist two distinct major forms of climate risk management: The first is *mitigation*, aimed at reducing the size and frequency of climate impacts. The second is *adaptation*, aimed at reducing the system's exposure and vulnerability to a given impact, or at enhancing its resilience.[1]

Mitigation is defined in the IPCC Fourth Assessment Report as "an anthropogenic intervention to reduce the anthropogenic forcing of the climate system; it includes strate-

[1] My notion of adaptation is somewhat different from IPCC (2012), who view adaptation as the goal to be advanced and extreme event and disaster risk management as methods for supporting and advancing that goal.

gies to reduce greenhouse gas sources and emissions and enhancing greenhouse gas sinks." (IPCC, 2007a, p. 878). It is widely recognized that mitigation is necessary to prevent future climate change, and that mitigation requires concerted effort on an international level because the global climate system is affected by the aggregate greenhouse gas concentration in the atmosphere, while the point of emission is irrelevant. In economic terms, mitigation is a global public good: a country that reduces its greenhouse gas emissions bears the mitigation costs in private, whereas all countries enjoy the benefits from mitigation. This private-cost, public-benefits constellation raises the problem of free riding and results in a social dilemma. The mitigation dilemma is hard to overcome because there is no 'world authority' that could enforce cooperation. Nevertheless, the world community seeks to reach agreement, as evident in the United Nations Framework Convention on Climate Change (UNFCCC). The objective of the treaty is to "stabilize greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UNFCCC Article 2). Countries have developed various mitigation policies to turn the UNFCCC objectives into action. Examples include policies to reduce the demand for high-carbon goods such as cap-and-trade schemes, requirements, bans and rules; CO2 sequestration with carbon capture and storage; subsidies for the development of low-carbon technologies such as wind energy or solar power; and, though still in its infancy, geoengineering projects such as the release of stratospheric aerosols or ocean iron fertilization.[2]

Adaptation is defined as an "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." (IPCC, 2007a, p. 869). As explicated above, adaptation refers to the various conditions and predispositions of a system affected by a climatic impact; accordingly, adaptation strategies are much more multi-faceted than mitigation strategies. Adaptation strategies can be categorized in several dimensions, e.g. by spatial scale, by sector, by actor, by timing. Some adaptation strategies reduce the exposure of a system, for example migration (Black et al., 2011) and land use planning (Martine, 2013). Other adaptation strategies reduce the vulnerability of a system, for example coastal protection, adjustments of crop and livestock variety and irrigation. Yet other adaptation strategies enhance the resilience of a system, for example disaster management and climate risk insurance. In contrast to mitigation, adaptation typically works on the scale of the impacted system (Klein et al., 2007), i.e., at a local or at most re-

[2] Many researchers treat geoengineering as a third climate change policy measure distinct from mitigation and adaptation (e.g. Barrett, 2008b; Lenton and Vaughan, 2013). This distinction is useful and sensible, particularly in the context of regulation. For the mechanisms described in this work, subsuming geoengineering under mitigation is an acceptable simplification.

gional level. Both costs and benefits of adaptation accrue to those who adapt. Some anticipative, large-scale adaptation measures such as e.g. coastal protection benefit the inhabitants of whole areas; they can thus be regarded as regional public goods. Yet, on a highly aggregated level that treats countries as rational unitary agents, adaptation is a private good, provided that externalities arising between individuals within a country can be internalized by means of taxation. Due to its private good character, there are no immediate external effects from adaptation.

There is broad consent that even the most stringent mitigation effort cannot prevent climate change from happening; neither can adaptation alone cover all expected damages arising from unmitigated climate change (Klein et al., 2007). Hence follows that mitigation and adaptation are not perfect substitutes. On the other hand, there is good reason to consider mitigation and adaptation as imperfect substitutes: "the more mitigation is undertaken, the less adaptation is necessary and vice versa" (Klein et al., 2007, p. 753). Moreover, mitigation and adaptation strategies are costly and thus compete for scarce resources: investing in one policy reduces the budget left for the other. This view can be challenged by the fact that some responses to climate change are 'technical complements' that foster both mitigation and adaptation. Afforestation, for example, has a double effect: trees sequester carbon (mitigation), and their roots prevent soil erosion (adaptation) (Klein et al., 2005). Yet other responses are 'technical substitutes' that put adaptation and mitigation in conflict. A prominent example is air conditioning (Tol, 2005): it alleviates heat stress (adaptation), but also causes greenhouse gas emissions. Most responses are indeed 'technically neutral', i.e., they neither contain an inherent synergy nor an inherent antagonism. Ingham et al. (2005) systematically address the substitutes-vs.-complements debate by stepwise extending a simple basic model. The analysis shows that it is basically appropriate to consider adaptation and mitigation as substitutes. Two exemptions may suggest a complementary relationship of the two. First, adaptation costs may depend on the amount of mitigation. Second, the marginal effectiveness of mitigation may depend on an exogenous increase in risk as described by Kane and Shogren (2000). In due consideration of the debate, I treat mitigation and adaptation as substitutes.

Finally, special attention must be paid to the institutional environment in which international climate policy decisions are made. Following microeconomic tradition, I model countries as rational, self-interested agents who choose from a set of possible alternatives in order to maximize the utility function which represents its preference relations. This implies that countries do not cooperate unless doing so is in their self interest. Moreover, even if countries are willing to cooperate, the absence of strong international institutions and the lack of enforcement capacity make it difficult to establish binding agreements (Gerber and Wichardt, 2009). This being the case, I consider international climate change policy to take place in a non-cooperative, non-institutional environment. It may seem overly cautious or even pessimistic to presume noncooperation as a basic principle; however, the presumption of non-cooperation does not exclude the possibility of cooperation. In particular, the rational choice approach is flexible enough to model preferences and utility functions beyond immediate material interests, e.g. equity preferences and reciprocity.

The first paper "The Strategic Interdependencies of Mitigation and Adaptation" is a theoretical work. It has been presented at the AURÖ Nachwuchsworkshop "Umwelt- und Ressourcenökonomie" of the Verein für Socialpolitik in Bern in Feb 2012 and at the EAERE 19th Annual Conference in Prague in June 2012. Basing on the economic characteristics of mitigation and adaptation, the paper features a novel game-theoretic model that explains how the possibility to adapt to climate change affects a country's position in non-cooperative strategic interactions. The model is set up in general terms with the levels of mitigation and adaptation as individual decision variables. I explicitly model the particular structure of expected utilities under climate risk by applying an endogenous probability distribution over different states of nature. Adaptation alleviates the individual damage suffered if an extreme weather event occurs, whereas aggregate mitigation reduces the probability of an extreme weather event to occur. I find that the additional possibility to invest in adaptation can cause a welfare loss in the Nash equilibrium. Two opposite effects account for this phenomenon: on the one hand, a single country substitutes mitigation by adaptation in order to increase its *individual* benefit (positive direct effect); on the other hand, this same substitution lowers the *aggregate* mitigation level and thereby increases the probability of an extreme weather event for all countries (negative strategic effect). The model predicts that the strategic effect tends to outweigh the direct effect if (i) the number of countries involved is large, (ii) the damage from climate change is large, and (iii) the relative marginal costs of adaptation are high.

The second paper "The Impact of Adaptation Costs and Group Size on Mitigation and Adaptation" has been presented at the PhD Seminar in Economics in Hamburg in July 2012 and at the 3rd Young Scientists Excellence Cluster Conference in Kiel in Oct 2012. The aim of the paper is to empirically test the strategic impact of adaptation on investment decisions regarding mitigation and adaptation and on the resulting expected payoffs. The data were collected in a controlled computerized laboratory experiment conducted in Hamburg in June 2012. The experimental design derives from the theoretical model presented in the first paper. The experiment is set up as a non-cooperative, symmetric, one-shot game with homogeneous players. Six treatments were played in order to independently set three treatment variables: (i) possibility to adapt (yes/no), (ii) unit cost of adaptation (low/high), and (iii) group size (small/large). The experimental results yield qualitative support for the hypotheses derived from the theoretical model: adaptation decreases and mitigation increases as adaptation costs increase. Payoffs behave non-monotonically; they are lower for medium high adaptation cost than for low adaptation cost, but higher for prohibitively high adaptation cost than for medium high adaptation cost. The positive direct effect of substitution outweighs the negative strategic effect for smaller groups, and the negative strategic effect outweighs the positive direct effect for larger groups.

The third paper "Mitigation and Adaptation with Heterogeneous Unit Cost of Adaptation" empirically tests the implications of adaptation cost heterogeneity for investment decisions regarding mitigation and adaptation. A particular focus is set on interpersonal differences in expected payoffs. The data were collected in a controlled computerized laboratory experiment conducted in Hamburg in April 2013. As in the second paper, the experiment is designed as a non-cooperative one-shot game, based upon the theoretical model presented in the first paper; however, this experiment features heterogeneous adaptation cost. I define three cost types differing with respect to their unit cost of adaptation. Subjects are assigned to these cost types and split into groups of four according to nine treatments covering different group compositions. Subjects respond to their co-players' cost type as predicted by the model: mitigation decreases as the co-players' adaptation cost increase, adaptation remains unchanged, and the average expected payoff increases. Within heterogeneous groups, the higher-cost type contributes a bigger share to the aggregate mitigation level than the lower-cost type. Beyond these confirmative results, we observe some interesting quantitative deviations from the model predictions. In the heterogeneous games, the type-specific proportional shares of group aggregate mitigation are less divergent than predicted, which leads to more equitable payoffs, but also entails an efficiency loss. I attribute this behavior to inequity aversion.

This dissertation makes three key contributions to the economic research on international climate change policy. First, it provides a model of international climate policy that uniquely reflects the idea of climate policy as climate risk management. Second, the model enables us to clearly separate direct from strategic effects of adaptation, and to disentangle the determinants that account for either effect. Third, the validity of the theoretical model is successfully tested in two experiments. Besides the validity test, the third paper exhibits some interesting behavioral findings regarding belief formation and inequity aversion. In future research, the model could probably be used to analyze existing climate treaties; moreover, it may enhance our understanding about treaty formation and negotiation in particular with respect to heterogeneous positions, threat points, and outside options determined by adaptation possibilities.

Chapter 2

The Strategic Interdependencies of Mitigation and Adaptation

Abstract Besides immediate costs and benefits, policymakers concerned with climate change have to consider the strategic interdependencies of mitigation and adaptation when acting internationally. This paper proposes a non-cooperative game-theoretic model that incorporates both policies as decision variables. By comparing the equilibrium outcomes of the mitigation-adaptation model and the established mitigation-only model, we find that the additional opportunity to invest in adaptation increases welfare in the social optimum, but can cause a welfare loss in the Nash equilibrium. This happens because countries replace mitigation by adaptation whenever doing so is individually beneficial (direct effect); however, this same substitution lowers the aggregate level of mitigation and thus deprives all other countries of the positive externalities from mitigation (strategic effect). The strategic effect tends to prevail if (i) the number of countries involved is large, (ii) the damage from climate change is large, and (iii) the relative marginal costs of adaptation are high. The theoretical results are illustrated by means of a numerical example.

Keywords climate change, mitigation, adaptation, social dilemma, public good, risk
JEL Classification C72, Q54, H41

2.1 Introduction

For a long time, international climate change policy focused solely on the mitigation of climate change by reducing greenhouse gas emissions. Adaptation to climate change was treated as a side issue. In recent years, the agenda has changed: adaptation is now an integral part of climate change policy. In 2010, the parties to the United Nations Framework Convention on Climate Change (UNFCCC) adopted the "Cancun Adaptation Framework", by which they affirmed that adaptation must be addressed with the same level of priority as mitigation.

Despite this development, policymakers as well as economic researchers dealing with international climate change policy miss out on the *strategic* interdependencies of mitigation and adaptation. To close this gap, this work proposes a generic game-theoretic model that incorporates both policy options as decision variables. I compare this novel mitigation-adaptation model with the conventional mitigation-only model and find that incorporating adaptation as an additional climate policy alternative *increases* global social welfare as could be achieved under full cooperation, whereas it may actually *decrease* the aggregate welfare in a non-cooperative environment.

Climate Risk and Climate Risk Management. Since pre-industrial times, the concentration of greenhouse gases in the atmosphere has increased significantly, mainly due to anthropogenic emissions (IPCC, 2007d; Rogner et al., 2007). The high concentration of greenhouse gases is most likely the main driver of climate change, and continued emissions at or above current rates will further accelerate climate change (Hegerl et al., 2007). Since the mid-20th century, climate change has already become evident in several phenomena such as increased average air and ocean temperatures, more frequent heat waves, more frequent heavy precipitation events, more and heavier droughts, increased tropical cyclone activity and rising sea level extremes (IPCC, 2007c; Trenberth et al., 2007). Predictions made on the basis of climate models indicate that these trends are likely to continue. Even if temperature and precipitation means change only slightly, it is still expected that the type, frequency and intensity of extreme weather events change considerably (Meehl et al., 2007, p. 783). Extreme weather events have significant impacts on many geophysical and biological systems, with direct or indirect consequences for economic welfare: cyclones and hurricanes cause physical damage and loss of life; droughts lead to crop failure, famine and water stress; floods and storm surges threaten coastal areas. The consequences of an impact for people's livelihood and economic welfare, however, not only depend on the severity and probability of the impact itself, but also on the exposure of the affected system, its vulnerability, and its resilience. Take river flooding as an example. With a certain probability, continuing heavy rainfall (impact) is experienced by a low-lying riverside area (exposure). Dikes and flood barriers can prevent damage (vulnerability); once damage has occurred, insurance benefits and emergency relief can foster recovery (resilience).

Climate change impacts are inherently probabilistic, and the combination of an *impact* and its *consequences* -determined by exposure, vulnerability and resilience- constitutes what is best described as climate risk. Thus, a risk management approach is the appropriate way to economically assess risk determinants and climate policies, as proposed by Jones (2004), Carter et al. (2007), and IPCC (2012). According to the two constituents of climate risk, we can distinguish between two major forms of climate risk management: one is mitigation, which aims at reducing the size and frequency of climate impacts; the other is adaptation, which aims at reducing the damage caused by an impact (Jones, 2004).

Mitigation is defined as "an anthropogenic intervention to reduce the anthropogenic forcing of the climate system; it includes strategies to reduce greenhouse gas sources and emissions and enhancing greenhouse gas sinks." (IPCC, 2007a, p. 878). A broad range of mitigation policies has been developed over the last decades. Some measures aim at reducing the demand for high-carbon goods, others aim at fostering low-carbon technologies such as wind power or solar power, yet other measures relate to geoengineering technologies. [1]

Adaptation is defined as an "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." (IPCC, 2007a, p. 869). After it became apparent that several climate change impacts have already occurred, and acknowledging the inertia inherent in the climate system (Adger et al., 2007), political decision makers attach increased importance to adaptation. Adaptation comes in many different forms, as elaborated by Smit et al. (2000) in their excellent anatomy of adaptation based on three key questions: "Adaptation to what?", "Who or what adapts?" and "How does adaptation occur?". In the context of international climate policy discussed here, the primary focus is on big-scale anticipatory adaptation that is carried out or funded by governments as a policy measure, e.g. coastal protection, urban planning, water resource management, and relocation plans.

For the analysis of the strategic interrelations between mitigation and adaptation, it

[1] Many researchers treat geoengineering as a third climate change policy measure distinct from mitigation and adaptation (e.g. Barrett, 2008b; Lenton and Vaughan, 2013). This distinction is useful and sensible, particularly in the context of regulation. For the mechanisms described in this work, subsuming geoengineering under mitigation is an acceptable simplification.

is crucial to be clear about their economic characteristics.

Substitutes vs. Complements. There is some disagreement in the literature whether mitigation and adaptation are substitutes or complements. Mitigation reduces the probability of extreme weather events, whereas adaptation moderates losses caused by extreme weather events: although through different channels, both strategies ultimately aim at reducing the *expected damage* from climate change. Mitigation and adaptation may thus rightly be regarded as substitutes: "the more mitigation is undertaken, the less adaptation is necessary and vice versa" (Klein et al., 2007, p. 753).

This argument is disputable, since some responses to climate change are 'technical complements' that foster mitigation and adaptation. Afforestation, for example, provides shade and protects the soil against erosion (adaptation); at the same time, trees provide a natural carbon storage (mitigation) (Klein et al., 2005). Other responses are 'technical substitutes', where adaptation and mitigation may conflict. This is the case with air conditioning (Tol, 2005): it alleviates heat stress (adaptation), but consumes energy at the same time. Most responses, however, are neither technical complements nor technical substitutes; yet, adaptation and mitigation can be regarded as substitutes because they compete for scarce resources: investing in one policy measure reduces the budget left for the other.

Using a systematic approach, an analysis by Ingham et al. (2005) suggests that adaptation and mitigation should fundamentally be considered as substitutes. Two exemptions may suggest a complementary relationship: first, adaptation costs may depend on the amount of mitigation; second, the marginal effectiveness of mitigation may depend on an exogenous increase in risk as described by Kane and Shogren (2000).

It remains to be said that a good deal of confusion arises from a blurred notion of complementarity and substitutability in everyday language as opposed to the more precise economic concept referring to the cross elasticity of demand. For example, Easterling et al. (2004) state that "Adaptation actions and strategies present a complementary approach to mitigation." (p. iii); by this statement, they merely intend to say that both mitigation and adaptation are indispensable elements of an efficient climate change policy. Similar claims can be found in large parts of the literature; yet, these statements refer to complementarity at the margin, indicating that there can be no *full* replacement of one policy alternative by the other. In economic terms, these limit properties are mostly a matter of prohibitively high costs at the margin and can be incorporated in a substitutes model by carefully setting the cost parameters. In due consideration of the exceptions discussed above, mitigation and adaptation are treated as substitutes in this paper.

Public vs. Private Goods. There is general consensus that the economics of climate change in one way or another relate to the provision of a global public good. However, most scholarly work is not very clear in what exactly constitutes this good. Some remain entirely silent, others attribute the global public good property to different concepts, e.g., "Control of the climate system" (Bradford, 2004, p. 4); "The environment", "International regimes" (Kaul et al., 1999, p. 13); "Cutting [...] CO2 emissions" (Barrett, 1999, p. 197); "Action to address global climate change" (Barrett, 2007, p. 5); "Global climate change mitigation" (Barrett, 2007, p. 74); or "Global warming" (Nordhaus, 2006, p. 32).

To be precise in the analysis, I consider mitigation and adaptation as two distinct intermediate goods or production factors. Both mitigation and adaptation contribute to our want to be free of damage from climate change, but do so in different ways: mitigation produces a low probability of extreme weather events; adaptation produces a low damage in the event of extreme weather.

Mitigation is a pure global public good: a single country that reduces its greenhouse gas emissions or enhances greenhouse gas sinks has to bear the cost of mitigation in private, while all countries benefit from its mitigation effort. No country can be excluded from the climatic effect of mitigation; nor does one country's benefit reduce the availability of mitigation for the other countries. These public-good features give rise to the problem of free riding and may lead to an underprovision of mitigation if cooperation fails due to weak institutions.

Adaptation is a private good: its effects are typically limited to the scale of the impacted system (Klein et al., 2007). Indeed, some anticipatory adaptation projects intend to benefit whole areas, as for example large-scale coastal protection plans. These measures can well be regarded as regional public goods. Yet, from an international policy point of view, we suppose that both costs and benefits of adaptation arise to the country that invests in adaptation. Due to its private good character, there are no immediate external effects from adaptation.

The public vs. private good property explains why, to date, research on strategic issues in climate change policy is primarily concerned with the global public good mitigation, whereas the strategic dimension of the private good adaptation has largely been overlooked.

2.2 Literature Review

The most commonly applied framework to analyze the strategic interaction of countries making climate change policy focuses on greenhouse gas emissions. The typical model provides a setting of n countries, where country i's $(i = 1, ..., n)$ welfare P_i consists of its benefits B_i generated by aggregate global abatement $M \equiv \sum_{j=1}^{n} m_j$ less cost C_i of its own individual abatement m_i. The basic structure is

$$P_i = B_i(M) - C_i(m_i)$$

(e.g. Barrett, 1992, 1994b; Hoel, 1991). In a parallel model set-up, country i's welfare P_i consists of benefits B_i generated by its own individual emissions, e_i, less damages D_i caused by the aggregate emissions released by all countries, $E \equiv \sum_{j=1}^{n} e_j$:

$$P_i = B_i(e_i) - D_i(E)$$

(e.g. Carraro and Siniscalco, 1993; Finus, 2002). It is easy to show that both approaches are equivalent: the level of abatement is just the amount of emissions *not* released; thus, the benefit from individual emissions can be interpreted as the opportunity cost of abatement, i.e.,

$$-B_i(e_i) = C_i(m_i).$$

Likewise, the damage averted by not releasing a certain amount of global emissions equates to the benefit from aggregate global abatement:

$$-D_i(E) = B_i(M).$$

Kane and Shogren (2000) pioneered research on the interdependencies of mitigation and adaptation. Their endogenous-risk model differentiates between self-protection efforts that reduce the likelihood of a bad state to occur (mitigation), and self-insurance efforts that reduce the damage realized once the bad state has occurred (adaptation). The research scope lies on the impact of an increased variability in climate change threats on the optimal mix of mitigation and adaptation. Strategic interactions between countries are not considered. My model presented in Section 2.3.2 transfers the concept of endogenous risk to a strategic context.

Barrett (2008a) introduces a parametric mitigation-adaptation model to investigate the effect of adaptation on efforts to overcome free-rider incentives in international climate treaties. The structure is similar to Barrett's earlier mitigation-only models with benefits from global mitigation and individual mitigation costs (Barrett, 1992, 1994b). The benefits from mitigation and adaptation are interdependent: an increase in adaptation leads to a decrease in the marginal benefit from mitigation and vice versa. In an N symmetric countries setting, Barrett analyses the non-cooperative Nash equilibrium, the full cooperative outcome and different treaty equilibria for various parameter scenarios.

There are, however, some limitations to the model proposed by Barrett (2008a). First, adaptation and mitigation are treated as binary choice variables, which limits the strategy space to four strategies only. Consequently, the equilibrium outcomes exhibit discrete jumps at certain parameter-given thresholds. Second, the results depend on the particular benefit and cost functions employed, on the benefit and cost parameters, and on additional parameters such as the degree of substitutability and the inherited concentration of greenhouse gases. The model presented in this paper overcomes these limitations and offers an analytical solution.

Another recent strand of research addresses mitigation and adaptation policies in a dynamic game-theoretic context with a particular focus on timing issues, although from different perspectives. Zehaie (2009) proposes a dynamic two-stage game setting where adaptation works as a commitment device chosen in stage 1, followed by the choice of mitigation in stage 2. He finds that proactive adaptation has strategic advantages as it enables a country to shift the responsibility for mitigation to others. Based on Zehaie (2009), De Bruin et al. (2011) present an enhanced three-stage dynamic model to investigate the coalition effects from proactive adaptation. A similar approach is employed by Auerswald et al. (2011), whose analysis focuses on the impact of a country's risk attitude on the optimal mix of mitigation and adaptation. Buob and Stephan (2011), in contrast, propose a dynamic two-stage game setting with the level of mitigation chosen in stage 1 and adaptation chosen in stage 2. Utility depends positively on consumption and environmental quality, where environmental quality can be improved by investing in mitigation and/or in adaptation (modeled as perfect substitutes), and investments in mitigation and adaptation cut the budget left for consumption. The authors describe the impact of initial endowments with income and environmental quality on the optimal mix of adaptation and mitigation.

2.3 Models

2.3.1 The Mitigation-Only Model

Although they slightly vary in structure, all mitigation-only models mentioned in the previous section yield the same results regarding the social and the individual optimum.

This section presents an augmented mitigation-only model that exactly reproduces the mechanisms, specifications and results of this model class but uses a different conception of payoffs in line with the endogenous-risk approach suggested by Kane and Shogren (2000). The mitigation-only model will later serve as a benchmark to compare and assess the results of the mitigation-adaptation model.

Consider a world consisting of n countries. Each country $i = 1, ..., n$ behaves as a rational unitary player who aims at maximizing her expected utility. The strategies available to the countries are the different levels of mitigation they might produce. Thus, each country i's strategy space is represented as $S_i = [0, \infty),$, and a typical strategy s_i is a mitigation level m_i. Each country i has an expected utility function $Eu_{i,m0}$, determined by its own mitigation level m_i and the aggregate mitigation of all other countries except i, hereafter denoted as $M_{-i} = \sum_{\substack{j=1 \\ j \neq i}}^{n} m_j$. There are two states of nature: in the "bad" state, an extreme weather event occurs; in the "good" state, the event does not occur. The good-state utility of country i is denoted as $u_i^g(m_i)$; the bad-state utility of country i is denoted as $u_i^b(m_i)$. Country i faces the bad state with probability $p_i(M) \in (0, 1)$, where $M = \sum_{j=1}^{n} m_j$ is the aggregate mitigation level, and the good state with probability $1 - p_i(M)$. In total, country i's expected utility is expressed by the von-Neumann-Morgenstern expected utility function

$$Eu_{i,m0} = p_i(M) \cdot u_i^b(m_i) + (1 - p_i(M)) \cdot u_i^g(m_i). \tag{2.1}$$

Assume that all functions p_i, u_i^b, u_i^g are twice continuously differentiable and that the following specifications hold:

$$\frac{dp_i}{dM} < 0\,; \tag{2.2}$$

$$\frac{d^2 p_i}{dM^2} > 0\,; \tag{2.3}$$

$$u_i^g(m_i) - u_i^b(m_i) > 0\,; \tag{2.4}$$

$$\frac{du_i^g}{dm_i} = \frac{du_i^b}{dm_i} < 0\,; \tag{2.5}$$

$$\frac{d^2 u_i^g}{dm_i^2} = \frac{d^2 u_i^b}{dm_i^2} \leq 0\,; \tag{2.6}$$

By specification (2.2), p_i is decreasing in M. We assume that a lower level of global aggregate greenhouse gas emissions reduces the probability of extreme weather events, irrespective of where mitigation takes place. By (2.3), the marginal effect of mitigation on the probability distribution is decreasing. Specification (2.4) describes country i's utility loss caused by an extreme weather event. Specification (2.5) indicates that country i's utility is decreasing in m_i in both states, which reflects i's cost of mitigation. The marginal cost of mitigation are assumed to be constant or increasing, as specified by (2.6).

To verify that the model just introduced represents the class of mitigation-only models mentioned in the previous section, let D_i denote the (constant) difference between u_i^g and u_i^b, i.e., the damage occurring in the bad state. Using (2.4), (2.5), and (2.6), the original expected utility function (2.1) can be simplified to

$$Eu_{i,m0} = u_i^g(m_i) - p_i(M) \cdot D_i. \tag{2.7}$$

Both functions are decreasing in m. Note that the first term on the right-hand side captures the cost of mitigation, whereas the second term captures the expected damage. Considering the fact that the amount of mitigation equates to the amount of emissions not released, the structure is equivalent to the commonly applied mitigation-only models mentioned in Section 2.2.

2.3.2 The Mitigation-Adaptation Model

I now introduce a new model variant that allows for investments in mitigation and adaptation. Country i's set of feasible strategies is enlarged: it contains any combination of non-negative levels of mitigation $m_i \geq 0$ and/or adaptation $a_i \geq 0$. Country i's expected utility function $Eu_{i,ma}$ is determined by its own adaptation level a_i, its own mitigation level m_i, and the global aggregate mitigation level $M = \sum_{j=1}^{n} m_j$. The good-state utility of country i is denoted as $u_i^g(a_i, m_i)$. The bad-state utility of country i is denoted as $u_i^b(a_i, m_i)$. As in the mitigation-only model, country i faces the bad state with probability $p_i(M) \in (0, 1)$ and the good state with probability $1 - p_i(M)$. In total, country i's expected utility is expressed by the von-Neumann-Morgenstern expected utility function

$$Eu_{i,ma} = p_i(M) \cdot u_i^b(a_i, m_i) + (1 - p_i(M)) \cdot u_i^g(a_i, m_i). \tag{2.8}$$

It is assumed that all functions p_i, u_i^b and u_i^g are twice continuously differentiable and that the following specifications hold:

$$\frac{dp_i}{dM} < 0\,; \tag{2.9}$$

$$\frac{d^2 p_i}{dM^2} > 0\,; \tag{2.10}$$

$$\frac{\partial u_i^g}{\partial m_i} = \frac{\partial u_i^b}{\partial m_i} < 0\,; \tag{2.11}$$

$$\frac{\partial^2 u_i^g}{\partial m_i^2} = \frac{\partial^2 u_i^b}{\partial m_i^2} \leq 0\,; \tag{2.12}$$

$$\frac{\partial u_i^g}{\partial a_i} < 0\,; \tag{2.13}$$

$$\frac{\partial^2 u_i^g}{\partial a_i^2} \leq 0\,; \tag{2.14}$$

$$\frac{\partial u_i^b}{\partial a_i} > \frac{\partial u_i^g}{\partial a_i} \forall a_i \tag{2.15}$$

$$\frac{\partial^2 u_i^b}{\partial a_i^2} \leq 0\,; \tag{2.16}$$

$$\frac{\partial^2 u_i^b}{\partial m_i \partial a_i} = \frac{\partial^2 u_i^g}{\partial m_i \partial a_i} \leq \frac{dp_i}{dM} \cdot \left(\frac{\partial u_i^g}{\partial a_i} - \frac{\partial u_i^b}{\partial a_i}\right) \tag{2.17}$$

$$u_i^g(a_i, m_i) > u_i^b(a_i, m_i)\,; \tag{2.18}$$

By specification (2.9), we assume that a lower level of global aggregate greenhouse gas emissions reduces the probability of an extreme weather event, no matter where mitigation takes place. By (2.10), the marginal benefit of mitigation is decreasing.

Specifications (2.11), (2.12), (2.13), and (2.14) reflect the assumption that the marginal cost of mitigation in the good state and the marginal cost of adaptation in the good state are constant or increasing. By specification (2.15), it is made explicit that adaptation compensates for damages suffered in the bad state. Note that adaptation affects the bad-state utility in two respects: on the one hand, adaptation comes at cost, which decreases utility; on the other hand, adaptation partially or fully compensates for the loss, which increases utility. The marginal compensation power of adaptation is decreasing. The overall impact of adaptation on the bad-state utility depends on the relative size of costs and benefits. We do not prescribe a particular sign for the first derivative of u_i^b with respect to a_i; yet we assume by (2.16) that the marginal *net* benefit of adaptation is decreasing. Specification (2.17) is necessary to qualify mitigation and adaptation as substitutes. Finally, specification (2.18) describes the “bad-stays-bad” condition, stating that losses cannot be overcompensated: the good-state utility always exceeds the bad-state utility.

A simple example that satisfies specifications (2.9) - (2.18) is made up of the following additively separable functions with constant marginal costs:

$$p_i = \frac{1}{M+1};$$

$$u_i^g = y_i - k_i a_i - l_i m_i;$$

$$u_i^b = z_i - k_i a_i - l_i m_i + \ln(a_i + 1);$$

with $y_i, z_i, k_i, l_i \in \mathbb{R}^+$ if a_i is restricted to the set of a_i such that $y_i - z_i > \ln(a_i + 1)$. These particular functions will be used in the numerical example in Section 2.4.3.

Implicit Assumptions, Strengths and Weaknesses. The model implies that mitigation and adaptation are (imperfect) substitutes: adaptation reduces the marginal benefit of mitigation, and mitigation reduces the marginal benefit of adaptation. An increase in adaptation makes mitigation less profitable and vice versa. Technically speaking, the cross partial derivatives of the expected utility function are negative:

$$\frac{\partial^2 Eu_{i,ma}}{\partial m_i \partial a_i} = \frac{\partial^2 Eu_{i,ma}}{\partial a_i \partial m_i} = \frac{dp_i}{dM} \cdot \left(\frac{\partial u_i^b}{\partial a_i} - \frac{\partial u_i^g}{\partial a_i}\right) + \frac{\partial^2 u_i^g}{\partial m_i \partial a_i} \leq 0.$$

We implicitly assume that mitigation and adaptation are homogeneous goods that can be aggregated. This assumption is contestable since, in reality, climate change impacts are diverse, and so are the responses to these impacts. With CO2 equivalents serving as a metric, it is rather easy to measure and aggregate mitigation levels (Rogner et al., 2007). Adaptation practices, however, are much more diverse. Different systems adapt to different stimuli in different ways (Smit et al., 2000); thus, it is difficult to aggregate all adaptation efforts into one single good (see Tol, 2005). In particular, it is hardly possible to express the benefits of adaptation in a single metric (Klein et al., 2007, p. 750).

Unlike other models, my model explicitly accounts for the particular structure of expected utilities in the face of extreme weather events caused by climate change. An endogenous probability distribution is applied over different states of nature. Adaptation alleviates the damage suffered in the bad state, whereas mitigation reduces the probability of the bad state to occur. This structure is a more differentiated portrait of reality than models that only consider costs and residual damages, thereby mixing up different effects. Another feature of my model is the generalized setup. There is no particular function involved; instead, the functions are only specified in general terms. Other than in Barrett (2008a), who treats the choices of adaptation and mitigation as binary variables, adaptation and mitigation are continuous here, which is a more realistic image that allows for a better understanding of the mechanisms at work. Finally, the model is reduced to the immediate effects of mitigation vs. adaptation without considering the time dimension or other determinants such as initial wealth, risk attitude, degree of substitutability, inherited greenhouse gas concentration etc.

2.4 Results

2.4.1 Social Optimum

If there were a "world authority", in the sense of a benevolent social planner who could decide in place of individual countries, what would be its optimal choices? In this section, we determine the socially optimal choices in a world of n countries for both models. The social optima will later serve as a first-best benchmark to evaluate the non-cooperative outcomes resulting from the strategic interaction of countries behaving as self-interested rational players. Consider at first the optimal choices for m_i in the mitigation-only model. The social planner's objective function is the sum of individual utilities:[2]

$$\max_{(m_i)_{i=1,\ldots,n}} \sum_{i=1}^{n} Eu_{i,m0} = \max_{(m_i)_{i=1,\ldots,n}} \sum_{i=1}^{n} \Big(p_i(M) \cdot u_i^b(m_i) + (1 - p_i(M)) \cdot u_i^g(m_i) \Big),$$

where the n first-order-conditions are

$$\frac{dp_i}{dM} \cdot u_i^b(m_i) + p_i \cdot \frac{du_i^b(m_i)}{dm_i} - \frac{dp_i}{dM} \cdot u_i^g(m_i) + (1 - p_i) \cdot \frac{du_i^g(m_i)}{dm_i}$$

$$+ \sum_{\substack{j=1 \\ j \neq i}}^{n} \big(\frac{dp_j}{dM} \cdot u_j^b(m_j) - \frac{dp_j}{dM} \cdot u_j^g(m_j) \big) = 0$$

$$\Leftrightarrow \; \frac{du_i^g}{dm_i} = \frac{du_i^b}{dm_i} = \frac{dp_i}{dM} \cdot (u_i^g - u_i^b) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{dp_j}{dM} \cdot (u_j^g - u_j^b). \tag{2.19}$$

The social optimum requires that country i's marginal cost of mitigation, represented by the left-hand side terms of (2.19), equal the sum of all countries' individual marginal

[2] For the sake of practicability, we assume a sort of Utilitarian social welfare function and leave the problems of cardinally measuring and interpersonally comparing individual utilities aside.

benefits from country i's mitigation. The first term on the right-hand side of (2.19) depicts country i's own marginal benefit from its own mitigation effort. The summation at the end of (2.19) represents the marginal benefit from country i's mitigation effort to all other countries except i, i.e., the external effect. This result reflects the Samuelson condition (Samuelson, 1954) for the efficient provision of public goods.

To prove the existence of a solution to the optimization problem, it is necessary to show that the set of mutually dependent first-order conditions can be solved simultaneously:

Proof. We assume $\frac{\partial Eu_{i,m0}}{\partial m_i} < 0$ for sufficiently large M. Then, with $Eu_{i,m0}$ being strictly concave in m_i, there exists a unique maximizer $\bar{m}_i$ for any M_{-i}, i.e., a continuous function $\bar{m}_i(M_{-i})$. To determine the slope of this function, we rewrite (2.19) as

$$\frac{\partial p_i(\bar{m}_i(M_{-i}) + M_{-i})}{\partial M} \cdot (u_i^g - u_i^b) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{dp_j(\bar{m}_i(M_{-i}) + M_{-i})}{dM} \cdot (u_j^g - u_j^b) - \frac{\partial u_i^b}{\partial m_i} = 0 \quad (2.20)$$

Differentiating (2.20) with respect to M_{-i} and rearranging yields

$$\frac{d\bar{m}_i}{dM_{-i}} = -\frac{\frac{d^2 p_i}{dM^2} \cdot (u_i^g - u_i^b) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{d^2 p_j}{dM^2} \cdot (u_j^g - u_j^b)}{\frac{d^2 p_i}{dM^2} \cdot (u_i^g - u_i^b) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{d^2 p_j}{dM^2} \cdot (u_j^g - u_j^b) - \frac{\partial^2 u_i^b}{\partial m_i^2}},$$

i.e., $-1 \leq \frac{\partial \bar{m}_i}{\partial M_{-i}} < 0$. Since $\bar{m}_i$ is decreasing in M_{-i} and non-negative, the range C_i of $\bar{m}_i(M_{-i})$ is non-empty, convex and compact. Let $C = \times_{i=1}^{n} C_i$, and let $\bar{m}(m_1, ..., m_n) = (\bar{m}_1(M_{-1}), ..., \bar{m}_n(M_{-n}))$ with $\bar{m} : C \to C$. Since $\bar{m}$ is a continuous function, and C is a non-empty, convex and compact set, it follows by Brouwer's fixed point theorem that there exists a fixed point m^+ where $\bar{m}(m^+) = m^+$. By definition, m^+ simultaneously solves all n first-order conditions (2.19) and hence constitutes a social optimum. □

Next, consider the social planner's optimal choices for m_i and a_i in the mitigation-adaptation model. The optimization problem can be written as

$$\max_{((a_i, m_i))_{i=1,\ldots,n}} \sum_{i=1}^{n} Eu_{i,ma} = \max_{((a_i, m_i))_{i=1,\ldots,n}} \sum_{i=1}^{n} \Big(p_i(M) \cdot u_i^b(a_i, m_i) + (1 - p_i(M)) \cdot u_i^g(a_i, m_i) \Big)$$

The socially optimal values $(m_i^+, a_i^+)_{i=1,\ldots,n}$ must satisfy a set of $2n$ first-order conditions:

$$\frac{dp_i}{dM} \cdot u_i^b + p_i \cdot \frac{\partial u_i^b}{\partial m_i} - \frac{dp_i}{dM} \cdot u_i^g + (1 - p_i) \cdot \frac{\partial u_i^g}{\partial m_i} + \sum_{\substack{j=1 \\ j \neq i}}^{n} \left(\frac{dp_j}{dM} \cdot u_j^b - \frac{dp_j}{dM} \cdot u_j^g\right) = 0$$

$$\Leftrightarrow \frac{\partial u_i^g}{\partial m_i} = \frac{\partial u_i^b}{\partial m_i} = \frac{dp_i}{dM} \cdot (u_i^g - u_i^b) + \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{dp_j}{dM} \cdot (u_j^g - u_j^b) \tag{2.21}$$

and

$$p_i \cdot \frac{\partial u_i^b}{\partial a_i} + (1 - p_i) \cdot \frac{\partial u_i^g}{\partial a_i} = 0 \; \forall i = 1, ..., n$$

$$\Leftrightarrow \frac{\partial u_i^g}{\partial a_i} = p_i \cdot (\frac{\partial u_i^g}{\partial a_i} - \frac{\partial u_i^b}{\partial a_i}) \; \forall i = 1, ..., n. \tag{2.22}$$

As in the mitigation-only model, social optimality requires that the individual marginal cost of mitigation equal the sum of individual marginal benefits from mitigation (2.21). Furthermore, social optimality requires that country i's individual marginal cost of adaptation equal country i's individual marginal benefit from adaptation, as given by (2.22).

To prove the existence of a solution, I use a similar approach as in the mitigation-only case. The proof is slightly more complex because of the reciprocal effects at work. It needs to be shown that (1) the first-order conditions can be solved simultaneously and that (2) this simultaneous solution constitutes a maximum.

Proof. We assume that $\frac{\partial E u_{i,ma}}{\partial m_i} < 0$ and $\frac{\partial E u_{i,ma}}{\partial a_i} < 0$ for sufficiently large M. Consider i's reaction $(\bar{m}_i(M_{-i}), \bar{a}_i(M_{-i}))$ to an increase in M_{-i}. The reaction is twofold: on the one hand, since the marginal benefit of mitigation decreases in M_{-i} as given by specifications (2.9) and (2.10), $\bar{m}_i$ decreases in M_{-i}. This part of i's best response corresponds to the mitigation-only case discussed earlier. On the other hand, considering that the marginal benefit of adaptation also decreases in M_{-i} as given by (2.9) and (2.15), $\bar{a}_i$ decreases in M_{-i}. This, in turn, leads to an increase in $\bar{m}_i$ as given by specification (2.17). It follows that monotonicity of $\bar{m}_i(M_{-i})$ cannot be guaranteed as it was the case in the mitigation-only model. However, this ambiguity only exists for $\bar{a}_i(M_{-i}) > 0$. Given the above assumption that $\frac{\partial E u_{i,ma}}{\partial a_i} < 0$ for large M_{-i}, the optimal adaptation level for such M_{-i} is zero; consequently, the mitigation-increasing effect eventually disappears while the mitigation-diminishing effect remains. Thus, although there may exist an interval of M_{-i} where $\frac{\partial \bar{m}_i}{\partial M_{-i}}$ is positive, $\frac{\partial \bar{m}_i}{\partial M_{-i}}$ is definitely negative as M_{-i} becomes sufficiently large. This implies that the range C_i of the continuous function $\upsilon_i(M_{-i}) = (\bar{m}_i(M_{-i}), \bar{a}_i(M_{-i}))$ is non-empty, convex and compact. Let $C = \times_{i=1}^{n} C_i$ with $\upsilon : C \to C$ given by $\upsilon\Big(((m_i, a_i))_{i=1,...,n}\Big) = (\upsilon_i(M_{-i}))_{i=1,...,n}$. With υ being a continuous function and C being a non-empty, convex and compact set, it follows by Brouwer's fixed point theorem that there exists a fixed point (m_i^+, a_i^+) where $\upsilon((m_i^+, a_i^+)) = (m_i^+, a_i^+)$. By definition, this pair simultaneously solves all $2n$ first-order conditions. In order for this solution to constitute a social optimum, it is furthermore assumed that the second-order conditions are met. This is in particular the case if

$$\frac{\partial^2 Eu_i}{\partial m_i^2} \cdot \frac{\partial^2 Eu_i}{\partial a_i^2} - \Big(\frac{\partial^2 Eu_i}{\partial m_i \partial a_i}\Big)^2 \geq 0. \qquad \square$$

A first conclusion can be drawn immediately by comparing the optimization problems based on the two models. The mitigation-adaptation model grants the social planner the additional option to invest in adaptation, which she will exercise as long as doing so is more profitable than investing in mitigation. In this case, mitigation is to some extent substituted by adaptation. However, if the relative cost of adaptation are so high that adaptation does not add to social welfare, the social planner is free to abandon the option to invest in adaptation, which leaves him at worst with a choice situation identical to the mitigation-only model.

Proposition 1 *In the social optimum, the aggregate expected utility is at least as high in the mitigation-adaptation model as it is in the mitigation-only model (here and in the following, superscript* $^+$ *designates the social optimum):*

$$\sum_{i=1}^{n} Eu_{i,m0}^{+} \leq \sum_{i=1}^{n} Eu_{i,ma}^{+}$$

Next, I show by comparison how country i's socially optimal level of mitigation changes as adaptation comes into play. For simplicity, let the world consist of n identical countries, i.e., $p_i \equiv p$, $u_i^b \equiv u^b$, and $u_i^g \equiv u^g$ $\forall i = 1, ..., n$. In this case, there exists a symmetric interior solution with $m_i = m$ and $a_i = a$ $\forall i = 1, ..., n$. We use the fact that a is set to zero by default in the mitigation-only model and apply the implicit function theorem. Define $f(m, a)$ as follows:

$$f(m,a) := \frac{\partial u^b(a,m)}{\partial m} - n\Big(\frac{dp(n \cdot m)}{dM}(u^g(a,m) - u^b(a,m))\Big) \tag{2.23}$$

For given a, let $m(a)$ solve $f(m(a), a) = 0$. By definition of optimality, this equation holds for any given a, which implies that its total differential df is always zero. Since $\frac{\partial f}{\partial m} \neq 0$, the function $m(a)$ is implicitly defined by equation (2.23). By the implicit function theorem,

$$df = 0 = \frac{\partial f}{\partial a} + \frac{\partial f}{\partial m} \cdot \frac{dm}{da} \Leftrightarrow \frac{dm}{da} = -\frac{\frac{\partial f}{\partial a}}{\frac{\partial f}{\partial m}};$$

i.e.,considering (2.11),

$$\frac{dm}{da} = -\frac{\frac{\partial^2 u^b}{\partial m \partial a} - n \cdot \frac{\partial p}{\partial M} \cdot (\frac{\partial u^g}{\partial a} - \frac{\partial u^b}{\partial a})}{\frac{\partial^2 u^b}{\partial m^2} - n \cdot \frac{\partial^2 p}{\partial M^2} \cdot (u^g - u^b)}.$$

To determine the sign of $\frac{dm}{da}$, we use specifications (2.9), (2.10), (2.12), (2.13), (2.15), (2.17), and (2.18). It follows that m is non-increasing in a.

Proposition 2 *In the social optimum, the level of mitigation is at least as high in the mitigation-only model as it is in the mitigation-adaptation model:*

$$m^+_{m0} \geq m^+_{ma}.$$

2.4.2 Nash Equilibrium

In a world of sovereign countries, there is no such institution as a social planner. Even if countries multilaterally agree to reduce their greenhouse gas emissions, the world community lacks supranational authority to enforce compliance with the agreement. In this section, I determine the Nash equilibrium choices in a non-cooperative version of the two models. As before, the analysis starts with the mitigation-only model and is then extended to the mitigation-adaptation model.

Consider a situation where n countries engage in a one-stage, non-cooperative game. In the mitigation-only game, the set of feasible strategies available to country $i = 1, .., n$ consists of any choice of mitigation $m_i \geq 0$. Country i's expected utility function is given by

$$Eu_{i,m0} = p_i(m_i + M_{-i}) \cdot u_i^b(0, m_i) + (1 - p_i(m_i + M_{-i})) \cdot u_i^g(0, m_i).$$

In the Nash Equilibrium, for each country i, m_i^* is country i's best response to the strategies chosen by the $n-1$ other countries, $(m_1^*, ..., m_{i-1}^*, m_{i+1}^*, ..., m_n^*)$; that is, for all m_i,

$$Eu_{i,m0}(m_1^*, ..., m_{i-1}^*, m_i^*, m_{i+1}^*, ..., m_n^*) \geq Eu_{i,m0}(m_1^*, ..., m_{i-1}^*, m_i, m_{i+1}^*, ..., m_n^*).$$

In the Nash equilibrium, all countries i simultaneously choose m_i^* to solve

$$\max_{m_i} Eu_{i,m0} = p_i(m_i + M_{-i}^*) \cdot u_i^b(0, m_i) + (1 - p_i(m_i + M_{-i}^*)) \cdot u_i^g(0, m_i), \qquad (2.24)$$

where $M_{-i}^* = m_1^* + ... + m_{i-1}^* + m_{i+1}^* + ... + m_n^*$ denotes the aggregate mitigation by all countries except i. The Nash equilibrium satisfies a set of n first-order conditions:

$$\frac{\partial u_i^g(0,m_i^*)}{\partial m_i} = \frac{\partial u_i^b(0,m_i^*)}{\partial m_i} = \frac{dp_i(m_i^* + M_{-i}^*)}{dm_i} \cdot (u_i^g(0,m_i^*) - u_i^b(0,m_i^*)). \tag{2.25}$$

Proof. (Existence of a Nash equilibrium). We assume that $\frac{\partial Eu_{i,m0}}{\partial m_i} < 0$ for sufficiently large M. Given, in addition, that $Eu_{i,m0}$ is strictly concave in m_i, there exists a unique maximizer $\bar{m}_i$ for any M_{-i}, i.e., a continuous best-response function $\bar{m}_i(M_{-i})$. In order to determine the slope of this function, consider the first-order condition

$$\frac{dp_i(\bar{m}_i(M_{-i}) + M_{-i})}{dm_i} \cdot \Big(u_i^g(0,\bar{m}_i(M_{-i})) - u_i^b(0,\bar{m}_i(M_{-i}))\Big) - \frac{\partial u_i^b}{\partial m_i} = 0. \tag{2.26}$$

Differentiating (2.26) with respect to M_{-i} and rearranging yields

$$\frac{d\bar{m}_i}{dM_{-i}} = -\frac{\frac{d^2p_i}{dm_i^2} \cdot (u_i^g - u_i^b)}{\frac{d^2p_i}{dm_i^2} \cdot (u_i^g - u_i^b) - \frac{\partial^2 u_i^b}{\partial m_i^2}},$$

, i.e., $-1 \leq \frac{\partial \bar{m}_i}{\partial M_{-i}} < 0$. Since $\bar{m}_i$ is decreasing in M_{-i} and non-negative, the range C_i of $\bar{m}_i(M_{-i})$ is non-empty, convex and compact. Let $C = \times_{i=1}^n C_i$, and let $\bar{m}(m_1,...,m_n) = (\bar{m}_1(M_{-1}),...,\bar{m}_n(M_{-n}))$ with $\bar{m}: C \to C$. Since $\bar{m}$ is a continuous function, and C is a non-empty, convex and compact set, it follows by Brouwer's fixed point theorem that there exists a fixed point m^* where $\bar{m}(m^*) = m^*$, which, by definition, constitutes a Nash equilibrium. $\square$

In the mitigation-adaptation game, the set of feasible strategies available to country $i = 1,..,n$ consists of all affordable combinations of mitigation and adaptation, i.e., all pairs (a_i, m_i), $a_i \geq 0$ and $m_i \geq 0$. Country i's expected utility function is given by

$$Eu_{i,ma} = p_i(\sum_{j=1}^n m_j) \cdot u_i^b(a_i,m_i) + (1 - p_i(\sum_{j=1}^n m_j) \cdot u_i^g(a_i,m_i).$$

In the Nash equilibrium, for each country i, (a_i^*, m_i^*) is country i's best response to the strategies chosen by the $n-1$ other countries,
$((a_1^*,m_1^*),...,(a_{i-1}^*,m_{i-1}^*),(a_{i+1}^*,m_{i+1}^*),...,(a_n^*,m_n^*))$; thus, all countries i simultaneously choose (a_i^*, m_i^*) so as to solve

$$\max_{a_i,m_i} Eu_{i,ma} = p_i(m_i + M_{-i}^*) \cdot u_i^b(a_i,m_i) + (1 - p_i(m_i + M_{-i}^*)) \cdot u_i^g(a_i,m_i) \tag{2.27}$$

The Nash equilibrium satisfies the $2 \cdot n$ first-order conditions

$$\frac{dp_i(m_i^*+M_{-i}^*)}{dM}u_i^b+p_i(m_i^*+M_{-i}^*)\frac{\partial u_i^b}{\partial m_i}-\frac{dp_i(m_i^*+M_{-i}^*)}{dM}u_i^g+(1-p_i(m_i^*+M_{-i}^*))\frac{\partial u_i^g}{\partial m_i}=0$$

$$\Leftrightarrow \frac{\partial u_i^g}{\partial m_i} = \frac{\partial u_i^b}{\partial m_i} = \frac{dp_i(m_i^* + M_{-i}^*)}{dM} \cdot (u_i^g - u_i^b) \tag{2.28}$$

and

$$p_i(m_i^* + M_{-i}^*) \cdot \frac{\partial u_i^b}{\partial a_i} + (1 - p_i(m_i^* + M_{-i}^*)) \cdot \frac{\partial u_i^g}{\partial a_i} = 0$$

$$\Leftrightarrow \frac{\partial u_i^g}{\partial a_i} = p_i(m_i^* + M_{-i}^*) \cdot (\frac{\partial u_i^g}{\partial a_i} - \frac{\partial u_i^b}{\partial a_i}). \tag{2.29}$$

The existence proof for the mitigation-adaptation social optimum, as explicated above, applies analogously to the Nash equilibrium.

Unlike in the social optimum, countries do not consider the positive externalities from mitigation. In the Nash equilibrium, optimality requires that each country i's marginal cost of mitigation (represented by the left-hand side of (2.28)) equal its *individual* marginal benefits from its own mitigation effort given that the other countries provide best-response levels of mitigation (right-hand side of (2.28)). A comparison of (2.21) and (2.28) reveals that the aggregate level of mitigation M is lower in the Nash equilibrium than in the social optimum. Thus, if cooperation fails, countries have an incentive to free-ride, which results in an underprovision of mitigation.

Next, as in the analysis of social optima, I compare the Nash equilibrium levels of mitigation in the mitigation-adaptation model, $m_{i,ma}^*$, to the Nash equilibrium levels of mitigation in the mitigation-only model, $m_{i,m0}^*$ by using the implicit function theorem. Again, it is assumed that countries are identical so that there exists a symmetric Nash equilibrium with $m_i = m$ and $a_i = a$ $\forall i = 1, ..., n$. Using the same approach as in the social optimum comparison, define function $g(m, a)$ as follows:

$$g(m, a) := \frac{\partial u^b(a, m)}{\partial m} - \frac{dp(n \cdot m)}{dM} \cdot (u^g(a, m) - u^b(a, m)). \tag{2.30}$$

For given a, let $m(a)$ solve $g(m(a), a) = 0$. By definition of optimality, this equation holds for any given a, which implies that its total differential dg is always zero. Since $\frac{\partial g}{\partial m} \neq 0$, the function $m(a)$ is implicitly defined by equation (2.30). By the implicit function theorem,

$$dg = 0 = \frac{\partial g}{\partial a} + \frac{\partial g}{\partial m} \cdot \frac{dm}{da} \;\Leftrightarrow\; \frac{dm}{da} = -\frac{\frac{\partial g}{\partial a}}{\frac{\partial g}{\partial m}};$$

i.e., with (2.11),

$$\frac{dm}{da} = -\frac{\frac{\partial^2 u^b}{\partial m \partial a} - \frac{dp}{dM} \cdot (\frac{\partial u^g}{\partial a} - \frac{\partial u^b}{\partial a})}{\frac{\partial^2 u^b}{\partial m^2} - \frac{d^2 p}{dM^2} \cdot (u^g - u^b)}.$$

In consideration of specifications (2.9), (2.10), (2.12), (2.13), (2.15), (2.17) and (2.18), it follows that m^* is non-increasing in a.

Proposition 3 *In the Nash equilibrium, the mitigation level is at least as high in the mitigation-only model as it is in the mitigation-adaptation model:*

$$m^*_{m0} \geq m^*_{ma}, \tag{2.31}$$

This result is not surprising because, just as in the social optimum, countries substitute mitigation by adaptation to increase their individual utility.

The more interesting question is: how does the Nash equilibrium expected utility, hereafter denoted as ϕ_i, change as adaptation comes into play? The answer is not straightforward as in the social optimum case. In the following comparative statics analysis, the levels of adaptation are treated as parameters, denoted by the vector $a = (a_1, ..., a_n)$, to account for the effects of exogenous variation in a. The strategy set of country i is thus reduced to i's choice of $m_i(a)$. It is again assumed that countries are identical, i.e., $a_i = a \,\forall i$ and $m_i = m \,\forall i$.

In the Nash equilibrium, given parameter a, $(m_i^*(a))$ is each country i's best response to the strategies chosen by the $n-1$ other countries, $(m_1^*(a)), ..., (m_{i-1}^*(a)), (m_{i+1}^*(a)), ...$ $..., (m_n^*(a)))$; thus, all countries i simultaneously choose $(m_i^*(a))$ to solve

$$\phi_i(a) \equiv \max_{m_i} Eu_{i,m(a)} = p_i(m_i + M^*_{-i}(a)) \cdot u_i^b(m_i, a) + (1 - p_i(m_i + M^*_{-i}(a)) \cdot u_i^g(m_i, a).$$

Under consideration of the first-order condition (2.28), differentiating with respect to a and rearranging yields

$$\frac{d\phi_i(a)}{da} = \frac{\partial u_i^g}{\partial a} + p_i \cdot (\frac{\partial u_i^b}{\partial a} - \frac{\partial u_i^g}{\partial a}) - \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{dp_i}{dm_j^*} \frac{dm_j^*}{da} \cdot (u_i^g - u_i^b) \tag{2.32}$$

The first term on the right-hand side reflects country i's marginal cost of adaptation. By specification (2.13), this term is negative. The second term reflects the probability-weighted damage averted through adaptation, i.e., country i's marginal net benefit of adaptation. By specifications (2.13) and (2.15), this term is positive. The last term reflects the change in country i's expected damages caused by the impact of all other countries' mitigation on country i's probability distribution. By specifications (2.9), (2.18) and (2.31), this term is negative.

To sum up, introducing adaptation into the model causes two separate effects. The first one is the direct effect, expressed by the first two terms on the right-hand side of (2.32). The direct effect results from the explicit appearance of a in country i's expected utility function and the consequent partial substitution of m by a up to the point where the new optimality conditions are met. As discussed earlier, the direct effect is greater than or equal to zero because the possibility to invest in adaptation enlarges country i's strategy space. The second effect is the strategic effect, expressed by the last term of (2.32). The strategic effect results from the substitution of m by a by the other countries, leading to a lower global aggregate level of mitigation. The strategic effect is smaller than zero because less aggregate mitigation increases the probability of the bad state to occur for country i.

Proposition 4 *Depending on the relative size of the two opposite effects, three cases may occur:*

Case 1. $\phi_{i,m0} < \phi_{i,ma}$ *if the direct effect exceeds the strategic effect;*

Case 2. $\phi_{i,m0} = \phi_{i,ma}$ *if the effects cancel out;*

Case 3. $\phi_{i,m0} > \phi_{i,ma}$ *if the strategic effect exceeds the direct effect.*

Case 3 is most remarkable: unlike in the social optimum, the additional opportunity to adapt may actually *decrease* the countries' expected utility. This is due to the fact that, in the mitigation-only model, countries are forced to invest in the public good mitigation, thereby exerting positive externalities on all other countries. In the mitigation-adaptation model, however, mitigation is partly substituted by the private good adaptation, which is beneficial for the country itself but deprives all other countries of the positive externality resulting from mitigation.

The derivative (2.32) suggests that case 3 is likely to occur when (i) the number of countries involved is large; (ii) the damage suffered in the bad state is large; (iii) the marginal costs of adaptation are relatively high in comparison to the marginal costs of mitigation.

2.4.3 Numerical Example

To illustrate the analytical results, consider a numerical example. The functions are defined as follows:

$$p_i(M) = \frac{1}{M+1} \tag{2.33}$$

$$u_i^g(a_i, m_i) = y_i - k_i a_i - l_i m_i \tag{2.34}$$

$$u_i^b(a_i, m_i) = z_i - k_i a_i - l_i m_i + \ln(a_i + 1) \tag{2.35}$$

The parameter $k_i \geq 0$ denotes country i's marginal cost of adaptation. The parameter $l_i \geq 0$ denotes country i's marginal cost of mitigation. The parameter $y_i \geq 0$ denotes the initial good-state utility of country i. The parameter $z_i \geq 0$ denotes the initial bad-state utility of country i. As required by specification (2.18), the domain of $a_i \geq 0$ is restricted by $y_i - z_i > \ln(a_i + 1)$. It is assumed that countries $i = 1, ..., n$ are identical and thus share the same parameters y_i, z_i, k_i, l_i. The total expected utility function of country i is given by

$$Eu_i = \frac{1}{M+1} \cdot (z_i - k_i a_i - l_i m_i + \ln(a_i + 1)) + \frac{M}{M+1} \cdot (y_i - k_i a_i - l_i m_i).$$

Variation of Group Size. First, we analyze the impact of n, the number of countries involved. Table 2.1 shows the values for m_i, a_i, and Eu_i for variations of n in the social optimum and in the Nash equilibrium.

In the social optimum, the country-average level of mitigation is decreasing in n in both models. Although the socially optimal aggregate level of mitigation M increases with the number of countries involved, each single country's share in the aggregate level of mitigation is reduced. Adaptation is also decreasing in n because, as the aggregate level of mitigation rises, the probability for the bad state to occur becomes smaller; thus, there is less need for adaptation. For $n < 4$, the expected utility is higher in the mitigation-adaptation model than in the mitigation-only model because it is profitable to substitute some mitigation by adaptation. For $n \geq 7$, the aggregate level of mitigation is already so high that the social planner does not invest in adaptation anymore at all; thus, the models coincide.

In the Nash equilibrium, the aggregate level of mitigation M is constant in n in both models; accordingly, the country-average level of mitigation is inversely proportional to n. Due to the possibility to substitute mitigation by adaptation in the mitigation-adaptation model, we observe $m^*_{i,ma} < m^*_{i,m0}$ and, accordingly, $M^*_{ma} < M^*_{m0}$. For large values of

Table 2.1: Variation of n

Parameter values: $y_i = 25$, $z_i = 10$, $k_i = 0.1$, $l_i = 1 \ \forall i = 1, ..., n$

	Social optimum					**Nash equilibrium**				
n	$m^+_{i,m0}$	$m^+_{i,ma}$	a^+_i	$Eu^+_{i,m0}$	$Eu^+_{i,ma}$	$m^*_{i,m0}$	$m^*_{i,ma}$	a^*_i	$\phi_{i,m0}$	$\phi_{i,ma}$
2	2.239	2.181	0.865	20.02	20.05	1.437	1.372	1.671	19.69	19.72
3	1.903	1.872	0.512	20.86	20.87	0.958	0.915	1.671	20.17	20.17
4	1.687	1.669	0.303	21.38	21.38	0.718	0.686	1.671	20.41	20.40
5	1.532	1.523	0.161	21.74	21.74	0.575	0.549	1.671	20.55	20.54
6	1.415	1.412	0.056	22.00	22.00	0.479	0.457	1.671	20.65	20.63
7	1.321	1.321	0	22.22	22.22	0.410	0.392	1.671	20.72	20.70
8	1.244	1.244	0	22.39	22.39	0.359	0.343	1.671	20.77	20.75

n, $m^*_{i,m0}$ and $m^*_{i,ma}$ converge to zero. The adaptation levels chosen by the individual countries are independent of n. For small n, in particular, for $n \leq 3$, expected utilities are higher in the mitigation-adaptation-model than in the mitigation-only model: each country has to contribute a high amount to mitigation, and there is only little scope to free-ride on the other countries' mitigation efforts. Thus, the positive direct effect from the possibility to invest in adaptation outweighs the negative strategic effect from the cutback in mutually beneficial mitigation. For larger n, in particular, for $n \geq 4$, the reverse is true: $\phi_{i,m0} > \phi_{i,ma}$, which corresponds to case 3. The aggregate level of mitigation is now shared by more countries so that each single country's contribution is rather small. Consequently, the opportunity to free-ride on the joint mitigation effort increases, which causes an overall welfare loss: the negative strategic effect from the cutback in mutually beneficial mitigation outweighs the positive direct effect from the possibility to invest in adaptation.

Variation of Initial Damage. The second analysis illustrates the effect of changes in the initial damage, described by $y_i - z_i$. Since only the difference matters, the variation of y_i with a constant z_i, as depicted in Table 2.2, is inversely equivalent to the variation of z_i with a constant y_i. A high value for y_i corresponds to a high utility loss occurring in the bad state.

In the social optimum, adaptation is decreasing and mitigation is increasing in y_i in the mitigation-adaptation model. Mitigation is also increasing in y_i in the mitigation-

Table 2.2: Variation of y_i

Parameter values: $n = 4$, $z_i = 10$, $k_i = 0.1$, $l_i = 1$ $\forall i = 1, ..., n$

	Social optimum					**Nash equilibrium**				
y_i	$m^+_{i,m0}$	$m^+_{i,ma}$	a^+_i	$Eu^+_{i,m0}$	$Eu^+_{i,ma}$	$m^*_{i,m0}$	$m^*_{i,ma}$	a^*_i	$\phi_{i,m0}$	$\phi_{i,ma}$
20	1.331	1.293	0.621	17.09	17.10	0.541	0.491	2.374	16.30	16.31
25	1.687	1.669	0.303	21.38	21.38	0.718	0.686	1.671	20.41	20.40
30	1.986	1.980	0.121	25.78	25.79	0.868	0.845	1.284	24.66	24.65

only model. This is due to the fact that the marginal net benefit of mitigation increases in y_i, whereas the marginal net benefit of adaptation is constant in y_i, i.e., independent of the potential loss. Accordingly, the marginal rate of substitution of mitigation for adaptation, $MRS_{m,a}$, increases as y_i increases. For small values of y_i, adaptation is still relatively profitable, so the socially optimal expected utility is significantly higher in the mitigation-adaptation model than in the mitigation-only model. As y_i increases, however, adaptation is more and more substituted by mitigation. For large y_i, the level of adaptation is so low that expected utilities are merely slightly higher in the mitigation-adaptation model than in the mitigation-only model.

In the Nash equilibrium, we observe the same interdependencies as in the social optimum: also here, adaptation is decreasing and mitigation is increasing in y_i in the mitigation-adaptation model, induced by the increasing $MRS_{m,a}$. As the potential loss y_i increases, adaptation becomes comparatively unprofitable, which implies that the possibility to invest in adaptation becomes less and less advantageous.

Mitigation is also increasing in y_i in the mitigation-only model. However, due to the lack of opportunity to invest in adaptation, the Nash-optimal aggregate level of mutually beneficial mitigation is always higher in the mitigation-only model than it is in the mitigation-adaptation model. This gap is narrowing as y_i increases; thus, the negative strategic effect of the possibility to invest in adaptation is becoming less pronounced. The results suggest that for small y_i, e.g., $y_i = 20$, the positive direct effect predominates the negative indirect effect so that expected utilities are higher in the mitigation-adaptation-model than in the mitigation-only model; for large y_i, the reverse is true: $\phi_{i,m0} > \phi_{i,ma}$, which again corresponds to case 3.

Variation of Adaptation Cost. The third analysis (Table 2.3) illustrates the effects of changes in the price of adaptation, k_i.

Table 2.3: Variation of k_i

Parameter values: $n = 4$, $y_i = 25$, $z_i = 10$, $l_i = 1\ \forall i = 1, ..., n$

	Social optimum					**Nash equilibrium**				
k_i	$m^+_{i,m0}$	$m^+_{i,ma}$	a^+_i	$Eu^+_{i,m0}$	$Eu^+_{i,ma}$	$m^*_{i,m0}$	$m^*_{i,ma}$	a^*_i	$\phi_{i,m0}$	$\phi_{i,ma}$
0.05	1.687	1.622	1.671	21.38	21.42	0.718	0.662	4.485	20.41	20.47
0.1	1.687	1.669	0.303	21.38	21.38	0.718	0.686	1.671	20.41	20.40
0.2	1.687	1.687	0	21.38	21.38	0.718	0.710	0.303	20.41	20.39

In the social optimum, adaptation is decreasing in k_i and mitigation is increasing in k_i in the mitigation-adaptation model (obviously, a variation of k_i does not affect the $m0$-values in the mitigation-only model). This result reflects the positive cross price elasticity which characterizes substitute goods. For small k_i, i.e., when adaptation is relatively cheap, the benefit from the possibility to invest in adaptation is high, so that expected utilities are significantly higher in the mitigation-adaptation model than in the mitigation-only model. As k_i increases, adaptation becomes less profitable. A value of $k_i = 0.2$ is already above the prohibitive price of adaptation: the social planner does not invest in adaptation anymore at all; thus, the models coincide.

In the Nash equilibrium, adaptation is also substituted by mitigation in the mitigation-adaptation model as k_i increases. For small values of k_i, e.g., $k_i = 0.05$, the additional possibility to invest in adaptation is very advantageous, which leads to higher expected utilities in the mitigation-adaptation model than in the mitigation-only model. When k_i rises, this positive effect is diminishing. The opposite effect, as in the previous example, results from the lower aggregate level of mutually beneficial mitigation in the mitigation-adaptation model compared to the mitigation-only model. Although the negative strategic effect is particularly high for small k_i and becomes less pronounced as k_i increases, it predominates for sufficiently high values of k_i. For $k_i = 0.2$, we have $\phi_{i,m0} > \phi_{i,ma}$, which reflects case 3 again.

Variation of Mitigation Cost. The fourth analysis (Table 2.4) illustrates the effect of changes in the price of mitigation, l_i.

In the social optimum, adaptation is increasing in l_i and mitigation is decreasing in l_i in the mitigation-adaptation model. As in the previous example, this result reflects the positive cross price elasticity. Mitigation is also decreasing in l_i in the mitigation-only model, which reveals that its own price elasticity is negative; however, for lack

Table 2.4: Variation of l_i

Parameter values: $n = 4$, $y_i = 25$, $z_i = 10$, $k_i = 0.1$ $\forall i = 1, ..., n$

	Social optimum					**Nash equilibrium**				
l_i	$m^+_{i,m0}$	$m^+_{i,ma}$	a^+_i	$Eu^+_{i,m0}$	$Eu^+_{i,ma}$	$m^*_{i,m0}$	$m^*_{i,ma}$	a^*_i	$\phi_{i,m0}$	$\phi_{i,ma}$
0.5	2.489	2.489	0	22.39	22.39	1.119	1.091	0.865	21.70	21.69
1	1.687	1.669	0.303	21.38	21.38	0.718	0.686	1.671	20.41	20.40
2	1.119	1.091	0.865	20.02	20.05	0.435	0.403	2.827	18.65	18.68

of a substitute, the decrease is less substantial. For small l_i, i.e., when mitigation is relatively cheap, the social planner has no incentive to invest in adaptation at all; thus, the models coincide. The higher l_i, the more profitable it is to replace some mitigation by adaptation; thus, for large values of l_i, expected utilities are significantly higher in the mitigation-adaptation model than in the mitigation-only model.

In the Nash equilibrium, as in the social optimum, mitigation is substituted by adaptation in the mitigation-adaptation model when l_i increases. Consequently, the possibility to invest in adaptation yields a substantially positive contribution for large l_i, i.e., when adaptation is comparatively profitable. The substitution advantage is less pronounced for small l_i. In the mitigation-only model, mitigation is also decreasing in l_i; yet, due to the lack of alternatives, the level of mutually beneficial mitigation is still higher than in the mitigation-adaptation model for any value of l_i. As in the previous examples, this mitigation gap accounts for the negative strategic effect of adaptation. When l_i is sufficiently small, e.g., for $l_i = 2$, this effect predominates the positive direct effect so that $\phi_{i,m0} > \phi_{i,ma}$, which again corresponds to case 3.

The findings from the numerical example confirm that, depending on the parameter setting, cases 1 and 3 from Proposition 4 may indeed occur.

2.5 Conclusion

To mitigate or to adapt? The model presented in this work suggests that, besides immediate costs and benefits, adaptation is also strategically relevant in international climate change policy. By using comparative statics, I could show that the additional opportunity to adapt increases welfare in the social optimum, but can cause an overall welfare loss when cooperation fails. This happens because countries individually benefit from substituting mitigation by adaptation (positive direct effect); however, the resulting deficit in aggregate mitigation increases the probability for an extreme weather event to occur for all countries (negative strategic effect). The theoretical results are supported by the outcomes of a numerical example. Parameter variations show that, ceteris paribus, the welfare-diminishing strategic effect of adaptation tends to outweigh the welfare-enhancing direct effect if and when (i) the number of countries involved is large; (ii) the damage suffered in the bad state is large; and (iii) the relative marginal costs of adaptation versus mitigation are high.

The findings deepen our understanding of how adaptation possibilities relate to mitigation efforts. Admittedly, due to the fundamental uncertainties inherent in climate predictions as well as in climate impact assessment, it is virtually impossible to perform empirical studies based on field data in order to confirm the theoretical results and to quantify the effects. Yet, the model allows for a systematic analysis of qualitative mitigation-adaptation interdependencies. In particular, we can derive some important implications for international climate change policy:

Considering that countries can and do invest in both adaptation and mitigation, the potential overall welfare under full cooperation is actually higher, and the non-cooperative outcome is probably lower, than what is predicted by mitigation-only models. Thus, allowing for adaptation widens the welfare gap between the social optimum and the Nash equilibrium, which constitutes an additional incentive to achieve the full cooperative outcome, e.g. by means of a treaty.

Considering that countries can and do substitute mitigation by adaptation, the optimal level of mitigation is actually lower than predicted by mitigation-only models. This holds for the social optimum achievable under full cooperation as well as for the non-cooperative Nash equilibrium. Consequently, it is recommended to reassess mitigation targets in due consideration of adaptation possibilities.

Considering that countries differ with respect to their adaptive capacity, relative adaptation costs and vulnerability, some countries will substitute more mitigation by adaptation than others. Those who have a comparative advantage in adaptation are less likely to adopt mitigation policies and less ambitious to sign a mitigation treaty than those who have not. The mitigation-adaptation model can be applied to assess which countries are likely to join a treaty, and whether or not their mitigation commitments are credible.

Finally, the mitigation-adaptation model might give valuable indications to a more accurate design of international climate policy treaties, e.g. regarding the determination of mitigation targets and the allocation of subsidies and side payments.

Chapter 3

The Impact of Adaptation Costs and Group Size on Mitigation and Adaptation

Abstract Even though the immediate effect of adaptation to climate change is spatially limited, adaptation is strategically relevant in international climate change policy. This empirical work tests the validity of a model proposed by Probst (2011) which describes the strategic interdependencies of mitigation and adaptation in a non-cooperative setting with endogenous risk. According to the model, the possibility to adapt to climate change has two opposite effects on welfare: first, a positive direct effect that results from substituting mitigation by adaptation; second, a negative strategic effect that results from the lower aggregate level of mutually beneficial mitigation. By means of a computer lab experiment, I test the impact of adaptation costs and group size on investments in mitigation and adaptation and on the resulting expected payoffs. The results support the model hypotheses based on Nash equilibrium predictions. Adaptation increases and mitigation decreases as adaptation costs decrease. Payoffs behave non-monotonically: they are lower for medium high adaptation cost than for low adaptation cost, but higher for prohibitively high adaptation cost than for medium high adaptation cost. The positive direct effect of substitution outweighs the negative strategic effect for smaller groups, and the negative strategic effect outweighs the positive direct effect for larger groups.

Keywords climate change, mitigation, adaptation, public good, experiment, risk
JEL Classification C91, Q54, H41

3.1 Introduction

The adaptation to climate change has become an important priority in international climate change policy and has initiated a strand of economic research; however, the strategic interdependencies of mitigation and adaptation are not very well analyzed so far. One of the few studies on this issue is Probst (2011) who introduces a generic game-theoretic model of mitigation and adaptation choices in an international climate change policy environment.

The aim of this work is to test a number of hypotheses derived from the Probst (2011) model. Due to the long-term nature of climate change and the high degree of uncertainty, reliable field data on the cost and benefits of mitigation and adaptation are currently not available; thus, the empirical tests are conducted with data collected in a controlled computer lab experiment. The empirical results suggest that, in line with the hypothetical predictions, mitigation is substituted by adaptation as the unit cost of adaptation decrease. We observe a u-shaped payoff pattern: initially, payoffs decrease as adaptation costs increase from low to medium high; however, they *increase* as adaptation costs further increase from medium high to prohibitively high.

Theoretical Background. This section summarizes the key arguments that motivate the theoretical climate risk model used in this work as postulated by Probst (2011). Changes in the global climate system have already become evident in several phenomena such as increased average air and ocean temperatures, more frequent heat waves, more frequent heavy precipitation events, more and heavier droughts, increased tropical cyclone activity and rising sea level extremes (IPCC, 2007c; Trenberth et al., 2007). It is expected that climate change will continue in the future (Hegerl et al., 2007), with significant impacts on many geophysical and biological systems. The consequences of these impacts for people's livelihood and economic welfare depend on the exposure of the affected system, its vulnerability, and its resilience (IPCC, 2012).

Climate change impacts are inherently probabilistic, and the combination of an *impact* and its *consequences* constitute what can best be described as climate risk. We therefore adopt a risk management approach for economically assessing impacts, consequences and climate policies, as proposed by Carter et al. (2007) and Jones (2004).
According to the two constituents of climate risk, we can distinguish two major forms of climate risk management: mitigation and adaptation. Mitigation is defined as "an anthropogenic intervention to reduce the anthropogenic forcing of the climate system; it includes strategies to reduce greenhouse gas sources and emissions and enhancing greenhouse gas sinks." (IPCC, 2007a, p. 878). Adaptation is defined as an "adjustment in

natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." (IPCC, 2007a, p. 869). Mitigation aims at reducing the size and frequency of climate impacts, whereas adaptation aims at reducing the system's exposure and vulnerability to a given impact or at enhancing its resilience to a given impact. Using the lingo of risk management, mitigation reduces the probability of a loss event. Adaptation reduces the damage in case the loss event actually occurs.

Two economic characteristics are crucial to understanding the strategic interdependencies of mitigation and adaptation: (1) the public vs. private good property; (2) the substitutability of the two (see Probst (2011) for a detailed discussion of these characteristics).

Mitigation is a pure global public good: the costs of mitigation are borne by the individual or entity that curtails greenhouse gas concentrations, whereas the benefits of mitigation are global. This cost-benefit constellation leads to free-riding and thus to an underprovision of mitigation if cooperation fails. In contrast, adaptation is a private good. The effects of adaptation are spatially limited to the impacted system (Klein et al., 2007), i.e., adaptation works at a local or at most regional level.

Mitigation and adaptation are substitutes. Both contribute to the same final end, namely, being free of damage from climate change, and one policy can at least partly replace the other. Moreover, mitigation and adaptation compete for scarce resources: investing in mitigation reduces the budget left for adaptation and vice versa.

Finally, climate change policymaking is a global challenge. Even if countries are willing to cooperate, the absence of strong institutions makes it difficult to establish binding agreements (Gerber and Wichardt, 2009). Moreover, informal sanctions such as reciprocity or retaliation are not applicable to the climate change issue (Guzman, 2008). This being the case, the non-cooperative setting chosen for the experiment appears well suited to mimic the real-world international climate change policymaking process.

Literature Review. Most previous empirical and experimental research on the economics of climate change bases on variants of a public goods game where players voluntarily contribute to the global public good "climate protection". The voluntary contribution game has emerged as the standard design for a great number of experiments on different aspects related to climate change (for a survey, see Sturm and Weimann, 2006). An alternative setting introduced by Milinski et al. (2008) captures the idea of endogenous risk that is also part of my model: in successive rounds, players voluntarily contribute to reach a group mitigation target that pays safe; if the target is missed, all group members

suffer a loss with a certain probability.
Hasson et al. (2010) made -to my knowledge- so far the only contribution that incorporates adaptation into an economic experiment. The authors introduce a one-shot game where players face an all-or-nothing binary choice between mitigation and adaptation. Treatments differ with respect to vulnerability, where “adapt” is the weakly dominant strategy for all treatments. Following Berger and Hershey (1994), Hasson et al. incentivize the participants’ investment decisions with stochastic returns.

Apart from climate change research, some basic features of my model can be found in other fields. The idea of an individually beneficial private good that crowds out a public good and thereby causes negative externalities is reflected in Peltzman (1975). Peltzman empirically investigates the effects of automobile safety regulation. He analyzes time-series and cross-sectional field data and finds that the positive effects of automobile safety devices is offset by more risky driving. This being the case, automobile safety regulation has not affected the highway death rate. A number of empirical examples support Peltzman’s “offset hypothesis”, e.g. from road transport (Sagberg et al., 1997; Winston et al., 2006), winter sports (Shealy et al., 2005), and children’s injury-risk behavior (Morrongiello et al., 2007). In the insurance literature, the determination of endogenous risk is known as ex ante moral hazard (Rees and Wambach, 2008). There exists a strand of research on self-insurance (equivalent to adaptation) vs. self-protection (equivalent to mitigation) based on the theoretical work by Ehrlich and Becker (1972). Shogren (1990) investigates the impact of self-protection and self-insurance on individual response to risk in an experiment where different risk management mechanisms are offered to players in an auction. The experiment presented in this paper is one of the first attempts to systematically and empirically analyze the strategic interrelations of mitigation and adaptation in a non-cooperative setting. In particular, I assess the effects of changes in relative adaptation costs and in group size on the levels of adaptation and mitigation as well as on the resulting payoffs.

3.2 Model

3.2.1 Theoretical Model

The experiment bases on a simplified specific variant of the generic mitigation-adaptation model with endogenous damage probabilities described by Probst (2011). Probst sets up an n-player game with von-Neumann-Morgenstern expected utility functions

$$Eu_{i,ma} = p_i(M) \cdot u_i^b(a_i, m_i) + (1 - p_i(M)) \cdot u_i^g(a_i, m_i),$$

where a_i denotes the level of adaptation for country $i = 1, ..., n$, m_i denotes the level of mitigation for country i, and $M = \sum_{j=1}^{n} m_j$ represents the global aggregate mitigation level of all countries including i. There are two states of nature, "bad", in which an extreme weather event occurs, and "good", in which no extreme weather event occurs. The good-state utility of country i is denoted as $u_i^g(a_i, m_i)$, the bad-state utility of country i is denoted as $u_i^b(a_i, m_i)$. $u_i^g(a_i, m_i) - u_i^b(a_i, m_i) > 0 \ \forall i$ denotes the loss caused by the extreme weather event. Country i faces the bad state with probability $p_i(M) \in (0, 1)$ and the good state with probability $1 - p_i(M)$.

Probst (2011) specifies the functions such that the following properties apply: (i) global aggregate mitigation, irrespective of its origin, lowers the probability for the loss event to occur; (ii) adaptation partially or fully compensates for the individual loss suffered in the bad state; (iii) the marginal benefits of mitigation and adaptation are decreasing; (iv) the costs of mitigation and adaptation are private and the the marginal costs of mitigation and adaptation are non-decreasing. Provided that certain assumptions are satisfied, a Nash equilibrium exists. Probst compares the Nash outcome of a model with mitigation and adaptation to the Nash outcome of a model where adaptation is not available, e.g. due to prohibitive costs. The formal analysis identifies a crowding-out reaction resulting in an ambiguous welfare effect: countries substitute mitigation by adaptation whenever doing so is individually beneficial (positive direct effect); however, this substitution causes a lower global aggregate level of mitigation and thus increases the loss probability for all countries (negative strategic effect). In a numerical example, the author shows that the negative strategic effect tends to outweigh the positive direct effect if (i) the number of countries involved is large, (ii) the damage from climate change is large, and (iii) the relative marginal costs of adaptation compared to marginal costs of mitigation are high.

3.2.2 Model Variant Used in the Experiment

The theoretical model does not prescribe any particular functions; instead, the functions are only specified in general terms. Both continuous and discrete functions may be used; for the purpose of the experiment, however, it was crucial to reduce complexity and to minimize the cognitive burden for the participants. Therefore, I chose a particular variant of the model with discrete choice variables.

Subjects participate in a non-cooperative n-player decision game. Each player $i = 1, ..., n$ receives an initial endowment y_i which she can spend on non-negative integer units of mitigation $m_i \in \mathbb{N}_0$ at a price of $l_i > 0$ and/or on non-negative integer units of adaptation $a_i \in \mathbb{N}_0$ at a price of $k_i > 0$. Players are also free to keep (i.e., not to invest) all or part of their endowment. Their total investment is limited by the budget constraint $k_i a_i + l_i m_i \leq y_i$. The expected payoff function for player i is defined as

$$Eu_i = p_i(M) \cdot (1 - L_i(a_i)) \cdot (y_i - k_i a_i - l_i m_i) + (1 - p_i(M)) \cdot (y_i - k_i a_i - l_i m_i)$$

$$\Leftrightarrow Eu_i = (1 - p_i(M) \cdot L_i(a_i)) \cdot (y_i - k_i a_i - l_i m_i).$$

$p_i(M) \in (0, 1]$ denotes the probability of loss for player i depending on the group aggregate level of mitigation, $M = \sum_{j=1}^{n} m_j$. $L_i(a_i) \in (0, 1]$ denotes the loss rate of player i. The loss probability function $p_i(M)$ and the loss rate function $L_i(a_i)$ are defined on $\mathbb{N}_0$ as listed in Table 3.1. The parameters y_i (initial endowment of player i) and $l_i > 0$ (unit cost of mitigation for player i) are fixed for all treatments and identical for all subjects with $y_i = 100$ Taler and $l_i = 10$ Taler.

Within each treatment, the marginal cost of mitigation and adaptation are constant; thus, the price per unit of mitigation and adaptation is also constant. The marginal benefit of mitigation and the marginal benefit of adaptation are decreasing. This framework is more demanding than the standard linear public goods framework frequently used in experiments. In the linear public goods framework with constant marginal per capita returns, the size of marginal per capita returns determines on which side of a binary scale the system ends up. My non-linear model, in contrast, allows for interior Nash equilibria which are necessary to detect the size of differences between treatments (for a detailed analysis of public goods experiments with interior Nash equilibria, see Laury et al. (1999); Laury and Holt (2008)).

3.3 Experiment

3.3.1 Treatments

The experiment is designed to cover three treatment variables: (i) model (mitigation only (m0) vs. mitigation and adaptation (ma)); (ii) group size n (5 vs. 3 subjects in one group); (iii) unit cost of adaptation k_i (15 Taler (high) vs. 5 Taler (low)). The mitigation-only treatments can best be interpreted as a special case of the mitigation-adaptation model with prohibitively high unit cost of adaptation, i.e., $k_i > 100$ Taler. In order to avoid confusion, this economically meaningful interpretation was not made explicit to the subjects. Instead, adaptation was *a priori* unavailable in the mitigation-only treatments. Varying all treatment variables independently requires a total of 6 treatments as summarized in Table 3.2.

Table 3.1: Parameters $p_i(M)$, $L_i(a_i)$

M	$p_i(M)$	a_i	$L_i(a_i)$
0	1	0	1
1	0.7	1	0.6
2	0.5	2	0.4
3	0.4	3	0.3
4	0.3	4	0.25
5	0.25	5	0.21
6	0.2	6	0.18
7	0.18	7	0.16
8	0.16	8	0.14
9	0.14	9	0.12
10	0.12	≥ 10	0.1
11	0.10		
12	0.09		
13	0.08		
14	0.07		
15	0.06		
≥ 16	0.05		

3.3.2 Theoretical Predictions

Consider a game (S, Eu) with n players. Let $x_i = (a_i, m_i)$ be a strategy profile of player i and let $x_{-i} = (a_{-i}, m_{-i})$ be a strategy profile of all players except i. S_i denotes the strategy set for player i, $S = S_1 \times S_2 ... \times S_n$ denotes the set of strategy profiles, and $Eu = (Eu_1(x), ..., Eu_n(x))$ denotes the profile of payoff functions for $x \in S$. When each player i chooses strategy x_i yielding strategy profile $x = (x_1, ..., x_n)$, then player i's payoff is $Eu_i(x)$. A strategy profile $x^* \in S$ is a Nash equilibrium if no player can benefit from her unilateral deviation, i.e. if, for all i,

$$x_i \in S_i,\, x_i \neq x_i^* : Eu_i(x_i^*, x_{-i}^*) \geq Eu_i(x_i, x_{-i}^*).$$

For the experimental game, there exist a number of Nash equilibria in pure strategies as described in Table 3.3 (the table contains only one representative Nash equilibrium

Table 3.2: Treatments

Treatment	**Model**	**Adaptation cost k_i**	**Group size n**
$m0_3$	mitigation only	–	3
$m0_5$	mitigation only	–	5
ma_3^l	mitigation and adaptation	5 Taler	3
ma_5^l	mitigation and adaptation	5 Taler	5
ma_3^h	mitigation and adaptation	15 Taler	3
ma_5^h	mitigation and adaptation	15 Taler	5

of each type; all other permutations of the explicitly listed strategy profiles together with the resulting payoffs constitute Nash equilibria as well). The Nash equilibria were identified with Mathematica by testing all possible combinations of strategy profiles for being mutual best responses. As a reference, I also calculated the socially optimal strategy combinations with the resulting payoffs as listed in Table 3.4. Social optimality requires that each group member choose her a_i and m_i such that the group sum of expected payoffs is maximized.[1]

It becomes apparent that there exists a single Nash equilibrium value for M for each level of adaptation cost. The Nash equilibrium value for $M = \sum m_i^*$ is 0 in the ma^l-setting, 2 in the ma^h-setting, and 4 in the $m0$-setting, i.e., for prohibitively high unit cost of adaptation. The Nash optimal M is independent of the group size n, which implies that the average m_i^* is smaller in the $n = 5$ treatments than in the $n = 3$ treatments. The Nash equilibrium value for adaptation a_i^* is 4 in the low-cost treatments ma_3^l and ma_5^l, and 1 in the high-cost treatments ma_3^h and ma_5^h. Based on these theoretical insights, I propose the following hypotheses to be tested in the experiment:

In a non-cooperative environment,

- (H1a) adaptation increases as the unit cost of adaptation (k_i) decreases.
- (H1b) the adaptation level is independent of the group size (n).
- (H2) mitigation decreases as k_i decreases: the average m_i^* level is highest in the $m0$-treatments, medium high in the ma^h-treatments and lowest in the ma^l-treatments.

[1] For simplicity, we assume a sort of Utilitarian social welfare function and suppose that an individual's utility solely depends on her expected payoff.

(H3) the group aggregate mitigation level M is constant in n; thus, for given k_i, the individual mitigation level m_i^* is higher for $n = 3$ than for $n = 5$. The difference is largest for $m0$-treatments, smaller for ma^h-treatments and smallest for ma^l-treatments.

(H4) payoffs respond non-monotonically to an increase of k_i: the payoffs obtained in the ma^l-treatments are *higher* than those obtained in the ma^h-treatments; whereas the ma^h-payoffs are *lower* than the $m0$-payoffs.

(H5) the positive group size effect on payoffs diminishes as k_i decreases: while the payoff $Eu_i(m0_5)$ is distinctly higher than $Eu_i(m0_3)$, the group-size specific difference in payoffs is smaller but still positive for ma^h-treatments and even smaller for ma^l-treatments.

3.3.3 Experimental Design

The experiment was programmed with the software z-Tree (Fischbacher, 2007) and conducted in June 2012 in the Laboratory for Experiments in Economics at the University of Hamburg. It consisted of four identical sessions with 30 participants each. Using the recruitment system ORSEE (Greiner, 2004), 120 undergraduate and graduate students were recruited from the University of Hamburg student body. The group of participants represented a variety of majors including economics and finance/business administration (57% of the subjects), but also other majors such as law, sociology, history, and natural sciences. The average age of the participants was 24.7 years; 56% were female. Most students had already participated in other economic experiments at the laboratory before.

Each session started with subjects entering the laboratory. After signing a consent form, subjects were randomly assigned to curtained computer cubicles. They were not allowed to communicate before and during the experiment. All subjects were provided with a copy of the experiment instructions (Appendix 3.A), which the experimenter also read aloud. Within the instructions, the language was kept neutral in order to avoid uncontrollable suggestive influences and/or biases caused by emotional and/or political attitudes regarding climate change policy. Expressions related to climate change and climate change policy like “mitigation”, “adaptation”, “extreme weather event” were avoided. Instead, subjects made decisions on “probability reduction” and “loss reduction” in order to manage a “loss event”. In this respect, I diverge from previous works such as Hasson et al. (2010) and Milinski et al. (2008) who explicitly framed their experiments with reference to climate change policy. The subjects were then asked to answer a number

Table 3.3: Nash equilibria

Treatment	**NE strategy profiles** $(a_i, m_i)_i$	**NE payoffs (Taler)**	**av. NE** a_i^{*1}	**av. NE** m_i^{*1}	**av. NE payoff**[1]
$m0_3$	((0,0),(0,0),(0,4))	(70,70,42)	0	1.333	60.666667
	((0,0),(0,1),(0,3))	(70,63,49)	0	1.333	60.666667
	((0,0),(0,2),(0,2))	(70,56,56)	0	1.333	60.666667
	((0,1),(0,1),(0,2))	(63,63,56)	0	1.333	60.666667
$m0_5$	((0,0),(0,0),(0,0),(0,0),(0,4))	(70,70,70,70,42)	0	0.8	64.4
	((0,0),(0,0),(0,0),(0,1),(0,3))	(70,70,70,63,49)	0	0.8	64.4
	((0,0),(0,0),(0,0),(0,2),(0,2))	(70,70,70,56,56)	0	0.8	64.4
	((0,0),(0,0),(0,1),(0,1),(0,2))	(70,70,63,63,56)	0	0.8	64.4
	((0,0),(0,1),(0,1),(0,1),(0,1))	(70,63,63,63,63)	0	0.8	64.4
ma_3^l	((4,0),(4,0),(4,0))	(60,60,60)	4	0	60
ma_5^l	((4,0),(4,0),(4,0),(4,0),(4,0))	(60,60,60,60,60)	4	0	60
ma_3^h	((1,0),(1,0),(1,2))	(59.5,59.5,45.5)	1	0.667	54.833333
	((1,0),(1,1),(1,1))	(59.5,52.5,52.5)	1	0.667	54.833333
ma_5^h	((1,0),(1,0),(1,0),(1,0),(1,2))	(59.5,59.5,59.5,59.5,45.5)	1	0.4	56.7
	((1,0),(1,0),(1,0),(1,1),(1,1))	(59.5,59.5,59.5,52.5,52.5)	1	0.4	56.7

[1] av. = average (mean values) for Nash equilibrium a_i^*, m_i^* and Eu_i^*

Table 3.4: Social optima

Treatment	**SO strategy profiles** $(a_i, m_i)_i$	**SO payoffs (Taler)**	**av. SO** a_i[1]	**av. SO** m_i[1]	**av. SO payoff**[1]
$m0_3$	((0,0),(0,0),(0,6))	(80,80,32)	0	2	64
	((0,0),(0,1),(0,5))	(80,72,40)	0	2	64
	⋮	⋮			
	((0,2),(0,2),(0,2))	(64,64,64)	0	2	64
$m0_5$	((0,0),(0,0),(0,0),(0,0),(0,8))	(84,84,84,84,16.8)	0	1.6	70.56
	((0,0),(0,0),(0,0),(0,1),(0,7))	(84,84,84,75.6,25.2)	0	1.6	70.56
	⋮	⋮			
	((0,1),(0,1),(0,2),(0,2),(0,2))	(75.6,75.6,67.2,67.2,67.2)	0	1.6	70.56
ma^l_3	((2,0),(2,0),(1,4))[2]	(79.2,79.2,45.1)	1.666667	1.333333	67.833333
ma^l_5	((1,0),(1,0),(1,0),(1,0),(0,6))[2]	(83.6,83.6,83.6,83.6,32)	0.8	1.2	73.28
ma^h_3	((0,0),(0,0),(0,6))	(80,80,32)	0	2	64
	((0,0),(0,1),(0,5))	(80,72,40)	0	2	64
	⋮	⋮			
	((0,2),(0,2),(0,2))	(64,64,64)	0	2	64
ma^h_5	((0,0),(0,0),(0,0),(0,0),(0,8))	(84,84,84,84,16.8)	0	1.6	70.56
	((0,0),(0,0),(0,0),(0,1),(0,7))	(84,84,84,75.6,25.2)	0	1.6	70.56
	⋮	⋮			
	((0,1),(0,1),(0,2),(0,2),(0,2))	(75.6,75.6,67.2,67.2,67.2)	0	1.6	70.56

[1] av. = average (mean values) for socially optimal a_i, m_i and Eu_i

[2] The asymmetry of the unique SO in the ma^l-treatments is due to the particular payoff function employed: In the SO, one player bears the whole mitigation burden. With a relatively small residual, adaptation is less beneficial for this particular player than for the other players.

of control questions via computer. The answers were checked automatically so that subjects entered the next stage only after they had answered the control questions correctly. The instruction phase ended with a trial run which mimicked the real experiment but used different parameter values. In the trial run, unlike in the real experiment, subjects were not matched to groups. Instead, the contributions of the other group members were simulated by a random number generator to prevent anchoring. The subjects were instructed that the trial run would not affect their earnings.

In the decision stage of the experiment, all subjects performed all six choice tasks covering the six treatments. By this method, we automatically control for unobservable personal idiosyncrasies (Friedman and Sunder, 1994, p. 25; Friedman and Cassar, 2004, p. 35-7). Moreover, we acquire a large number of independent within-subject datasets. Indeed, the within-subject differences were of particular interest for us, since all hypotheses put to test refer to comparisons and not mere absolute values.

At the beginning of each choice task, subjects were individually informed about the treatment. They learned about the number of subjects per group in this particular round, the availability of adaptation in this round, and -where available- the unit price of adaptation. Every subject was endowed with a budget of 100 Taler, which they could invest in probability reduction (mitigation) and/or loss reduction (adaptation). They were also free to retain all or part of their budget. Based on this information, subjects made their investment decision by entering the desired units of mitigation and/or -if available- adaptation. The computers were equipped with a payoff calculator so that subjects could preview the payments they would receive in the good state and the bad state respectively. Before making their final choice, subjects could try out different combinations of mitigation and adaptation.

To control for order effects such as practice, fatigue or boredom (Friedman and Cassar, 2004, p. 35-7), the sequence of the six treatments was randomized for each subject. During the whole decision stage, the choices of the other subjects were kept secret. I refrained from providing any feedback in order to minimize learning effects and reputational effects. Acknowledging the risk that, due to lack of feedback, subjects may fail to fully grasp the effects of their decisions, I attached great importance to the instruction phase with very detailed experiment instructions and a dry run with simulated data in lieu of a real group matching.

After all subjects had run through the whole sequence of choice tasks, one treatment was randomly drawn as the paying period. For this definite treatment, subjects were randomly matched into groups. For each group, the computer calculated the group aggregate level of mitigation and -based thereon- the group-specific probability distribution for the occurrence of the loss event. Then, for each group, a random number was drawn from the group probability distribution to determine whether or not the loss event had occurred to the group. If "no loss" was realized, group members kept their retained budget, i.e., the share of their initial endowment that was not spent on mitigation and/or adaptation. If "loss" was realized, they received their retained budget minus a loss which depended on their individual level of adaptation. This payment scheme was aimed at creating a monetary incentive most suitable to the one-shot, "all-or-nothing" character of the underlying climate change issue (see also Andreoni and Croson, 2008). Moreover, I chose a payment structure with an initial endowment at the risk of loss that reflects the real-world climate change policy decision, acknowledging that factors such as loss aversion and the endowment effect might influence decision behavior as most prominently described by Kahneman and Tversky (1979); Tversky and Kahneman (1992). In this respect, the current experiment is in line with previous experiments on mitigation and/or adaptation such as Milinski et al. (2008) and Hasson et al. (2010).

The session ended after all subjects had filled out a final computerized questionnaire containing socio-economic and personality items as well as questions on framing and strategy (Appendix 3.B). The participants were called up for payment individually and anonymously. The average session duration was 1h 20 m including instruction time. Each participant was paid a show-up fee of 7 Euro plus the individual earnings of the paying period at a conversion rate of 8 Taler = 1 Euro. Payments (including show-up fee) ranged between 7.00 Euro and 19.5 Euro with an average of 15.95 Euro over all sessions which is slightly above usual earnings in student jobs.

3.4 Data and Methods of Analysis

3.4.1 Data Description

The descriptive statistics of the average choices and the resulting expected payoffs are summarized in Table 3.5. The mean values for m_i and a_i are reported directly from the observations. To calculate the average expected payoffs (EU_av_i), I use the individual loss rates of the subjects (depending on a_i) and the residual budgets (depending on m_i and a_i). The loss probabilities $p_i(M)$ are first determined group-wise for each treatment using the group aggregate M and then averaged over all groups. In order to eliminate noise caused by the group effect, I use these treatment-specific, group-average loss probabilities for the calculation of average expected payoffs. To check for robustness, however, all statistical analyses reported in this section are also conducted with the actual expected payoffs (EU_i) resulting from one particular randomly chosen group

Table 3.5: Summary statistics

Treatment	Variable	Mean	Std. Dev.	Min.	Max.	N
$m0_3$	m	2.217	0.954	0	5	120
	a	0	0	0	0	120
	EU	62.025	6.507	42	75.6	120
	EU_av	62.306	7.639	40.025	80.05	120
$m0_5$	m	1.633	0.925	0	4	120
	a	0	0	0	0	120
	EU	70.138	7.176	51.6	90	120
	EU_av	70.315	7.776	50.425	84.042	120
ma_3^l	m	0.9	1.032	0	8	120
	a	2.933	1.228	0	6	120
	EU	63.529	8.285	9.6	78	120
	EU_av	63.233	8.894	8.05	72.569	120
ma_3^h	m	1.317	0.953	0	4	120
	a	1.058	0.748	0	2	120
	EU	56.038	6.809	36.9	72	120
	EU_av	55.075	6.228	35.759	67.545	120
ma_5^l	m	0.683	0.733	0	3	120
	a	2.817	1.202	0	5	120
	EU	67.456	6.465	45	80.75	120
	EU_av	67.166	6.643	47.233	75.255	120
ma_5^h	m	1.075	0.945	0	3	120
	a	1.008	0.750	0	3	120
	EU	60.709	8.819	36	84	120
	EU_av	60.226	7.549	35.547	72.167	120

matching. The results are very similar.

By means of the post-experimental questionnaire (see Appendix 3.B), I gathered subject-specific data on the following treatment-invariant control variables: (1) personality items: extraversion (*Extra*), agreeableness (*Agree*) , conscientiousness (*Consc*), neuroticism (*Neuro*) , openness (*Open*), risk aversion (*RiskAv*) (data source: self-reported in the questionnaire on a 1-5 scale as proposed in Rammstedt and John, 2007); (2) socioeconomic variables: age (*Age*), sex (*Female*), experimental experience (*Experience*), major subject (*Econ*), job, and income (data source: self-reported in the questionnaire). Finally, I create dummy variables for $period_{it}$ and *session* to control for order effects and sessions effects.

My hypotheses refer to within-subject differences between treatments. I thus treat the dataset as a panel with the SubjectID as the panel variable and the treatment as the time variable. y_{it} denotes the level of y for subject i in treatment t.

3.4.2 Analytical Methods

Linear Regressions. In the first step of the analysis, I run a random-effects GLS regression based on a multiple linear regression model with treatment dummy variables. The model is described by

$$(R1)\ y_{it} = \alpha_i + \beta_0 + \beta_1 treatments_t + \epsilon_{it}.$$

The dependent variables vector y_{it} consists of the individual treatment-specific levels of mitigation(m_{it}), adaptation (a_{it}), and average expected payoff (Eu_av_{it}). The *treatments* vector contains a set of three treatment dummy variables: *adapt* (player can adapt; yes=1, no=0), *low* (unit cost of adaptation; low=1 (5 Taler), high=0 (15 Taler)), and *size* (number of players per group; small=0 (3 group members), large=1 (5 group members)). The interaction effects of these three dummies are included as *adapt*×*size*, and *adapt*×*low*×*size*. Based on the reference treatment $m0_3$, all treatment effects can be explained independently by the dummy and interaction variables as summarized in Table 3.6. The time effects not captured by the treatment variables are negligible. The idiosyncratic variance is represented by the error term $u_{it} = \alpha_i + \epsilon_{it}$.

In a second linear regression, I add a control vector ind_i to the model:

$$(R2)\ y_{it} = \alpha_i + \beta_0 + \beta_1 treatments_t + \beta_2 ind_i + \epsilon_{it}.$$

Table 3.6: Treatment dummy variables

Treatment	**adapt**	**size**	**low**	**a×s**	**a×l×s**
$m0_3$	0	0	0	0	0
$m0_5$	0	1	0	0	0
ma_3^l	1	0	1	0	0
ma_5^l	1	1	1	1	1
ma_3^h	1	0	0	0	0
ma_5^h	1	1	0	1	0

adapt (a) = player can adapt (0=no, 1=yes)
size (s) = group size (0=small (3 group members), 1=large (5 group members))
low (l) = unit cost of adaptation (0=high (15 Taler), 1=low (5 Taler))

The majority of control variables proved insignificant and small-sized. By backward elimination, I removed most of them; the only variables left in the final ind_i vector are *Open* and *Experience*. The *session* and $period_{it}$ dummies could also be dropped from the final model due to insignificance. As before, ϵ_{it} captures the unexplained variance.

Poisson Regressions. Aware of the fact that the subjects' choices for m_{it} and a_{it} are counts (i.e., non-negative integers), I set up a second regression series based on the assumption that m and a are Poisson distributed. As recommended by Cameron and Trivedi (2009, chap. 17.3), I employ Poisson regression models with robust standard errors to deal with complications that can occur when count data are estimated with linear models. These complications result from heteroscedasticity, the small mean property of the dependent variable and truncations in the observed distribution of the dependent variable. The Poisson models are specified as

$$(P1)\ y_{it} = \exp\left(\alpha_i + \beta_0 + \beta_1 treatments_t + \epsilon_{it}\right)$$

and

$$(P2)\ y_{it} = \exp\left(\alpha_i + \beta_0 + \beta_1 treatments_t + \beta_2 ind_i + \epsilon_{it}\right).$$

Robustness Checks. As an additional check for robustness, I run both the GLS and the Poisson regressions again with subject fixed effects. Since the time effects not captured by the treatment variables are negligible, the results of the fixed effect model are qualitatively identical to those of the first random effects regression model R1; moreover, after conversion, the GLS and Poisson fixed effects regression results are identical in terms of coefficients and exhibit only minor differences in significance levels. The fixed effects regression results are listed in Appendix 3.C.

I also conduct paired difference tests on the within-subject differences of any two variables. Since it could not with certainty be assumed that the differences are interval and normally distributed, I use the non-parametric Wilcoxon signed rank test for this purpose. Paired t-tests are conducted as well and yield very similar results. All calculations for the statistical analysis are performed using Stata v12.1.

3.5 Results

The estimation results from the GLS random effects regressions are listed in Table 3.7. The estimation results from the Poisson random effects regressions are listed in Table 3.8. After conversion, the coefficients of both model types are identical, with only very minor differences in significance levels, which is an indicator for robustness. For the sake of convenience, unless noted otherwise, I refer in the following analysis to the results from the GLS regression model R1 (Table 3.7). Without individual effects, the regression outcomes can easily be compared with the benchmarks: the constants from model R1 equate to the expected means of the dependent variables for the reference case $m0_3$, and the expected means for the other treatments can easily be computed by just adding the respective coefficients.

3.5.1 Treatment Effects

Adaptation. Adaptation increases as the unit cost of adaptation decrease. Obviously, adaptation is zero in the $m0_3$ and the $m0_5$ treatments. In the high-cost ma^h treatments, the average adaptation level is approx. 1; in the low-cost ma^l-treatments, the average adaptation level is approx. 2.9, which is almost three times as high. The coefficient for the *low* dummy is positive and highly significant. On the basis of Wilcoxon signed ranks tests, the null hypotheses H0: $a_i(ma_3^l) = a_i(ma_3^h)$ and H0: $a_i(ma_5^l) = a_i(ma_5^h)$ can be rejected with ($p = 0.0000$). These observations support (H1a).

Adaptation levels do not depend on the group size. The *size* coefficient is negligible; there is no significant difference in adaptation levels between treatments with equal unit cost of adaptation that differ in group size only. On the basis of Wilcoxon signed ranks tests, the null hypotheses H0: $a_i(ma_3^l) = a_i(ma_5^l)$ and H0: $a_i(ma_3^h) = a_i(ma_5^h)$ cannot be rejected at any meaningful significance level ($p = 0.3356$ and 0.5560, respectively). These observations support (H1b).

Table 3.7: Treatment effects: m, a and EU_av (GLS random effects regression)

regressand	m		a		EU_av	
model	R1	R2	R1	R2	R1	R2
adapt	-0.900***	-0.900***	1.058***	1.058***	-7.231***	-7.231***
	(0.102)	(0.102)	(0.0922)	(0.0922)	(0.793)	(0.793)
size	-0.583***	-0.583***	2.23e-14	-3.61e-14	8.009***	8.009***
	(0.102)	(0.102)	(0.0922)	(0.0922)	(0.793)	(0.793)
low	-0.417***	-0.417***	1.875***	1.875***	8.158***	8.158***
	(0.102)	(0.102)	(0.0922)	(0.0922)	(0.793)	(0.793)
a×s	0.342**	0.342**	-0.0500	-0.0500	-2.859**	-2.859**
	(0.144)	(0.144)	(0.130)	(0.130)	(1.121)	(1.121)
a×l×s	0.0250	0.0250	-0.0667	-0.0667	-1.217	-1.217
	(0.144)	(0.144)	(0.130)	(0.130)	(1.121)	(1.121)
Open		0.115**		-0.0198		-1.147**
		(0.0537)		(0.0487)		(0.452)
Experience		-0.238***		-0.0130		2.016***
		(0.0784)		(0.0712)		(0.661)
_cons	2.217***	2.526***	-1.94e-14	0.0944	62.31***	60.18***
	(0.0847)	(0.284)	(0.0752)	(0.258)	(0.685)	(2.386)
N	720	720	720	720	720	720
R^2	0.2313	0.2647	0.6775	0.6777	0.2975	0.3355

Robust standard errors in parentheses

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

Table 3.8: Treatment effects: m and a (Poisson random effects regression)

regressand	m		a	
model	P1	P2	P1	P2
adapt	-0.521***	-0.521***		
	(0.100)	(0.100)		
size	-0.305***	-0.305***	-0.0484	-0.0484
	(0.0941)	(0.0941)	(0.127)	(0.127)
low	-0.380***	-0.380***	1.019***	1.019***
	(0.125)	(0.125)	(0.104)	(0.104)
a×s	0.103	0.103		
	(0.151)	(0.151)		
a×l×s	-0.0726	-0.0726	0.00781	0.00781
	(0.189)	(0.189)	(0.148)	(0.148)
Open		0.0871**		-0.0153
		(0.0412)		(0.0376)
Experience		-0.154***		-0.00999
		(0.0546)		(0.0544)
_cons	0.796***	0.950***	0.0567	0.129
	(0.0667)	(0.207)	(0.0899)	(0.210)
lnalpha				
_cons	-2.497***	-2.840***	-3.672***	-3.684***
	(0.351)	(0.444)	(0.865)	(0.873)
N	720	720	480	480

Robust standard errors in parentheses

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

Mitigation. Mitigation decreases as the unit cost of adaptation decrease. Without consideration of group size, the average level of mitigation is highest in the $m0$-treatments, i.e., where adaptation is not available or prohibitively costly. The average level of mitigation is by 0.9 units lower in the ma^h-treatments than in the $m0$-treatments (coefficient for *adapt*), and by 0.417 units lower in the ma^l-treatments than in the ma^h-treatments (coefficient for $adapt \times low$). The regression results indicate that decreasing adaptation costs have a strongly negative and significant effect on mitigation on a 99% confidence level. The significance is further confirmed by a series of Wilcoxon signed rank tests on the treatment-specific (cost-induced) mitigation differences: the null hypotheses H0: $m_i(m0_3) = m_i(ma_3^h)$, H0: $m_i(m0_5) = m_i(ma_5^h)$, H0: $m_i(m0_3) = m_i(ma_3^l)$, H0: $m_i(m0_5) = m_i(ma_5^l)$, H0: $m_i(ma_3^h) = m_i(ma_3^l)$ and H0: $m_i(ma_5^h) - m_i(ma_5^l)$ can all be rejected with $p = 0.0000$. These observations support (H2).

The average level of mitigation decreases as the group size increases. Without consideration of adaptation cost, the average level of mitigation for n=3 treatments exceeds the average level of mitigation for n=5 treatments by 0.583 units. The group-size induced differences are highly significant on the basis of the regression analysis as well as based on the Wilcoxon signed rank tests (H0: $m_i(m0_3) = m_i(m0_5)$ can be rejected with $p = 0.0000$, H0: $m_i(ma_3^h) = m_i(ma_5^h)$ can be rejected with $p = 0.0008$, and H0: $m_i(ma_3^l) = m_i(ma_5^l)$ can be rejected with $p = 0.0013$). The difference is largest (1.52 units) for $m0$-treatments, slightly smaller (1.43 units) for ma^h-treatments and smallest (0.72 units) for ma^l-treatments. These observations support (H3).

Other than hypothesized, the average group aggregate level of mitigation M is not constant in n. (H3) implies that the average individual level of mitigation is 0.6 times lower for n=5 treatments than for the corresponding n=3 treatments; however, the actual factors are 0.74 for $m0$-treatments, 0.76 for ma^l-treatments and 0.82 for ma^h-treatments.

Payoffs. Payoffs respond non-monotonically to an increase in unit cost of adaptation. The regression analysis shows that, without consideration of group size, the average expected payoffs are by 8.158 Taler higher in the ma^l-treatments than in the ma^h-treatments, and by 7.231 Taler lower in the ma^h-treatments than in the $m0$-treatments. These results are highly significant, as additionally confirmed by a series of Wilcoxon signed rank tests on the cost-induced payoff differences: the null hypotheses of the difference tests H0: $Eu_i(ma_5^l) = Eu_i(ma_5^h)$, H0: $Eu_i(ma_3^l) = Eu_i(ma_3^h)$, H0: $Eu_i(ma_5^h) = Eu_i(m0_5)$ and H0: $Eu_i(ma_3^h) = Eu_i(m0_3)$ can all be rejected with $p = 0.0000$, which yields support for (H4).

The positive group size effect on payoffs diminishes as the unit cost of adaptation

decrease. Irrespective of adaptation cost, average payoffs are significantly higher for n=5 than for n=3. The size effect is largest in the $m0$-treatments (*size* coefficient of 8.009). It is by 2.859 Taler smaller in the ma^h-treatments ($adapt \times size$ coefficient, significant on a 95% confidence level) and even smaller -yet not significant- for ma^l-treatments as indicated by the $adapt \times low \times size$ coefficient of -1.217.
The significance of the differences-in-differences is confirmed by the according Wilcoxon signed rank tests: H0: $(Eu_i(m0_5) - Eu_i(m0_3)) = (Eu_i(ma^h_5) - Eu_i(ma^h_3))$ can be rejected with $p = 0.0001$, H0: $(Eu_i(m0_5) - Eu_i(m0_3)) = (Eu_i(ma^l_5) - Eu_i(ma^l_3))$ can be rejected with $p = 0.0000$, and $(Eu_i(ma^h_5) - Eu_i(ma^h_3)) = (Eu_i(ma^l_5) - Eu_i(ma^l_3))$ can be rejected with $p = 0.0031$. This result supports (H5).

3.5.2 Benchmark Comparison: Nash Equilibrium and Social Optimum

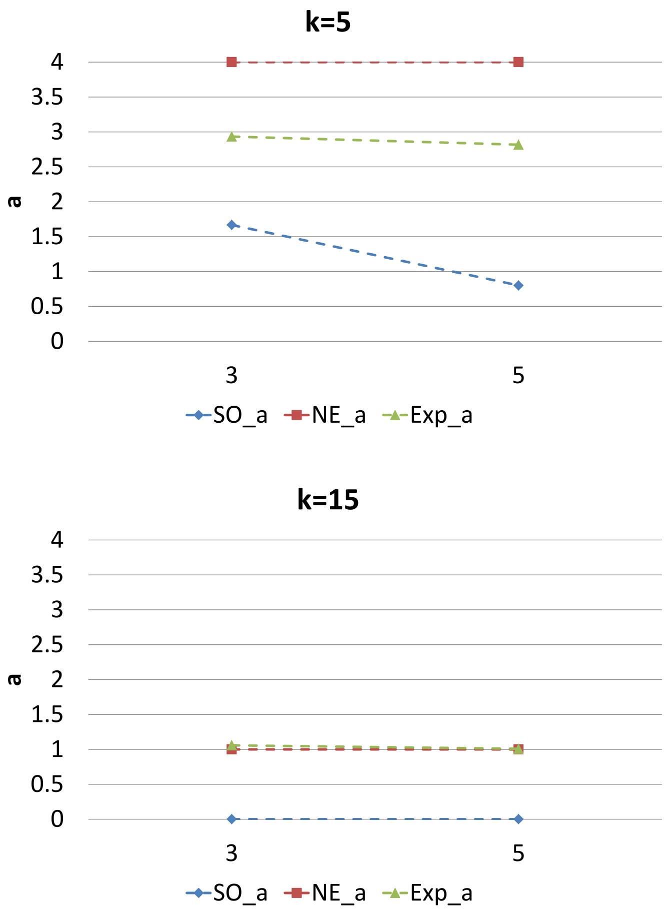
Qualitatively, the experimental results corroborate all hypotheses that were derived from the theory. By comparing our observations with the corresponding Nash equilibria (see Table 3.3) and social optima (see Table 3.4), we can make some statements about quantities as well. Figures 3.1 to 3.6 provide an additional summary of the benchmark comparison.

Adaptation. Figures 3.1 and 3.2 visualize the impact of group size and adaptation cost on the level of adaptation. In the ma^l-treatments, the average observed level of adaptation is 2.9, which is approx. one unit below the Nash equilibrium level. Both the Nash equilibrium level of adaptation and the observed level of adaptation are independent of the group size n. In contrast, the socially optimal level of adaptation decreases in n: it ranges about 1.3 units below the average observed level of adaptation for $n = 3$ and even 2 units below the average observed level of adaptation for $n = 5$.

In the ma^h-treatments, the average observed level of adaptation is 1, which is approximately equal to the Nash equilibrium level of adaptation. As in the low-cost treatments, both the Nash equilibrium level of adaptation and the observed level of adaptation are independent of the group size n. The socially optimal level of adaptation in the ma^h-treatments is zero.

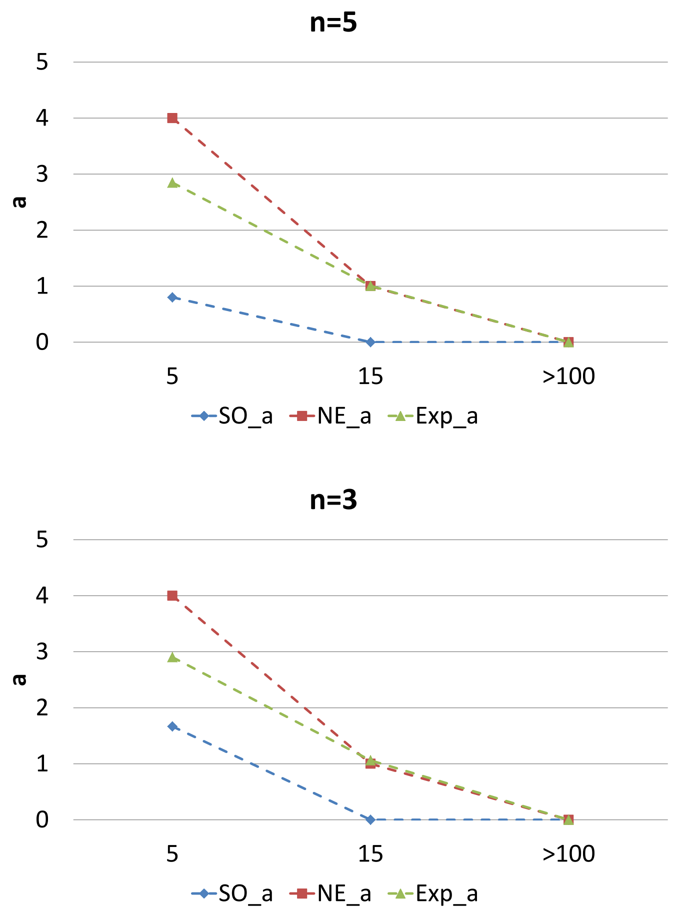
Mitigation. Figures 3.3 and 3.4 visualize the impact of group size and adaptation cost on the level of mitigation. In the ma^l- and ma^h-treatments, the average observed level of mitigation ranges between the Nash equilibrium level and the social optimum level. In the $m0$-treatments, i.e., where adaptation is not available, the average observed level of mitigation approximately equals the social optimum level for n=5 and even slightly

Figure 3.1: Adaptation levels depending on group size n



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

Figure 3.2: Adaptation levels depending on adaptation cost k_i



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

exceeds it for $n = 3$. Unlike predicted by the Nash equilibrium, the observed group aggregate level of mitigation is higher for n=5 than for n=3 for all levels of adaptation cost.

Payoffs. Figures 3.5 and 3.6 visualize the impact of group size and adaptation cost on the average expected payoff. As predicted by the Nash equilibrium, the average expected payoff calculated from the observations (for simplicity, hereafter denoted as observed payoff) responds non-monotonically on variations of k_i. In all six treatments, the observed payoff ranges between the Nash equilibrium payoff (lower bound) and the socially optimal payoff (upper bound). The subjects performed best in the $m0$-treatments and almost hit the social optimum in the $m0_5$-treatment. The observed payoffs are widest off the social optimum in the ma^h-treatments. The lowest payoff can be observed in the ma^h_3-treatment, where it approximately equals the Nash equilibrium payoff.

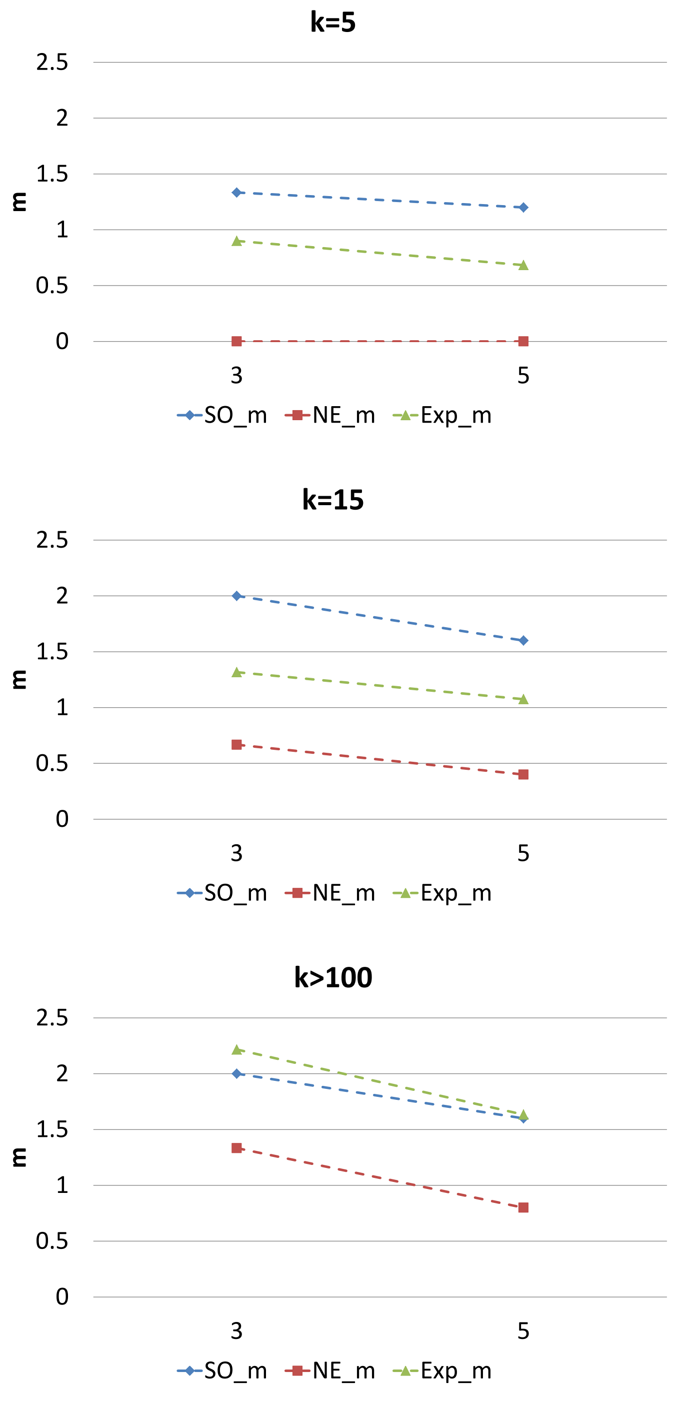
3.5.3 Effects of Socioeconomic Data and Order Effects

As already discussed, I chose a within-subject design for this experiment in order to control for unobservable idiosyncrasies. Moreover, I randomized the order of treatments to minimize order effects. Beyond these design elements, I tested for effects of socioeconomic characteristics and for session- and order effects. I did not find any evidence that the results depend on the order in which the tasks were performed.

The GLS and the Poisson regressions finally reported contain those variables that contribute discernibly to the R^2; all other variables such as number of siblings or monthly income were omitted as they proved irrelevant in previous regression runs. The between-subjects effect is small compared to the treatment effect. Two variables have a relatively small yet significant impact on mitigation and on the resulting payoffs: first, openness (subjects who reported themselves as more open contributed more to the public good mitigation and thus received a lower payoff in comparison to subjects who claimed to be less "open"); second, experimental experience (subjects who previously participated in economic experiments contributed significantly less to the public good mitigation and thus received a higher payoff due to free riding).

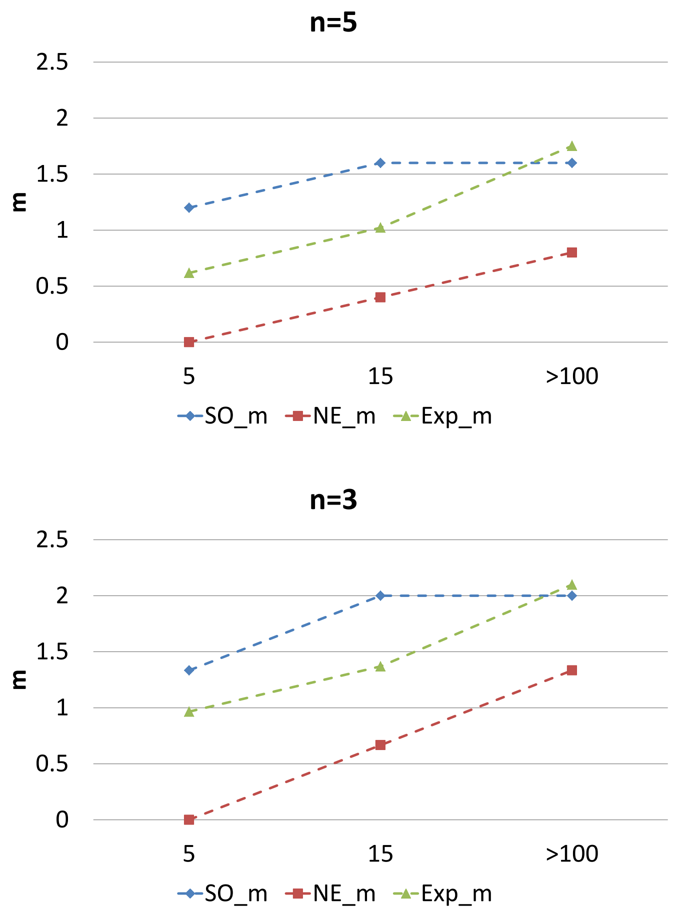
In addition to the treatment-average analysis, I also let the individual variables interact with the treatment dummies. By regressing m and a on the interaction terms, I tested for the effects of the individual variables conditional on treatments in order to find out whether they apply universally or depending on the context. Indeed, we find that the effects only occur in certain treatments. A high openness score goes along with a significantly higher level of mitigation in treatments $m0_5$ and ma^l_3, which we cannot

Figure 3.3: Mitigation levels depending on group size n



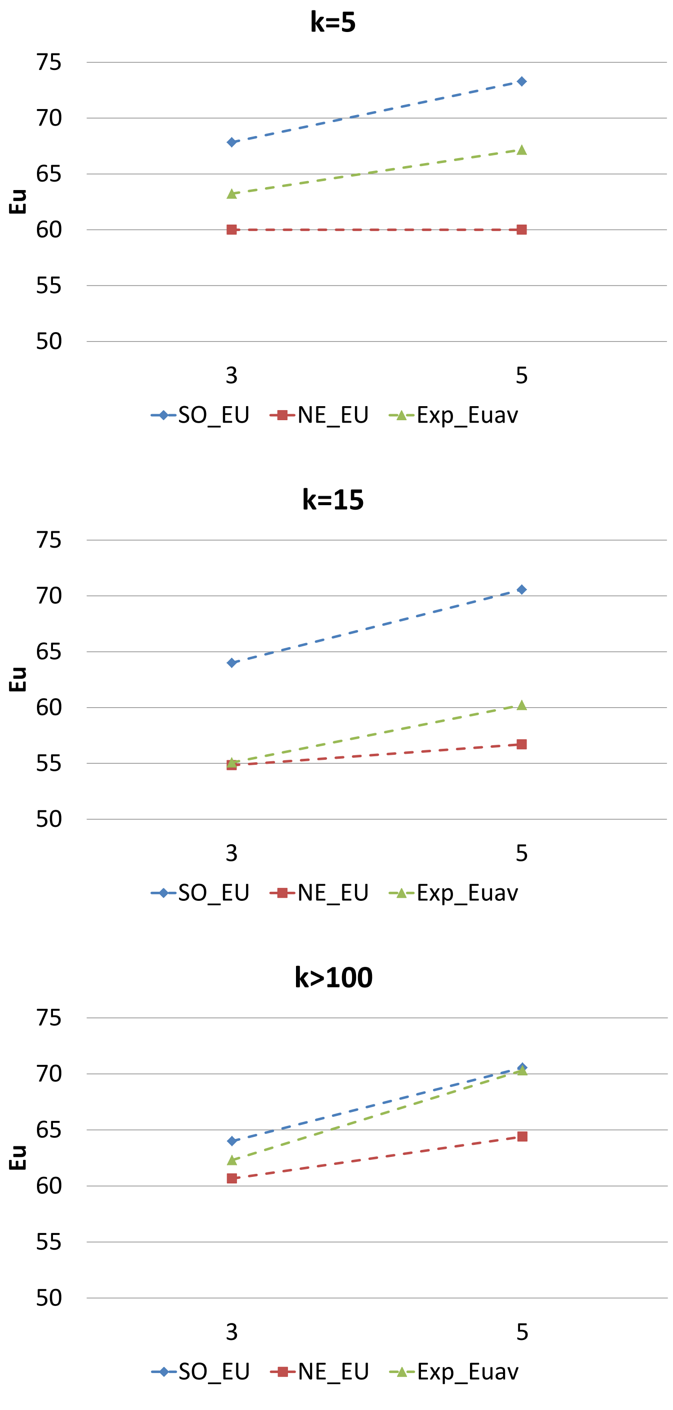
SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

Figure 3.4: Mitigation levels depending on adaptation cost k_i



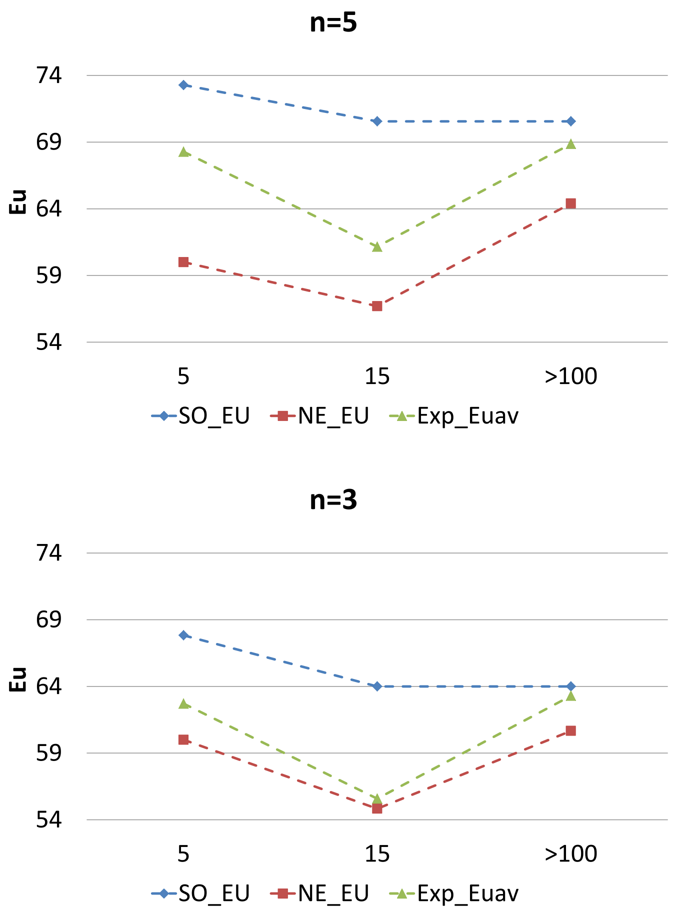
SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

Figure 3.5: Payoffs depending on group size n



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

Figure 3.6: Payoffs depending on adaptation cost k_i



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

interpret in a meaningful way. Interestingly, however, more experience goes along with significantly lower mitigation levels only in the treatments where adaptation was available but not in the $m0$ treatments. This indicates that more experienced players are more inclined to free riding than less experienced players.

3.6 Conclusion

The analysis suggests that the theoretical model proposed by Probst (2011) is suitable to explain the observations made in the laboratory.

Qualitatively, the experimental results provide substantial empirical support for the hypotheses stated on the basis of the model. In particular, the non-monotonic reaction of payoffs on variations of adaptation cost is even more evident in the experimental results than predicted by the Nash equilibrium.

In the $m0$-treatments, free riding on other group members' mitigation is not an issue: the average observed mitigation levels and thus the average observed payoffs are very close to the social optimum and thus well above the predictions made on the basis of the Nash equilibrium. Mitigation is even higher than socially optimal in the $m0_3$-treatment.

However, these socially optimal investment choices can only be observed in the absence of adaptation. As soon as adaptation becomes available, inefficiencies due to free riding arise. Although the socially optimal levels of mitigation and adaptation and the highest achievable payoffs are *identical* in the ma^h-treatments and the $m0$-treatments, subjects chose to substitute some mitigation by adaptation in both ma^h-treatments, which results in a considerably *lower* average observed payoff than in the corresponding $m0$-treatments. The average observed ma^h payoffs range at the Nash equilibrium level far below the social optimum. This is due to the negative strategic external effect which outweighs the comparatively small positive direct effect of substitution.

In the ma^l-treatments, the total effect of investments in adaptation is less clear-cut because the positive substitution effect is more pronounced: according to the regression results, the average observed payoff is by 0.927 Taler higher in ma^l_3 than in $m0_3$, whereas it is by 3.149 Taler lower in ma^l_5 than in $m05$. This indicates that the positive direct effect of substitution outweighs the negative strategic effect for smaller groups ($n{=}3$), and that the strategic effect outweighs the direct effect for larger groups ($n{=}5$).

Quantitatively, we observe that subjects systematically over-contribute to mitigation in all treatments. Such positive deviations from Nash equilibrium public good levels have previously been observed in many experimental studies (see, for example, Andreoni (1995); Croson (2008); Fischbacher and Gächter (2010); Fischbacher et al. (2001); Palfrey and Prisbrey (1997); Goeree et al. (2002)). The behavioral economics literature proposes different explanations for voluntary contributions to public goods (Holt and Laury, 2008), some of which (such as e.g. reciprocity and learning) only apply to repeated games. In our one-shot context, the above-Nash contributions to mitigation could possibly be traced back to non-monetary utility components like altruism or inequity aversion as modeled by Fehr and Schmidt (1999) and, similarly, Bolton and Ockenfels (2008).

3.A Experimental Instructions

Experimentanleitung

Allgemeine Informationen

Herzlich Willkommen! Sie werden gleich an einem Experiment teilnehmen. Die Durchführung des Experiments wird ca. 90 Minuten in Anspruch nehmen. Alle Teilnehmerinnen und Teilnehmer befinden sich in derselben Entscheidungssituation und haben dieselben Entscheidungsmöglichkeiten. Das Experiment besteht aus 6 voneinander unabhängigen Spielen. Ihre Entscheidungen in einem Spiel haben also keinen Einfluss auf die anderen Spiele.

Für Ihre Teilnahme erhalten Sie eine Basisvergütung (Fixbetrag) von 7 Euro. Abhängig von Ihren Entscheidungen, den Entscheidungen der anderen Teilnehmer und einem gewissen Maß an Zufall können Sie zusätzliches Geld verdienen. Zur Ermittlung Ihres Verdienstes wird am Ende des Experiments aus den 6 gespielten Spielen ein Spiel ausgelost. Sie erhalten zusätzlich zur Basisvergütung die in diesem Spiel erzielte Auszahlung. Im Experiment werden alle Zahlungen in Talern berechnet, die am Ende in Euro umgerechnet und in bar an Sie ausgezahlt werden, ohne dass andere Teilnehmerinnen und Teilnehmer erfahren, wie viel Geld Sie erhalten. Der Umrechnungskurs der Spielwährung beträgt

8 Taler = 1 Euro.

Alle Entscheidungen im Experiment bleiben anonym, d.h. keine andere Teilnehmerin und kein anderer Teilnehmer erhält Informationen über ihre Identität, weder während noch nach dem Experiment. Genauso erhalten Sie keine Information über die Identität der anderen Teilnehmerinnen und Teilnehmer.

Es ist wichtig, dass Sie die Anleitung zu dem Experiment vollständig verstehen. Bitte lesen Sie sich die folgenden Seiten deshalb gründlich durch. Wenn Sie Fragen haben, dann heben Sie bitte die Hand und der Experimentleiter wird ihre Fragen beantworten. Um sicherzustellen, dass Sie die Anleitung verstanden haben, bitten wir Sie, im Anschluss an die Instruktionsphase einige Kontrollfragen zu beantworten. Es folgt noch eine Proberunde, bevor dann das eigentliche Experiment beginnt.

Nach Abschluss des Experiments gibt es noch einen Fragebogen, den Sie bitte am Computer ausfüllen.

Während des Experiments ist es nicht gestattet, mit den anderen Teilnehmern zu kommunizieren. Mobiltelefone müssen während des gesamten Experiments ausgeschaltet sein. Außerdem dürfen Sie am Computer nur diejenigen Funktionen bedienen, die für den Ablauf des Experiments bestimmt sind. Kommunikation oder Herumspielen am Computer führen zum Ausschluss vom Experiment und zum Verlust aller Einnahmen.

Experimentbeschreibung

Zu Beginn des ersten Spiels werden alle Teilnehmerinnen und Teilnehmer zufällig in gleich große Gruppen eingeteilt. Die Gruppengröße kann von Spiel zu Spiel variieren; Ihnen wird vor Spielbeginn mitgeteilt, wie viele Personen in Ihrer Gruppe sind. Vor jedem weiteren Spiel werden die Gruppen neu eingeteilt, und zwar so, dass in jedem neuen Spiel andere Mitspieler aufeinandertreffen. Sie werden also während des gesamten Experiments in einem Spiel niemals wieder auf Mitspieler treffen, mit denen Sie zuvor schon einmal in einer Gruppe waren. Die Gruppeneinteilung erfolgt anonym, d.h. weder während noch nach dem Experiment erfahren Sie, wann Sie mit welchen anderen Personen in einer Gruppe sind oder waren.

Zu Beginn eines jeden Spiels erhalten Sie 100 Taler als persönliches Guthaben. Mit einer bestimmten Wahrscheinlichkeit tritt ein Ereignis ein, durch welches Sie diese 100 Taler ganz oder teilweise verlieren. Sie haben zwei Möglichkeiten, diesem Risiko zu begegnen:

(1.) Wahrscheinlichkeitsreduktion. Diese Möglichkeit haben Sie in allen 6 Spielen.
(2.) Verlustreduktion. Diese Möglichkeit haben Sie in einigen der 6 Spiele, in anderen nicht.

Sie können Ihr Guthaben ganz oder teilweise in Wahrscheinlichkeitsreduktion und/oder in Verlustreduktion (sofern im Spiel verfügbar) investieren. Ob Sie die Möglichkeit zur Verlustreduktion haben oder nicht, erfahren Sie zu Beginn eines jeden Spiels. Alle Gruppenmitglieder treffen ihre Entscheidung geheim und anonym. Einmal getroffene Entscheidungen können nicht rückgängig gemacht werden.

(1.) Wahrscheinlichkeitsreduktion. Wenn Sie und/oder andere Mitglieder Ihrer Gruppe in Wahrscheinlichkeitsreduktion investieren, reduziert sich die Wahrscheinlichkeit für den Eintritt des Verlustereignisses für alle Gruppenmitglieder (einschließlich Ihnen). In welchem Maße die Wahrscheinlichkeit abnimmt, hängt von der Gesamtanzahl der in der Gruppe gekauften Einheiten Wahrscheinlichkeitsreduktion ab. Es ist dabei unerheblich, durch welches Gruppenmitglied/welche Gruppenmitglieder die Investition erfolgt.

Ob das Verlustereignis für Ihre Gruppe eintritt oder nicht, entscheidet ein Zufallsgenerator, der eine Kugel aus einem (virtuellen) Behälter mit 100 Kugeln zieht. Ist die gezogene Kugel rot, so ist das Verlustereignis eingetreten; ist sie weiß, so ist das Verlustereignis nicht eingetreten. Zunächst sind alle 100 Kugeln im Behälter rot, d.h., es ist zu 100% sicher, dass das Verlustereignis eintritt. Durch den Kauf von Wahrscheinlichkeitsreduktion können Sie und die anderen Gruppenmitglieder rote Kugeln durch weiße Kugeln ersetzen. Jede Einheit Wahrscheinlichkeitsreduktion kostet **10 Taler**. Die durch Ihre Gruppe gekaufte Wahrscheinlichkeitsreduktion verringert die Wahrscheinlichkeit für das Verlustereignis wie folgt:

Wahrscheinlichkeitsreduktion Gruppe gesamt (in Einheiten)	Anzahl Kugeln weiß	Anzahl Kugeln rot =Verlustwahrscheinlichkeit in %
0	0	100
1	30	70
2	50	50
3	60	40
4	70	30
5	75	25
6	80	20
7	82	18

Wahrscheinlichkeitsreduktion Gruppe gesamt (in Einheiten)	Anzahl Kugeln weiß	Anzahl Kugeln rot =Verlustwahrscheinlichkeit in %
8	84	16
9	86	14
10	88	12
11	90	10
12	91	9
13	92	8
14	93	7
15	94	6
16 … 50	95	5

Ab der 17. Einheit Wahrscheinlichkeitsreduktion verringert sich die Verlustwahrscheinlichkeit nicht mehr weiter. Die Restwahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt dann 5% (d.h., 5 rote Kugeln bleiben immer im Behälter).

(2.) Verlustreduktion. Wenn das Verlustereignis eintritt (d.h. der Zufallsgenerator zieht eine rote Kugel), verlieren Sie Ihr gesamtes Guthaben. Durch Investition in Verlustreduktion können Sie Ihren persönlichen Verlust begrenzen. Die Verluste der anderen Gruppenmitglieder bleiben davon unberührt. Der Preis für eine Einheit Verlustreduktion wird Ihnen zu Beginn eines jeden Spiels bekanntgegeben. Er kann von Spiel zu Spiel variieren.

Die von Ihnen gekaufte Verlustreduktion verringert Ihre persönliche Verlustquote wie folgt:

Ihre Verlustreduktion (in Einheiten)	Ihr Verlust bei Eintritt des Verlustereignisses (in % des nicht ausgegebenen Guthabens)
0	100 %
1	60 %
2	40 %
3	30 %
4	25 %
5	20 %
6	18 %
7	16 %
8	14 %
9	12 %
10 … 20	10 %

Ab der 11. Einheit Verlustreduktion verringert sich die Verlustquote nicht mehr weiter. Die Rest-Verlustquote beträgt dann 10 %.

Achtung: In den Spielen ohne Möglichkeit zur Verlustreduktion können Sie Ihren persönlichen potenziellen Verlust <u>nicht</u> durch den Kauf von Verlustreduktion begrenzen. Bei Eintritt des Verlustereignisses (d.h., der Zufallsgenerator zieht eine rote Kugel) ist Ihr gesamtes Guthaben verloren.

==

Sie erhalten mit dieser Anleitung ein separates Blatt mit den Tabellen zur Wahrscheinlichkeits- und Verlustreduktion, dem Sie während des Experiments alle Angaben entnehmen können, ohne blättern zu müssen.

==

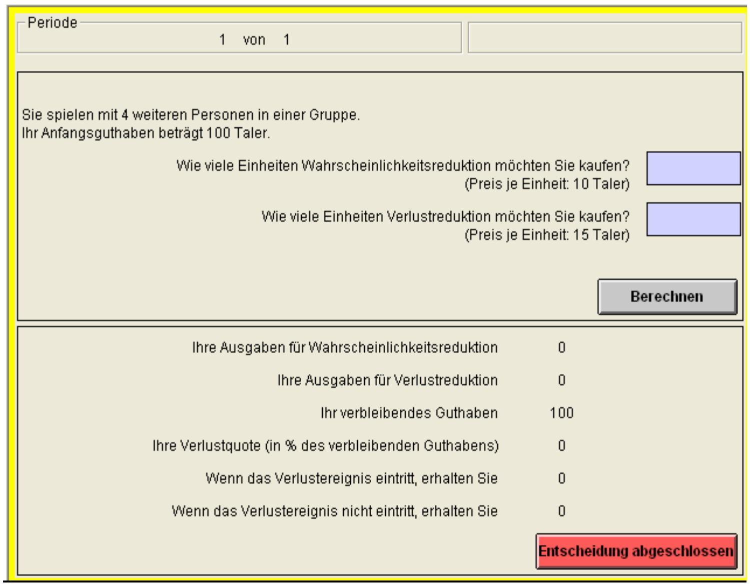
Experimentablauf im Detail

Vor dem Start eines jeden Spiels erscheint folgender Eingangsbildschirm:

Hier erfahren Sie, wie **viele Mitglieder** Ihre Gruppe in diesem Spiel hat, ob die **Möglichkeit zur Verlustreduktion** besteht und wie hoch der **Preis für eine Einheit Verlustreduktion** ist (sofern Verlustreduktion verfügbar ist). Das Spiel beginnt automatisch, sobald Sie auf „Spiel starten" geklickt haben.

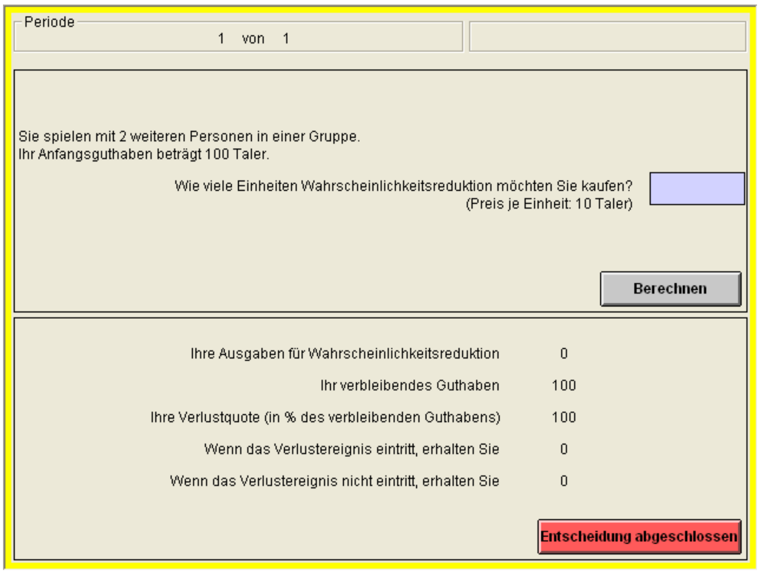
(1.) Entscheidung.

Ihre Aufgabe besteht nun darin, eine Kaufentscheidung zu treffen. Sie sehen auf dem Bildschirm:



Geben Sie im ersten Feld ein, wie viele Einheiten Wahrscheinlichkeitsreduktion Sie kaufen möchten. Geben Sie im zweiten Feld ein, wie viele Einheiten Verlustreduktion Sie kaufen möchten.

In den Spielen ohne Möglichkeit zur Verlustreduktion sieht der Bildschirm so aus:



Geben Sie ein, wie viele Einheiten Wahrscheinlichkeitsreduktion Sie kaufen möchten.

Wenn Sie keine Wahrscheinlichkeitsreduktion und/oder keine Verlustreduktion kaufen möchten, geben Sie bitte „0“ in das/die jeweilige(n) Feld(er) ein.

Klicken Sie anschließend auf „Berechnen“. Im unteren Teil des Bildschirms können Sie nun Ihre Ausgaben und Ihr verbleibendes Guthaben ablesen sowie Ihre Verlustquote und die Auszahlung, die Sie erhalten, wenn das Verlustereignis eintritt bzw. nicht eintritt. Solange Sie noch nicht auf „Entscheidung abgeschlossen“ geklickt haben, können Sie Ihre Kaufentscheidung beliebig oft revidieren. Wenn Sie eine oder beide Eingaben geändert haben, klicken Sie bitte anschließend auf „Berechnen“; dadurch werden die Informationen im unteren Teil des Bildschirms neu berechnet und aktualisiert.

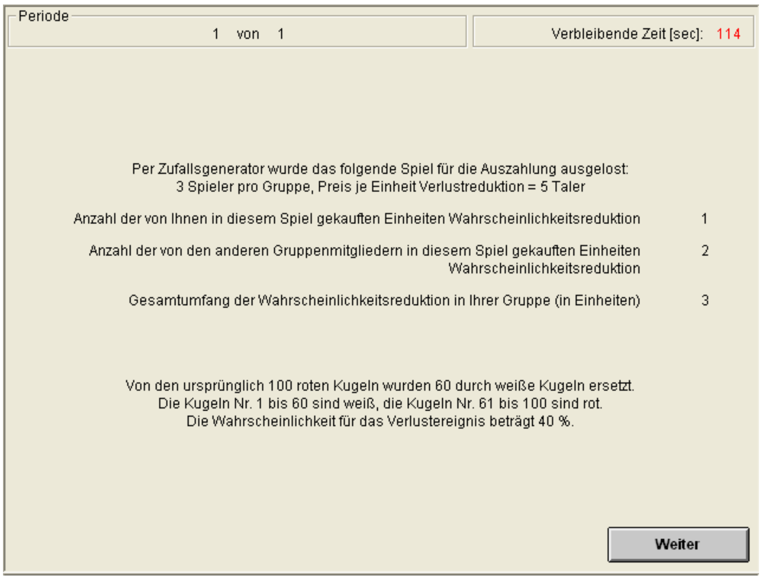
Wenn Sie Ihre endgültige Entscheidung getroffen haben, klicken Sie auf „Entscheidung abgeschlossen“, um dieses Spiel zu beenden. Ihre Eingaben sind jetzt gespeichert.

Das nächste Spiel startet daraufhin automatisch - wiederum mit dem Eingangsbildschirm wie oben beschrieben.

Wenn Sie alle 6 Spiele gespielt haben, erscheint ein Wartebildschirm (hier nicht gezeigt).

(2.) Auslosung des zahlungsrelevanten Spiels und Ermittlung der Wahrscheinlichkeit.

Wenn alle Teilnehmer die sechs Spiele durchlaufen und ihre Entscheidungen getroffen haben, erscheint folgender Bildschirm:

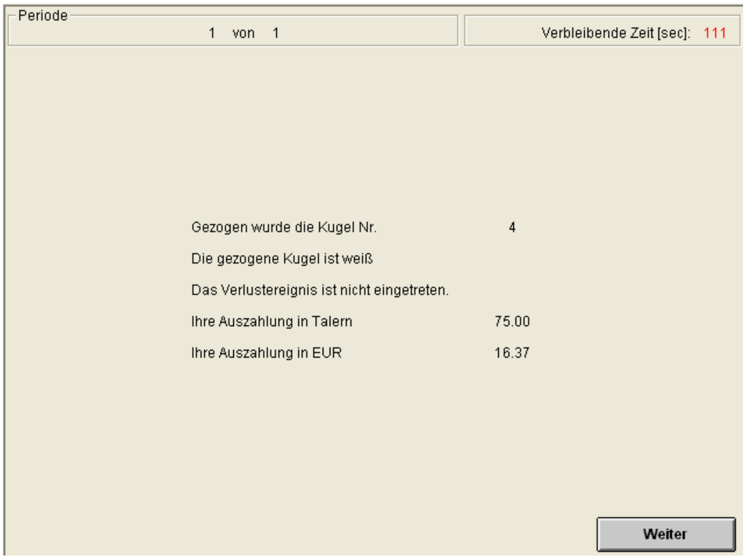


Sie erfahren nun, welches der sechs Spiele für die Auszahlung ausgelost wurde und wie viele Einheiten Wahrscheinlichkeitsreduktion in diesem Spiel von Mitgliedern Ihrer Gruppe gekauft wurden. Der Gesamtumfang der Wahrscheinlichkeitsreduktion bestimmt, wie viele rote Kugeln durch weiße Kugeln ersetzt werden und damit die Wahrscheinlichkeit für den Eintritt des Verlustereignisses.

Klicken Sie anschließend auf „Weiter".

(3.) Zufall und Auszahlung.

In der letzten Phase des Spiels wird per Zufallsgenerator aus den 100 Kugeln im Behälter eine Kugel gezogen. Sie sehen auf dem Bildschirm:



Angezeigt werden die Nummer der gezogenen Kugel (Zahl zwischen 1 und 100) und die Farbe dieser Kugel entsprechend der von Ihrer Gruppe gekauften Wahrscheinlichkeitsreduktion. Ist die gezogene Kugel rot, so ist das Verlustereignis eingetreten und Sie erhalten als Auszahlung in Talern Ihr verbleibendes Guthaben nach Ausgaben für Wahrscheinlichkeits- und Verlustreduktion abzüglich des Verlustes. Die Höhe des Verlustes hängt in den Spielen mit Möglichkeit zur Verlustreduktion davon ab, wie viele Einheiten Verlustreduktion Sie gekauft haben. Ist die gezogene Kugel weiß, so ist das Verlustereignis nicht eingetreten und Sie erhalten als Auszahlung in Talern Ihr verbleibendes Guthaben nach Abzug der Ausgaben für Wahrscheinlichkeits- und Verlustreduktion.

Die Auszahlung in EUR ergibt sich nach der Umrechnungsformel: $7 + \frac{Auszahlung\ in\ Talern}{8}$.

-Ende des Spiels-

Beispiel 1: Verlustreduktion möglich.

Ihre Gruppe besteht aus 3 Mitgliedern: Ihnen, Person B und Person C. Eine Einheit Verlustreduktion kostet 5 Taler.

Entscheidung.

Sie kaufen eine Einheit Wahrscheinlichkeitsreduktion und 2 Einheiten Verlustreduktion. Von Ihrem Anfangsguthaben bleiben also 80 Taler übrig (100 - 1*10 - 2*5 = 80). Gleichzeitig mit Ihnen treffen B und C ihre Investitionsentscheidungen. Weder Sie noch B noch C wissen, wie sich die beiden anderen Personen entschieden haben.

Wahrscheinlichkeit.

Nachdem alle Gruppenmitglieder ihre Entscheidung getroffen haben, wird die Wahrscheinlichkeit für den Eintritt des Verlustereignisses berechnet. Sie kauften eine Einheit Wahrscheinlichkeitsreduktion, B kaufte 2 Einheiten, und C kaufte 0 Einheiten. Insgesamt hat Ihre Gruppe also 3 Einheiten Wahrscheinlichkeitsreduktion gekauft. Von den ursprünglich 100 roten Kugeln werden die Kugeln Nr. 1 bis 60 durch weiße Kugeln ersetzt. Im Behälter sind jetzt 60 weiße Kugeln (Nr. 1 bis 60) und 40 rote Kugeln (Nr. 61 bis 100). Die Wahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt also 40%.

Zufall und Auszahlung.

Aus den 100 Kugeln im Behälter wird zufällig eine Kugel gezogen. Wenn die gezogene Kugel rot ist, dann ist das Verlustereignis eingetreten; wenn sie weiß ist, dann ist das Verlustereignis nicht eingetreten.

(Fall a): Der Zufallsgenerator hat die Kugel Nr. 27 gezogen. Diese Kugel ist weiß. Das Verlustereignis ist somit nicht eingetreten. Sie erhalten 80 Taler (Anfangsguthaben 100 Taler abzüglich 20 Taler Ausgaben für Wahrscheinlichkeitsreduktion und Verlustreduktion).

(Fall b): Der Zufallsgenerator hat die Kugel Nr. 85 gezogen. Diese Kugel ist rot. Das Verlustereignis ist eingetreten. Sie haben 2 Einheiten Verlustreduktion gekauft. Von Ihrem verbleibenden Guthaben in Höhe von 80 Talern (Anfangsguthaben abzüglich 20 Taler Ausgaben) verlieren Sie 40% = 32 Taler. Sie erhalten 80 - 32 = 48 Taler.

Beispiel 2: Verlustreduktion nicht möglich.

Ihre Gruppe besteht aus 3 Mitgliedern: Ihnen, Person B und Person C.

Entscheidung.

Sie kaufen 2 Einheiten Wahrscheinlichkeitsreduktion. Von Ihrem Anfangsguthaben bleiben also 80 Taler übrig (100 - 2*10 = 80). Gleichzeitig mit Ihnen treffen B und C ihre Investitionsentscheidungen. Weder Sie noch B noch C wissen, wie sich die beiden anderen Personen entschieden haben.

Wahrscheinlichkeit.

Nachdem alle Gruppenmitglieder ihre Entscheidung getroffen haben, wird die Wahrscheinlichkeit für den Eintritt des Verlustereignisses berechnet. Sie kauften 2 Einheiten Wahrscheinlichkeitsreduktion, B kaufte ebenfalls 2 Einheiten, und C kaufte 1 Einheit. Insgesamt hat Ihre Gruppe also 5 Einheiten Wahrscheinlichkeitsreduktion gekauft. Von den ursprünglich 100 roten Kugeln werden die Kugeln Nr. 1 bis 75 durch weiße Kugeln ersetzt. Im Behälter sind jetzt 75 weiße Kugeln (Nr. 1 bis 75) und 25 rote Kugeln (Nr. 76 bis 100). Die Wahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt also 25%.

Zufall und Auszahlung.

Aus den 100 Kugeln im Behälter wird zufällig eine Kugel gezogen. Wenn die gezogene Kugel rot ist, dann ist das Verlustereignis eingetreten; wenn sie weiß ist, dann ist das Verlustereignis nicht eingetreten.

(Fall a): Der Zufallsgenerator hat die Kugel Nr. 27 gezogen. Diese Kugel ist weiß. Das Verlustereignis ist somit nicht eingetreten. Sie erhalten 80 Taler (Anfangsguthaben 100 Taler abzüglich 20 Taler Ausgaben für Wahrscheinlichkeitsreduktion).

(Fall b): Der Zufallsgenerator hat die Kugel Nr. 85 gezogen. Diese Kugel ist rot. Das Verlustereignis ist eingetreten. Sie erhalten 0 Taler.

3.B Questionnaire

Fragebogen

Teil 1: Fragen zum Experiment. Bitte beantworten Sie die folgenden Fragen:

Die im Experiment gestellte Aufgabe war eher abstrakt und allgemein formuliert. Hatten Sie eine konkrete Situation im Kopf, als Sie Ihre Entscheidungen getroffen haben? Wenn ja, woran haben Sie gedacht (bitte kurz und stichwortartig beschreiben)?

____

____

Bitte beschreiben Sie kurz, was für Ihre Strategie ausschlaggebend war!

____

____

Teil 2: Persönlichkeitseigenschaften. Inwieweit treffen die folgenden Aussagen auf Sie zu?

	trifft voll und ganz zu	trifft eher zu	weder noch	trifft eher nicht zu	trifft überhaupt nicht zu
Ich bin eher zurückhaltend, reserviert.	○	○	○	○	○
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	○	○	○	○	○
Ich bin bequem, neige zur Faulheit.	○	○	○	○	○
Ich bin im Allgemeinen ein risikobereiter Mensch.	○	○	○	○	○
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	○	○	○	○	○
Ich habe nur wenig künstlerisches Interesse.	○	○	○	○	○
Ich gehe aus mir heraus, bin gesellig.	○	○	○	○	○
Ich neige dazu, andere zu kritisieren.	○	○	○	○	○
Ich erledige Aufgaben gründlich.	○	○	○	○	○

Ich werde leicht nervös und unsicher.	○	○	○	○	○
Ich bin eher vorsichtig und versuche, Risiken und Gefahren zu vermeiden.	○	○	○	○	○
Ich habe eine aktive Vorstellungskraft, bin phantasievoll.	○	○	○	○	○
Ich bin rücksichtsvoll zu anderen, einfühlsam.	○	○	○	○	○

Teil 3: Angaben zu Ihrer Person
Bitte beantworten Sie die folgenden Fragen:

Wie alt sind Sie?	________					
Ihr Geschlecht?	________					
Wie viele Geschwister haben Sie?	________					
Wie häufig haben Sie schon an Experimenten teilgenommen?	noch nie	weniger als 3 mal		weniger als 5 mal	5 mal und häufiger	
Studieren Sie? Wenn ja, in welchem Semester?	nein	1.-3. Semester		4.-7. Semester	8. und höheres Semester	
Was studieren Sie (wenn Sie studieren)?	________					
Sind Sie in einem festen Arbeitsverhältnis mit mehr als 10 Arbeitsstunden/Woche?	ja	nein				
Wie viele Euro stehen Ihnen monatlich zur Verfügung?	<400	400 - 700	700 - 1000	1000 - 1300	1300 - 1600	>1600

Vielen Dank für Ihre Teilnahme!
Es folgt nun die Auszahlung. Bitte warten Sie die Instruktionen des Experimentleiters ab.

3.C Fixed Effects Regression Results

Table 3.9: Treatment effects: m, a, EU_av, EU (GLS fixed effects regression)

regressand	m	a	EU_av	EU
adapt	-0.900***	.	-7.231***	-5.987***
	(0.120)	.	(0.803)	(0.781)
size	-0.583***	-0.0500	8.009***	8.113***
	(0.0754)	(0.0641)	(0.618)	(0.662)
low	-0.417***	1.875***	8.158***	7.491***
	(0.127)	(0.136)	(0.957)	(0.971)
a×l	.	.	.	.
	.	.	.	.
a×s	0.342***	.	-2.859***	-3.443***
	(0.102)	.	(0.912)	(1.278)
a×l×s	0.0250	-0.0667	-1.217	-0.744
	(0.135)	(0.114)	(1.206)	(1.391)
_cons	2.217***	1.058***	62.31***	62.02***
	(0.0771)	(0.0668)	(0.591)	(0.522)
N	720	480	720	720
R^2	0.334	0.657	0.432	0.372

Standard errors in parentheses

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

Table 3.10: Treatment effects: m and a (Poisson fixed effects regression)

regressand	m	a
adapt	-0.521***	
	(0.0691)	
size	-0.305***	-0.0484
	(0.0379)	(0.0534)
low	-0.380***	1.019***
	(0.112)	(0.0670)
a×s	0.103	
	(0.0700)	
a×l×s	-0.0726	0.00781
	(0.127)	(0.0562)
N	714[1]	472[2]
Wald chi2	202.12	349.91

[1] 1 subject (6 obs.) dropped because of all zero outcomes
[2] 2 subjects (8 obs.) dropped because of all zero outcomes
Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

Mitigation and Adaptation with Heterogeneous Unit Cost of Adaptation

Abstract The costs of adaptation are an important but widely overlooked determinant for strategic climate change policy decisions in an international context, as described by Probst (2011) by means of a non-cooperative game-theoretic model with endogenous risk. Based on this model, I conducted a computer lab experiment to empirically test for the effects of within-group adaptation cost heterogeneity on investments in mitigation and adaptation and on the resulting expected payoffs. A particular focus is put on the distribution of mitigation efforts. The experimental evidence suggests that players with low adaptation cost tend to free-ride on players with high adaptation cost, which leads to payoff disparity; however, payoffs diverge less than theoretically predicted, which I attribute to inequity aversion. The analysis of elicited beliefs about the co-players' decisions reveals that both the beliefs and the players' actual decisions can partly be ascribed to idiosyncratic preferences regarding risk and equity.

Keywords climate change, mitigation, adaptation, public good, experiment, risk
JEL Classification C91, Q54, H41

4.1 Introduction

Although the narrow focus on mitigation has widened in the recent past and the role of adaptation has gained more attention both in climate change research and in political decision making, the strategic relevance of adaptation in international climate change policy is still widely ignored. The aim of this work is to test a number of hypotheses derived from a non-cooperative game-theoretic model of mitigation and adaptation choices introduced by Probst (2011). I use data from a laboratory experiment to analyze the impact of adaptation cost heterogeneity on the levels of mitigation and adaptation and on the resulting payoffs in a non-cooperative setting. Special attention is paid to analyzing how agents respond to different group constellations. I find that, when choosing their level of mitigation, players not only consider their own adaptation cost, but also on the adaptation cost of their co-players. In particular, players with low adaptation cost tend to free-ride on players with high adaptation cost; that is, those players who are already disadvantaged due to higher adaptation cost also contribute a higher share to the aggregate mitigation effort. Yet, we also find evidence for inequity aversion. Moreover, we can make some inferences about the formation and impact of beliefs.

Theoretical Background. This section recaps the climate-scientific and economic rationale that underpins the climate risk model used in this work as postulated by Probst (2011). There is clear evidence that the global climate system has changed considerably in the past 150 years. It is virtually certain that anthropogenic GHG emissions are the main driver of this climate change, and that climatic impacts on geophysical and biological systems will become more severe and more frequent in the future (Trenberth et al., 2007; Hegerl et al., 2007; IPCC, 2007c). The size and frequency of climatic impacts, however, only partially explain the consequences for human livelihood and economic welfare. The second constituent of climate risk is the vulnerability of the affected system, i.e., the degree to which it is susceptible to a given impact (Jones, 2004, p. 254). According to these two determinants of climate risk, there exist two distinct kinds of climate risk management: one is mitigation, defined in the IPCC Fourth Assessment Report as "an anthropogenic intervention to reduce the anthropogenic forcing of the climate system; it includes strategies to reduce greenhouse gas sources and emissions and enhancing greenhouse gas sinks." (IPCC, 2007a, p. 878). The other is adaptation, defined as an "adjustment in natural or human systems in response to their actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (IPCC, 2007a, p. 869).

Mitigation addresses the cause of climate change: by curtailing GHG emissions, it seeks to reduce the size and frequency of climate impacts. Adaptation, on the other hand, addresses the symptoms of climate change: while taking climate impacts as given, it seeks to reduce the system's vulnerability to these impacts. The strategic interdependencies of the two policies can be explained by two economic characteristics: (1) the substitutability of mitigation and adaptation; (2) the public vs. private good property (see also Probst (2011) who discusses these features in detail). Mitigation and adaptation both contribute to a common final end; moreover, they compete for shares in a common budget. This being the case, the model treats both policies as substitutes. Mitigation is a global public good, characterized by non-excludability and non-rivalry in consumption. The costs of mitigation are private, whereas the benefits are universal in terms of individuals and countries. These features give rise to the well-known free rider problem and lead to an underprovision of mitigation. Adaptation, on the other hand, is a private good: the benefits of adaptation are spatially limited to a certain region; thus, other countries are automatically excluded. Due to its private good character, there are no immediate external effects from adaptation; yet, adaptation inheres a strategic dimension which results from the premise of being a substitute for mitigation.

Literature Review. Few attempts have been made to theoretically model the strategical interrelations of mitigation and adaptation. Barrett (2008a) investigates the effect of the option to adapt on the extent of free-riding in international climate treaties in a parametric mitigation-adaptation model. He uses an augmented version of his earlier mitigation-only models (Barrett, 1992, 1994a,b) to analyse the non-cooperative Nash equilibrium, the full cooperative outcome and different treaty equilibria for distinct parameter scenarios. In agreement with the theoretical and experimental results presented in this work, Barrett (2008a) finds that asymmetries in the ability to adapt lead to severe welfare disparity.

The empirical and experimental research on the economics of climate change mainly focuses on voluntary contributions in a public goods game. This setting has turned out to be the standard design for a variety of experiments on different aspects related to climate change, as summarized in a survey by Sturm and Weimann (2006). The concept of endogenous and collective risk which is also captured in the model used here was an integral part of an experiment conducted by Milinski et al. (2008). In the experiment, a group needs to reach a fixed mitigation target through successive monetary contributions, while everyone loses their residual with a certain probability if they miss the target. Hasson et al. (2010) were -to my knowledge- the first to analyze the strategical impact of adaptation by means of an economic experiment. In a symmetric game, players

can choose whether to invest their endowment in mitigation or in adaptation, where the treatment variable is the degree of vulnerability.
The experiment I present here bases on a model proposed by Probst (2011) which features a generalized non-linear set-up with endogenous damage probabilities. The validity of this model has already been empirically supported in a previous experiment with homogeneous players (Probst, 2012), which analyzes the effects of variations in adaptation cost and group size on investment decisions.

The current experiment is the first one with an asymmetric design and heterogeneous adaptation cost. My intention is to reflect the heterogeneity of actors on the global political stage, e.g. in the encounter of developing countries and developed countries. Developing countries are the least able to adapt to climate change due to their poor financial and technical resources, their heavy reliance on subsistence agriculture, and the lack of strong institutions; at the same time, their geographical exposure to climate change impacts is relatively high. Although absolute economic losses from weather and climate extremes are higher in developed countries, losses relative to countries' GDP and fatality rates are much higher in developing countries, most notably in the highly vulnerable small island developing states (IPCC, 2012). An important aim of this work is to empirically investigate whether agents with high adaptation costs are systematically disadvantaged.

4.2 Model

4.2.1 Theoretical Model

The model I used to set up the empirically testable hypotheses is a variant of the generic mitigation-adaptation model described by Probst (2011). Probst formulates an n-player game with von-Neumann-Morgenstern expected utility functions

$$Eu_{i,ma} = p_i(M) \cdot u_i^b(a_i, m_i) + (1 - p_i(M)) \cdot u_i^g(a_i, m_i).$$

a_i denotes the level of adaptation for country $i = 1, ..., n$, m_i denotes the level of mitigation for country i, and $M = \sum_{j=1}^{n} m_j$ denotes the global aggregate level of mitigation of all countries including i. Each country i faces a lottery over two states of nature: a bad state, in which an extreme weather event occurs, and a good state, in which no event occurs. The bad-state utility of country i, $u_i^b(a_i, m_i)$, is realized with probability $p_i(M) \in (0, 1)$, and the good-state utility of country i, $u_i^g(a_i, m_i)$, is realized with probability $1 - p_i(M)$. The difference $u_i^g(a_i, m_i) - u_i^b(a_i, m_i) > 0 \; \forall i$ describes the loss caused by the extreme weather event. The loss probability $p_i(M)$ is endogenous, i.e., it is decreasing in the level of global aggregate mitigation M, no matter which country mitigates. By investing in adaption a_i, each country can reduce the size of its own individual loss, while the losses of other countries remain unchanged. A number of functional properties are assumed in order to prove the existence of a Nash equilibrium. Then, the Nash equilibrium outcome of a model with mitigation and adaptation is compared to the Nash equilibrium outcome of a model without adaptation. The comparative analysis shows that, under certain conditions, mutually beneficial mitigation is replaced by individually beneficial adaptation, which results in an ambiguous welfare effect: a positive direct effect due to a comparative cost advantage of adaptation over mitigation, and a negative strategic effect due to the declining positive externalities from mitigation.

4.2.2 Model variant used in the experiment

Since the generic model by Probst (2011) only specifies the functions in general terms, it was necessary to formulate a particular variant for the experimental set-up. The model variant I employ here has already proven to be useful in a previous experiment (Probst, 2012).

It features discrete choice variables and simple functions that make it easily comprehensible to the participants. As already described in Probst (2012), the experimental set-up is a non-cooperative n-player decision game. Player $i = 1, ..., n$ can spend her individual initial endowment y_i on non-negative integer units of mitigation $m_i \in \mathbb{N}_0$ at a price of $l_i > 0$ per unit and/or adaptation $a_i \in \mathbb{N}_0$ at a price of $k_i > 0$ per unit. There is no obligation to invest. The upper limit of investments is given by the budget constraint $k_i a_i + l_i m_i \leq y_i$. In the good state, the payoff for player i is $(y_i - k_i a_i - l_i m_i)$, i.e., her residual budget. In the bad state, the payoff for players i is $(1 - L_i(a_i)) \cdot (y_i - k_i a_i - l_i m_i)$, i.e., a fraction of her residual budget, where $L_i(a_i) \in (0, 1]$ denotes player i's loss rate. The bad-state probability $p_i(M) \in (0, 1]$ negatively depends on the group aggregate level of mitigation. The functions for loss probability $p_i(M)$ and for loss rate $L_i(a_i)$ are defined on $\mathbb{N}_0$ as listed in Table 4.1. The parameters y_i (initial endowment) and l_i (unit cost of mitigation) are fixed for all treatments and identical over all subjects with $y_i = 100$ Taler and $l_i = 10$ Taler.

Within each treatment, and for each single player, the price per unit of mitigation and adaptation is constant, and the marginal cost of mitigation and adaptation are also constant. The marginal benefits of mitigation and adaptation are decreasing. This non-linear framework provides the potential for interior Nash equilibria which enable us to

Table 4.1: Parameters $p_i(M)$, $L_i(a_i)$

M	$p_i(M)$	a_i	$L_i(a_i)$
0	1	0	1
1	0.7	1	0.6
2	0.5	2	0.4
3	0.4	3	0.3
4	0.3	4	0.25
5	0.25	5	0.21
6	0.2	6	0.18
7	0.18	7	0.16
8	0.16	8	0.14
9	0.14	9	0.12
10	0.12	≥ 10	0.1
11	0.10		
12	0.09		
13	0.08		
14	0.07		
15	0.06		
≥ 16	0.05		

measure the size of differences between treatments, as noted by Laury et al. (1999) and Laury and Holt (2008).

4.3 Experiment

4.3.1 Treatments

My intention is to analyze the behavior of agents in groups that are heterogeneous with respect to the group members' adaptation cost. For this purpose, I defined three player types that differ in their unit cost of adaptation: type l (low) with $k_i = 5$ Taler, type h (high) with $k_i = 15$ Taler, and type *0* (zero) with $k_i = 101$ Taler. Type *0* can de facto not invest in adaptation at all (zero adaptation), because her unit cost of adaptation are prohibitively high. In order to avoid confusion, this economically meaningful interpretation was not made explicit to the subjects. Instead, adaptation was made *a priori* unavailable for players of type *0*. The subjects are divided into groups of four according to the following group compositions that form the six games: 0000, llll, hhhh, 00hh, 00ll, hhll. The homogeneous games 0000, llll and hhhh constitute reference cases. For the heterogeneous games 00hh, 00ll and hhll, we match two players of the same type with two players of another type. Each participant plays all six games. The heterogeneous games are played twice, once for each cost type. In total, this makes nine treatments: 0_0000, h_hhhh, l_llll, 0_00hh, h_00hh, 0_00ll, l_00ll, h_hhll, and l_hhll (here and in the following notation, the first character denotes a player's own cost type, while the four-digit string denotes the group composition of the respective game. For player i, 0_00hh describes the treatment in which i herself is of type *0* and encounters one other player of type *0* and two other players of type h).

4.3.2 Theoretical Predictions

Consider a game (S, Eu) with n players. S_i denotes the strategy set for player i. $S = S_1 \times S_2 ... \times S_n$ denotes the set of strategy profiles. $Eu = (Eu_1(x), ..., Eu_n(x))$ denotes the profile of payoff functions for $x \in S$. Let $x_i = (a_i, m_i)$ be a strategy profile of player i and let $x_{-i} = (a_{-i}, m_{-i})$ be a strategy profile of all players except i. When each player i chooses strategy x_i yielding strategy profile $x = (x_1, ..., x_n)$, then player i's payoff is $Eu_i(x)$. A strategy profile $x^* \in S$ is a Nash equilibrium if no player can benefit from her unilateral deviation, i.e., for all i,

$$x_i \in S_i,\, x_i \neq x_i^* : \, Eu_i(x_i^*, x_{-i}^*) \geq Eu_i(x_i, x_{-i}^*).$$

For each of the six games, there exists at least one Nash equilibrium in pure strategies. All Nash equilibria are described in Tables 4.2 and 4.3 (only one representative Nash equilibrium of each kind is explicitly listed; all other within-type permutations of the listed strategy profiles together with the resulting payoffs constitute Nash equilibria as well). In order to identify the Nash equilibria, I tested all possible combinations of strategy profiles for being mutual best responses with Mathematica. As a reference, I also calculated the social optima as listed in Tables 4.4 and 4.5. Social optimality requires that each group member choose her a_i and m_i so as to maximize the group sum of expected payoffs.[1]

[1] I assumed a sort of Utilitarian social welfare function for the sake of simplicity; moreover, I assumed that the expected payoff is the only determinant of an individual's utility.

Table 4.2: Nash equilibria

Game	**NE strategy profiles** $(a_i, m_i)_i$	**NE payoffs (Taler)**
0000	((0,0),(0,0),(0,0),(0,4))	(70,70,70,42)
	((0,0),(0,0),(0,1),(0,3))	(70,70,63,49)
	((0,0),(0,0),(0,2),(0,2))	(70,70,56,56)
	((0,0),(0,1),(0,1),(0,2))	(70,63,63,56)
	((0,1),(0,1),(0,1),(0,1))	(63,63,63,63)
hhhh	((1,0),(1,0),(1,0),(1,2))	(59.5,59.5,59.5,45.5)
llll	((4,0),(4,0),(4,0),(4,0))	(60,60,60,60)
hhll	((1,0),(1,2),(3,0),(3,0))	(59.5,45.5,72.25,72.25)
	((1,1),(1,1),(3,0),(3,0))	(52.5,52.5,72.25,72.25)
hh00	((0,0),(0,0),(0,0),(0,4))	(70,70,70,42)
	((0,0),(0,0),(0,1),(0,3))	(70,70,63,49)
	((0,0),(0,0),(0,2),(0,2))	(70,70,56,56)
ll00	((2,0),(2,0),(0,0),(0,4))	(79.2,79.2,70,42)
	((2,0),(2,0),(0,1),(0,3))	(79.2,79.2,63,49)
	((2,0),(2,0),(0,2),(0,2))	(79.2,79.2,56,56)

Within the strategy profiles and resulting payoff vectors, cost types are ordered corresponding to their position in the four-digit identifier of the game (e.g. hhll: first and second strategy pairs pertain to type h, third and fourth strategy pairs pertain to type l).

Table 4.3: Nash equilibrium type average values

Game	**av. NE a_i^{*}**[1]			**av. NE m_i^{*}**[1]			**av. NE payoffs**[1]			**NE group aggregate**		
	type *0*	type *h*	type *l*	type *0*	type *h*	type *l*	type *0*	type *h*	type *l*	$\sum a_i^*$	$\sum m_i^*$	$\sum Eu_i^*$
0000	0	–	–	1	–	–	63	–	–	0	4	252
hhhh	–	1	–	–	0.5	–	–	56	–	4	2	224
llll	–	–	4	–	–	0	–	–	60	16	0	240
hhll	–	1	3	–	1	0	–	52.5	72.25	8	2	249.5
hh00	0	0	–	2	0	–	56	70	–	0	4	252
ll00	0	–	2	2	–	0	56	–	79.2	4	4	270.4

[1] av. = type averages (mean values) for Nash equilibrium a_i^*, m_i^* and Eu_i^*

Table 4.4: Social optima

Game	**SO Strategy profiles** $(a_i, m_i)_i$	**SO Payoffs (Taler)**
0000	((0,0),(0,0),(0,0),(0,6))	(80,80,80,32)
	((0,0),(0,0),(0,1),(0,5))	(80,80,72,40)
	⋮	⋮
	((0,1),(0,1),(0,2),(0,2))	(72,72,64,64)
hhhh	((0,0),(0,0),(0,0),(0,6))	(80,80,80,32)
	((0,0),(0,0),(0,1),(0,5))	(80,80,72,40)
	⋮	⋮
	((0,1),(0,1),(0,2),(0,2))	(72,72,64,64)
llll	((0,6),(1,0),(1,0),(1,0))	(32,83.6,83.6,83.6)
hhll	((0,0),(0,6),(1,0),(1,0))	(80,32,83.6,83.6)
	((0,1),(0,5),(1,0),(1,0))	(72,40,83.6,83.6)
	⋮	⋮
	((0,3),(0,3),(1,0),(1,0))	(56,56,83.6,83.6)
hh00	((0,0),(0,0),(0,0),(0,6))	(80,80,80,32)
	((0,0),(0,0),(0,1),(0,5))	(80,80,72,40)
	⋮	⋮
	((0,3),(0,3),(0,0),(0,0))	(56,56,80,80)
ll00	((1,0),(1,0),(0,0),(0,6))	(83.6,83.6,80,32)
	((1,0),(1,0),(0,1),(0,5))	(83.6,83.6,72,40)
	⋮	⋮
	((1,0),(1,0),(0,3),(0,3))	(83.6,83.6,56,56)

Within the strategy profiles and resulting payoff vectors, cost types are ordered corresponding to their position in the four-digit identifier of the game (e.g. hhll: first and second strategy pairs pertain to type h, third and fourth strategy pairs pertain to type l).

Table 4.5: Social optimum type average values

	av. SO a_i^{*1}			**av. SO m_i^{*1}**			**av. SO payoffs**[1]			**SO group aggregate**		
Game	type *0*	type *h*	type *l*	type *0*	type *h*	type *l*	type *0*	type *h*	type *l*	$\sum a_i^*$	$\sum m_i^*$	$\sum eu_i^*$
0000	0	–	–	1.5	–	–	68	–	–	0	6	272
hhhh	–	0	–	–	1.5	–	–	68	–	0	6	272
llll	–	–	0.75	–	–	1.5	–	–	70.7	3	6	282.8
hhll	–	0	1	–	3	0	–	56	83.6	2	6	279.2
hh00	0	0	–	2	1	–	72	64	–	0	6	272
ll00	0	–	1	3	–	0	56	–	83.6	2	6	279.2

[1] av. = type averages (mean values) for socially optimal a_i^*, m_i^* and Eu_i^*

The Nash equilibrium predicts that, irrespective of the group composition, type l never invests in mitigation. In the homogeneous llll matching, each type l player buys 4 units of adaptation. When matched with type h in the llhh matching, type l reduces her adaptation to 3 units; when matched with type *0* in the 00ll matching, type l further reduces her adaptation to 2 units. A type l player anticipates that the other group members buy less adaptation and more mitigation as their unit costs of adaptation increase. Due to the higher group aggregate level of mitigation, type l enjoys positive external effects in terms of a lower loss probability, which in turn reduces her need for adaptation. Consequently, for type l players, payoffs are highest in the ll00 game, medium level in the llhh game and lowest in the llll game.

In the homogeneous hhhh matching, the average mitigation level of a type h player is 0.5. When a type h player encounters type l players in the hhll matching, she anticipates that type l players would not contribute to mitigation; consequently, she rises her level of mitigation to 1. In contrast, when matched with type *0* in the hh00 matching, type h does not mitigate at all: she anticipates that, due to the lack of alternatives, *0* would have a high propensity to mitigate. On average, type h players buy one unit of adaptation both in the hhhh and the hhll matching and zero adaptation in the hh00 matching. Hence, their payoffs are highest in the hh00 game, medium level in the hhhh game and lowest in the hhll game.

Due to prohibitively high costs, adaptation is not available for type *0* players in any game. In the homogeneous 0000 matching, the average mitigation level of a type *0* player is 1. It doubles to 2 units when type *0* encounters type h in the 00hh matching or type l in the 00ll matching. Consequently, payoffs are highest in the 0000 game and lowest in games 00hh and 00ll.

These theoretical insights constitute the basis for the following hypotheses to be tested in the experiment:

(H1) The type average mitigation level is *non-increasing* in the other type's unit cost of adaptation.

(H2) The type average adaptation level is also *non-increasing* in the other type's unit cost of adaptation.

(H3) The type average payoff is *non-decreasing* in the other type's unit cost of adaptation.

(H4) Within the heterogeneous matchings, the type with lower adaptation cost contributes a smaller percentage share to the group aggregate mitigation level than the type with higher adaptation cost.

(H5) The type average mitigation level is *non-decreasing* in the own type's unit cost of adaptation.

(H6) The type average adaptation level is *non-increasing* in the own type's unit cost of adaptation.

Hypotheses (H1) to (H4) have not been tested before. The assessment of the effects that result from heterogeneous group compositions is in the focus of this paper. Hypotheses (H5) and (H6) have already been empirically supported in an earlier experiment with a design similar to the current one that based on the same model (Probst, 2012); however, the previous experiment was restricted to cost-homogeneous groups.

4.3.3 Experimental Design

I conducted the computerized experiment in April 2013 in the Laboratory for Experiments in Economics at the University of Hamburg as a series of five substantially identical sessions. Sessions 1 to 4 were carried out with six groups of four = 24 participants each; in session 5, one group had to be dropped due to no-shows such that the session was conducted with five groups of four = 20 participants. The experiment was programmed and conducted with the software z-tree (Fischbacher, 2007).

Aided by the recruitment system ORSEE (Greiner, 2004), 116 students were recruited from the University of Hamburg undergraduate and graduate student body. Half of the participants were economics and finance/business administration students, but other majors such as law, sociology, natural sciences, and psychology were represented as well. The average age of the participants was 24.9 years, 51.7% were female. Most students had already participated in economic experiments at the Lab before.

After entering the lab, the participants were asked to sign a consent form and were then randomly assigned to curtained computer cubicles. Throughout the experiment, communication among subjects was not allowed. The experiment instructions (see Appendix 4.A) were read out aloud by the experiment leader; additionally, all participants were provided with a hard copy. In the instruction, I used a neutral wording in order to avoid uncontrollable bias due to emotional and/or political attitudes towards climate change policy. Terms like “adaptation”, “mitigation”, “climate change”, or “disastrous weather event” were avoided; instead, I described a decision situation where subjects could invest in “probability reduction” and “loss reduction” to manage the risk of a “loss event”. This neutral framing draws on the experience gained from the prior experiment (Probst, 2012) and diverges from other experiments on climate change policy decisions such as Hasson et al. (2010) and Milinski et al. (2008), who explicitly refer to climate change policy.

After they had received the instructions, the participants were asked to answer a number of control questions. The answers were checked automatically so that subjects could enter the next stage only after they had answered all control questions correctly. The instruction phase ended with a trial run which mimicked the real experiment but used different parameter values. Unlike in the real experiment, subjects were not matched to groups in the trial run. To prevent anchoring, the contributions of the other group members were instead simulated by a random number generator. The subjects were instructed that the trial run would not affect their earnings.

In the actual experiment, every subject played nine rounds covering the nine treatments: 0_0000, h_hhhh, l_llll, 0_00hh, h_00hh, 0_00ll, l_00ll, h_hhll, and l_hhll. By this procedure, we automatically controlled for unobservable personal idiosyncrasies, as suggested by Friedman and Sunder (1994, p. 25) and Friedman and Cassar (2004, p. 35-7). In addition to that, we acquire a large number of independent within-subject datasets. We are mainly interested in exactly these within-subject differences rather than absolute values, since all hypotheses put to test refer to comparisons. In each round, every player was endowed with a budget of 100 Taler, which she could invest in probability reduction (mitigation) and/or loss reduction (adaptation). Players were also free to keep (i.e., not to invest) all or part of their budget.

At the beginning of each round, all players received complete information about the group composition, their own unit cost of adaptation and the other players' unit cost of adaptation. Each round consisted of two tasks: in the first task, players stated their beliefs about the investments in mitigation and/or -if available- adaptation of the other three group members in this particular round. They were asked to enter their belief about how many units of mitigation/adaptation each of the other three group members would buy. In the second task, players were asked to make their own investment decision by entering the desired units of mitigation and/or -if available- adaptation. The computers were equipped with a payoff calculator so that subjects could preview the payments they would receive in the good state and the bad state respectively, and try out different combinations before making their final choice and entering the next task.

To control for order effects such as practice, fatigue or boredom (Friedman and Cassar, 2004, p. 35-7), the sequence of the nine treatments was randomized for each subject. All choices remained undisclosed during the whole decision stage, i.e., the participants did not receive any feedback or information about any other players' beliefs or actual investment decisions. This design was chosen for two reasons: first, it enabled us to perfectly randomize the individual order in which the treatments were played; second, I intended to minimize learning effects and reputational effects. Acknowledging the risk that, due to lack of feedback, subjects may fail to fully grasp the effects of their decisions, I attached great importance to the instruction phase with very detailed experiment instructions and a dry run with simulated data in lieu of a real group matching.

After all subjects had run through the whole sequence of games, one of the six games was randomly drawn as the paying game. For this definite game, subjects were randomly matched into groups of four according to the game-specific group composition. For each group, the computer calculated the group aggregate level of mitigation and -based thereon- the group-specific probability distribution for the occurrence of the loss event. Then, for each group, a random number was drawn from the group probability distribution to determine whether or not the loss event had occurred. If "no loss" was realized, each group member kept her retained budget, i.e., the share of the initial endowment that was not spent on mitigation and/or adaptation. If "loss" was realized, she received her retained budget minus a loss which depended on her individual level of adaptation.

This payment scheme was chosen to create a monetary incentive that is most suitable to the one-shot, all-or-nothing character of the underlying climate change issue (see also Andreoni and Croson, 2008). Moreover, I chose a payment structure with an initial endowment at the risk of loss that reflects the real-world climate change policy decision, acknowledging that factors such as loss aversion and the endowment effect might influence decision behavior as most prominently described by Kahneman and Tversky (1979), Tversky and Kahneman (1992). In this respect, the current experiment is in line with previous experiments on mitigation and/or adaptation such as Milinski et al. (2008) and Hasson et al. (2010).

Besides the payment from the actual game, players received an additional reward of 3 Taler for each of their stated beliefs that exactly matched the respective investment decision of the other group members in the paying period. If the unit cost of mitigation and adaptation were equal for two or all three other group members, both the beliefs and the actual investments were averaged, i.e., the correctness of beliefs did not depend on the group members' identities but only on their cost type. I chose this incentive scheme following Gächter and Renner (2010), who found, in the context of public good experiments, that belief accuracy is significantly higher when beliefs are incentivized compared to beliefs that are not incentivized.

The session ended after all subjects had filled out a computerized questionnaire containing socio-economic and personality items as well as questions on motivation and framing (Appendix 4.B). The participants were one by one and anonymously called up for payment. The average session duration was 1h 10m including instruction time. Each subject was paid a show-up fee of 7 Euro plus the individual earnings as well as the reward for correct beliefs of the paying period at a conversion rate of 10 Taler = 1 Euro. Payments (including show-up fee) ranged between 7.00 Euro and 17.30 Euro with an average of 13.52 Euro over all sessions which approximates usual earnings in student jobs.

4.4 Data and Methods of Analysis

4.4.1 Data description

Table 4.6 summarizes the descriptive statistics of the participants' choices and the resulting expected payoffs listed by treatment. The levels of mitigation (m_i) and adaptation (a_i) are reported directly from the observations. The expected payoffs (EU_av_i) are calculated using the subject-individual loss rates $L_i(a_i)$ and residual budgets (depending on spendings for m_i and a_i). The loss probabilities $p(M)$ are first determined group-wise for each treatment based on the group aggregate M and then averaged over all groups. I chose this procedure for the calculation of expected payoffs in order to eliminate noise caused by the group effect. As a check for robustness, however, all statistical analyses reported in this section are also conducted with the actual expected payoffs resulting from one particular random group matching(EU_i). The results are very similar.

Table 4.7 summarizes the descriptive statistics of the subjects' beliefs about their co-players' choices of m and a which they had expressed prior to making their own actual choices. The beliefs about the units of mitigation and adaptation bought by the other three group members are calculated as per-capita averages by adaptation cost type (own/other), which results in four explanatory variables: $Bel\_m\_own_i$, $Bel\_m\_other_i$, $Bel\_a\_own_i$ and $Bel\_a\_other_i$.

By means of the post-experimental questionnaire, I gathered subject-specific data on the following variables: (1) preferences for investment decisions: high individual payoff ($MaxEU_i$), low individual risk ($MinRisk_i$), high payoffs for all group members ($MaxAll_i$), low probability of loss ($MinRiskAll_i$), fair allocation of payoffs ($Fair_i$), high individual payoff in the event of loss ($MaxMin_i$), data source: self-reported in the questionnaire on a 1-5 scale from 1="not important for the decisions" to 5="very important for the decisions"; (2) personality traits: extraversion (*Extra*), agreeableness (*Agree*), conscientiousness (*Consc*), risk aversion (*Riskav*), neuroticism (*Neuro*), openness (*Open*) (data source: self-reported in the questionnaire on a 1-5 scale as proposed in Rammstedt and John (2007); (3) socioeconomic variables: age (*Age*), sex (*Female*), experimental experience (*Exp*), major subject (*Econ*), job (*Job*), income (*Income*) (data source: self-reported in the questionnaire, see Appendix 4.B). Finally, I create dummy variables for $period_{it}$ and *session* to control for order effects and sessions effects.

My hypotheses refer to within-subject differences between treatments. The dataset is thus treated as a panel with the Subject ID being the panel variable and the treatment being the time variable. In the notation, y_{it} denotes the y-level of the ith subject in treatment t. On this panel, I conduct a number of regression analyses described in the following sections.

4.4.2 Analytical methods

Linear regressions. We start the analysis with two random-effects GLS regressions based on two consecutive multiple linear regression models with treatment dummy variables. The first linear regression model is described by

$$(R1)\ y_{it} = \alpha_i + \beta_0 + \beta_1 treatments_t + \epsilon_{it}.$$

The dependent scalar y_{it} contains the individual treatment-specific levels of mitigation (m_{it}), adaptation (a_{it}), expected average payoff (EU_av_{it}) and -as a check for robustness-expected payoff in one particular group matching (EU_{it}). For the estimation of a_{it}, I restrict the dataset to those treatments in which adaptation is actually available, i.e., treatments h_hhhh, l_llll, h_00hh, l_00ll, h_hhll, and l_hhll. The $treatments_t$ vector consists of a set of four individual-invariant treatment dummy variables: *adapt* (own type can adapt; yes=1, no=0), *low* (own type's unit cost of adaptation; low=1 (5 Taler), high=0 (15 Taler)), *withadapt* (other type within group can adapt; yes=1, no=0), and *withlow* (other type's unit cost of adaptation; low=1 (5 Taler), high=0 (15 Taler)), as well as the interaction dummies $adapt \times withadapt$ ($a{\times}wa$), $adapt \times withadapt \times withlow$ ($a{\times}wa{\times}wl$), $adapt \times low \times withadapt$ ($a{\times}l{\times}wa$) and $adapt \times low \times withadapt \times withlow$ ($a{\times}l{\times}wa{\times}wl$). Based on the reference treatment 0_0000, the treatment effects can be separated and discerned by the dummy variables and interaction variables as described in Table 4.8. All idiosyncratic variance is captured in the error term $u_{it} = \alpha_i + \epsilon_{it}$.

The second model contains an additional vector ind_i which contains subject-specific, treatment-invariant control variables. The model is described by

$$(R2)\ y_{it} = \alpha_i + \beta_0 + \beta_1 treatments_t + \beta_2 ind_i + \epsilon_{it}.$$

After by backward elimination removing all individual control variables that proved insignificant and/or of minor importance, the relevant vector ind_i consists of the pref-

Table 4.6: Summary statistics: decisions and payoffs

Treatment	Variable	Mean	Std. Dev.	Min.	Max.	N
0_0000	m	1.716	0.912	0	3	116
	EU	67.038	6.857	52.5	84	116
	EU_av	67.19	7.395	56.772	81.103	116
0_00hh	m	2.086	1.154	0	6	116
	EU	59.632	11.553	0	82	116
	EU_av	60.295	8.792	30.476	76.19	116
0_00ll	m	2.216	1.07	0	5	116
	EU	58.307	8.58	27	82	116
	EU_av	58.827	8.084	37.784	75.569	116
h_00hh	m	0.888	0.902	0	4	116
	a	1.06	0.794	0	3	116
	EU	62.712	10.226	0	76.84	116
	EU_av	63.22	8.537	32.5	76.19	116
h_hhhh	m	1.233	0.99	0	4	116
	a	1.078	0.866	0	4	116
	EU	57.691	10.078	14.55	75.600	116
	EU_av	57.154	9.302	13.67	70.448	116
h_hhll	m	1.457	1.075	0	5	116
	a	0.983	0.834	0	4	116
	EU	52.788	10.646	9.5	77.86	116
	EU_av	52.831	9.553	9.097	66.587	116
l_00ll	m	0.629	0.84	0	4	116
	a	2.784	1.171	0	6	116
	EU	72.446	7.284	43.92	83.52	116
	EU_av	72.656	7.666	42.801	81.205	116
l_hhll	m	0.655	0.845	0	3	116
	a	2.724	1.227	0	6	116
	EU	68.704	7.761	30	82.8	116
	EU_av	68.938	7.83	37.401	77.003	116
l_llll	m	0.690	0.838	0	4	116
	a	2.784	1.156	0	6	116
	EU	65.562	7.502	27	80.41	116
	EU_av	65.081	7.955	35.338	72.373	116

Table 4.7: Summary statistics: beliefs

Treatment	**Variable**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
0_0000	Bel_m_own	1.859	0.921	0.667	9	116
0_00hh	Bel_m_own	2.190	0.884	0	5	116
	Bel_m_other	1.224	0.861	0	5.5	116
	Bel_a_other	1.159	0.693	0	3	116
0_00ll	Bel_m_own	2.172	0.878	0	5	116
	Bel_m_other	0.828	0.662	0	3	116
	Bel_a_other	2.703	0.955	0	5	116
h_00hh	Bel_m_own	0.922	0.759	0	3	116
	Bel_m_other	2.030	0.667	0.5	4	116
	Bel_a_own	1.233	0.838	0	5	116
h_hhhh	Bel_m_own	1.368	0.688	0	4	116
	Bel_a_own	1.121	0.723	0	4	116
h_hhll	Bel_m_own	1.560	0.794	0	4	116
	Bel_m_other	0.974	0.785	0	4	116
	Bel_a_own	0.912	0.705	0	3	116
	Bel_a_other	2.677	0.974	0.5	5	116
l_00ll	Bel_m_own	0.741	0.924	0	5	116
	Bel_m_other	1.996	0.715	0.5	5.5	116
	Bel_a_own	2.845	0.974	1	6	116
l_hhll	Bel_m_own	0.836	0.978	0	7	116
	Bel_m_other	1.543	0.864	0	5.5	116
	Bel_a_own	2.802	1.049	0	6	116
	Bel_a_other	0.987	0.637	0	2.5	116
l_llll	Bel_m_own	0.974	0.699	0	4	116
	Bel_a_own	2.664	0.910	1	5	116

Table 4.8: Treatment dummy variables

Treatment	*adapt*	*low*	*withadapt*	*withlow*	$a \times wa$	$a \times wa \times wl$	$a \times l \times wa$	$a \times l \times wa \times wl$
0_0000	0	0	0	0	0	0	0	0
0_00hh	0	0	1	0	0	0	0	0
0_00ll	0	0	1	1	0	0	0	0
h_00hh	1	0	0	0	0	0	0	0
h_hhhh	1	0	1	0	1	0	0	0
h_hhll	1	0	1	1	1	1	0	0
l_00ll	1	1	0	0	0	0	0	0
l_hhll	1	1	1	0	1	0	1	0
l_llll	1	1	1	1	1	1	1	1

adapt (a) = own type can adapt (0=no, 1=yes)
low (l) = own unit cost of adaptation (0=high (15 Taler), 1=low (5 Taler))
withadapt (wa) = other type within group can adapt (0=no, 1=yes)
withlow (wl) = other type's unit cost of adaptation (0=high (15 Taler), 1=low (5 Taler))

erence factors $MaxEU_i$, $MinRisk_i$, $MinRiskAll_i$, and $MaxMin_i$. The initially included $period_{it}$ and *session* dummies are dropped in the final model due to insignificance.

Besides treatment effects and subject-specific control variables, I estimate the impact of beliefs about m and a on actual decisions regarding m and a. I use a third multiple linear regression model described by

$$(R3)\ y_i = \beta_0 + \beta_1 beliefs_i + \beta_2 ind_i + \epsilon_i.$$

The dependent scalar y_i contains the individual levels of mitigation (m_i) and adaptation (a_i). The vector $beliefs_i$ contains the beliefs about the co-players' choices of m and a, i.e., $Bel\_m\_own_i$, $Bel\_m\_other_i$, $Bel\_a\_own_i$ and $Bel\_a\_other_i$. The individual control vector ind_i contains the preference factors $MaxEU_i$, $MinRisk_i$, $MinRiskAll_i$, and $MaxMin_i$; and the personality traits "risk aversion" (*Riskav*) and "neuroticism" (*Neuro*). The error term ϵ_i represents the unexplained idiosyncratic variance.

Obviously, the beliefs strongly depend on the treatment they refer to; thus, in order to avoid multicollinearity issues, I use between regressions on the cross-treatments subject means of m and a. In addition, I run separate regressions for each single treatment.

Poisson regressions. In the next step of the analysis, I explicitly account for the fact that the subjects' choices for m_{it} and a_{it} are counts, i.e., non-negative integers. The microeconometric literature warns about potential shortcomings of linear regression models when the dependent variable is a count (see e.g. Winkelmann, 2008). Standard complications include heteroscedasticity, the presence of unobserved heterogeneity, the small-mean property of the dependent variable in the presence of many zeros, and truncations in the observed distribution of the dependent variable (Cameron and Trivedi, 2009, p. 553 pp). Therefore, I set up an alternative series of Poisson regressions for the estimation of m_{it} and a_{it}, based on the assumption that these data are Poisson distributed, i.e., $E(y_{it}) = Var(y_{it})$. As recommended by Cameron and Trivedi (2009, chap. 17.3), I use robust standard errors for the Poisson models. This procedure ensures correct standard errors even in the event of overdispersion. The Poisson regression models are specified as follows:

$$(P1)\ y_{it} = \exp\left(\alpha_i + \beta_0 + \beta_1 treatments_t + \epsilon_{it}\right)$$

$$(P2)\ y_{it} = \exp\left(\alpha_i + \beta_0 + \beta_1 treatments_t + \beta_2 ind_i + \epsilon_{it}\right)$$

$$(P3)\ y_i = \exp\left(\beta_0 + \beta_1 beliefs_i + \beta_2 ind_i + \epsilon_i\right).$$

Robustness checks. As another test for robustness, I run both the GLS and the Poisson regressions again with subject fixed effects. Since the time effects not captured by the treatment variables are of minor size, the results of the fixed effect model are qualitatively identical to those of the first random effects regression model R1; moreover, the GLS and Poisson fixed effects regression results are identical in terms of coefficients and exhibit only minor differences in significance levels (for detailed results, see Appendix 4.C).

Finally, to double-check the regression results, I conduct paired difference tests on the within-subject, between-treatment differences. Since it was not certain that the differences are interval and normally distributed, I chose the non-parametric Wilcoxon signed rank test method for this purpose. Paired t-tests are conducted as well and yield very similar results. All calculations are performed with Stata v12.1.

4.5 Results

4.5.1 Treatment Effects

The estimation results for the GLS random effects regression models R1 and R2 are listed in Tables 4.9 and 4.10. The estimation results for the Poisson random effects regression models P1 and P2 are listed in 4.11. After conversion, the coefficients from the GLS and the Poisson model types are identical, with only minor differences in significance levels, which is an indicator for the robustness of the results. For the sake of convenience, unless noted otherwise, all numerical results presented in this section refer to the GLS random effects regression model R1 results as listed in the second columns of Tables 4.9 and 4.10. In model R1, the individual-specific effects are suppressed, so that the regression results can easily be compared with the benchmarks: the constants from model R1 equate to the expected means of the dependent variables for the reference treatment 0_0000, and the expected means for the other treatments can easily be computed by adding the coefficients for the respective treatment dummies and interaction variables.

Mitigation

As their co-players' unit cost of adaptation decrease, agents buy more mitigation in some constellations, while in other constellations their level of mitigation remains unchanged. On average across all treatments, interacting with a type who can adapt increases individual mitigation by 0.37 units compared to interacting with type *0* (coefficient for *withadapt*). This result is highly statistically significant in all regressions. If the other type can adapt at low cost, the own treatment-average mitigation further increases by another 0.13 units (coefficient for *withlow*); yet, this result is not significant.

Table 4.9: Treatment effects: m and a (GLS random effects regression)

regressand	m		a	
model	R1	R2	R1	R2
adapt	-0.828***	-0.828***		
	(0.0990)	(0.0990)		
low	-0.259***	-0.259***	1.685***	1.685***
	(0.0990)	(0.0990)	(0.0720)	(0.0720)
withadapt	0.371***	0.371***	-0.0216	-0.0216
	(0.0990)	(0.0990)	(0.0720)	(0.0720)
withlow	0.129	0.129		
	(0.0990)	(0.0990)		
a×wa	-0.0259	-0.0259		
	(0.140)	(0.140)		
a×wa×wl	0.0948	0.0948	-0.0754	-0.0754
	(0.140)	(0.140)	(0.0953)	(0.0953)
a×l×wa	-0.319**	-0.319**		
	(0.140)	(0.140)		
a×l×wa×wl	-0.190	-0.190	0.116	0.116
	(0.140)	(0.140)	(0.125)	(0.125)
MaxEU		-0.386***		-0.258***
		(0.0749)		(0.0832)
MinRisk		0.0907		0.222***
		(0.0718)		(0.0797)
MinRiskAll		0.152**		-0.227***
		(0.0612)		(0.0680)
MaxMin		0.0351		0.342***
		(0.0698)		(0.0775)
_cons	1.716***	2.316***	1.080***	0.840*
	(0.0896)	(0.421)	(0.0879)	(0.465)
N	1044	1044	696	696
adj. R^2	0.2695	0.3557	0.4172	0.5044

Standard errors in parentheses

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

Table 4.10: Treatment effects: EU_av and EU (GLS random effects regression)

regressand	EU_av		EU	
model	R1	R2	R1	R2
adapt	-3.970***	-3.970***	-4.326***	-4.326***
	(0.813)	(0.813)	(0.999)	(0.999)
low	9.436***	9.436***	9.734***	9.734***
	(0.813)	(0.813)	(0.999)	(0.999)
withadapt	-6.895***	-6.895***	-7.406***	-7.406***
	(0.813)	(0.813)	(0.999)	(0.999)
withlow	-1.468*	-1.468*	-1.325	-1.325
	(0.813)	(0.813)	(0.999)	(0.999)
a×wa	0.829	0.829	2.385*	2.385*
	(1.150)	(1.150)	(1.412)	(1.412)
a×wa×wl	-2.855**	-2.855**	-3.578**	-3.578**
	(1.150)	(1.150)	(1.412)	(1.412)
a×l×wa	2.347**	2.347**	1.280	1.280
	(1.150)	(1.150)	(1.412)	(1.412)
a×l×wa×wl	0.466	0.466	1.761	1.761
	(1.150)	(1.150)	(1.412)	(1.412)
MaxEU		3.788***		2.465***
		(0.692)		(0.691)
MinRisk		-1.008		0.00962
		(0.663)		(0.662)
MinRiskAll		-0.824		0.0923
		(0.565)		(0.565)
MaxMin		-0.874		-1.930***
		(0.645)		(0.644)
_cons	67.19***	61.27***	67.04***	63.43***
	(0.778)	(3.876)	(0.844)	(3.889)
N	1044	1044	1044	1044
R^2	0.3331	0.4196	0.2962	0.3328

Standard errors in parentheses

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

Table 4.11: Treatment effects: m and a (Poisson random effects regression)

regressand	m		a	
model	P1	P2	P1	P2
adapt	-0.659***	-0.659***		
	(0.121)	(0.121)		
low	-0.344*	-0.344*	0.946***	0.946***
	(0.153)	(0.153)	(0.0748)	(0.0748)
withadapt	0.196*	0.196*	-0.0113	-0.0113
	(0.0957)	(0.0957)	(0.0672)	(0.0672)
withlow	0.0601	0.0601		
	(0.0896)	(0.0896)		
a×wa	0.132	0.132		
	(0.161)	(0.161)		
a×wa×wl	0.107	0.107	-0.0784	-0.0784
	(0.145)	(0.145)	(0.118)	(0.118)
a×l×wa	-0.288	-0.288		
	(0.209)	(0.209)		
a×l×wa×wl	-0.116	-0.116	0.0950	0.0950
	(0.196)	(0.196)	(0.132)	(0.132)
MaxEU		-0.310***		-0.150***
		(0.0562)		(0.0435)
MinRisk		0.0934		0.120**
		(0.0598)		(0.0430)
MinRiskAll		0.154**		-0.121***
		(0.0497)		(0.0356)
MaxMin		0.0307		0.210***
		(0.0539)		(0.0453)
_cons	0.540***	0.771*	0.0723	-0.141
	(0.0811)	(0.315)	(0.0762)	(0.248)
lnalpha	-1.713***	-2.276***	-2.561***	-3.746***
	(0.203)	(0.254)	(0.307)	(0.685)
N	1044	1044	696	696

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Differentiating by the player's own cost type (table 4.12), we find that players of type *h* respond most sensitively to lower adaptation cost of co-players. If a type *h* player encounters type *h* players rather than type *0* players, her average level of mitigation increases by 0.34 units; if a type *h* player encounters type *l* players rather than type *h* players, her average level of mitigation further increases by 0.22 units. Both results are highly significant on a 99% confidence level in the GLS regression and on a 95% confidence level in the Poisson regression. Players of type *0* respond less sensitively to lower adaptation cost of co-players. If a type *0* player encounters type *h* players rather than type *0* players, her average level of mitigation increases by 0.37 units ($p = 0.0000$); if a type *0* player encounters type *l* players rather than type *h* players, her average level of mitigation increases by 0.13 units; however, the increase is not statistically significant ($p = 0.17$). Finally, type *l* players do not respond significantly to lower adaptation cost of co-players.

The significance of these observations is further confirmed by a series of directional (one-sided) Wilcoxon signed rank tests on the treatment-specific mitigation differences induced by the other type's adaptation cost: the null hypotheses H0: m0_0000 > m0_00hh can be rejected with $p = 0.0001$; H0: m0_0000 > m0_00ll can be rejected with $p = 0.0000$; H0: m0_00hh > m0_00ll can be rejected with $p = 0.0239$; H0: mh_00hh > mh_hhhh can be rejected with $p = 0.0002$; H0: mh_00hh > mh_hhll can be rejected with $p = 0.0000$; H0: mh_hhhh > mh_hhll can be rejected with $p = 0.0134$; H0: ml_00ll = ml_hhll cannot be rejected ($p > |z| = 0.3781$); H0: ml_00ll = ml_llll cannot be rejected ($p > |z| = 0.1629$); H0: ml_hhll = ml_llll cannot be rejected ($p > |z| = 0.4375$). These observations support (H1), as visualized in Figure 4.1

As the own unit cost of adaptation decrease, the level of mitigation decreases. The average mitigation level is highest in those treatments where adaptation is not available, i.e., if the own cost type is *0*. Mitigation is by 0.8 units lower if the own cost type is *h* rather than *0* (coefficient for *adapt*), and by another 0.26 units lower if the own cost type is *l* rather than *h* (coefficient for *low*). The regression results indicate that a decrease in an agent's own unit cost of adaptation significantly lowers this agent's level of mitigation on a 99% confidence level. The significance is further confirmed by a series of directional Wilcoxon signed rank tests on differences in mitigation levels induced by the own unit cost of adaptation (all tests confirm the regression results with $p = 0.0000$). This result supports (H5). The result corroborates the findings from an earlier experiment with a similar design (Probst, 2012).

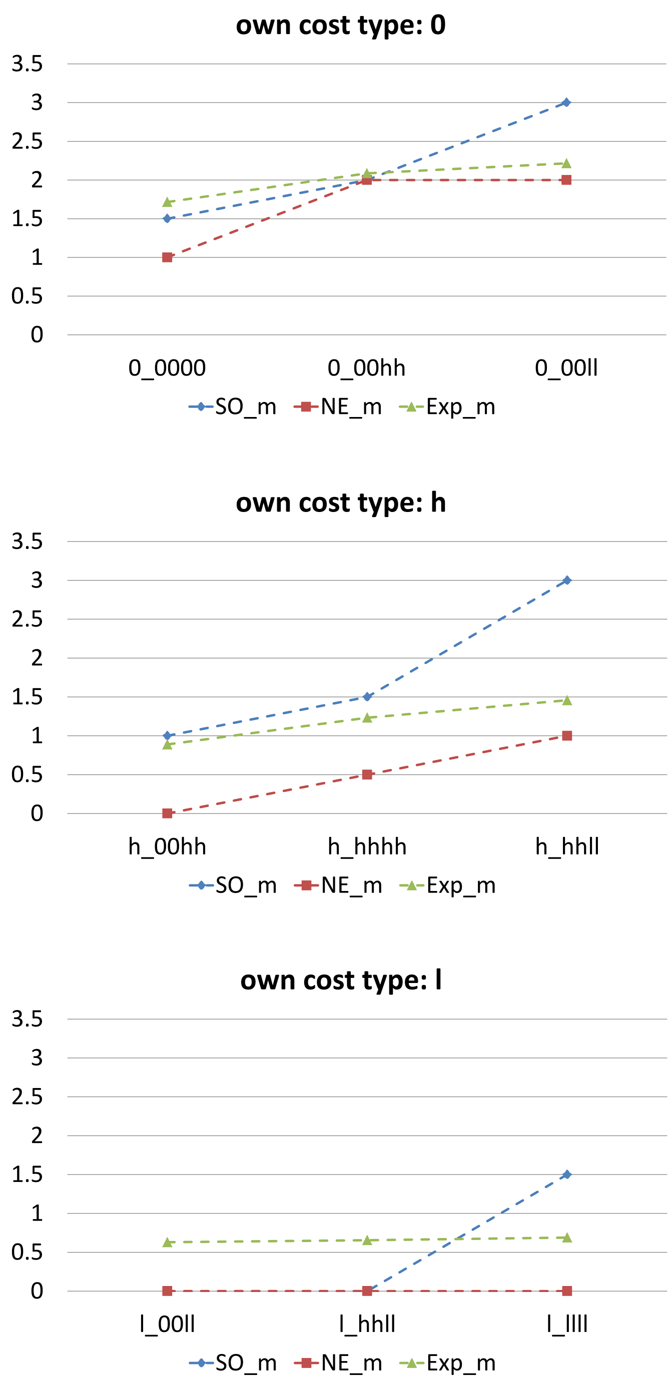
Table 4.12: Impact of other type's adaptation cost, by own cost type

regressand		*m*		*a*			*EU_av*	
own cost type	0	h	1	h	1	0	h	1
withadapt	0.371***	0.345***	0.0259	0.0172	-0.0603	-6.895***	-6.066***	-3.718***
	(0.0937)	(0.0870)	(0.0564)	(0.0693)	(0.0870)	(0.721)	(0.733)	(0.537)
withlow	0.129	0.224***	0.0345	-0.0948	0.0603	-1.468**	-4.323***	-3.857***
	(0.0937)	(0.0870)	(0.0564)	(0.0693)	(0.0870)	(0.721)	(0.733)	(0.537)
_cons	1.716***	0.888***	0.629***	1.060***	2.784***	67.19***	63.22***	72.66***
	(0.0975)	(0.0920)	(0.0781)	(0.0773)	(0.110)	(0.753)	(0.849)	(0.726)
N	348	348	348	348	348	348	348	348
R^2	0.2226	0.2328	0.1444	0.3206	0.1437	0.2222	0.2206	0.1286

Standard errors in parentheses

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

Figure 4.1: Mitigation levels depending on other type's adaptation cost



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

The level of mitigation observed in the experiment is consistently higher than predicted by the Nash equilibrium. In the 0_0000 treatment, the average observed level of mitigation is 1.72 units. This value is well above the Nash equilibrium level of mitigation (1 unit) and even exceeds the average social optimum level of mitigation (1.5 units). In the 0_00hh treatment, the average observed level of mitigation is 2.09 units. This value is very close to the optimal level of mitigation of 2 units both in the Nash equilibrium and in the social optimum. In the 0_00ll treatment, the average observed level of mitigation level (2.22 units) ranges between the Nash equilibrium level of mitigation (2 units) and the socially optimal level of mitigation (3 units). In the h_00hh treatment, the average observed level of mitigation is 0.89 units, which is only slightly below the social optimum level of mitigation (1 unit), but clearly above the Nash equilibrium level of mitigation (0 units). In the h_hhhh treatment, the average level of mitigation is 1.23 units, which is also slightly below the average social optimum level of mitigation (1.5 units) and clearly above the average Nash equilibrium level of mitigation (0.5 units). In the h_hhll treatment, the observed average level of mitigation is 1.46 units. This value exceeds the Nash equilibrium level of mitigation (1 unit), but falls well below the social optimum level of mitigation (3 units). For players of type l, the average observed level of mitigation is almost constant at 0.66 units in all three group constellations. The social optimum level of mitigation is 1.5 units in the l_llll treatment and zero in the l_hhll and the l_00ll treatments. The Nash equilibrium level of mitigation for type l is zero in all three group constellations.

Besides the absolute levels of mitigation, we also analyzed the effect of the group composition on the type-specific percentage shares in the group aggregate level of mitigation. We find that, in the heterogeneous games, the higher-cost type contributes substantially more to M than the lower-cost type.

For the analysis, we define the dependent variable $shareM_i$ as a subject's own mitigation m_i divided by the group aggregate mitigation M based on one particular random group matching, and the dependent variable $shareM\_av_i$ as m_i divided by the average game-specific M (averaged over all groups). In 20 out of 1044 observations, we found $M = 0$; for these cases, $shareM_i$ was set to 0.25. $shareM$ and $shareM\_av$ were then regressed on the treatment dummy variables and interaction variables as described in Table 4.8. The regression results are displayed in Table 4.13.

Quite obviously, all group members contribute the same share (0.25) to the group aggregate mitigation level in the homogeneous games. In the heterogeneous games, however, shares are significantly different depending on the cost type. In the 00hh game, the

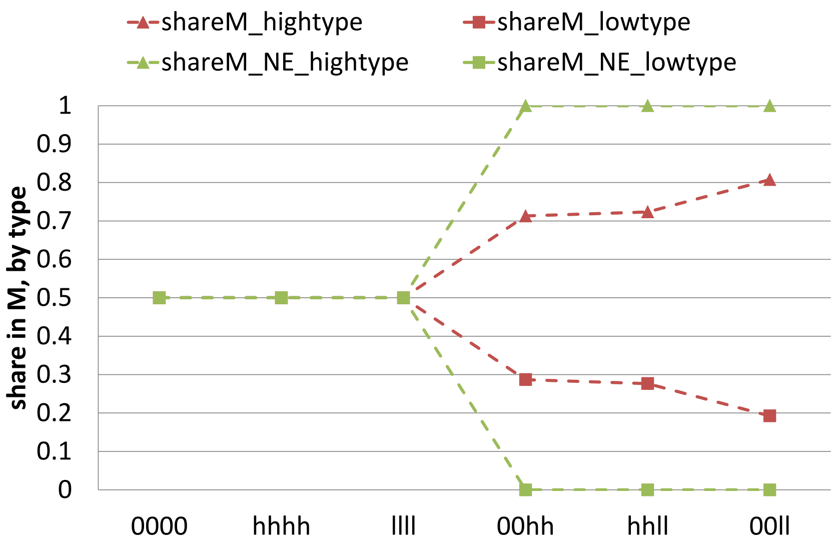
Table 4.13: Per capita percentage shares in M, by treatment

regressand	*shareM*	*shareM_ av*
adapt	-0.107***	-0.101***
	(0.0236)	(0.0209)
low	-0.0472**	-0.0387*
	(0.0236)	(0.0209)
withadapt	0.107***	0.101***
	(0.0236)	(0.0209)
withlow	0.0472**	0.0387*
	(0.0236)	(0.0209)
a×wa	-9.63e-16	7.94e-16
	(0.0334)	(0.0295)
a×wa×wl	0.0645*	0.0562*
	(0.0334)	(0.0295)
a×l×wa	-0.0645*	-0.0562*
	(0.0334)	(0.0295)
a×l×wa×wl	-2.08e-16	5.88e-17
	(0.0334)	(0.0295)
_cons	0.250***	0.250***
	(0.0167)	(0.0148)
N	1044	1044
R^2	0.172	0.182

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

two type *0* players together contribute 71% of the group aggregate mitigation, whereas the two type h players together contribute only 29%. A similar distribution can be observed in the hhll game, where type h players contribute 72% while type l players contribute 28%. The imbalance is even more pronounced in game 00ll, where type *0* players contribute 81% and type l players contribute 19% of the group aggregate mitigation level (all results are significant). These observations support (H4). The observed contributions to M are indeed heavily imbalanced at the expense of the higher-cost type in the heterogeneous games; yet, they are less divergent than predicted by the Nash equilibrium, where the type with lower unit cost of adaptation does not mitigate at all, while the entire group aggregate mitigation level is provided by the type with higher unit cost of adaptation. Figure 4.2 illustrates this comparison.

Figure 4.2: Shares in group aggregate mitigation, by cost type



Adaptation

The level of adaptation does not depend on the other type's unit cost of adaptation. In all regressions we run on a_{it}, the coefficients for *withadapt* and *withlow* were small-sized and not significant. This indicates that an agent's level of adaptation is not affected by her co-players' unit cost of adaptation. This observation holds for all cost types, as shown in Table 4.12, columns 5 and 6. The two-sided Wilcoxon signed rank tests confirm the regression results: none of the Null hypotheses we tested against could be rejected. For H0: ah_00hh = ah_hhhh, $p > |z| = 0.7019$; for H0: ah_00hh = ah_hhll,

$p > |z| = 0.2097$; for H0: ah_hhhh = ah_hhll $p > |z| = 0.1057$; for H0: al_00ll = al_hhll, $p > |z| = 0.5653$; for H0: al_00ll = al_llll, $p > |z| = 0.4607$; and for H0: al_hhll = al_llll, $p > |z| = 0.3939$. Thus, we find support for (H2).

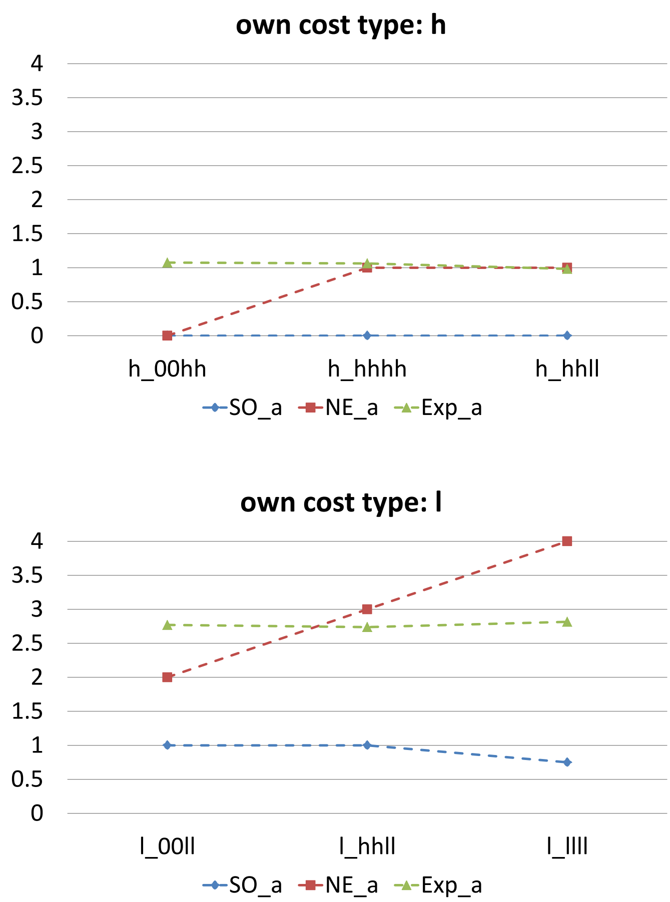
The level of adaptation increases as the own unit cost of adaptation decrease. Players of type h buy approx. 1 unit of adaptation on average. Players of type l buy 2.77 units of adaptation on average. The *low* coefficient is positive (approx. 1.7) and highly significant, which is also confirmed by directional Wilcoxon signed rank tests: the Null hypotheses of equal means H0: ah_hhhh = al_hhll and H0: ah_hhll = al_llll can be rejected with $p = 0.0000$. The result supports (H6) and corroborates the findings from the experiment in Probst (2012).

The observed average levels of adaptation are qualitatively in line with the Nash equilibrium predictions. Yet, we do not observe the Nash-predicted increase in adaptation as the other type's adaptation cost decrease. The observed average level of adaptation ranges well above the socially optimal level of adaptation, which is zero in all three treatments for type h and 0.75 units (treatment l_llll) and 1 unit (treatments l_hhll and l_00ll), respectively, for type l. Figure 4.3 provides a summary and visualization of the benchmark comparison.

Payoffs

The average expected payoff *EU_ av* decreases as the other type's unit cost of adaptation decrease. Independent of the own unit cost of adaptation, the average expected payoff decreases by 6.9 Taler if the other type can invest in adaptation (coefficient for *with-adapt*, significant on a 99% confidence level as shown in Table 4.10). If the co-players' cost type is l, the average expected payoff further decreases by 1.5 Taler (coefficient for *withlow*, weakly significant on a 90% level). We run additional GLS fixed effects regression analyses differentiated by own cost types (see Table 4.12, columns 7-9): the average expected payoff of type *0* is by 6.90 Taler lower in the 0_00hh treatment than in the 0_0000 treatment. It is by 1.47 Taler lower in the 0_00ll treatment than in the 0_00hh treatment. Both coefficients are significant. The average expected payoff of type h is by 6.07 Taler lower in the h_hhhh treatment than in the h_00hh treatment. It is by 4.32 Taler lower in the h_hhll treatment than in the h_hhhh treatment. Both coefficients are highly significant. Finally, the average expected payoff of type l is by 3.72 Taler lower in the l_hhll treatment than in the l_00ll treatment. It is by 3.86 Taler lower in the l_llll treatment than in the l_hhll treatment. Both coefficients are highly significant. We conducted directional Wilcoxon signed-rank tests and one-sided paired t-tests on all payoff differences induced by the other type's unit cost of adaptation. In each of the tests,

Figure 4.3: Adaptation levels depending on other type's adaptation cost



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

the Null hypothesis of equal means could be rejected with $p = 0.0000$. These findings support (H3), as also depicted in Figure 4.4.

On average, players receive higher payoffs than the Nash equilibrium predicts in all three cost-homogeneous games. In the 0000 game, the observed average payoff almost hits the social optimum. In the llll game, the observed average payoff ranges halfway between the Nash equilibrium and the social optimum. In the hhhh game, the observed average payoff only exceeds the Nash equilibrium payoff by 1.15 Taler, while it falls almost 11 Taler below the social optimum. In the heterogeneous games, we observe that players with comparatively high adaptation cost fare better in the experiment than the Nash equilibrium predicts, while their co-players with comparatively low adaptation cost fare worse. In all three heterogeneous games, the observed game-average sum of expected payoffs within a group is lower than predicted by the Nash equilibrium. The largest deviations from the socially optimal payoffs are born by those players who encounter players of type h, irrespective of their own type.

4.5.2 Effects induced by other factors

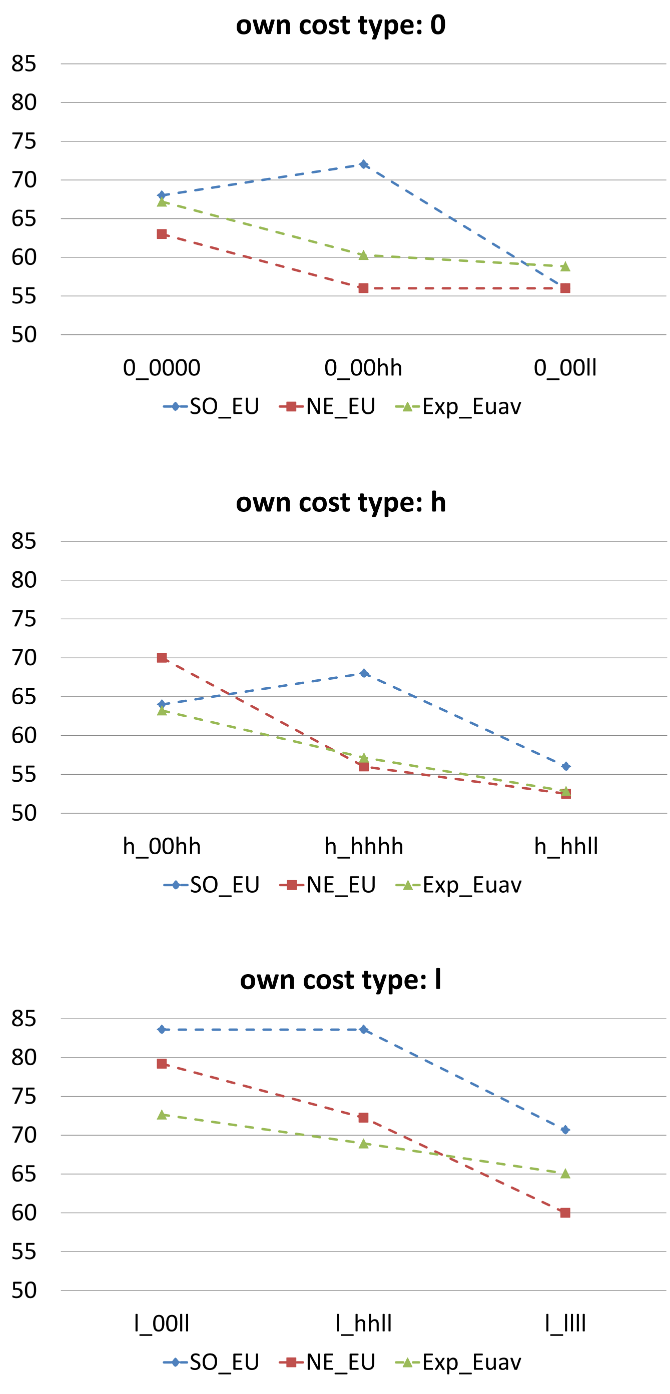
As reported in the previous sections, we find sound empirical support for all hypotheses; yet, in terms of quantities, we also observe some significant deviations from the predictions. The following step of our analysis scrutinizes the deviations. The hypotheses are based upon the concept of Nash equilibrium, which presumes complete information about the set-up of the game and common knowledge of rationality; moreover, we implicitly assume that players' utility proportionally depends on their expected payoff. These presumptions give rise to several objections. In particular, deviations of the empirical data from the Nash equilibrium predictions may arise from (1) erroneous beliefs about co-players' investment decisions, and (2) deviating utility functions (e.g. due to risk aversion, fairness preferences, inequity aversion, utility beyond the monetary payoff).[2]

Beliefs

We are interested in three questions: First, are the beliefs correct? Or do subjects systematically over- or underestimate their co-players' decisions? Second, how do players' beliefs affect their actual investment decisions? Third, where do the beliefs come from?

[2] Even if all players had correct beliefs about their co-players' investment decisions, and if we exactly knew their utility functions, deviations from the Nash equilibrium could still arise, e.g. due to input data error or due to strategically irrational behavior (decisions are not best responses to beliefs). I disregard these effects for two reasons: first, they are virtually not detectable from the data; second, I consider them as rather unimportant.

Figure 4.4: Payoffs depending on other type's adaptation cost



SO=Social Optimum, NE=Nash Equilibrium, Exp=Experimental Results (mean values)

Are they influenced by preferences and/or by personality traits? Are they universal or do they depend on the context?

Accuracy of Beliefs. Subjects systematically overestimate mitigation levels, and hold correct beliefs about adaptation levels. To assess the accuracy of beliefs, I calculate the treatment-average actual decisions regarding the own type's and the other type's level of mitigation (m_own and m_other), and the own type's and the other type's level of adaptation (a_own and a_other) over all subjects for each single treatment. These averages are put to comparison with the subjects' beliefs about the respective decisions. A summary of these data is provided in Table 4.14.

To assess the significance of over-/underestimations, I use a series of Wilcoxon signed rank tests. I test the null hypotheses H0: Bel_m_own = m_own; H0: Bel_m_other = m_other; H0: Bel_a_own = a_own; H0: Bel_a_other = a_other, both by average across all treatments as well as for each single treatment. Across treatments, we find that the own type's and the other type's level of mitigation are systematically over-estimated (H0 rejected with $p = 0.0022$ for m_own and with $p = 0.0476$ for m_other). The mean differences between the beliefs about adaptation and the actual levels of adaptation are not significant (H0 is accepted in both cases).

The analysis by treatment shows significant overestimation of m_own for the treatments h_00hh (H0 rejected with $p = 0.0394$), h_hhll (H0 rejected with $p = 0.0000$), and l_llll (H0 rejected with $p = 0.0062$). Beliefs are found to be accurate for 0_0000, 0_00hh, 0_00ll, h_hhhh, and l_hhll. Finally, we find with weak significance (H0 rejected with $p = 0.0802$) that m_own is systematically underestimated in treatment l_00ll. Regarding m_other, we observe beliefs that range significantly above the actual decisions in treatments 0_00hh (H0 rejected with p=0.0000), 0_00ll ($p = 0.0129$), h_hhll ($p = 0.0000$), and l_hhll ($p = 0.0629$). Beliefs range significantly below the actual decisions in treatments h_00hh ($p = 0.0180$) and l_00ll ($p = 0.0022$). For a_own, the tests indicate overestimation in treatment h_hhll (H0 rejected with $p = 0.0211$) and underestimation in treatment l_llll (H0 rejected with $p = 0.0679$). In all other treatments, beliefs about a_own are accurate. For a_other, we find that beliefs range significantly below the actual decisions in treatment 0_00ll (H0 rejected with $p = 0.0366$). In all other treatments, beliefs about a_other are accurate.

Impact of Beliefs. Subjects' own actual investment decisions and their beliefs about the own type's decisions exhibit a highly significant positive correlation. I infer that the effects of beliefs on actual decisions are not strategically motivated.

For the analysis of how beliefs affect decisions, consider the between regression on

Table 4.14: Accuracy of beliefs, by treatment

Treatment	**own type's *m***		**other type's *m***		**own type's *a***		**other type's *a***	
	actual	beliefs	actual	beliefs	actual	beliefs	actual	beliefs
0_0000	1.7155	1.8592	–	–	–	–	–	–
0_00hh	2.0862	2.1897	0.8879	1.2241	–	–	1.0603	1.1595
0_00ll	2.2155	2.1724	0.6293	0.8276	–	–	2.7845	2.7026
h_00hh	0.8879	0.9224	2.0862	2.0302	1.0603	1.2328	–	–
h_hhhh	1.2328	1.3678	–	–	1.0776	1.1207	–	–
h_hhll	1.4569	1.5603	0.6552	0.9741	0.9828	0.9138	2.7241	2.6767
l_00ll	0.6293	0.7414	2.2155	1.9957	2.7845	2.8448	–	–
l_hhll	0.6552	0.8362	1.4569	1.5431	2.7241	2.8017	0.9828	0.9871
l_llll	0.6897	0.9741	–	–	2.7845	2.6638	–	–
average	1.2854	1.4026	1.3218	1.4325	1.9023	1.9296	1.8879	1.8815

Table 4.15: Impact of beliefs (between-effects regression)

	m	a	EU_av
Est_m_own	0.625***	-0.00351	-5.847***
	(0.206)	(0.126)	(1.860)
Est_m_other	0.155	-0.183	-1.241
	(0.317)	(0.198)	(2.858)
Est_a_own	-0.00267	0.653***	-1.749
	(0.227)	(0.143)	(2.044)
Est_a_other	-0.00292	0.437	-0.426
	(0.330)	(0.348)	(2.978)
MaxEU	-0.238***	-0.225***	2.349***
	(0.0652)	(0.0679)	(0.588)
MinRisk	0.123**	0.143**	-1.171**
	(0.0599)	(0.0632)	(0.540)
MinRiskAll	0.0290	-0.0946*	0.0656
	(0.0540)	(0.0558)	(0.487)
MaxMin	0.00201	0.167***	-0.290
	(0.0604)	(0.0628)	(0.545)
Riskav	-0.0614	0.00627	0.556
	(0.0586)	(0.0610)	(0.529)
Neuro	0.0741	0.0820	-0.642
	(0.0570)	(0.0592)	(0.514)
Open	0.0865*	-0.0287	-0.721*
	(0.0479)	(0.0504)	(0.432)
_cons	0.344	0.511	73.08***
	(0.479)	(0.500)	(4.319)
N	1044	696	1044
R^2	0.513	0.588	0.532

Between regression: regressands are cross-treatment averages
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

subject-average, cross-treatment means based on the regression model R3 displayed in Table 4.15. The regression results indicate that if the belief about the own type's level of mitigation *Bel_m_own* increases by one unit, the own level of mitigation increases by 0.625 units. In consequence, the average expected payoff *EU_av* decreases by 2.6 Taler. If the belief about the own type's level of adaptation *Bel_a_own* increases by one unit, the own level of adaptation increases by 0.65 units. The beliefs about the other type's level of mitigation *Bel_m_other* and the belief about the other type's level of adaptation *Bel_a_other* have no significant impact on actual decisions or the resulting payoff. The treatment-wise estimation results based on the regression models R3 and P3 confirm these findings (see Appendix 4.D, Tables 4.19, 4.20, 4.21, 4.22, and 4.23).

We find that beliefs and decisions are closely interrelated: there are highly significant positive correlations between a subject's m, her *Bel_m_own*, and her *Bel_a_other*; as well as between a subject's a, her *Bel_a_own*, and her *Bel_m_other*. The former three variables m, *Bel_m_own*, and *Bel_a_other* are negatively correlated with the latter three variables a, *Bel_a_own*, and *Bel_m_other*. A correlation matrix is provided in Appendix 4.E.

The results suggest that the effects of beliefs on actual decisions do not arise from strategic behavior: if subjects reacted strategically rational, they would actually buy *less* mitigation if they believed their co-players would buy more mitigation, which is due to the decreasing marginal benefit of group aggregate mitigation M.[3] In contrast, the co-players' level of adaptation is strategically irrelevant - we would not expect a strategical change in a player's level of adaptation in response to her belief about the co-players' level of adaptation.

A possible explanation for our observations is that both the beliefs and the actual decisions are partly determined by underlying preferences such as e.g. risk attitude or non-monetary utility: subjects tend to hold their own preferences to be universal; thus, they project them onto their co-players (Kelley and Stahelski, 1970; Neugebauer et al., 2009). This conjecture is tested in the following.

Belief formation. The more importance a subject attaches to a high individual payoff, the lower is her belief about her own type's level of mitigation. The more importance a subject attaches to a low probability of loss, the higher is her belief about her own type's and the other type's level of mitigation. The more importance a subject attaches to a high individual payoff in the event of loss, the higher is her belief about her own type's and the other type's level of adaptation. Subjects with a high degree of risk aversion

[3] Schram et al. (2008) provide empirical evidence for a significant positive relationship between the estimated probability of being pivotal and the inclination to contribute to a step-level public good.

tend to overestimate the own type's and the other type's level of mitigation. Subjects with a high degree of neuroticism tend to underestimate the own type's and the other type's mitigation.

To enhance our understanding about belief formation, I treat the beliefs (*Bel_* variables) as dependent variables and regress them on the preferences and the personality traits reported in the questionnaire (I also controlled for order and session effects and for socioeconomic variables but did not find any significant effects). The results are shown in Table 4.16. I also let the preferences interact with the treatment dummies and regress the beliefs on the interaction terms, i.e., I test for the effects of the preferences conditional on treatments to check whether the preferences are universal or depend on the context. The results are shown in Appendix 4.F, Tables 4.25 and 4.26.

Table 4.16: Belief formation (GLS random effects regression)

	Est_m_own	Est_m_other	Est_a_own	Est_a_other
MaxEU	-0.186***	-0.134***	-0.0463	-0.0138
	(0.0688)	(0.0451)	(0.0510)	(0.0349)
MinRisk	-0.0701	-0.0351	0.0740	0.0196
	(0.0637)	(0.0418)	(0.0473)	(0.0324)
MinRiskAll	0.156***	0.110***	-0.104**	-0.0738***
	(0.0543)	(0.0356)	(0.0403)	(0.0276)
MaxMin	0.0717	0.0385	0.133***	0.0755**
	(0.0632)	(0.0415)	(0.0469)	(0.0321)
Riskav	0.131**	0.0902**	0.0127	0.0143
	(0.0631)	(0.0414)	(0.0468)	(0.0321)
Neuro	-0.152**	-0.114***	-0.00561	0.0115
	(0.0603)	(0.0396)	(0.0448)	(0.0307)
_cons	1.651***	1.158***	1.042***	0.715***
	(0.447)	(0.293)	(0.332)	(0.227)
N	1044	1044	1044	1044
R^2	0.141	0.172	0.104	0.075

Standard errors in parentheses

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

Since the preferences are measured on an ordinal scale, caution is advised when interpreting the absolute size of the coefficients; yet, we can make inferences about their relative size and significance. We find that, as subjects attach more importance to a high individual payoff (*MaxEU*), the mitigation level they believe the own type would choose (*Bel_m_own*) decreases. The effect is most pronounced for types *0*, and smaller in size and less significant for the types *h*and *l*. As subjects attach more importance to a high individual payoff (*MaxEU*), the mitigation level they believe the other type would choose (*Bel_m_other*) decreases. The effect is considerable in size and at least weakly significant (90% confidence level) for all six heterogeneous treatments. The beliefs about adaptation levels do not significantly depend on *MaxEU* in the overall regression; yet, for type *h*, there is a negative significant effect of *MaxEU* on *Diff_a_own* in treatments h_hhhh and h_hhll. There is also a significant yet small negative effect of *MaxEU* on *Diff_a_other* in all four heterogeneous treatments in which the other type can adapt.

A high importance attached to low individual risk (*MinRisk*) has no significant effect in the overall regression. In the treatment-specific analysis, we can observe that type *0*'s beliefs about type *h*'s and type *l*'s level of mitigation decrease in *MinRisk*, and that type *l*'s belief about her own type's level of mitigation decreases in *MinRisk*.

As subjects attach more importance to a low probability of loss (*MinRiskAll*), the mitigation level they believe the own type and the other type would choose increases. The treatment-specific analysis reveals that the effect is significant for beliefs about type *h*'s and type *l*'s mitigation, but not for beliefs about type *0*'s mitigation. As subjects attach more importance to a low probability of loss (*MinRiskAll*), the adaptation level they believe the own type and the other type would choose decreases. The effect is most pronounced for the own-type beliefs of type *l* players. The effect is significant in all four heterogeneous treatments in which the other type can adapt.

As subjects attach more importance to a high individual payoff in the event of loss (*MaxMin*), the adaptation level they believe the own type and the other type would choose significantly increases. The treatment-specific analysis shows that the increase in beliefs about adaptation is largest and most significant in treatments h_00hh and h_hhhh (Bel_a_own) and treatments h_hhll and l_hhll (Bel_a_other).

Finally, the regression results suggest that subjects with a high degree of risk aversion tend to state high beliefs about the own type's and the other type's level of mitigation. Subjects with a high degree of neuroticism tend to state low beliefs about the own type's and the other type's level of mitigation.

Preferences

We can identify a preference-dependent pattern in belief formation; moreover, the results suggest that there is a significant interrelation of beliefs and actual investment decisions. This indicates that both the beliefs and the actual decisions have their common origin in the players' preferences and personality traits. In the final step of the analysis, I discuss the (direct) impact of preferences on the actual investment decisions. For this purpose, I again refer to the results of the GLS regressions (see Tables 4.9 and 4.10, model R2). In addition to the treatment-average analysis, I also let the preferences interact with the treatment dummies as I did before when estimating the beliefs. The results are shown in Appendix 4.F, Table 4.27. By regressing m and a on the interaction terms, I test for the effects of the preferences conditional on treatments in order to find out whether the preferences are universal or depend on the context. As in the beliefs regression, the absolute size of the coefficients has to be interpreted with caution, because the preferences are measured on an ordinal scale.

As subjects attach more importance to a high individual payoff (*MaxEU*), the levels of both mitigation and adaptation decrease. The effect occurs in all treatments. It is more pronounced for mitigation than for adaptation and significant on a 99% confidence level. The regression results show that a high motivation to maximize payoffs indeed has a positive and highly significant effect on the average expected payoff EU_av. A possible explanation is that payoff maximizers are less risk-averse and more willing to free-ride, i.e., to contribute less to the public good mitigation.

As subjects attach more importance to a low individual risk (*MinRisk*), the levels of both mitigation and adaptation increase, and the average expected payoff decreases. The *MinRisk* coefficients are smaller in size and less significant than those for *MaxEU*. A plausible interpretation is that risk minimizers sacrifice a larger share of their budget for risk reduction and make use of both instruments. The treatment-specific analysis suggests that a higher *MinRisk* score causes a higher level of mitigation in treatments 0_0000, 0_00hh and 0_00ll. In all other treatments, a higher *MinRisk* score leads to an increase in adaptation, whereas the level of mitigation remains unchanged. We infer that risk minimizers prefer to raise their level of adaptation, but resort to mitigation if adaptation is not available.

As subjects attach more importance to a low probability of loss (*MinRiskAll*), the level of mitigation increases, and the level of adaptation decreases in those treatments where adaptation is available. Type *0* players are only marginally affected by *MinRiskAll*. We reason that subjects who prefer to prevent a loss event rather than to deal with the consequences of a loss shift their budget towards mitigation.

Finally, as subjects attach more importance to a high individual payoff in the event of loss (*MaxMin*), the level of adaptation is increasing whereas the level of mitigation does not change. The increase in adaptation is considerable in size and significant on a 99% confidence level in all six treatments where adaptation is available. Type *0* players with a high *MaxMin* score increase their level of mitigation; yet the effect is not significant.

4.6 Conclusion

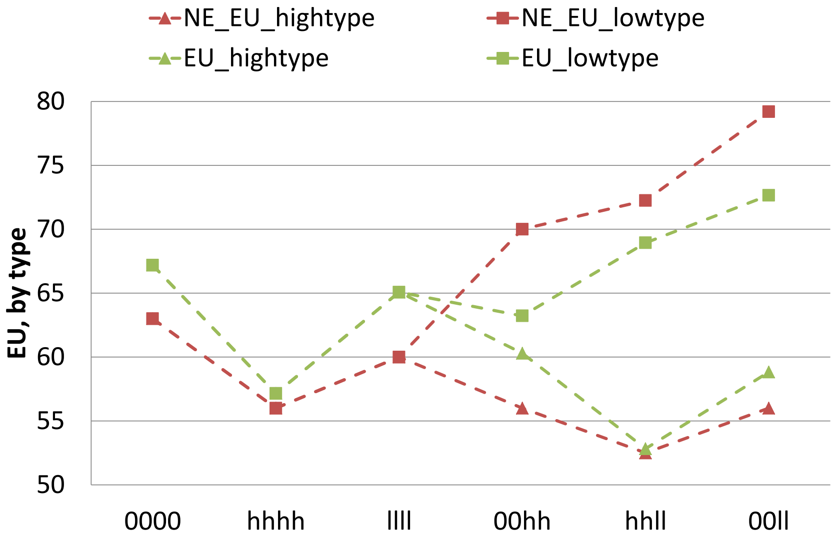
The analysis of the experimental data yields that all hypotheses on treatment effects are qualitatively supported: as their co-players' adaptation cost increase, agents respond by reducing their own mitigation level, whereas the adaptation level remains unchanged. The average expected payoff increases. Within heterogeneous groups, agents with higher adaptation cost contribute a higher share to the aggregate mitigation level than agents with lower adaptation cost.
Despite these confirmative results, the observed choices deviated from the Nash equilibrium predictions in quantitative terms. The players in the experiment contribute systematically more to the public good mitigation than predicted by the Nash equilibrium, whereas the investments in adaptation range around the Nash equilibrium level. In the homogeneous games, above-Nash contributions to mitigation result in higher average expected payoffs than predicted by the Nash equilibrium.

In the heterogeneous games, average expected payoffs critically depend on the *relative* shares in M. The Nash equilibrium predicts that the type with higher adaptation cost contributes 100% of the group aggregate level of mitigation, while the type with lower adaptation cost contributes zero. In the experiment, we indeed observe some degree of freeriding; yet, the divergence is less extreme than predicted (see Figure 4.2). In consequence, the observed average payoff gap between the higher-cost type and the lower-cost type is smaller than predicted by the Nash equilibrium (see Figure 4.5). However, this distribution takes its toll: the game-average payoff across both types of players falls below the Nash equilibrium level in all three heterogeneous games (see Figure 4.6).

I tested for two factors that could possibly explain these deviations: first, I conjectured that subjects responded to erroneous beliefs; second, I conjectured that the investment decisions are driven by utility components beyond the expected payoff, in particular (i) risk aversion and (ii) inequity aversion.

By eliciting the beliefs about the other players' decisions, I was able to control for erroneous beliefs. The results indicate that subjects systematically overestimate their co-players' levels of mitigation; at the same time, the actual investments in mitigation are

Figure 4.5: Payoff equity, by game



higher than predicted by the Nash equilibrium. This runs contrary to the expectation of strategically rational decisions; instead, we have good reason to attribute both the beliefs about the co-players' decisions and the actual own decisions to idiosyncratic preferences regarding risk and equity.

To check whether the results are sensitive to changes in risk attitude, I re-calculate the Nash equilibria on the alternative expected utility function

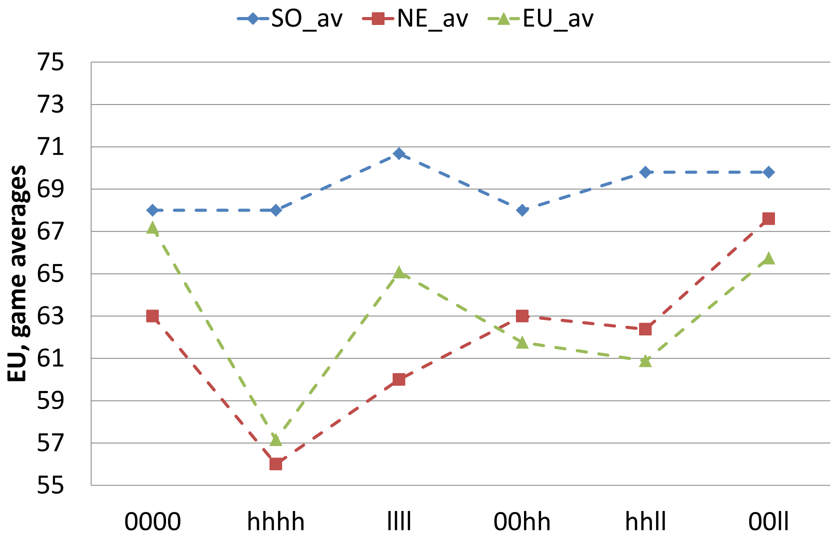
$$Eu_i = p_i(M) \cdot ((1 - L_i(a_i)) \cdot (y_i - k_i a_i - l_i m_i))^{0.8} + (1 - p_i(M)) \cdot (y_i - k_i a_i - l_i m_i)^{0.8}.$$

The Nash equilibrium strategies turn out to be quite robust to this variation: only in treatment h_00hh, the Nash equilibrium value for a increases from 0 to 1; all other equilibrium values remain unchanged. I repeat the robustness check assuming an even more concave expected utility function

$$Eu_i = p_i(M) \cdot ((1 - L_i(a_i)) \cdot (y_i - k_i a_i - l_i m_i))^{0.5} + (1 - p_i(M)) \cdot (y_i - k_i a_i - l_i m_i)^{0.5}.$$

The Nash equilibrium m for type *0* increases by 0.5 units in all three treatments (0_0000, 0_00hh and 0_00ll); all other equilibrium values remain unchanged. These observations are in line with the results of Dionne and Eeckhoudt (1985) and Briys and Schlesinger (1990) who show in a model of choice under risk that the level of self-insurance (here: adaptation) is monotonically increasing in an individual's degree of risk aversion, whereas

Figure 4.6: Payoff efficiency, by game



the impact of risk aversion on the level of self-protection (here: mitigation) is ambiguous.

In the heterogeneous games, we observe that, while all players contribute more to the aggregate level of mitigation than predicted by the Nash equilibrium, the excess ("above-Nash") contribution of players with lower adaptation cost is significantly higher than the excess contribution of players with higher adaptation cost. As a result, the difference in average expected payoffs between types is smaller than it is in the Nash equilibrium. A possible explanation for this behavior is that subjects incorporate fairness in the sense of self-centered inequity aversion into their utility function as described by Fehr and Schmidt (1999) and, similarly, by Bolton and Ockenfels (2008). Their models explain that, under certain conditions, people are ready to sacrifice monetary payoff in exchange for a more equitable outcome in terms of relative payoffs. Lange and Vogt (2003) and Lange (2006) apply the Bolton and Ockenfels (2008) model to the context of climate change policymaking. They show that, under certain conditions, parties negotiating climate treaties can reach higher cooperation rates if their utility functions contain an element of inequity aversion. Our empirical results point in the same direction.

Equity considerations have been an inherent part of international negotiations on climate change policy: in article 3 of the UNFCCC framework, it is demanded that

> (t)he Parties should protect the climate system for the benefit of present and future generations of humankind, on the basis of equity and in accordance with their common but differentiated responsibilities and respective

> capabilities. Accordingly, the developed country Parties should take the lead in combating climate change and the adverse effects thereof.

My experiment shows that even if agents are equal in terms of endowment, mitigation cost and marginal benefits from mitigation, payoffs can diverge substantially only because of heterogeneous adaptation cost. The non-cooperative outcome favors those who profit from low adaptation cost anyway, whereas those who do not have the opportunity to adapt are even further disadvantaged because their co-players free ride on them. This has important implications for negotiations on international climate change agreements: an agent's adaptive capacity and adaptation cost affect her outside option and thus the threat point of the bargaining problem. It is therefore suggested that, in considerations of equity, the parties to international climate change agreements pay particular attention to differences in relative adaptation cost and adaptive capacities.

4.A Experimental Instructions

Experimentanleitung

Allgemeine Informationen

Herzlich willkommen! Sie werden gleich an einem Experiment teilnehmen. Die Durchführung des Experiments wird ca. 90 Minuten in Anspruch nehmen. Alle Teilnehmerinnen und Teilnehmer befinden sich in derselben Entscheidungssituation und haben dieselben Entscheidungsmöglichkeiten. Das Experiment besteht aus 9 voneinander unabhängigen Spielen. Ihre Entscheidungen in einem Spiel haben also keinen Einfluss auf die anderen Spiele.

Für Ihre Teilnahme erhalten Sie eine Basisvergütung (Fixbetrag) von 7 Euro. Abhängig von Ihren Entscheidungen, den Entscheidungen der anderen Teilnehmer und einem gewissen Maß an Zufall können Sie zusätzliches Geld verdienen. Zur Ermittlung Ihres Verdienstes wird am Ende des Experiments aus den 9 gespielten Spielen ein Spiel ausgelost. Sie erhalten zusätzlich zur Basisvergütung die in diesem Spiel erzielte Auszahlung. Im Experiment werden alle Zahlungen in Talern berechnet, die am Ende in Euro umgerechnet und in bar an Sie ausgezahlt werden, ohne dass andere Teilnehmerinnen und Teilnehmer erfahren, wie viel Geld Sie erhalten. Der Umrechnungskurs der Spielwährung beträgt

10 Taler = 1 Euro.

Alle Entscheidungen im Experiment bleiben anonym, d.h. keine andere Teilnehmerin und kein anderer Teilnehmer erhält Informationen über ihre Identität, weder während noch nach dem Experiment. Genauso erhalten Sie keine Information über die Identität der anderen Teilnehmerinnen und Teilnehmer.

Es ist wichtig, dass Sie die Anleitung zu dem Experiment vollständig verstehen. Bitte lesen Sie sich die folgenden Seiten deshalb gründlich durch. Wenn Sie Fragen haben, dann heben Sie bitte die Hand und der Experimentleiter wird ihre Fragen beantworten. Um sicherzustellen, dass Sie die Anleitung verstanden haben, bitten wir Sie, im Anschluss an die Instruktionsphase einige Kontrollfragen zu beantworten. Es folgt noch eine Proberunde, bevor dann das eigentliche Experiment beginnt.

Nach Abschluss des Experiments gibt es noch einen Fragebogen, den Sie bitte am Computer ausfüllen.

Während des Experiments ist es nicht gestattet, mit den anderen Teilnehmern zu kommunizieren. Mobiltelefone müssen während des gesamten Experiments ausgeschaltet sein. Außerdem dürfen Sie am Computer nur diejenigen Funktionen bedienen, die für den Ablauf des Experiments bestimmt sind. Kommunikation oder Herumspielen am Computer führen zum Ausschluss vom Experiment und zum Verlust aller Einnahmen.

Experimentbeschreibung

Sie spielen in Vierergruppen. Vor jedem Spiel werden die Gruppen neu eingeteilt, und zwar so, dass in jedem neuen Spiel andere Mitspieler aufeinandertreffen. Die Gruppeneinteilung erfolgt anonym, d.h. weder während noch nach dem Experiment erfahren Sie, wann Sie mit welchen anderen Personen in einer Gruppe sind oder waren.

Zu Beginn eines jeden Spiels erhalten Sie 100 Taler als persönliches Guthaben. Mit einer bestimmten Wahrscheinlichkeit tritt ein Ereignis ein, durch welches Sie diese 100 Taler ganz oder teilweise verlieren. Sie haben zwei Möglichkeiten, diesem Risiko zu begegnen:

(1.) Wahrscheinlichkeitsreduktion. Diese Möglichkeit haben Sie in allen 9 Spielen.
Der Preis je Einheit Wahrscheinlichkeitsreduktion beträgt 10 Taler.
(2.) Verlustreduktion. Diese Möglichkeit haben Sie in einigen der 9 Spiele, in anderen nicht.
Der Preis je Einheit Verlustreduktion kann von Spiel zu Spiel variieren.

Sie können Ihr Guthaben ganz oder teilweise in Wahrscheinlichkeitsreduktion und/oder in Verlustreduktion investieren. Zu Beginn eines jeden Spiels erfahren Sie, ob Sie die Möglichkeit zur Verlustreduktion haben und wie hoch der Preis je Einheit Verlustreduktion ist (sofern im Spiel verfügbar). Sie erfahren außerdem, ob und zu welchem Preis die anderen drei Gruppenmitglieder in Verlustreduktion investieren können. Alle Gruppenmitglieder treffen ihre Entscheidung geheim und anonym. Einmal getroffene Entscheidungen können nicht rückgängig gemacht werden.

(1.) Wahrscheinlichkeitsreduktion. Wenn Sie und/oder andere Mitglieder Ihrer Gruppe in Wahrscheinlichkeitsreduktion investieren, reduziert sich die Wahrscheinlichkeit für den Eintritt des Verlustereignisses für alle Gruppenmitglieder (einschließlich Ihnen). In welchem Maße die Wahrscheinlichkeit abnimmt, hängt von der Gesamtanzahl der in der Gruppe gekauften Einheiten Wahrscheinlichkeitsreduktion ab. Es ist dabei unerheblich, durch welches Gruppenmitglied/welche Gruppenmitglieder die Investition erfolgt.

Ob das Verlustereignis für Ihre Gruppe eintritt oder nicht, entscheidet ein Zufallsgenerator, der eine Kugel aus einem (virtuellen) Behälter mit 100 Kugeln zieht. Ist die gezogene Kugel rot, so ist das Verlustereignis eingetreten; ist sie weiß, so ist das Verlustereignis nicht eingetreten. Zunächst sind alle 100 Kugeln im Behälter rot, d.h., es ist zu 100% sicher, dass das Verlustereignis eintritt. Durch den Kauf von Wahrscheinlichkeitsreduktion können Sie und die anderen Gruppenmitglieder rote Kugeln durch weiße Kugeln ersetzen. Jede Einheit Wahrscheinlichkeitsreduktion kostet **10 Taler**. Die durch Ihre Gruppe gekaufte Wahrscheinlichkeitsreduktion verringert die Wahrscheinlichkeit für das Verlustereignis wie folgt:

Wahrscheinlichkeitsreduktion Gruppe gesamt (in Einheiten)	Anzahl Kugeln weiß	Anzahl Kugeln rot =Verlustwahrscheinlichkeit in %
0	0	100
1	30	70
2	50	50
3	60	40
4	70	30
5	75	25
6	80	20
7	82	18
8	84	16
9	86	14
10	88	12
11	90	10
12	91	9
13	92	8
14	93	7
15	94	6
16 … 50	95	5

Ab der 17. Einheit Wahrscheinlichkeitsreduktion verringert sich die Verlustwahrscheinlichkeit nicht mehr weiter. Die Restwahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt dann 5% (d.h., 5 rote Kugeln bleiben immer im Behälter).

(2.) Verlustreduktion. Wenn das Verlustereignis eintritt (d.h. der Zufallsgenerator zieht eine rote Kugel), verlieren Sie Ihr gesamtes Guthaben. Durch Investition in Verlustreduktion können Sie Ihren persönlichen Verlust begrenzen. Die Verluste der anderen Gruppenmitglieder bleiben davon unberührt. Der Preis für eine Einheit Verlustreduktion wird Ihnen zu Beginn eines jeden Spiels bekanntgegeben. Er kann von Spiel zu Spiel variieren.

Die von Ihnen gekaufte Verlustreduktion verringert Ihre persönliche Verlustquote wie folgt:

Ihre Verlustreduktion (in Einheiten)	Ihr Verlust bei Eintritt des Verlustereignisses (in % des nicht ausgegebenen Guthabens)
0	100 %
1	60 %
2	40 %
3	30 %
4	25 %
5	20 %
6	18 %
7	16 %
8	14 %
9	12 %
10 … 20	10 %

Ab der 11. Einheit Verlustreduktion verringert sich die Verlustquote nicht mehr weiter. Die Rest-Verlustquote beträgt dann 10 %.

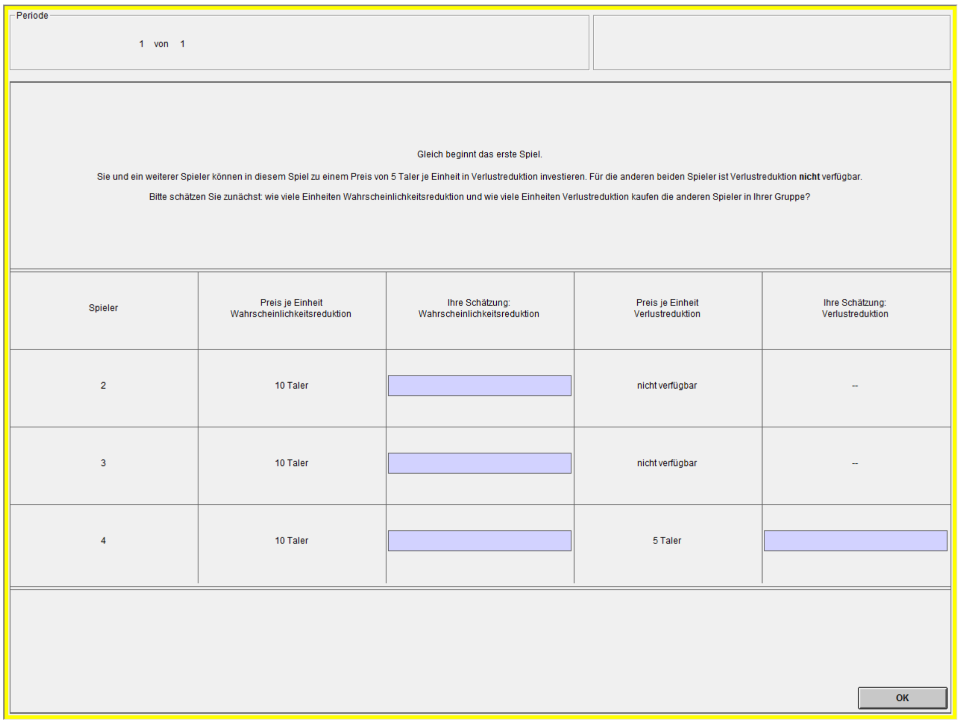
Achtung: In den Spielen ohne Möglichkeit zur Verlustreduktion können Sie Ihren persönlichen potenziellen Verlust <u>nicht</u> durch den Kauf von Verlustreduktion begrenzen. Bei Eintritt des Verlustereignisses (d.h., der Zufallsgenerator zieht eine rote Kugel) ist Ihr gesamtes Guthaben verloren.

Experimentablauf im Detail

(1.) Schätzrunde.

Zu Beginn eines jeden Spiels bitten wir Sie zu schätzen, wie die anderen drei Mitglieder Ihrer Gruppe in diesem Spiel entscheiden werden. Jeder Spieler gibt seine Schätzungen ab, bevor er/sie seine/ihre eigenen Entscheidungen trifft. Pro Schätzung, die mit der tatsächlich gekauften Anzahl von Einheiten Wahrscheinlichkeits- und/oder Verlustreduktion übereinstimmt, erhalten Sie 3 Taler.

Es erscheint folgender Bildschirm:



Hier erfahren Sie, wie viele Mitglieder Ihre Gruppe in diesem Spiel in Verlustreduktion investieren können und wie hoch der Preis für eine Einheit Verlustreduktion ist (sofern verfügbar).

Für jeden der anderen drei Spieler in Ihrer Gruppe gibt es eine Tabellenzeile. Bitte geben Sie Ihre Schätzung darüber ab, wie viele Einheiten Wahrscheinlichkeitsreduktion und/oder Verlustreduktion die anderen Mitspieler kaufen werden.

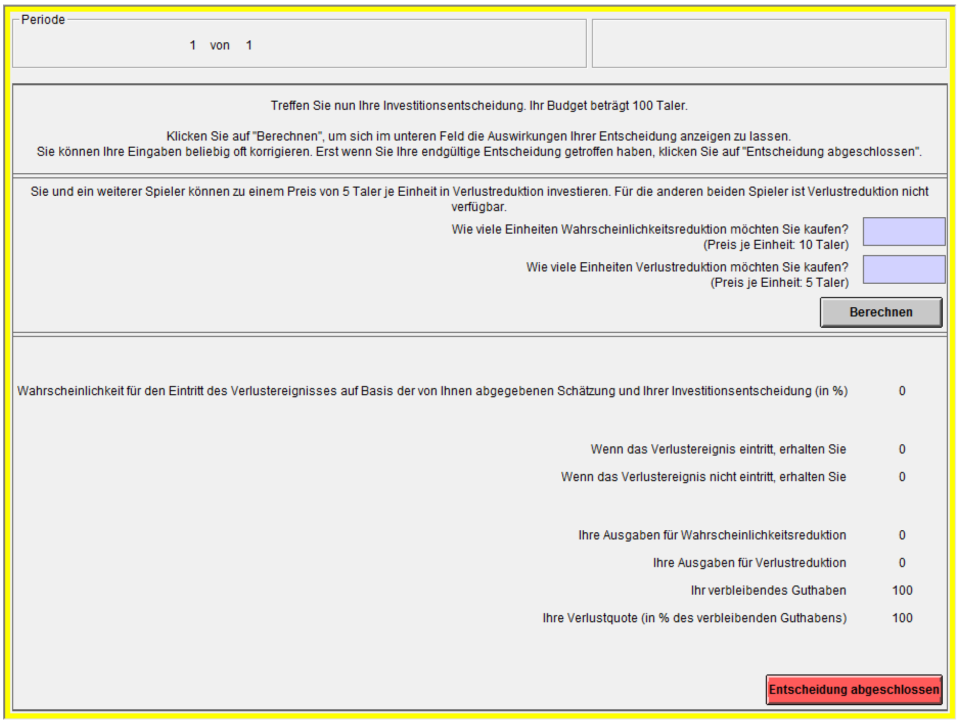
Wenn mehrere Gruppenmitglieder zu gleichen Kosten in Wahrscheinlichkeits- und Verlustreduktion investieren können, werden sowohl Ihre Schätzungen als auch die tatsächlich gekauften Einheiten gemittelt, d.h., es kommt nicht auf die Identität des Spielers an, sondern lediglich auf den Kostentyp. Beispiel: Sie schätzen die Wahrscheinlichkeitsreduktion für Spieler 2 und 3 auf jeweils 2 Einheiten. Tatsächlich kauft Spieler 2 eine Einheit, Spieler 3 kauft 3

Einheiten. In diesem Fall ist Ihre Schätzung dennoch korrekt, da der Mittelwert 2 Einheiten beträgt.

Wenn Sie Ihre Schätzung abgegeben haben, klicken Sie bitte auf OK.

(1.) Entscheidungsrunde.

Ihre Aufgabe besteht nun darin, Ihre eigene Kaufentscheidung zu treffen. Sie sehen auf dem Bildschirm:



Geben Sie im ersten Feld ein, wie viele Einheiten Wahrscheinlichkeitsreduktion Sie kaufen möchten. Geben Sie im zweiten Feld ein, wie viele Einheiten Verlustreduktion Sie kaufen möchten. Wenn Sie keine Wahrscheinlichkeitsreduktion und/oder keine Verlustreduktion kaufen möchten, geben Sie bitte „0“ in das/die jeweilige(n) Feld(er) ein.

Klicken Sie anschließend auf „Berechnen“. Im unteren Teil des Bildschirms können Sie nun Ihre Ausgaben und Ihr verbleibendes Guthaben ablesen sowie Ihre Verlustquote und die Auszahlung, die Sie erhalten, wenn das Verlustereignis eintritt bzw. nicht eintritt. Die ebenfalls angezeigte Wahrscheinlichkeit für den Eintritt des Verlustereignisses basiert auf der von Ihnen abgegebenen Schätzung sowie Ihrer Investitionsentscheidung. Sie entspricht also nicht unbedingt der tatsächlichen Eintrittswahrscheinlichkeit (diese hängt von den eigentlichen Kaufentscheidungen Ihrer Mitspieler ab), sondern dient lediglich zu Ihrer Orientierung.

Solange Sie noch nicht auf „Entscheidung abgeschlossen“ geklickt haben, können Sie Ihre Kaufentscheidung beliebig oft korrigieren. Wenn Sie eine oder beide Eingaben geändert haben, klicken Sie bitte anschließend erneut auf „Berechnen"; dadurch werden die Informationen im unteren Teil des Bildschirms neu berechnet und aktualisiert.

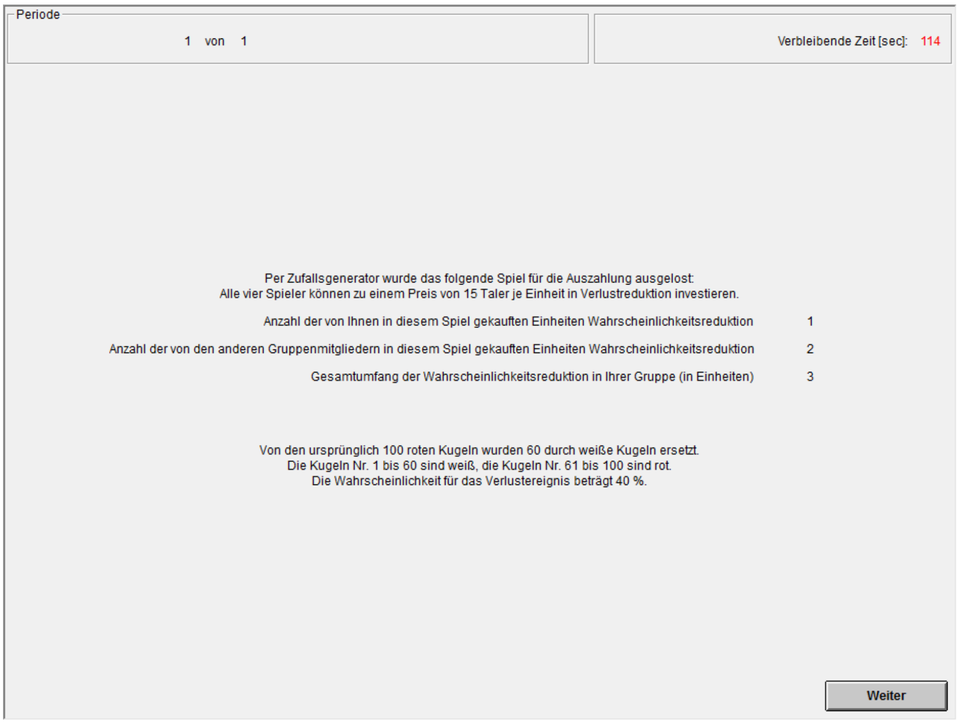
Wenn Sie Ihre endgültige Entscheidung getroffen haben, klicken Sie auf „Entscheidung abgeschlossen", um dieses Spiel zu beenden. Ihre Eingaben sind jetzt gespeichert.

Das nächste Spiel startet daraufhin automatisch - wiederum mit der Schätzrunde wie oben beschrieben.

Wenn Sie alle 9 Spiele gespielt haben, erscheint ein Wartebildschirm (hier nicht gezeigt).

(2.) Auslosung des zahlungsrelevanten Spiels und Ermittlung der Wahrscheinlichkeit.

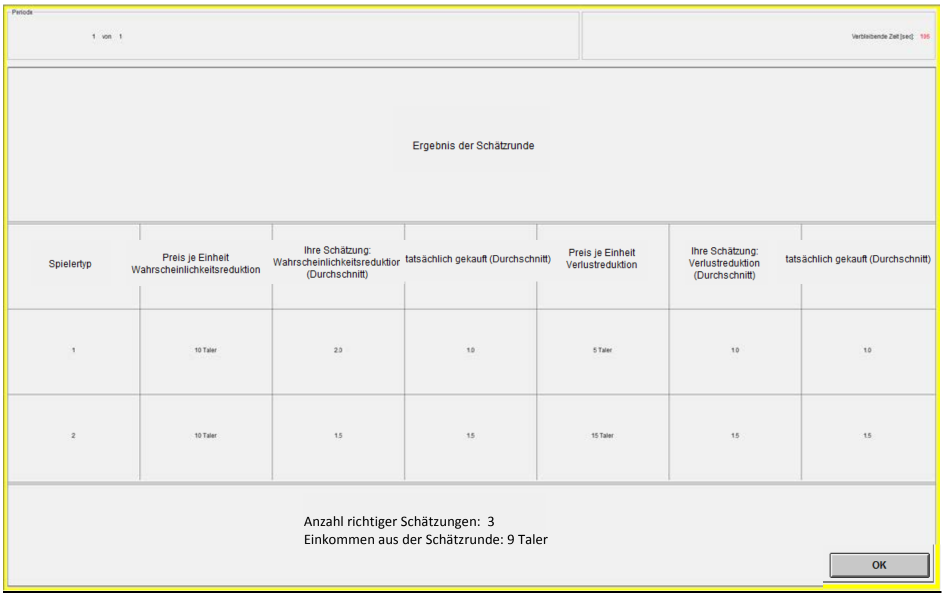
Wenn alle Teilnehmer die neun Spiele durchlaufen und ihre Entscheidungen getroffen haben, erscheint folgender Bildschirm:



Sie erfahren nun, welches der neun Spiele für die Auszahlung ausgelost wurde und wie viele Einheiten Wahrscheinlichkeitsreduktion in diesem Spiel von Mitgliedern Ihrer Gruppe gekauft wurden. Der Gesamtumfang der Wahrscheinlichkeitsreduktion bestimmt, wie viele rote Kugeln durch weiße Kugeln ersetzt werden und damit die Wahrscheinlichkeit für den Eintritt des Verlustereignisses.

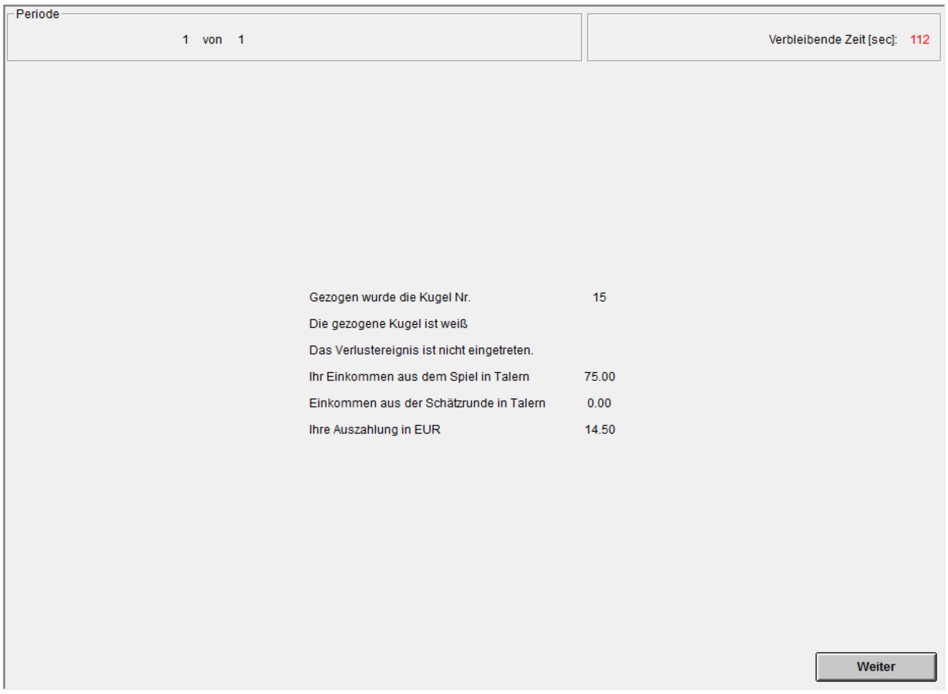
Klicken Sie anschließend auf „Weiter".

Als nächstes erfolgt die Auswertung der Schätzrunde. Es erscheint der folgende Bildschirm. Für jede richtige Schätzung (Durchschnitt aller Spieler mit gleichem Preisprofil) erhalten Sie 3 Taler.



(3.) Zufall und Auszahlung.

In der letzten Phase des Spiels wird per Zufallsgenerator aus den 100 Kugeln im Behälter eine Kugel gezogen. Sie sehen auf dem Bildschirm:



Angezeigt werden die Nummer der gezogenen Kugel (Zahl zwischen 1 und 100) und die Farbe dieser Kugel entsprechend der von Ihrer Gruppe gekauften Wahrscheinlichkeitsreduktion. Ist die gezogene Kugel rot, so ist das Verlustereignis eingetreten und Sie erhalten als Auszahlung in Talern Ihr verbleibendes Guthaben nach Ausgaben für Wahrscheinlichkeits- und Verlustreduktion abzüglich des Verlustes. Die Höhe des Verlustes hängt in den Spielen mit Möglichkeit zur Verlustreduktion davon ab, wie viele Einheiten Verlustreduktion Sie gekauft haben. Ist die gezogene Kugel weiß, so ist das Verlustereignis nicht eingetreten und Sie erhalten als Auszahlung in Talern Ihr verbleibendes Guthaben nach Abzug der Ausgaben für Wahrscheinlichkeits- und Verlustreduktion.

Zusätzlich erhalten Sie, unabhängig vom Ausgang des Spiels, aus der Schätzrunde 3 Taler pro korrekte Schätzung.

Die Auszahlung in EUR ergibt sich nach der Umrechnungsformel: $7 + \frac{Auszahlung\ in\ Talern}{10}$.

-Ende des Spiels-

Beispiel 1: Verlustreduktion möglich.

Ihre Gruppe besteht aus 4 Mitgliedern: Ihnen, Person B, Person C und Person D. Eine Einheit Verlustreduktion kostet 5 Taler.

Entscheidung.

Sie kaufen eine Einheit Wahrscheinlichkeitsreduktion und 2 Einheiten Verlustreduktion. Von Ihrem Anfangsguthaben bleiben also 80 Taler übrig (100 - 1*10 - 2*5 = 80). Gleichzeitig mit Ihnen treffen B, C und D ihre Investitionsentscheidungen. Weder Sie noch B noch C noch D wissen, wie sich die drei anderen Personen entschieden haben.

Wahrscheinlichkeit.

Nachdem alle Gruppenmitglieder ihre Entscheidung getroffen haben, wird die Wahrscheinlichkeit für den Eintritt des Verlustereignisses berechnet. Sie kauften eine Einheit Wahrscheinlichkeitsreduktion, B kaufte ebenfalls eine Einheit, C kaufte 0 Einheiten und D kaufte 2 Einheiten. Insgesamt hat Ihre Gruppe also 4 Einheiten Wahrscheinlichkeitsreduktion gekauft. Von den ursprünglich 100 roten Kugeln werden die Kugeln Nr. 1 bis 70 durch weiße Kugeln ersetzt. Im Behälter sind jetzt 70 weiße Kugeln (Nr. 1 bis 70) und 30 rote Kugeln (Nr. 71 bis 100). Die Wahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt also 30%.

Zufall und Auszahlung.

Aus den 100 Kugeln im Behälter wird zufällig eine Kugel gezogen. Wenn die gezogene Kugel rot ist, dann ist das Verlustereignis eingetreten; wenn sie weiß ist, dann ist das Verlustereignis nicht eingetreten.

(Fall a): Der Zufallsgenerator hat die Kugel Nr. 27 gezogen. Diese Kugel ist weiß. Das Verlustereignis ist somit nicht eingetreten. Sie erhalten 80 Taler (Anfangsguthaben 100 Taler abzüglich 20 Taler Ausgaben für Wahrscheinlichkeitsreduktion und Verlustreduktion).

(Fall b): Der Zufallsgenerator hat die Kugel Nr. 85 gezogen. Diese Kugel ist rot. Das Verlustereignis ist eingetreten. Sie haben 2 Einheiten Verlustreduktion gekauft. Von Ihrem verbleibenden Guthaben in Höhe von 80 Talern (Anfangsguthaben abzüglich 20 Taler Ausgaben) verlieren Sie 40% = 32 Taler. Sie erhalten 80 - 32 = 48 Taler.

Beispiel 2: Verlustreduktion nicht möglich.

Ihre Gruppe besteht aus 4 Mitgliedern: Ihnen, Person B, Person C und Person D.

Entscheidung.

Sie kaufen 2 Einheiten Wahrscheinlichkeitsreduktion. Von Ihrem Anfangsguthaben bleiben also 80 Taler übrig (100 - 2*10 = 80). Gleichzeitig mit Ihnen treffen B, C und D ihre Investitionsentscheidungen. Weder Sie noch B noch C noch D wissen, wie sich die drei anderen Personen entschieden haben.

Wahrscheinlichkeit.

Nachdem alle Gruppenmitglieder ihre Entscheidung getroffen haben, wird die Wahrscheinlichkeit für den Eintritt des Verlustereignisses berechnet. Sie kauften 2 Einheiten Wahrscheinlichkeitsreduktion, B kaufte eine Einheit, C kaufte 0 Einheiten und D kaufte 2 Einheiten. Insgesamt hat Ihre Gruppe also 5 Einheiten Wahrscheinlichkeitsreduktion gekauft. Von den ursprünglich 100 roten Kugeln werden die Kugeln Nr. 1 bis 75 durch weiße Kugeln ersetzt. Im Behälter sind jetzt 75 weiße Kugeln (Nr. 1 bis 75) und 25 rote Kugeln (Nr. 76 bis 100). Die Wahrscheinlichkeit für den Eintritt des Verlustereignisses beträgt also 25%.

Zufall und Auszahlung.

Aus den 100 Kugeln im Behälter wird zufällig eine Kugel gezogen. Wenn die gezogene Kugel rot ist, dann ist das Verlustereignis eingetreten; wenn sie weiß ist, dann ist das Verlustereignis nicht eingetreten.

(Fall a): Der Zufallsgenerator hat die Kugel Nr. 27 gezogen. Diese Kugel ist weiß. Das Verlustereignis ist somit nicht eingetreten. Sie erhalten 80 Taler (Anfangsguthaben 100 Taler abzüglich 20 Taler Ausgaben für Wahrscheinlichkeitsreduktion).

(Fall b): Der Zufallsgenerator hat die Kugel Nr. 85 gezogen. Diese Kugel ist rot. Das Verlustereignis ist eingetreten. Sie erhalten 0 Taler.

4.B Questionnaire

Fragebogen

Teil 1: Fragen zum Experiment. Bitte beantworten Sie die folgenden Fragen:

Die im Experiment gestellte Aufgabe war eher abstrakt und allgemein formuliert. Hatten Sie eine konkrete Situation im Kopf, als Sie Ihre Entscheidungen getroffen haben? Wenn ja, woran haben Sie gedacht (bitte kurz und stichwortartig beschreiben)?

____

____

Inwieweit waren die nachfolgend genannten Kriterien für Ihre Entscheidungen ausschlaggebend? Bitte kreuzen Sie an:

	sehr wichtig	eher wichtig	weder noch	eher unwichtig	völlig unwichtig
Hohe Auszahlung für mich persönlich	○	○	○	○	○
Wenig Risiko für mich persönlich	○	○	○	○	○
Hohe Auszahlungen für alle Mitglieder meiner Gruppe	○	○	○	○	○
Geringe Wahrscheinlichkeit für den Eintritt des Verlustereignisses	○	○	○	○	○
Gerechte Verteilung der Auszahlungen auf die Gruppenmitglieder	○	○	○	○	○
Hohe Auszahlung für mich persönlich im Verlustfall	○	○	○	○	○

Teil 2: Persönlichkeitseigenschaften. Inwieweit treffen die folgenden Aussagen auf Sie zu?

	trifft voll und ganz zu	trifft eher zu	weder noch	trifft eher nicht zu	trifft überhaupt nicht zu
Ich bin eher zurückhaltend, reserviert.	○	○	○	○	○
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.	○	○	○	○	○
Ich bin bequem, neige zur Faulheit.	○	○	○	○	○
Ich bin im Allgemeinen ein risikobereiter Mensch.	○	○	○	○	○
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.	○	○	○	○	○

Ich habe nur wenig künstlerisches Interesse.	◯	◯	◯	◯	◯
Ich gehe aus mir heraus, bin gesellig.	◯	◯	◯	◯	◯
Ich neige dazu, andere zu kritisieren.	◯	◯	◯	◯	◯
Ich erledige Aufgaben gründlich.	◯	◯	◯	◯	◯
Ich werde leicht nervös und unsicher.	◯	◯	◯	◯	◯
Ich bin eher vorsichtig und versuche, Risiken und Gefahren zu vermeiden.	◯	◯	◯	◯	◯
Ich habe eine aktive Vorstellungskraft, bin phantasievoll.	◯	◯	◯	◯	◯
Ich bin rücksichtsvoll zu anderen, einfühlsam.	◯	◯	◯	◯	◯

Teil 3: Angaben zu Ihrer Person

Bitte beantworten Sie die folgenden Fragen:

Wie alt sind Sie?	________					
Ihr Geschlecht?	________					
Wie viele Geschwister haben Sie?	________					
Wie häufig haben Sie schon an Experimenten teilgenommen?	noch nie	weniger als 3 mal		weniger als 5 mal	5 mal und häufiger	
Studieren Sie? Wenn ja, in welchem Semester?	nein	1.-3. Semester		4.-7. Semester	8. und höheres Semester	
Was studieren Sie (wenn Sie studieren)?	________					
Sind Sie in einem festen Arbeitsverhältnis mit mehr als 10 Arbeitsstunden/Woche?	ja	nein				
Wie viele Euro stehen Ihnen monatlich zur Verfügung?	<400	400 - 700	700 - 1000	1000 - 1300	1300 - 1600	>1600

Vielen Dank für Ihre Teilnahme!

Es folgt nun die Auszahlung. Bitte warten Sie die Instruktionen des Experimentleiters ab.

4.C Fixed Effects Regression Results

Table 4.17: Treatment effects (GLS fixed effects regression)

regressand	m	a	EU_av
adapt	-0.828***		-3.970***
	(0.118)		(0.934)
low	-0.259***	1.685***	9.436***
	(0.0866)	(0.109)	(0.750)
withadapt	0.371***	-0.0216	-6.895***
	(0.104)	(0.0576)	(0.807)
withlow	0.129		-1.468*
	(0.102)		(0.777)
a×wa	-0.0259		0.829
	(0.138)		(1.099)
a×wa×wl	0.0948	-0.0754	-2.855***
	(0.134)	(0.0751)	(1.008)
a×l×wa	-0.319***		2.347**
	(0.102)		(0.938)
a×l×wa×wl	-0.190**	0.116	0.466
	(0.0957)	(0.107)	(0.952)
_cons	1.716***	1.080***	67.19***
	(0.0718)	(0.0590)	(0.601)
N	1044	696	1044
R^2	0.400	0.597	0.503

Standard errors in parentheses

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

Table 4.18: Treatment effects (Poisson fixed effects regression)

regressand	m	a
adapt	-0.659***	
	(0.100)	
low	-0.344***	0.946***
	(0.112)	(0.0614)
withadapt	0.196***	-0.0113
	(0.0500)	(0.0273)
withlow	0.0601	
	(0.0448)	
a×wa	0.132	
	(0.0986)	
a×wa×wl	0.107	-0.0784
	(0.0746)	(0.0635)
a×l×wa	-0.288**	
	(0.115)	
a×l×wa×wl	-0.116	0.0950
	(0.0900)	(0.0675)
N	1017	684

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.D Impact of Beliefs on Decisions and Payoffs, by Treatment

Table 4.19: Impact of beliefs on a, by treatment (GLS regression)

	h_hhhh	l_llll	h_00hh	l_00ll	h_hhll	l_hhll
Bel_m_own	-0.0307	-0.257	-0.0473	-0.0926	-0.103	-0.0946
	(0.0980)	(0.156)	(0.0860)	(0.143)	(0.0991)	(0.130)
Bel_m_other	0	0	0.0175	-0.0341	0.155	-0.0876
	(0)	(0)	(0.0892)	(0.145)	(0.137)	(0.136)
Bel_a_own	0.601***	0.720***	0.338***	0.641***	0.341**	0.539***
	(0.112)	(0.110)	(0.0922)	(0.140)	(0.133)	(0.124)
Bel_a_other	0	0	0	0	0.127*	0.136
	(0)	(0)	(0)	(0)	(0.0708)	(0.178)
MaxEU	-0.149	-0.213	-0.237**	-0.383***	-0.0893	-0.409***
	(0.0932)	(0.160)	(0.0931)	(0.133)	(0.0711)	(0.138)
MinRisk	0.109	0.123	0.147**	0.101	0.187**	0.213*
	(0.0793)	(0.0935)	(0.0705)	(0.112)	(0.0800)	(0.114)
MinRiskAll	-0.110	-0.0529	-0.0959*	-0.117	-0.142	-0.185**
	(0.0771)	(0.0955)	(0.0567)	(0.103)	(0.105)	(0.0828)
MaxMin	0.258***	0.151	0.272***	0.321**	0.254***	0.144
	(0.0766)	(0.100)	(0.0781)	(0.124)	(0.0728)	(0.132)
_cons	0.0634	1.163	0.392	1.553**	-0.478	2.372**
	(0.466)	(0.948)	(0.531)	(0.783)	(0.498)	(0.924)
N	116	116	116	116	116	116
R^2	0.423	0.402	0.348	0.393	0.283	0.343

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.20: Impact of beliefs on a, by treatment (Poisson regression)

	h_hhhh	l_llll	h_00hh	l_00ll	h_hhll	l_hhll
Bel_m_own	-0.0850	-0.0963*	-0.102	-0.0366	-0.0411	-0.0536
	(0.0713)	(0.0529)	(0.0676)	(0.0520)	(0.102)	(0.0479)
Bel_m_other			-0.0260	-0.0136	0.0684	-0.0327
			(0.0734)	(0.0494)	(0.127)	(0.0493)
Bel_a_own	0.488***	0.234***	0.258***	0.211***	0.381***	0.183***
	(0.0726)	(0.0339)	(0.0664)	(0.0408)	(0.134)	(0.0411)
Bel_a_other					0.0852	0.0453
					(0.0755)	(0.0623)
MaxEU	-0.235***	-0.0730	-0.314***	-0.143***	-0.146*	-0.152***
	(0.0894)	(0.0589)	(0.0844)	(0.0499)	(0.0822)	(0.0476)
MinRisk	0.102	0.0523	0.148*	0.0489	0.204***	0.0803*
	(0.0849)	(0.0341)	(0.0827)	(0.0425)	(0.0774)	(0.0416)
MinRiskAll	-0.0984	-0.0261	-0.0834	-0.0518	-0.150	-0.0668**
	(0.0781)	(0.0345)	(0.0523)	(0.0369)	(0.0925)	(0.0299)
MaxMin	0.440***	0.0651	0.424***	0.131**	0.390***	0.0662
	(0.0944)	(0.0454)	(0.107)	(0.0575)	(0.102)	(0.0575)
_cons	-1.268***	0.411	-0.815*	0.554**	-1.879***	0.839***
	(0.454)	(0.328)	(0.465)	(0.250)	(0.545)	(0.312)
N	116	116	116	116	116	116
Wald chi2	100.27	89.56	76.81	85.84	51.76	72.26

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.21: Impact of beliefs on m, by treatment (GLS regression)

	0_0000	h_hhhh	l_llll	0_00hh	h_00hh	0_00ll	l_00ll	h_hhll	l_hhll
Bel_m_own	0.282***	0.599***	0.640***	0.448***	0.489***	0.507***	0.500***	0.237*	0.532***
	(0.0897)	(0.110)	(0.140)	(0.126)	(0.139)	(0.104)	(0.104)	(0.140)	(0.117)
Bel_m_other	0	0	0	0.186*	-0.232**	-0.250	-0.0314	0.377**	-0.102
	(0)	(0)	(0)	(0.108)	(0.0990)	(0.179)	(0.108)	(0.181)	(0.135)
Bel_a_own	0	-0.0188	-0.133	0	0.0935	0	-0.123*	-0.307**	0.125
	(0)	(0.102)	(0.0809)	(0)	(0.154)	(0)	(0.0651)	(0.135)	(0.0841)
Bel_a_other	0	0	0	0.479***	0	0.164	0	0.205*	-0.180
	(0)	(0)	(0)	(0.135)	(0)	(0.112)	(0)	(0.107)	(0.154)
MaxEU	-0.266**	-0.268**	-0.143	-0.287*	-0.263***	-0.478***	-0.248***	-0.384**	-0.233**
	(0.114)	(0.119)	(0.0963)	(0.161)	(0.0913)	(0.156)	(0.0898)	(0.149)	(0.110)
MinRisk	0.225*	0.0881	0.0489	0.175	0.0460	0.275**	0.0988	0.0843	0.00544
	(0.115)	(0.117)	(0.0881)	(0.126)	(0.0883)	(0.108)	(0.0788)	(0.114)	(0.0906)
MinRiskAll	0.0577	0.280***	0.0366	0.0166	0.209***	0.0617	0.0718	-0.0356	0.133*
	(0.0904)	(0.0853)	(0.0802)	(0.109)	(0.0646)	(0.0935)	(0.0717)	(0.116)	(0.0776)
MaxMin	0.0820	-0.0140	-0.0125	0.0465	-0.173*	0.0231	0.0315	-0.141	0.104
	(0.0963)	(0.0946)	(0.0761)	(0.107)	(0.0881)	(0.0973)	(0.0624)	(0.0952)	(0.0849)
_cons	0.904	0.229	0.758	0.625	1.636***	1.537	0.957*	2.486***	0.272
	(0.638)	(0.599)	(0.576)	(0.889)	(0.569)	(1.121)	(0.567)	(0.898)	(0.703)
N	116	116	116	116	116	116	116	116	116
adj. R^2	0.181	0.349	0.383	0.370	0.326	0.415	0.412	0.251	0.334

Robust standard errors in parentheses

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

Table 4.22: Impact of beliefs on m, by treatment (Poisson regression)

	0_0000	h_hhhh	l_llll	0_00hh	h_00hh	0_00ll	l_00ll	h_hhll	l_hhll
Bel_m_own	0.119***	0.420***	0.727***	0.205***	0.563***	0.210***	0.494***	0.177*	0.705***
	(0.0368)	(0.0799)	(0.120)	(0.0564)	(0.130)	(0.0523)	(0.0991)	(0.0917)	(0.123)
Bel_m_other				0.0575	-0.347**	-0.110	0.00498	0.216**	-0.310**
				(0.0370)	(0.141)	(0.0803)	(0.152)	(0.0998)	(0.140)
Bel_a_own		-0.0449	-0.324**		0.116		-0.366**	-0.173*	0.241**
		(0.0731)	(0.132)		(0.171)		(0.146)	(0.0913)	(0.113)
Bel_a_other				0.227***		0.0786		0.101	-0.521**
				(0.0629)		(0.0480)		(0.0650)	(0.211)
MaxEU	-0.172***	-0.283***	-0.224*	-0.156**	-0.285***	-0.214***	-0.329**	-0.241***	-0.546***
	(0.0666)	(0.0842)	(0.124)	(0.0728)	(0.0902)	(0.0674)	(0.130)	(0.0791)	(0.143)
MinRisk	0.145*	0.101	0.113	0.0986	0.0497	0.139**	0.210	0.0810	0.0180
	(0.0775)	(0.106)	(0.152)	(0.0683)	(0.110)	(0.0595)	(0.155)	(0.0860)	(0.178)
MinRiskAll	0.0546	0.310***	0.173	0.0123	0.316***	0.0361	0.239*	-0.00588	0.449***
	(0.0562)	(0.0880)	(0.133)	(0.0519)	(0.0883)	(0.0454)	(0.132)	(0.0805)	(0.140)
MaxMin	0.0537	-0.0141	-0.00569	0.0232	-0.176**	0.0136	0.0387	-0.115*	0.191
	(0.0634)	(0.0762)	(0.119)	(0.0573)	(0.0859)	(0.0498)	(0.125)	(0.0658)	(0.169)
_cons	0.0361	-0.756*	-0.630	0.0376	0.245	0.350	-0.601	0.908*	-1.176
	(0.366)	(0.457)	(0.848)	(0.409)	(0.575)	(0.465)	(0.941)	(0.487)	(1.005)
N	116	116	116	116	116	116	116	116	116
Wald chi2	35.33	83.50	98.78	102.67	81.71	57.94	92.46	57.17	61.52

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.23: Impact of beliefs on EU_av, by treatment (GLS regression)

	0_0000	h_hhhh	l_llll	0_00hh	h_00hh	0_00ll	l_00ll	h_hhll	l_hhll
Bel_m_own	-2.287***	-5.494***	-5.546***	-3.411***	-4.007***	-3.828***	-4.736***	-1.551	-4.638***
	(0.728)	(1.240)	(1.251)	(0.959)	(1.212)	(0.789)	(0.902)	(1.074)	(1.137)
Bel_m_other	0	0	0	-1.416*	1.756	1.890	0.382	-4.160**	0.714
	(0)	(0)	(0)	(0.820)	(1.094)	(1.355)	(1.012)	(1.964)	(1.189)
Bel_a_own	0	-3.890***	0.661	0	-3.420**	0	-1.107*	1.228	-2.360***
	(0)	(1.399)	(0.755)	(0)	(1.470)	(0)	(0.645)	(1.387)	(0.876)
Bel_a_other	0	0	0	-3.653***	0	-1.236	0	-2.094**	1.941
	(0)	(0)	(0)	(1.027)	(0)	(0.846)	(0)	(1.024)	(1.443)
MaxEU	2.161**	3.120**	1.408	2.183*	4.225***	3.614***	2.992***	2.878**	2.198*
	(0.925)	(1.196)	(1.210)	(1.226)	(1.228)	(1.176)	(1.042)	(1.326)	(1.248)
MinRisk	-1.825*	-1.171	-0.515	-1.330	-1.215	-2.075**	-0.669	-1.292	0.150
	(0.933)	(1.024)	(0.819)	(0.957)	(0.934)	(0.814)	(0.789)	(0.849)	(0.882)
MinRiskAll	-0.468	-1.624*	-0.222	-0.127	-1.118	-0.466	-0.327	1.287	-0.913
	(0.733)	(0.820)	(0.830)	(0.832)	(0.727)	(0.706)	(0.739)	(1.123)	(0.812)
MaxMin	-0.665	-1.165	1.288	-0.354	-0.385	-0.175	-0.417	0.292	-0.359
	(0.781)	(0.974)	(1.065)	(0.815)	(0.899)	(0.736)	(0.690)	(0.830)	(1.035)
_cons	73.77***	70.93***	60.42***	71.43***	59.78***	63.95***	71.04***	50.28***	71.09***
	(5.176)	(5.397)	(6.756)	(6.771)	(7.072)	(8.474)	(6.260)	(8.647)	(6.831)
N	116	116	116	116	116	116	116	116	116
R^2	0.181	0.427	0.301	0.370	0.330	0.415	0.368	0.207	0.270

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.E Correlation of Beliefs and Decisions

Table 4.24: Pairwise correlation matrix of beliefs and decisions

	m	Bel_m_own	Bel_a_other	a	Bel_a_own	Bel_m_other
m	1					
Bel_m_own	0.6343 (0)	1				
Bel_a_other	0.3265 (0)	0.3227 (0)	1			
a	-0.4883 (0)	-0.4694 (0)	-0.2497 (0)	1		
Bel_a_own	-0.4716 (0)	-0.5116 (0)	-0.2791 (0)	0.8566 (0)	1	
Bel_m_other	-0.0503 (0.1045)	-0.0318 (0.3041)	-0.0065 (0.8333)	0.1749 (0)	0.226 (0)	1

p-values of correlation coefficients in parentheses.

4.F Impact of Preferences on Beliefs and Decisions, by Treatment

Table 4.25: Belief formation: *Bel_ m_ own* and *Bel_ m_ other*, by treatment

regressand	Bel_m_own		Bel_m_other	
	Coeff.	Std.Err.	Coeff.	Std.Err.
adapt	0.4187	(0.6949)	2.122***	(0.5338)
low	-1.7908**	(0.6949)	-0.2906	(0.5338)
withadapt	0.3192	(0.6949)	1.9307***	(0.5338)
withlow	-0.2269	(0.6949)	-0.7124	(0.5338)
a×wa	-0.3947	(0.9827)	-4.0527***	(0.7549)
a×waXwl	0.0054	(0.9827)	1.6196**	(0.7549)
a×l×wa	0.6072	(0.9827)	3.32***	(0.7549)
a×l×wa×wl	0.122	(0.9827)	-3.9365***	(0.7549)
MaxEU×0_0000	-0.2477**	(0.1075)	0	(0.0782)
MaxEU×0_00hh	-0.2945***	(0.1075)	-0.1853**	(0.0782)
MaxEU×0_00ll	-0.2025*	(0.1075)	-0.2485***	(0.0782)
MaxEU×h_00hh	-0.2056*	(0.1075)	-0.1741**	(0.0782)
MaxEU×h_hhhh	-0.2387**	(0.1075)	0	(0.0782)
MaxEU×h_hhll	-0.1215	(0.1075)	-0.3039***	(0.0782)
MaxEU×l_00ll	-0.1337	(0.1075)	-0.1425*	(0.0782)
MaxEU×l_hhll	-0.2281**	(0.1075)	-0.2737***	(0.0782)
MaxEU×l_llll	-0.2013*	(0.1075)	0	(0.0782)
MinRisk×0_0000	-0.0624	(0.1029)	0	(0.0749)
MinRisk×0_00hh	0.1510	(0.1029)	-0.1770**	(0.0749)
MinRisk×0_00ll	0.1166	(0.1029)	-0.1348*	(0.0749)
MinRisk×h_00hh	-0.1612	(0.1029)	0.0570	(0.0749)
MinRisk×h_hhhh	-0.0342	(0.1029)	0	(0.0749)
MinRisk×h_hhll	-0.0393	(0.1029)	-0.0172	(0.0749)
MinRisk×l_00ll	-0.2778***	(0.1029)	0.0624	(0.0749)
MinRisk×l_hhll	-0.1192	(0.1029)	-0.0042	(0.0749)
MinRisk×l_llll	-0.0523	(0.1029)	0	(0.0749)
MinRiskAll×0_0000	0.095	(0.0878)	0	(0.0639)
MinRiskAll×0_00hh	0.0131	(0.0878)	0.2791***	(0.0639)
MinRiskAll×0_00ll	-0.018	(0.0878)	0.2376***	(0.0639)
MinRiskAll×h_00hh	0.1839**	(0.0878)	0.0095	(0.0639)
MinRiskAll×h_hhhh	0.1252	(0.0878)	0	(0.0639)
MinRiskAll×h_hhll	0.1050	(0.0878)	0.2031***	(0.0639)
MinRiskAll×l_00ll	0.2735***	(0.0878)	-0.0183	(0.0639)
MinRiskAll×l_hhll	0.2341***	(0.0878)	0.1186*	(0.0639)
MinRiskAll×l_llll	0.1641*	(0.0878)	0	(0.0639)
MaxMin×0_0000	0.2139**	(0.1001)	0	(0.0729)
MaxMin×0_00hh	0.1296	(0.1001)	-0.0640	(0.0729)
MaxMin×0_00ll	0.1460	(0.1001)	0.0839	(0.0729)
MaxMin×h_00hh	-0.1624	(0.1001)	0.1027	(0.0729)
MaxMin×h_hhhh	-0.0664	(0.1001)	0	(0.0729)
MaxMin×h_hhll	-0.0668	(0.1001)	0.1745**	(0.0729)
MaxMin×l_00ll	0.1985**	(0.1001)	0.1541**	(0.0729)
MaxMin×l_hhll	0.0682	(0.1001)	-0.1841**	(0.0729)
MaxMin×l_llll	0.0982	(0.1001)	0	(0.0729)
_cons	1.9900***	(0.596)	0	(0.4338)

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

Table 4.26: Belief formation: *Bel_ a_ own* and *Bel_ a_ other*, by treatment

regressand	Bel_a_own		Bel_a_other	
	Coeff.	Std.Err.	Coeff.	Std.Err.
adapt	0.5316	(0.6393)	0***	(0.5201)
low	1.7195***	(0.6393)	0	(0.5201)
withadapt	0	(0.6393)	1.2368***	(0.5201)
withlow	0	(0.6393)	1.8276	(0.5201)
a×wa	0.4571	(0.9041)	-1.2368***	(0.7356)
a×waXwl	0.5782	(0.9041)	0.5918**	(0.7356)
a×l×wa	-0.6892	(0.9041)	0.4754***	(0.7356)
a×l×wa×wl	-0.2535	(0.9041)	-2.8948***	(0.7356)
MaxEU×0_0000	0	(0.0908)	0	(0.0708)
MaxEU×0_00hh	0	(0.0908)	-0.1655**	(0.0708)
MaxEU×0_00ll	0	(0.0908)	-0.0097***	(0.0708)
MaxEU×h_00hh	-0.1429	(0.0908)	0**	(0.0708)
MaxEU×h_hhhh	-0.2227**	(0.0908)	0	(0.0708)
MaxEU×h_hhll	-0.2206**	(0.0908)	-0.0893***	(0.0708)
MaxEU×l_00ll	-0.0099	(0.0908)	0*	(0.0708)
MaxEU×l_hhll	0.0353	(0.0908)	-0.0946***	(0.0708)
MaxEU×l_llll	0.1142	(0.0908)	0	(0.0708)
MinRisk×0_0000	0	(0.0869)	0	(0.0678)
MinRisk×0_00hh	0	(0.0869)	0.0749**	(0.0678)
MinRisk×0_00ll	0	(0.0869)	0.0275*	(0.0678)
MinRisk×h_00hh	0.0769	(0.0869)	0	(0.0678)
MinRisk×h_hhhh	0.1133	(0.0869)	0	(0.0678)
MinRisk×h_hhll	0.0613	(0.0869)	0.0559	(0.0678)
MinRisk×l_00ll	0.1483*	(0.0869)	0	(0.0678)
MinRisk×l_hhll	0.2012**	(0.0869)	0.0432	(0.0678)
MinRisk×l_llll	0.0827	(0.0869)	0	(0.0678)
MinRiskAll×0_0000	0	(0.0742)	0	(0.0578)
MinRiskAll×0_00hh	0	(0.0742)	-0.1867***	(0.0578)
MinRiskAll×0_00ll	0	(0.0742)	-0.1979***	(0.0578)
MinRiskAll×h_00hh	-0.1425*	(0.0742)	0	(0.0578)
MinRiskAll×h_hhhh	-0.106	(0.0742)	0	(0.0578)
MinRiskAll×h_hhll	-0.1105	(0.0742)	-0.1828***	(0.0578)
MinRiskAll×l_00ll	-0.1125	(0.0742)	0	(0.0578)
MinRiskAll×l_hhll	-0.2106***	(0.0742)	-0.0975*	(0.0578)
MinRiskAll×l_llll	-0.271***	(0.0742)	0	(0.0578)
MaxMin×0_0000	0	(0.0846)	0	(0.0659)
MaxMin×0_00hh	0	(0.0846)	0.2703	(0.0659)
MaxMin×0_00ll	0	(0.0846)	0.0842	(0.0659)
MaxMin×h_00hh	0.3974***	(0.0846)	0	(0.0659)
MaxMin×h_hhhh	0.2686***	(0.0846)	0	(0.0659)
MaxMin×h_hhll	0.1249	(0.0846)	0.0871**	(0.0659)
MaxMin×l_00ll	0.1193	(0.0846)	0**	(0.0659)
MaxMin×l_hhll	0.1584*	(0.0846)	0.2861**	(0.0659)
MaxMin×l_llll	0.1342	(0.0846)	0	(0.0659)
_cons	0	(0.5034)	0	(0.3924)

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

Table 4.27: Impact of preferences on m and a, by treatment

regressand	a		m	
	Coeff.	Std.Err.	Coeff.	Std.Err.
adapt	0.4949	(0.7132)	0.9058***	(0.7576)
low	2.3814***	(0.7132)	-1.4397	(0.7576)
withadapt	0	(0.7132)	1.1459***	(0.7576)
withlow	0	(0.7132)	0.1775	(0.7576)
a×wa	0.0908	(1.0086)	-1.9089***	(1.0714)
a×waXwl	-0.3005	(1.0086)	1.5572**	(1.0714)
a×l×wa	0.1839	(1.0086)	0.5732***	(1.0714)
a×l×wa×wl	-0.2692	(1.0086)	-1.3592***	(1.0714)
MaxEU×0_0000	0	(0.1021)	-0.3363	(0.1179)
MaxEU×0_00hh	0	(0.1021)	-0.5322**	(0.1179)
MaxEU×0_00ll	0	(0.1021)	-0.5202***	(0.1179)
MaxEU×h_00hh	-0.2785***	(0.1021)	-0.3362**	(0.1179)
MaxEU×h_hhhh	-0.2751***	(0.1021)	-0.4063	(0.1179)
MaxEU×h_hhll	-0.1876*	(0.1021)	-0.4407***	(0.1179)
MaxEU×l_00ll	-0.3716***	(0.1021)	-0.3087*	(0.1179)
MaxEU×l_hhll	-0.3578***	(0.1021)	-0.3045***	(0.1179)
MaxEU×l_llll	-0.0795	(0.1021)	-0.2866	(0.1179)
MinRisk×0_0000	0	(0.0978)	0.2074	(0.1129)
MinRisk×0_00hh	0	(0.0978)	0.2452**	(0.1129)
MinRisk×0_00ll	0	(0.0978)	0.3719*	(0.1129)
MinRisk×h_00hh	0.1818*	(0.0978)	-0.0387	(0.1129)
MinRisk×h_hhhh	0.1786*	(0.0978)	0.0655	(0.1129)
MinRisk×h_hhll	0.2167**	(0.0978)	0.0611	(0.1129)
MinRisk×l_00ll	0.22**	(0.0978)	-0.0602	(0.1129)
MinRisk×l_hhll	0.3393***	(0.0978)	-0.0401	(0.1129)
MinRisk×l_llll	0.1957**	(0.0978)	0.0043	(0.1129)
MinRiskAll×0_0000	0	(0.0834)	0.0845	(0.0963)
MinRiskAll×0_00hh	0	(0.0834)	-0.0152***	(0.0963)
MinRiskAll×0_00ll	0	(0.0834)	-0.0392***	(0.0963)
MinRiskAll×h_00hh	-0.1525*	(0.0834)	0.2833	(0.0963)
MinRiskAll×h_hhhh	-0.1773**	(0.0834)	0.3566	(0.0963)
MinRiskAll×h_hhll	-0.1823**	(0.0834)	0.0623***	(0.0963)
MinRiskAll×l_00ll	-0.214**	(0.0834)	0.2229	(0.0963)
MinRiskAll×l_hhll	-0.3444***	(0.0834)	0.2363*	(0.0963)
MinRiskAll×l_llll	-0.2901***	(0.0834)	0.1778	(0.0963)
MaxMin×0_0000	0	(0.0951)	0.1423	(0.1098)
MaxMin×0_00hh	0	(0.0951)	0.2222	(0.1098)
MaxMin×0_00ll	0	(0.0951)	0.0899	(0.1098)
MaxMin×h_00hh	0.4159***	(0.0951)	-0.2392	(0.1098)
MaxMin×h_hhhh	0.421***	(0.0951)	-0.0588	(0.1098)
MaxMin×h_hhll	0.3413***	(0.0951)	-0.1116**	(0.1098)
MaxMin×l_00ll	0.3737***	(0.0951)	0.1112**	(0.1098)
MaxMin×l_hhll	0.278***	(0.0951)	0.1274**	(0.1098)
MaxMin×l_llll	0.2226**	(0.0951)	0.0325	(0.1098)
_cons	0	(0.5663)	1.4649	(0.654)

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

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Eidesstattliche Versicherung

Hiermit erkläre ich, Wiebke Probst, an Eides statt, dass ich die Dissertation mit dem Titel

The Strategic Relevance of Adaptation in International Climate Change Policy

selbständig und ohne fremde Hilfe verfasst habe.

Andere als die von mir angegebenen Quellen und Hilfsmittel habe ich nicht benutzt. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet.