



**UNIVERSITA' CATTOLICA DEL SACRO CUORE
MILANO**

**Dottorato di ricerca in DEFAP - Economia e Finanza della
Pubblica Amministrazione
ciclo XXII
S.S.D: SECS-P/06 and SECS-S/06**

**Mitigation, Adaptation and Climate Change:
Policy Balance under Uncertainty**

**Tesi di Dottorato di : Chen Chen
Matricola: 3504427**

Anno Accademico 2009/10



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Coordinatore: Ch.mo Prof. Massimo Bordignon

Supervisor: Ch.mo Prof. Francesco Bosello

**Tesi di Dottorato di : Chen Chen
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DEDICATION

To Mom

The PhD thesis is composed of three chapters and discusses the policy choice under uncertainty and learning in the context of climate change.

The first chapter surveys the existing literatures, from both theoretical and empirical perspectives, about how uncertainty impacts the policy decision to deal with climate change. Various sources of uncertainty exist in the climate-economy reaction with changing climate. Among them, the impact uncertainty is the focal point of this survey. Theoretical studies indicate that basically the uncertain and irreversible outcome implies an earlier and ambitious mitigation strategy. But the sunk cost of policy implementation might delay and weaken this action. When adaptation is added into the policy portfolio, the irreversibility constraint is relaxed and it implies less mitigation effort. If another form of climate impact is considered, the discontinuous outcome with low probability but higher damage, theoretical studies show that it is optimal to enhance both mitigation effort and adaptive action. The empirical studies follow the integrated approach to link climate and economy, and incorporate uncertainty in several ways. With regards to the role of uncertainty, empirical studies indicate that more mitigation is in need considering the uncertain impact of climate change, and it is worthwhile to gain more information to reduce uncertainty.

The second chapter studies the policy balance between mitigation and adaptation under two sources of uncertainty. It enriches the rapidly expanding literature trying to devise normative indications on the optimal combination of the two introducing the role of catastrophic and spatial uncertainty related to climate change damages. Applying a modified version of the Nordhaus' Regional Dynamic Integrated Model of Climate and the Economy it is shown that in both cases uncertainty works in the direction to make mitigation a more attractive strategy than adaptation. When catastrophic uncertainty is concerned mitigation becomes relatively more important as, by curbing emissions, it helps to reduce temperature increase and hence the probability of the occurrence of the event. Adaptation on the contrary has no impact on this. It is also shown that optimal mitigation responses are much less sensitive than adaptation responses to spatial uncertainty. Mitigation responds to global damages, while adaptation to local damages. The first, being aggregated, change less than the sec-

ond in the presence of spatial uncertainty as higher expected losses in some regions are compensated by lower expected losses in other. Accordingly, mitigation changes less than adaptation. Thus if it cannot be really claimed that spatial uncertainty increases the weight of mitigation respect to that of adaptation, however its presence makes mitigation a “safer” or more robust strategy to a policy decision maker than adaptation.

The third chapter explores the effect of learning on climate policies. The possible reduction of uncertainty imposes effects on the policy implementation. Groups of papers have been studying passive learning, i.e. reducing uncertainty through the observation of relevant outcomes and then updating knowledge accordingly, and its role in policy choice. However, theoretically speaking it is also possible to learn in an active way, that is, to reduce uncertainty by investing in the learning activities. So far active learning has not well-explored by the literatures. This chapter fills the gap between the theoretical possibility and the modeling exercise regarding active learning. We stick to the uncertainty of catastrophic happening and try to find the effect of learning catastrophic sensitivity (a parameter bridging temperature increase and occurrence of catastrophes) on policy decision. A two-stage sequential learning module is added to the modified version of RICE to approximate the policy making process with the knowledge updating, which is achieved by the investment in learning activities. The modeling exercise shows although it crowds out other investment option, the learning investment is worthwhile in improving knowledge and controlling climate damage by choosing more beneficial policies. The effect on policy decision is influenced by the productivity of learning, i.e. learning rate. A higher learning rate implies an earlier arrival of information, thus more quickly the policy choice approaches to the optimal.

Chapter 1

CLIMATE POLICY AND UNCERTAINTY: A LITERATURE SURVEY

Abstract

Uncertainty is one of the most important features of climate change issue. It plays significant role in climate policies. This chapter surveys the existing literatures, from both theoretical and empirical perspectives, about how uncertainty impacts the policy decision to deal with climate change. Various sources of uncertainty exist in the climate-economy reaction with changing climate. Among them, the impact uncertainty is the focal point of this survey. Theoretical studies indicate that basically the uncertain and irreversible outcome implies an earlier and ambitious mitigation strategy. But the sunk cost of policy implementation might delay and weaken this action. When adaptation is added into the policy portfolio, the irreversibility constraint is relaxed and it implies less mitigation effort. If another form of climate impact is considered, the discontinuous outcome with low probability but higher damage, theoretical studies show that it is optimal to enhance both mitigation effort and adaptive action. The empirical studies follow the integrated approach to link climate and economy, and incorporate uncertainty in several ways. With regards to the role of uncertainty, empirical studies indicate that more mitigation is in need considering the uncertain impact of climate change, and it is worthwhile to gain more information to reduce uncertainty.

1.1 Introduction

In the form of radiation the Sun delivers energy to the Earth. 30% of the radiation is reflected by the Earth while the remaining is absorbed by the land, atmosphere and ocean. In 1824 Joseph Fourier discovered that some types of gases in the atmosphere capture the thermal infrared radiation emitted by the surface of the Earth. The thermal infrared radiation captured by the atmosphere in turn radiates back again to the surface of the Earth. In this way a proportion of the heat is kept between the atmosphere and the Earth surface. These certain types of gases in the atmosphere are referred to as greenhouse gases (GHG). The greenhouse effect, featured by the forward-and-back radiation between the surface of the Earth and the atmosphere, is the reason for the Earth to keep itself within the reasonable range of temperature for all the creatures that live on it.

However, the greenhouse effect has been enhancing since the mid 20th century. Human activities, primarily fossil fuel use or deforestation, are important attributes to the increasing concentration of GHG in the atmosphere (IPCC AR4, 2007). The process has been increasing the average temperature of the Earth's lower atmosphere: in the last 100 years the temperature has increased by $0.74 \pm 0.18^{\circ}\text{C}$ and it will continue to rise by 1.1 to 6.4°C during the 21st century (IPCC AR4, 2007). The temperature increase brings about a wide range of effects on the climate-economy system with the potential to induce severe harm to societies' welfare and threats of huge economic losses: sea level rise, the change of precipitation pattern, Arctic shrinkage, rainforest shrinkage, the increase of the intensity of extreme climate events, species extinctions, etc..

Since 1992, with the establishment of the UNFCCC, the international community has launched mitigation actions to stabilize the GHG concentration at levels that would prevent dangerous anthropogenic interference with the climate system. Since the seventh Conference of Parties (COP-7) in Marrakech in 2001, policy makers also have begun to administer a variety of strategies to adapt to those climate impacts. The policy-making process however is complicated by various sources of uncertainties, including: incomplete knowledge of the functioning of the climate system and of its sensitivity to human action; of the reactions of environmental systems to climatic changes (when, where, with which intensity impacts hit);

of the reactions of social economic systems to climatic and environmental changes. Given its pervasive role, uncertainty is one of the fundamental factors to be incorporated in the policy decisions on climate change policies.

This survey, aimed at investigating the existing literature in the context of climate change, will focus on the role of uncertainty in climate change issue and the treatment of it in the policy study. Section 2 describes various sources of uncertainty categorized by the literatures. Section 3 surveys the theoretical approach of studying uncertainty and summarizes the main findings. Section 4 covers the empirical studies, with special attention to the integrated assessment framework. Section 5 provides conclusions regarding the survey and the expectations of the upcoming studies.

1.2 Different Sources of Uncertainty in Policy Assessment

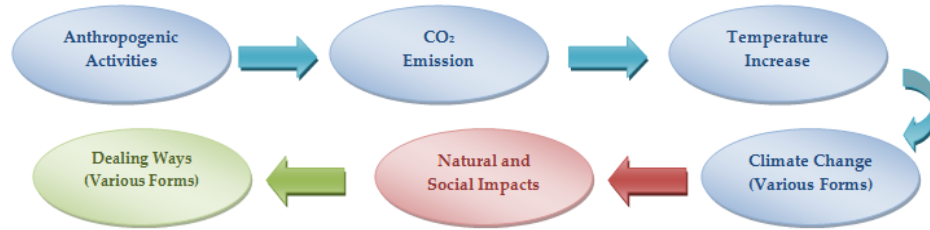


Figure 1.1: Climate-Economy Reaction of Climate Chang Issue

Uncertainty extensively exists in the climate-economy reaction chain of climate change phenomenon (Fig.1.1). It can be roughly categorized into three classes (Heal and Kriström, 2002) in different stages of the reaction chain, denoted by different colours in Fig.1.1. The first class is the scientific uncertainty, answering the question “what will the climate be?” Scientific uncertainty describes relations between emissions, temperature increases, and climatic and environmental responses, including the particular categories of catastrophic and irreversible events. It refers to the imperfect knowledge about the causal effect of anthropogenic emission on climate change, for example, the response of carbon cycle to emission (Webster et al., 2003; O’Neill and Melnikov, 2008); the climate sensitivity to GHG

concentration (Kelly and Kolstad, 1999a; Oppenheimer et al., 2008) or the occurrence of catastrophic event due to temperature increase (Tsur and Zemel, 1996; Bosello and Moretto, 1999; Weitzman, 2009). The second class is the impact uncertainty, answering the question “what does any climate change mean in natural and economic terms?” Impact uncertainty describes the relation between environmental impacts and societal impacts, and the economic quantification of these impacts. What and how impact is induced depend on the stock effect of GHG (Kolstad, 1996a, 1996b) and on the feature of the social-economic system like economic and population growth (Kelly and Kolstad, 2001; Nordhaus and Popp, 1997), degree of social risk-aversion (Gollier et al., 2000; Ingham et al., 2007), social preference (Ayong Le Kama and Schubert, 2004), inter-regional correlation (Ulph and Maddison, 1997). The third class is the policy uncertainty, answering the question “what is the optimal policy response to the likely impacts?” Policy uncertainty relates to uncertain cost-benefits / cost-effectiveness of climate change mitigation and adaptation policies. The first on its turn connected to the uncertain feedback of the economic system to the climate system through policy driven changes in emission regimes (Kolstad 1996c), institutional limits (Toman, 2003), and technical improvement (Dowlatabadi, 1998; Bosetti et al., 2008).

1.3 Theoretical Studies

The theoretical studies on uncertainty in the context of climate change mainly discuss the effect of irreversibility and the possibility of learning on the policy choice. The main topic developed by the literatures is the role played by uncertainty on climate impact. Within this stream, a subset of studies tackled high damage-low probability events (catastrophes) (Posner, 2004). Initially, these studies focused on mitigation, the strategy that by controlling the carbon emission reduces the anthropogenic interference over the climate system. Literatures try to find out how uncertainty, irreversibility and learning affect the mitigation strategy and the timing of its implementation. More recently, adaptation has been added. It cannot slow down the warming process, but helps the social-economic systems to reduce the adverse impacts and enhance the possible beneficial influence. While the society protects itself from the risk of climate change by both mitigation and adaptation, how to

balance the two when uncertainty is confronted becomes a new concern. From mitigation alone to the joint implementation of mitigation and adaptation, literatures provide insights on the role of uncertainty in climate policy decision.

1.3.1 Methodological Approaches

Two approaches diversify the research on the impact uncertainty. The first concentrates on impacts as partly unpredictable outcomes to be dealt with standard tools. The second considers the uncertainty originated by possible high damage low-probability climatic events. In either case, irreversibility is at the core of investigation. It refers to the loss of an option in the future due to the activity at present. The loss can be absolute or theoretically possible, but in practice not because of the extremely high cost of the correction (Arrow and Fisher, 1974).

In general, the theoretical studies parameterize uncertainty from a probability space and formulate a multi-period utility maximization problem under the constraint of irreversibility. Utility in the later period depends on the realization of the uncertain parameter at certain point before. Uncertainty, irreversibility, and the possible reduction of uncertainty – in a more widely-used term, learning – are integrated by this means in one theoretical framework. This basic approach is inherited from the most pioneering works on uncertainty and irreversibility (Arrow and Fisher, 1974; Henry, 1974; Freixas and Laffont, 1984). It was applied to environmental policies first and to the climate change issue after. Two kinds of irreversibility are usually compared – “climate irreversibility” and “economic irreversibility”. These two terms refer to the impossibility to emit negative amount of GHG in the future (“climate irreversibility”) or to withdraw the investment that has already been made previously (“economic irreversibility”) (Kolstad, 1996a). The two constraints are contrasted under different assumptions and model settings, which offer a wide range of results (Ulph and Ulph, 1997; Gollier et al. 2000; Pindyck, 2000, 2002; Fisher and Narain, 2003 etc.).

1.3.2 Findings in Theoretical Literatures

The two basic questions the theoretical studies are trying to answer are: in the presence of uncertainty should the policy be more cautious or not? Should the policy be adopted right now or later?

In the more general case, there are two distinct points of view. The first states that if the uncertain outcome of certain action is irreversible, the possibility of getting better information in the future about the future benefit/cost of current action leads to a more cautious action, that is more ambitious preventive action (Arrow and Fisher, 1974; Henry, 1974; Freixas and Laffont, 1984; Ulph and Ulph, 1997); if the uncertainty is big, the policy should be adopted earlier (Saphores, 2004). Put into the context of climate change, this viewpoint implies that if climate change induces irreversible damages, it is better to adopt more ambitious mitigation policy if better information is expected about the damage than if no information can be expected. However taking also economic irreversibility into consideration these result can vary according to different assumptions and model settings. In general the policy can be less stringent because when opportunity cost of the mitigation investment and stocks (e.g. energy saving, R&D investment for backstop technologies etc.) grow over time, it can be wiser to wait for more accurate information about climate damage and then implement the optimal policy. In terms of timing, the delayed action would be optimal under some very particular conditions¹ (Gollier et al., 2000; Fisher, 2001; Pindyck, 2000, 2002; Fisher and Narain, 2002). In all, the combined effect of irreversibility and learning on the current mitigation policy is ambiguous. But if adaptation is added into the policy portfolio, even if facing the irreversible outcome, mitigation policy becomes less urgent and can be adopted later (Ingham *et al.*, 2007). It is because in their model settings, adaptation acts to weaken the effect of irreversibility, hence the possibility to gain information in the future makes current inaction worthwhile.

When the uncertain catastrophic damages are involved, especially if irreversible, it is intuitive to expect a more ambitious emission control policy to reduce the risk (Clarke and

¹The technical detail of these conditions goes beyond the scope of this survey. The interested reader is addressed directly to Fisher (2001) and Fisher and Narain (2002) .

Reed, 1994, Baranzini, 2003; Ingham et al., 2005, 2007), and also more adaptive action to either prepare for or deal with the potential damages (Ingham et al., 2005). Theoretically, a certain interval of emission level could be considered “safe” without triggering the catastrophic event; beyond the interval the controlling policy should be adopted (Tsur and Zemel, 1996). If the catastrophic damage is irreversible, the risk also calls for the earlier actions (Ingham et al., 2007). However some authors showed that counter-intuitive results are possible: a reversible catastrophic outcome will result in the more ambitious policy than the irreversible event (Tsur and Zemel, 1998). This is due to the very specific modeling of the policy cost in that paper – it assumed that the penalty value, calculated as the value forgone because of irreversible event, will decrease with the emission level.

When mitigation and adaptation work together to deal with uncertain catastrophic events, the two strategies are substitute in the sense that increasing the usage of one strategy reduces another (Ingham et al., 2005). Therefore, the conclusion drawn in the same paper about the effect of catastrophic happening on either policies, which is also mentioned above, encounters a challenge. They stated that the uncertain catastrophic events calls for more effort of both mitigation and adaptation. However, the two strategies do not necessarily take the same effect in dealing with catastrophic damages. It is more probable that when facing the uncertainty of catastrophic events, one strategy is more beneficial than another since the two function in different ways. If so, due to the substitution between the two, intuitively it is also possible to enhance the more beneficial strategy while use less another. In Appendix A, a simple static model is developed to elaborate this point. So far, the discussion about the policy trade-off between mitigation and adaptation in the presence of catastrophic events is still very rare.

Uncertainty can affect the policy mix between mitigation and adaptation also outside the area of catastrophic events. For example, Kane and Shogren (2000) studied both the impact uncertainty and the policy uncertainty – the effectiveness of both strategies. They emphasize the cross effect of the two when uncertainty is present. They conclude that whether the climate risk increase or decrease the investment on either strategy depends on whether and to what extent the two strategies enhance or weaken the productivity of each other. Lecoq and Shalizi (2007) studied the uncertainty of the geographic distribution

of climatic damages. They consider the different function of mitigation and adaptation in the different scope, that mitigation is a global public good while adaptation functions to reduce the local damage. They suggest that when facing the uncertain distribution of climatic damages, the cost-effectiveness of mitigation is enhanced with respect to that of adaptation, and the need for mitigation should be strengthened.

1.4 Empirical Studies

In the context of climate change the dominant approach to conduct empirical investigation is Integrated Assessment (IA). IA models (IAM) link the economic and scientific aspects of climate change. This approach, applied to climate change issue, was firstly followed by the study on the optimal emission path (i.e. mitigation). Only recently has adaptation been incorporated into the framework. IAM is not necessarily belonging to the “top-down” modeling family, although for some cases, the optimal policy path is derived in a general equilibrium perspective.

1.4.1 Methodological Approaches

Earlier IAM built up the general framework to balance the emission reduction costs against the benefit in terms of the damage reduction (e.g. Manne and Richels, 1992; Peck and Teisberg, 1992; Hope et al., 1993; Nordhaus, 1993, 1994; Manne et al., 1995; Nordhaus and Yang, 1996). Adaptation is added later as another strategy to reduce the climate damage (De Bruin et al., 2009; Bosello, 2010; Bosello et al., 2010). This framework can be simplified by Fig.1.2. It illustrates the logic underneath the cost-benefit tradeoff of climate policies: mitigation and adaptation take up resources from the economic system at the cost of social production. Mitigation curbs the GHG emission and thus reduces the damages while adaptation acts directly on damage reduction. These models try to solve an inter-temporal welfare-maximization problem with the aim of either searching for or evaluating the climate policies (Kelly and Kolstad, 1999b).

Despite the common logic and the similar general framework, significant variation exists among groups of IAM cited above, regarding the level of climatic and economic complexity.

To link the climatic–economic system and the policy intervention, typical IAMs have several crucial components that make the policy study possible: climatic model, damage function, and modeling the policy costs.

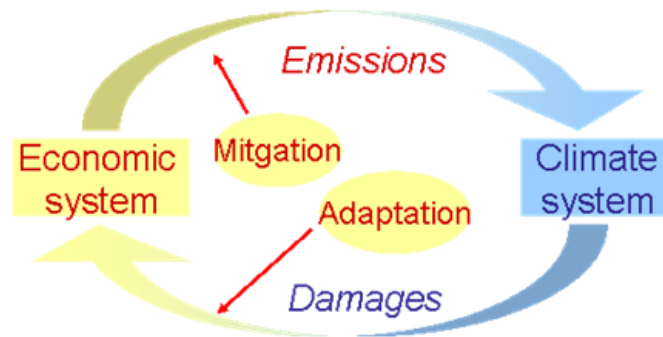


Figure 1.2: Integrated Assessment Modeling

From the perspective of economic modelers, to formulize reasonable damage functions and policy cost functions is no doubt the major challenge to describe how economic system responds; the development of the climate module, on the other hand, is not the main task of economic analyses, but incorporating a more precise geophysical submodel is still a precious contribution.

The first crucial component of IAM, damage function, is included into the IAM framework by two means. One is in a reduced form simply linking temperature increase to GDP losses (Peck and Teisberg, 1992; Bosello, 2010) and another adopts the specific function for the assessment of specific damage categories (e.g. Nordhaus, 1990; Dowlatabadi and Morgan, 1993; Hope et al., 1993; Tol and Verheyen, 2004). The classification of different damages varies based on the research topic. Different damage categories are treated separately, for example by Bosello et al.(2006) who estimated the climate-change impacts on human health; by (Bosello et al., 2007) on sea-level rise; by (Roson *et al.* , 2007) on energy demand; by (Bigano *et al.* , 2006) on sea-level rise and tourism; by (Cisar, 2009) on sea-level rise, agriculture, tourism, river floods; by (Wei & Aaheim, 2010) on sea-level rise, agriculture, health, energy demand, tourism, forestry, fisheries, extreme events, energy

supply, etc. All these studies model the sectoral details to allow the specification of climate change impact effects for the different sectors.

Adaptation itself is a component of the climate change damages function as it contributes to build up total climate change costs. Indeed in IAM the damage functions usually include the adaptation cost, but without being able to disentangle it from the residual damage. Therefore, in most of the studies of adaptation, it is not really treated as a policy decision variable. The calibration of adaptation costs and benefits become more uncertain in this sense. The few exceptions, like De Bruin *et al.*, (2009) and Bosello (2010) develop only recently. With this distinction, two ways to represent the cost of adaptation is either as part of the production (Bosello, 2010) or as a component of “imposed cost” (Fankhauser, 1998), either exogenous (Hope *et al.*, 1993) or endogenous (De Bruin *et al.*, 2009).

The policy cost of mitigation, on the other hand, is usually modeled explicitly by formulating energy using pattern, research and development activities, technical progress and ranges of emission scenarios. Early IAMs constructed two approaches to model mitigation cost, depending on the structure of the framework. If the model incorporates energy sectors, where GHG emission is induced and where the technical progress takes place, in general the mitigation cost is decided by the activities in the energy sector (Peck and Teisberg, 1992; Dowlatabadi and Morgan, 1993; Manne *et al.*, 1995). Otherwise mitigation cost is simplified as a proportion of the gross production, which is fair enough to delegate the aggregated cost no matter what specific sources are (Nordhaus, 1993; Nordhaus and Yang, 1996). IAMs nowadays, which have been developing in the latest decade, usually follow the first way, since there are emerging important technological developments that could fundamentally alter mitigation strategies. Integrated assessment modelers have developed more complete framework and added into those frameworks more factors that impact the mitigation cost (e.g. Manne and Richels, 2005; Bosetti, *et al.*, 2006; Bouwman *et al.*, 2006; Tol, 2009; Calvin *et al.*, 2009).

About the climatic module, from CETA (Peck & Teisberg, 1992) that built up a simple one-parameter mapping from GHG concentration to the atmospheric temperature, to RICE-2010 (Nordhaus, 2010) that includes carefully-calibrated equation series describing heat transfer in a three-layer climatic system, most of IAMs now use relatively enriched

description of carbon cycle - ocean atmospheric interactions.

With the damage function, policy cost and climatic module, IAM can be used to incorporate uncertainty in an interactive climate-economy environment.

In the large-scale energy-economic policy models, incorporating uncertainty should in principle bring about outcomes with these four aspects (Kann and Weyant, 2000): probability weighted output value; optimal decision in light of the imperfect knowledge; a measure of risk or dispersion of the outcome; and the information value of the key parameters. There are different approaches to get these information (Peterson, 2006). (1) Sensitivity analysis of the unknown / uncertain parameters which is a simple yet insightful way to test how the outputs vary because of the uncertain inputs (Nordhaus, 1994; Weyant et al., 1996; Kelly and Kolstad, 1999b), and the comparison of the outputs under the true and false knowledge helps to get the value of the information (Manne and Richels, 1992; Peck and Teisberg, 1993); (2) uncertainty propagation, which refers to mapping the uncertainty of inputs to the probability distribution of the outputs (Nordhaus and Popp, 1997) or taking the expectation of the output (Bosello and Moretto, 1999); (3) sequential decision-making under uncertainty, which introduces the possibility of reducing uncertainty, i.e. learning. Different modeling skills are applied according to different types of learning – passive learning and active learning². In passive learning, which has been so far the main approach followed by the existing literature, uncertainty is being reduced through the observation of the relevant outcomes. Bayesian learning is a well used and typical example of the autonomous reduction of uncertainty (Kelly and Kolstad, 1999a; Karp and Zhang, 2001; Leach 2007; Webster et al., 2008). By contrary, to our knowledge, so far there has not yet been any empirical studies on active learning, where the reduction of the uncertainty is achieved by investing in research and development (R&D). Nevertheless, the literatures about the effect of R&D on productivity improvement and cost reduction can provide some insights for the modeling of active learning in the upcoming studies.

The results of policy studies incorporating uncertainty depend on what specific source

²The terminology here is a bit different from Kolstad (1996c). Here we will not consider about the autonomous learning which refers to the reduction of uncertainty merely through the passage of time. Passive learning referred here equals to the “active learning” there while active learning equals to the “purchased learning”.

of uncertainty the study is taking care of. Generally speaking, however, the empirical literature so far confirmed the theoretical finding that imperfect knowledge implies more stringent policy to keep the system away from climatic damages (Nordhaus and Popp, 1997) while the possibility of learning, especially the autonomous learning, causes the trade-off between the benefit of the climate policy and the information (Kelly and Kolstad, 1999a). The three approaches to quantify uncertainty will be discussed in detail in the following, and the summary of the approaches, the methodologies and the selected findings are listed in Table B in Appendix.

Sensitivity analysis can deal with wide range of sources of uncertainty, as long as the sources can be parameterized in the IAM sub-models. There are two purposes of sensitivity analysis: to get the most relevant uncertainty and to estimate the information value. The first purpose can be fulfilled through analyzing the sensitivity of the output to uncertain parameters (Nordhaus, 1994) and calculating the correlation index between uncertainty and output (Hope et al., 1993)³. The estimation of the information value can be done by comparing the outputs under imperfect information and the true state and then drawing the information index like EVPI (Expected Value of Perfect Information) (Peck and Teisberg, 1993), EVDI (Expected Value of Dynamic Information) (Bosello and Moretto, 1999) and so forth.

Uncertainty propagation can also deal with variety of uncertainties. Monte-Carlo simulation could be carried out to “deliver” the uncertainty from inputs to outputs (Tol, 1999). Apart from the “uncertain parameters”, this approach can also incorporate the “uncertain events” through the expected output weighted by the event probability (Bosello and Moretto, 1998; Castelnovo et al., 2003).

Sequential decision making is the most demanding approach compared with the other two. Modeling complexity is greatly increased thus a relatively small pool of uncertainties so far has been studied following this approach. Active learning is not a common topic, but a group of models that incorporate the growth and cost reduction driven by technical progress can provide the insight for the foreseen studies (Nordhaus, 2002; Zwaan et al.,

³see Peterson (2006) for detail.

2002; Popp, 2004; Alberth and Hope, 2007; Bosetti et al., 2008). Passive learning has received more attention. The most popular investigation method in the field so far is Bayesian learning. Policy makers update their knowledge of some uncertain parameters (or the variability) through some observable variables, building up a learning module to describe the relationship between the observation and the uncertain parameter, and incorporating this relationship into the IAM framework. A typical example is learning the climate sensitivity (CS), which contributes to the mapping from GHG concentration to temperature increase (e.g. Kelly and Kolstad, 1999; Keller et al., 2004; Oppenheimer et al., 2008; Webster et al., 2008). They treat CS as a random variable that has a prior at 0th period, the posterior could keep on being updated at the end of each consecutive period by the observation of temperature and GHG concentrations. Following this approach, policy makers can also estimate the time that is needed to get close to the true knowledge (Kelly and Kolstad, 1999a). Although Bayesian learning has now become a widely used approach, it is well worth mentioning several shortcomings of it. First of all, it could be a good way to treat a univariate case where there is only one source of uncertainty for each run, nevertheless significant errors might occur in the bivariate case. For example, if two parameters in the temperature function are uncertain, to learn both of them through the single set of observation is proven to be misled; after all, for example, the observation of temperature “represents only a single draw from a complicated system about which we have limited knowledge” (Leach, 2007). Secondly, introducing variability in Bayesian learning is a must, without which the learning becomes a “one shot” thing because the uncertain parameter can be easily derived after the first observation. However, take CS again for an example, with variability, the learning process becomes “noisier”. The noise can be reduced through more emission to reveal more information. Therefore, to control emission and to acquire more information constitutes a pair of trade-offs (Kelly and Kolstad, 1999a). How to deal with these trade-offs has been discussed yet. The only thing we can say now is that Bayesian learning, at least in this context, makes things more complicated. Hence the work so far is still far away from reaching a functional conclusion.

1.4.2 Findings of Empirical Studies

The results from IAM exercises answer the same question raised for theoretical studies: in the presence of uncertainty how much the action should be taken? What is the appropriate time to take the action? Selected findings are included in Table B. The results for different topics are difficult to be compared. In general, the most intuitive and common conclusion is consistent with the theoretical results. With uncertainty, climate policies are more stringent to keep the society from the risks. The value of information is usually positive and able to justify the worth of getting correct information. But with learning, especially by passive learning, a less stringent policy might be needed to acquire more accurate information, (Webster et al., 2008) although by some numerical results they should only be “slightly” less stringent and the action should not be delayed (Karp and Zhang, 2001).

The uncertainty of catastrophic event causes a higher mitigation rate (e.g. Bosello and Moretto, 1998) and earlier preventive action if mitigation is with low cost and the time horizon is shorter (Guillerminet and Tol, 2008). Recently, however, a question was raised about the outcome of catastrophic event. Dismal Theorem (Weitzman, 2009) is a central argument stating that a fat-tail of the probability density function (PDF) of certain key parameter – for example, CS – indicates that the occurrence of catastrophes at the end part of the PDF does not decline exponentially but in a slower polynomial way. Therefore, the present cost of future catastrophic uncertainty might be infinitely large even if social preference rate is still applied. “The economic consequences of fat tailed structural uncertainty can readily outweigh the effects of discounting in climate-change policy analysis” (Weitzman, 2009). One of the outcomes of Dismal Theorem is the doubt about the CBA we are now using. Weitzman suggested that it is better to treat this structure uncertainty well rather than simply remove or truncate the end part of the PDF. Although he did not suggest an approach that could be more precise, he did point out something essential about the catastrophic climatic event and the possible incapacity of standard CBA for it.

The empirical study on uncertainty, however, so far has not been incorporated with the study on policy trade-off between mitigation and adaptation, which by itself is also a very recent topic. A volume of theoretical literatures, albeit still thin, give a hint that

uncertainty takes effect on the policy balance between the two; it is worthwhile also to develop an empirical framework following the integrated approach to investigate the policy choice taking into account certain sources of uncertainty.

1.5 Concluding Remarks

This chapter surveys the role of uncertainty in the policy study for the climate change problem, following both the theoretical and the empirical approach. As one of the most important features, uncertainty significantly impacts the policy decision. In general, the theoretical studies indicate that the irreversible uncertain outcome and the possibility of getting better information in the future call for more cautious actions – earlier and more ambitious mitigation policy. Two kinds of irreversibility – climate and economy irreversibility, however, contrast to each other and the policy choice is decided by the comparable strength of the two. To be specific, due to the sunk cost of the investment in emission control, if economy irreversibility prevails, the mitigation policy would be more relax and it is optimal to implement the policy later. When adaptation is added into the policy portfolio, the irreversibility constraint is weakened and to do less mitigation becomes a better choice. When the uncertainty of catastrophic happening is taken into account, both mitigation effort and adaptive actions are needed more to reduce the potential huge and discontinuous damages. But considering about the trade-off between the two, our simple model also shows that mitigation effort is enhanced in this case while adaptation is weakened.

IAM, as one of the most widely-used research tools for empirical study, so far has built up a relatively complete framework for the climate policy study. Following the integrated approach, climatic and economic system can be connected through the anthropogenic emission, interactive impact and the climate policies. Uncertainty is further incorporated into this framework through three different ways: sensitivity analysis, uncertainty propagation and sequential decision making. The third approach can further help to model the reduction of uncertainty and to study in depth the effect of learning on the policy choice. Empirical studies so far have got diverse results regarding different sources of uncertainty. Considering about the uncertainty of catastrophic happenings, more ambitious mitigation strategy

is usually more required.

The study on the policy trade-off in the presence of uncertainty is so far an uncovered topic for the empirical study, although theoretical works shed some light for this point. Fig.1.3 below displays the fields with related to the policy trade-off and uncertainty that can be explored following the integrated assessment approach. Apparently there are still great many topics in all three checked areas waiting to be studied on, but to study the relationship between the two policies in a world subject to uncertainty would be interesting and worthwhile.

<i>Integrated Assessment Approach</i>		<i>Policy</i>	
		Single Policy	Policy Relationship
Uncertainty	w/o	✓	✓
	w	✓	?

Figure 1.3: Uncovered Area of the Existing Literatures

Chapter 2

MITIGATION AND ADAPTATION: BALANCING THE CLIMATE POLICY UNDER UNCERTAINTY

Abstract

Nowadays, as stressed by important strategic documents like for instance the 2009 EU White Paper on Adaptation or the recent 2009 “Copenhagen Accord”, it is amply recognized that both mitigation and adaptation strategies are necessary to combat climate change. This chapter enriches the rapidly expanding literature trying to devise normative indications on the optimal combination of the two introducing the role of catastrophic and spatial uncertainty related to climate change damages. Applying a modified version of the Nordhaus’ Regional Dynamic Integrated Model of Climate and the Economy it is shown that in both cases uncertainty works in the direction to make mitigation a more attractive strategy than adaptation. When catastrophic uncertainty is concerned mitigation becomes relatively more important as, by curbing emissions, it helps to reduce temperature increase and hence the probability of the occurrence of the event. Adaptation on the contrary has no impact on this. It is also shown that optimal mitigation responses are much less sensitive than adaptation responses to spatial uncertainty. Mitigation responds to global damages, while adaptation to local damages. The first, being aggregated, change less than the second in the presence of spatial uncertainty as higher expected losses in some regions are compensated by lower expected losses in other. Accordingly, mitigation changes less than adaptation. Thus if it cannot be really claimed that spatial uncertainty increases the weight of mitigation respect to that of adaptation, however its presence makes mitigation a “safer” or more robust strategy to a policy decision maker than adaptation.

2.1 *Introduction and Background*

When the battle against climate change started it was focused on mitigation measures. The United Nations Framework Convention on Climate Change (UNFCCC) was signed in 1992 with the aim to stabilize GHG concentrations at a level “that would prevent dangerous anthropogenic interference with the climate system”. Ten years later the role of adaptation started to be considered fundamental as well to “reduce many of the adverse impacts of climate change and enhance beneficial impacts”(IPCC TAR, 2001). It indicated an increasing awareness that climate change could not be completely halted even with the aggressive mitigation effort — the strong inertias in the climate system will expose modern societies to some degree of warming no matter what they do to curb emissions. Furthermore, the constant difficulties encountered by international climate negotiations also make the implementation of aggressive mitigation even less optimistic, at least in the short term.

Important strategic documents, for instance the 2009 EU White Paper on Adaptation or the recent 2009 “Copenhagen Accord”, recognized that both mitigation and adaptation strategies are necessary to combat climate change. The knowledge of climate dynamics, of the related environmental damages, on their economic relevance and of the costs of climate change policies, especially when adaptation is involved, is still far from conclusive. However, decisions have to be made and given the abovementioned climatic inertias they cannot be postponed for long if they are expected to produce some results within the century. Against this background a rapidly expanding literature is trying to devise normative indications on the optimal combination of the two in a cost efficient policy. A very recent stream of research has been applying the Integrated Assessment Model (IAM) to analyze the optimal policy portfolio (De Bruin, et al. 2009, 2010; Bosello 2010; Bosello et al. 2010). The robust outcome of these studies is that mitigation and adaptation are strategic complements: the optimal policy consists of a mixture of adaptation investments and mitigation measures, this is also true in the short term even though mitigation will only decrease damages in later periods as emission cuts can slow down temperature increase and the related damages with a delay of 50 – 80 years. These authors also highlight the existence of a trade-off between the two strategies: with the scarcity of resources, more on one means less on

another. Moreover, successful adaptation reduces the marginal benefit of mitigation and a successful mitigation effort reduces the damage to which it is necessary to adapt, although the second effect is notably weaker than the first. Indeed mitigation, especially in the short-medium term, lowers only slightly environmental damage stock and therefore does little to decrease the need to adapt. In addition, in all these studies the bulk of resources are devoted to adaptation, especially when the discount rate is high and when investment in adaptation can build a cumulating stock of “defensive” infrastructures. From extant literatures adaptation appears far more effective than mitigation, especially in the short term, to contrast climate change damages.

The investigation on climate policy is complicated by many uncertainties that surround the climate change issue, for example, the uncertainty of climate impacts. One of the uncertain impacts is the changes in extreme conditions that will bring about a sharp decline of social welfare outside the coping range. The collapse of North Atlantic Thermohaline Circulation (THC), a "runaway" greenhouse effect (climate change could be much greater and occur much faster than the common consensus indicated), the disintegration of West Antarctic Ice Sheet (WAIS), are all examples of such discontinuous impact (Pearce et al., 1996; Guillerminet and Tol, 2008). Catastrophic events are usually associated with very low probability, but, once materialized, with great and sudden harm (Posner, 2004). This “event uncertainty” (Tsur and Zemel, 1996) is expected to influence the decision making process. In the climate change impact literature there is indeed a consolidated research showing that it induces higher mitigation rates (Clark and Reed, 1994; Yohe, 1996; Gjerde et al., 1999; Bosello and Moretto, 1999; Ingham et al. 2005) and earlier action of emission control (Baranzini et al., 2003; Guillerminet and Tol, 2008). However, the study so far on policy combination of mitigation and adaptation excludes this kind of low-probability, extremely damaging climatic events. They perform what Weitzman (2009) defines in a debated paper [see also (Nordhaus, 2009)] a “standard” cost-benefit analysis (CBA). With the presence of event uncertainty, are mitigation and adaptation still complementary? Does the trade-off still exist? Is the substitution of mitigation to adaptation weaker than the opposite? As shown by (Weitzman, 2009) the cost of a future irreversible event in the presence of uncertainty might be infinite, and accordingly, also the willingness to pay to avoid the risk of it

can become infinite. This, translated into the context of deciding how much it is worth to mitigate or adapt, (and assuming that adapting to a catastrophe even though physically possible can be extremely costly), would implicitly support the idea that uncertainty can shift the burden of climate change damage reduction from adaptation to mitigation. This analysis is not performed by Weitzman though. In fact, there is little literature so far truly revealing the knowledge of policy combination with the presence of event uncertainty, with the only notable exception of Ingham et al. (2005). They compound in a theoretical model of mitigation, adaptation and the risk of catastrophic happenings. They show that event uncertainty increases both the mitigation rate and adaptation investment while the two remain economic substitutes; in addition the optimal combination of the two depends on their relative cost. However, they assume that the damage can only be reduced by adaptation, which is incomplete because the damage linked to temperature increase can also be curbed through mitigation, although the effect is weaker and less direct than adaptation. Moreover, in their average approach they neglect the regular damage that exists if catastrophic events are not materialized.

Another form of damage uncertainty that can influence the combination of mitigation and adaptation is that of the geographical distribution of climate damages. Damages are obviously region- and site- specific. However, even though some general regional patterns and dynamics are well understood (for instance higher vulnerability of low than mid- and high latitudes, identified hot spots for sea-level rise or droughts and floods risk, etc.) an exact prediction of where and with which intensity a given impact is going to hit is not possible. This is particularly concerning for some anticipatory adaptation practices entailing huge and almost irreversible upfront investments. Typical examples are coastal or river hard defenses. In these circumstances the nature of adaptation as private good comes into play. Its benefits are fully appropriated to the community that implements adaptation, but the whole burden of a planning mistake also falls on the adapting community. Thus, in the presence of spatial uncertainty, anticipatory adaptation could be an unattractive option. Mitigation on the contrary is a global public good: in principle one ton of CO₂ abated benefits the world as a whole irrespectively of where it is abated. When a planner decides to mitigate she knows that the damage will be reduced independently upon the location

where it is going to manifest. In this sense mitigation is more mistake-free than adaptation. This issue has not received great attention. In our knowledge it has been tackled only by Lecocq and Shalizi (2007). Developing a simple theoretical model they conclude that spatial uncertainty enhances the importance of mitigation with regards to adaptation. The first is global and accordingly only marginally determined by the local dimension of climate change damages. The second is more sector- and site- specific and thus influenced by damage local specificities. This is the other source of uncertainty we would like to investigate with our applied model about the policy mix.

This chapter aims at filling the important knowledge gap in defining the effective optimal mix between mitigation and adaptation, their trade-off and complementarities under uncertainty. Two sources of impact uncertainty defined above are considered: event uncertainty and spatial uncertainty. Both of them are incorporated into an integrated assessment model where mitigation and adaptation are available policy choices for the decision maker. Section 2 introduces the integrated model, the inclusion of adaptation and uncertainty and describes the calibration process. Section 3 elaborates the results derived from the modeling exercise. Section 4 conducts sensitivity analysis and the test of robustness. Section 5 draws major conclusion.

2.2 Adaptation and Uncertainty Modeling

The modeling tool used here to analyze mitigation, adaptation and uncertainty is an improved version of the basic Nordhaus and Yang (1996) RICE model. RICE-96 is a climate-economic hard-linked integrated assessment tool originally designed to find the optimal abatement effort under cooperative or non-cooperative settings, in six major geo-political blocks: the United States (USA), Japan (JPN), the European Union (EEC), China (CHN), the Eastern Europe and Russia (FSU), and the rest of the world (ROW). Although RICE is a regional dynamic model, however, here we use it not for a regional quantitative exploration. Today the regionalization of IAM is much more specific than when Nordhaus and Yang first built up RICE; since our study will be more in the world vision, how to regionalize becomes less relevant. Therefore, we can still follow the way RICE-96 lumps

the countries. The economic component of RICE is a standard Ramsey-Keynes growth model. It is linked to climate dynamics through the emission flow, by product of economic activity, which induces temperature increase. This on its turn impacts the economic system through a damage function translating warming into GDP losses. The model is fully dynamic: regional (or global) decision makers maximize aggregated inter-temporal utility from consumption to decide investment and abatement rates. This structure is enriched including the adaptation policy option building upon Bosello (2010), then coupled in two different experiments with event uncertainty and spatial uncertainty.

The complete structure of the model is reported in the Appendix C. Below the description of the implementation of adaptation and of the two forms of uncertainty follows.

2.2.1 Adaptation Modeling and Calibration

Adaptation is modeled as a dedicated investment (IA), which cumulates over time subjected to a depreciation rate (the same as physical capital).

$$SAD(n, t) = (1 - \delta_{IA}) * SAD(n, t - 1) + IA(n, t) \quad (2.1)$$

The resulting stock of adaptation capital (SAD) reduces climate damages by decreasing the multiplicative coefficient $(1 - \Omega)$ in the climate change damage function.

$$\begin{aligned} \Omega = & [1 - b_1(t) * b_2(n) * \mu(n, t)^{b_3(n)}] / \\ & \{1 + 1/[1 + SAD(n, t)^{1/2}] * a_1(n) * [T(t)/2.5]^{a_2(n)}\} \end{aligned} \quad (2.2)$$

According to (2.2) adaptation shows decreasing marginal returns to scale by construction. Adaptation investment competes with investment in physical capital, consumption and mitigation cost in the income budget constraint (2.3), where the mitigation cost is implicitly included in Ω , the damage function, and Y_G and Y_N are respectively the gross production and the production net of climate bill, which is the total cost of climate change. It is comprised of mitigation costs, adaptation investments and the residual damage.

$$Y_N(n, t) = Y_G(n, t) * \Omega = C(n, t) + I(n, t) + IA(n, t) \quad (2.3)$$

Calibrating adaptation costs and benefits is however problematic. Firstly it is not clear if the original damage function in RICE includes optimal adaptation costs. If so, this would

require disentangling adaptation costs from that damage function as done for instance by De Bruin et al. (2009, 2010) and Bosello et al. (2009). Even so, and this is the second problem, estimates of climate change damages and of adaptation costs are so uncertain that, given the present knowledge, it is very hard to justify any assumptions on the size of this optimal adaptation. What could be done at best is to indicate some order of magnitude (Agrawala and Fankhauser 2008; Parry et al., 2009). Thus in the present work rather than engaging into complex calculations to extrapolate from a basically unknown damage another unknown optimal adaptation investment, it is assumed that adaptation costs are not included in the original damage specification of the RICE-96 model. Then the model is allowed to define its optimal adaptation level responding to local damages, but within some imposed reasonable “boundaries”. The reference point for the definition of these boundaries is a doubling of CO_2 concentration. When this happens, following Tol et al. (1998) and De Bruin et al. (2009) it is imposed that global adaptation expenditure ranges between 0.1% and 0.5% of GDP, and that the effectiveness of adaptation ranges between 30% – 80% of total damage.

Fig.2.1 displays the calibrated adaptation expenditure and effectiveness, in which at calibration point, 0.22% of adaptation brings about 53% damage reduction.

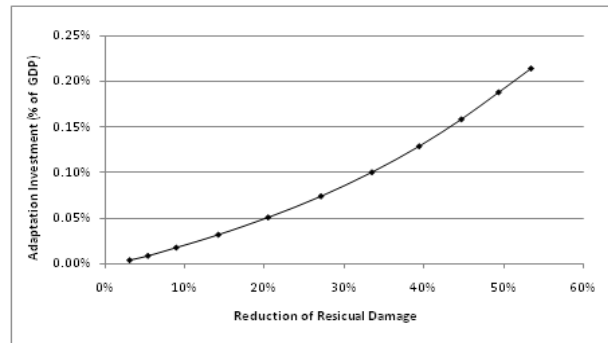


Figure 2.1: Effectiveness of Adaptation Investment

2.2.2 Event Uncertainty Modeling and Calibration

Event uncertainty is implemented through a failure distribution function of the duration of the climatic system i.e. the probability of the occurrence of the catastrophic event. It is denoted by a hazard rate which assumes a Weibull form (Kiefer 1988), a simple generalization of the exponential distribution.

$$P(t) = 1 - e^{-\int_{T(0)}^T \varphi * \eta * (TE(t) - TE(0))^{\eta-1} dTE} \quad (2.4)$$

Where $TE(t)$ is the temperature increase relative to the pre-industrial level.

(2.4) shows that the maintenance of the atmospheric temperature at the original level.

$T(0)$ eliminates the possibility of the occurrence of catastrophic events. Then, the higher the temperature increase, the higher the probability. This depends upon the two parameters and η .

To keep the convexity of the hazard rate function, we assign η the value of 2.5 (Gjerde et al. 1998). φ is calibrated in order to have a 7% probability of catastrophic happening, which means a GDP loss equaling the 25% for a temperature increase of $3^\circ C$ above pre-industrial period. In our model this happens at the end of the century. The 7% probability is an upward revision of the 4.8% value proposed by Nordhaus (1994), in view of more recent studies on the likelihood of catastrophic outcomes shown by Hadley Center (2005) (Tirpak *et al.*, 2005) and Arnell et al. (2005). According to both the probability of climate-induced catastrophes within this century are much higher: 30% for the shutdown of THC according to the first and 4% to 75% for a collapse of the Greenland ice sheet according to the second. This suggested us to increase by roughly 50% the initial Nordhaus' estimate, leading us to a still "optimistic" catastrophic probability estimate of the 7%. This benchmark, however, is still arbitrary. The parameter φ can be considered as another source of uncertainty embedded in the big uncertainty of catastrophic happenings. The sensitivity analysis in terms of φ will be conducted later to test the robustness of the main results displayed below. And for the uncertainty of φ itself, an improving knowledge should be anticipated as the research work carrying on about climate change. This kind of change of uncertainty itself can be another dimension of the problem for the advanced exploration in the further

studies.

Event uncertainty affects decision making as the planner now maximizes an (inter-temporal) expected utility function (2.5)

$$\begin{aligned}
 U = & P(t) * \sum_{n=1}^n \sum_{t=1}^t \{ (1+R)^{10*(1-t)} * \omega(n) * L(n, t) * \log [0.75 * C(n, t) / L(n, t)] \} \\
 & + (1 - P(t)) * \sum_{n=1}^n \sum_{t=1}^t \{ (1+R)^{10*(1-t)} * \omega(n) * L(n, t) * \log [C(n, t) / L(n, t)] \} \quad (2.5)
 \end{aligned}$$

In (2.5) utility is a weighted sum of its catastrophic and non catastrophic realizations, with weights given by the probability of the catastrophic happening. Following Nordhaus and Yang (1996), $\omega(n)$ is the Negishi weight that makes sure the marginal utility of consumption is equalized across the regions. Through mitigation the planner can lower the temperature increase and thus the probability of the catastrophic event, but of course it costs. In this formulation adaptation does not play any direct role in decreasing the catastrophic probability. Neither does it play a role in decreasing the post catastrophic penalty on utility as important as its way of decreasing the non-catastrophic damage — since the catastrophic outcome is proportional to the production free of catastrophes (25%), which is heavily influenced by adaptation measures, adaptation also functions in reducing catastrophic damage but in a weaker way.

2.2.3 Spatial Uncertainty Modeling and Calibration

The second source of impact uncertainty considered here is spatial uncertainty. It is modeled assuming six states of the world i ($i = 6$) where each region is assigned different possible damage parameters, $a_1(n, t)$ in eqn. (2.2), denoted as $a_{1i}(n, t)$ in this subsection. Each region experiences one state of the world with the probability $p(i)$. For simplicity it is assumed that all the damage parameters are equally probable, i.e. $p(i) = 1/6$. A robustness test will be conducted in the section of sensitivity analysis regarding this simplified assumption.

This replicates a situation in which the world planner (or the group of fully cooperating regional planners) does not know exactly with which intensity climate change damages are going to hit in different regions. Accordingly she has to maximize an expected utility which averages across the six possible outcomes, choosing one investment in physical capital, one

investment in adaptation and one mitigation level.

The utility function thus becomes:

$$U = P(i) * \sum_{n=1}^n \sum_{t=1}^t \sum_{i=1}^i \{(1 + R)^{10*(1-t)} * \omega(n) * L(n, t) * \log [C_i(n, t) / L(n, t)]\} \quad (2.6)$$

where $p(i) = 1/6$ and $C_i(n, t)$ depends on $a_{1i}(n, t)$.

2.3 Results

Results for the event uncertainty are displayed and analyzed for the world as a whole even though RICE is a regional model. The choice to focus on the global results is motivated by their ability to convey the main messages coupled with the simplicity of exposition. Results for the spatial uncertainty are shown by region, but still assuming full global cooperation on climate policies. The choice of the cooperative setting is necessary to observe some mitigation effort (and thus to have the possibility to compare mitigation and adaptation with and without uncertainty). In a non-cooperative environment the public good nature of emission reduction and the associated free riding incentive imply an almost null abatement, unless a possible catastrophe is imposed.

The business-as-usual (BAU) scenario chosen for the simulation is that of the no policy A2 IPCC SRES scenario. On one hand its storyline seems more plausible, even though rather pessimistic: it assumes the persistence of regional differences and an almost neutral technical change not too biased toward decarbonization of the economic systems. On the other hand current GHG emission trends are closer to that of the A2 IPCC SRES scenario than to other IPCC scenarios. Data for the benchmarking have been extracted from CIESIN database. The GDP projections are reported in Fig.2.2.

In addition to the BAU (denoted by (i) in figures hereafter) three other scenarios are proposed: mitigation adopted alone (denoted by (ii) in figures hereafter); adaptation adopted alone (denoted by (iii) in figures hereafter); joint implementation of mitigation and adaptation (denoted by (iv) in figures hereafter). The policy choice is discussed first in a context of event uncertainty and then of spatial uncertainty compared with the certainty case.

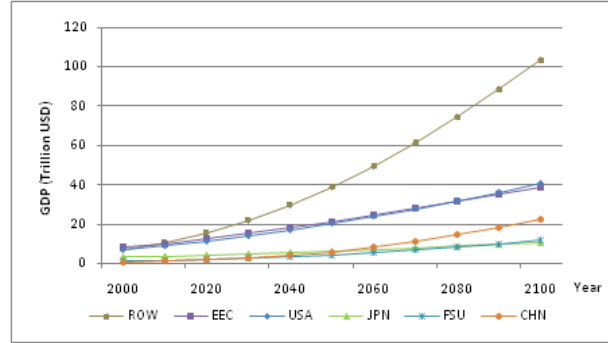


Figure 2.2: Regional GDP Projections

2.3.1 Mitigation and Adaptation under Event Uncertainty

Fig.2.3 and Fig.2.4 show the effect of event uncertainty on mitigation and adaptation effort respectively.

In a world absent of uncertainty, mitigation and adaptation confirm their strategic complementarity: both are used in an optimal policy portfolio as the possibility to introduce; mitigation (adaptation) does not eliminate the need to adapt (mitigate). They also confirm, in line with the theoretical and empirical literature in the field (Tol 2005; De Bruin et al. 2009, 2010; Bosello 2010) the existence of a trade-off. The presence of adaptation reduces the need to mitigate whereas a successful mitigation reduces the amount of damage one needs to adapt to. Moreover mitigation and adaptation compete for scarce funding, thus more placed on one decreases the amount available to the other.

When event uncertainty is introduced it pulls up, as expected, the optimal mitigation rate (by 51%, Fig.2.3). On the contrary adaptation investment remains almost unchanged (Fig.2.4). Since mitigation helps to reduce the probability of catastrophic events and adaptation's coping capacity becomes weaker when dealing with catastrophic damage than the non-catastrophic outcomes, a "catastrophic world" would require more mitigation, but not more adaptation. More mitigation reduces the probability of the catastrophic outcomes (Fig.2.5) from the 7.2% to the 5.4%, which means that the temperature increase will be curbed from $3.2^{\circ}C$ to $2.7^{\circ}C$ in 2090 (Fig.2.6).

Even in the presence of an uncertain catastrophic event a certain degree of crowding

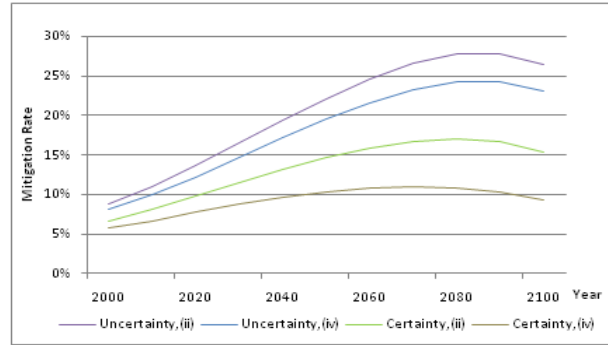


Figure 2.3: Mitigation Rate under Event Uncertainty

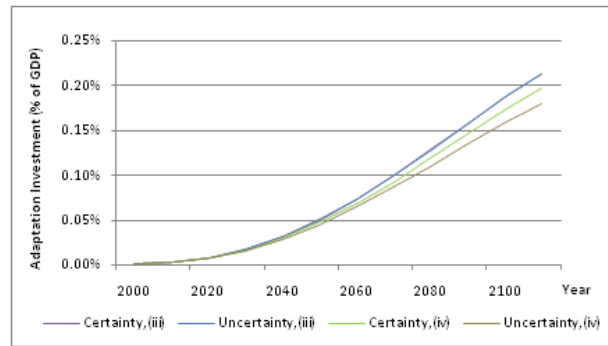


Figure 2.4: Adaptation Investment under Event Uncertainty

out of adaptation on mitigation (and vice versa) still remains. Indeed part of mitigation effort still works to reduce the regular damage component, and this action keeps on being influenced by adaptation activity. However, compared to the certainty case, the crowding out of adaptation on mitigation is greatly reduced (it is 68% smaller in 2100), while that of mitigation on adaptation is greatly amplified (114% larger in 2100). This result is quantified also in Table 2.1 which computes the elasticity of mitigation with respect to adaptation and vice versa. Table 2.1 shows that the elasticity of mitigation to adaptation is smaller under uncertainty than certainty case while that of adaptation to mitigation is larger.

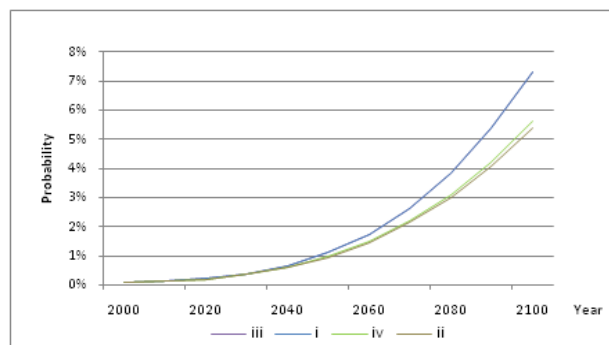


Figure 2.5: Probability of Catastrophic Happenings

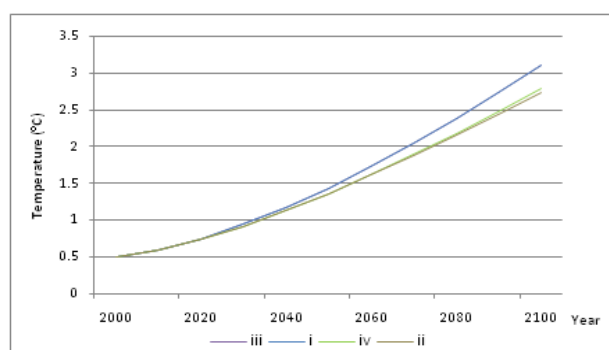


Figure 2.6: Temperature Increase

<i>Certainty Case</i>	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2010
Twice the Mitigation cost											
$\Delta IA/IA(\%)$	0	0.68	1.28	1.74	2.08	2.32	2.48	2.58	2.63	2.61	2.57
$\Delta\mu/\mu(\%)$	-30.94	-31.08	-31.24	-31.43	-31.66	-31.91	-32.18	-32.46	-32.74	-33.02	-33.33
Elasticity of IA to μ	0	-0.02	-0.04	-0.06	-0.07	-0.07	-0.08	-0.08	-0.08	-0.08	-0.08
Twice the Adaptation Cost											
$\Delta IA/IA(\%)$	-69.94	-65.76	-59.22	-50.98	-42.15	-33.66	-25.97	-19.16	-13.16	-7.89	-3.45
$\Delta\mu/\mu(\%)$	8.48	10.26	12.06	13.78	15.38	16.86	18.18	19.41	20.44	21.27	22.10
Elasticity of μ to IA	-0.12	-0.16	-0.20	-0.27	-0.36	-0.50	-0.70	-1.01	-1.55	-2.70	-6.41
<i>Uncertainty Case</i>	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2010
Twice the Mitigation cost											
$\Delta IA/IA(\%)$	-0.05	0.84	1.69	2.36	2.93	3.42	3.84	4.19	4.51	4.70	4.86
$\Delta\mu/\mu(\%)$	-30.72	-30.78	-30.85	-30.95	-31.07	-31.22	-31.38	-31.55	-31.71	-31.87	-32.01
Elasticity of IA to μ	0	-0.03	-0.05	-0.08	-0.09	-0.11	-0.12	-0.13	-0.14	-0.15	-0.15
Twice the Adaptation Cost											
$\Delta IA/IA(\%)$	-69.90	-65.78	-59.27	-51.10	-42.35	-33.94	-26.31	-19.58	-13.61	-8.39	-3.97
$\Delta\mu/\mu(\%)$	5.26	5.92	6.39	6.68	6.80	6.79	6.68	6.51	6.32	6.11	5.93
Elasticity of μ to IA	-0.08	-0.09	-0.11	-0.13	-0.16	-0.20	-0.25	-0.33	-0.46	-0.73	-1.50

Table 2.1: Elasticity of between Mitigation and Adaptation under Event Uncertainty

This outcome highlights that in the presence of an uncertain catastrophic event, more adaptation offers a weaker incentive to reduce mitigation. Indeed even though adaptation decreases the regular damage it cannot decrease the probability of the catastrophic occurrence, which is governed by temperature increase and thus by emissions that can be controlled only by mitigation.

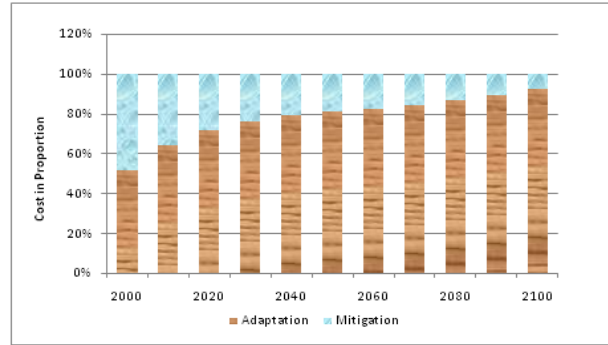


Figure 2.7: Expenditure Allocation across Mitigation and Adaptation: Certainty Case

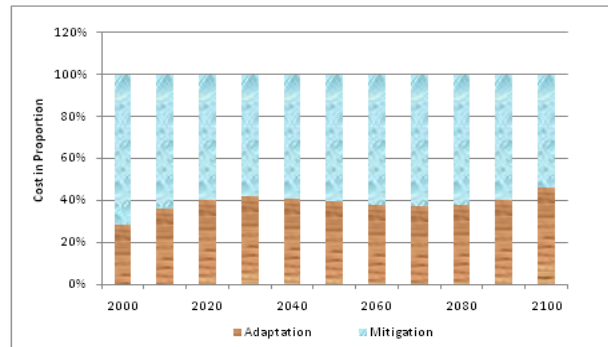


Figure 2.8: Expenditure Allocation across Mitigation and Adaptation: Uncertainty Case

This translates into a dramatically increased amount of resources devoted to mitigation than to adaptation (comparison of Fig.2.7 and Fig.2.8) and to an evident but more moderate increase of the percent of damage reduction due to mitigation with respect to adaptation (comparison of Fig.2.9 and Fig.2.10). All these findings provide a note that adaptation

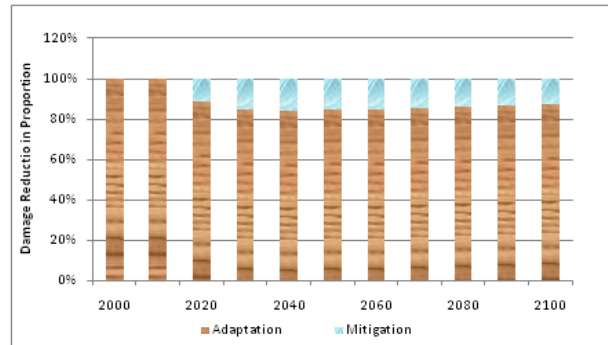


Figure 2.9: Proportion of Damage Reduction: Certainty Case

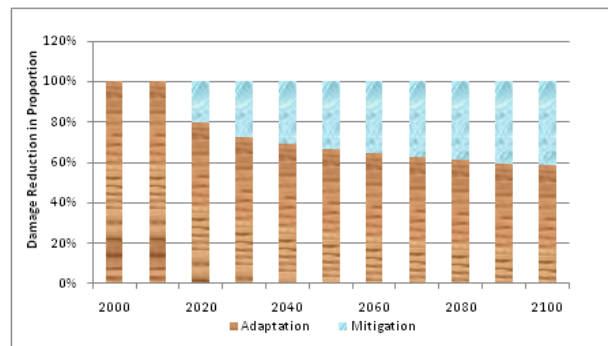


Figure 2.10: Proportion of Damage Reduction: Uncertainty Case

remains the strategy relatively more effective in damage reduction. This however refers to the non catastrophic damage component as well as the weaker yet still imposed effect on catastrophic damage. Even though uncertainty roughly increases mitigation by 50% this typically deploys its stronger effects with a delay, especially after the end of the century. Along the 21st century adaptation is still the main damage reducer.

As an exercise it can be interesting to compare these results with the mitigation targets currently debated in the international context. In the framework of its climate change strategy the EU proposed a safety threshold for temperature increase of 2°C with respect to pre-industrial levels within the century (CEC 2007). This target has been iterated in the 2009 Copenhagen Accord, which also proposed a set of non-binding commitments by many

countries ranging from explicit carbon reduction policies to carbon and energy efficiency targets. It has been estimated that if all these commitments were fulfilled and all the resources potentially mobilized were devoted to mitigation the temperature increase could be kept below 2.5°C (reasonably close to the goal of 2°C) (Carraro and Massetti 2010). Our model would replicate such an outcome if, keeping the catastrophic probability at its calibrated level (7%) the related damage would be increased to roughly the 75% of world GDP, or conversely if, with a damage kept at its calibrated level (25%), the catastrophic probability would be increased to 30%, for a temperature increase of 3°C . These simple estimates constitute some “back of the envelope” calculations revealing the implicit risk perception of the policy decision maker that interestingly enough are close to the scientific perception.

We find that compared to the certainty case the event uncertainty increases the optimal level of mitigation whereas the level of adaptation investment remains unchanged or even decreases. Accordingly, as far as the relationship of the two policies is concerned, the event uncertainty decreases the substitutability of adaptation with mitigation and increases the appeal of mitigation. This suggests an important policy implication. In a world characterized by regular climate damages mitigation is a marginal option, viable and welfare improving if coupled with adaptation, but anyway secondary if compared with what adaptation can cost efficiently achieve. In a world with catastrophic event uncertainty mitigation becomes the only strategy able to reduce the probability of the catastrophic outcomes and becomes the key policy variable. As a consequence mitigation should be decided at the outset on the basis of precautionary considerations (and not on “standard” cost-benefit approach based on perfect information) and adaptation has to be deployed to tackle the residual damage not accommodated by mitigation.

2.3.2 Mitigation and Adaptation under Spatial Uncertainty

In the presence of spatial uncertainty, the policy decision maker does not know exactly with which intensity climate change damage can hit a given region. The implication is an expected damage at the global level and at the regional level which differ from those

under certainty (Fig.2.11 and Fig.2.12). Differences however are more pronounced in the second than in the first case. Indeed, when the whole world is considered, higher expected damages in one region tend to be partially compensated by lower expected damages in another. Accordingly, expected damage at the global level differs from that under certainty by 18% at maximum in 2100, while regional damages differ from the certainty case in a range between the -36% and 52% in 2100.

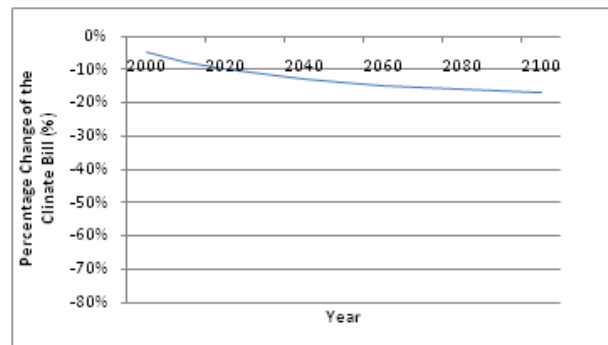


Figure 2.11: Percentage Change of the Global Climatic Damage under Spatial Uncertainty w.r.t. Certainty Case

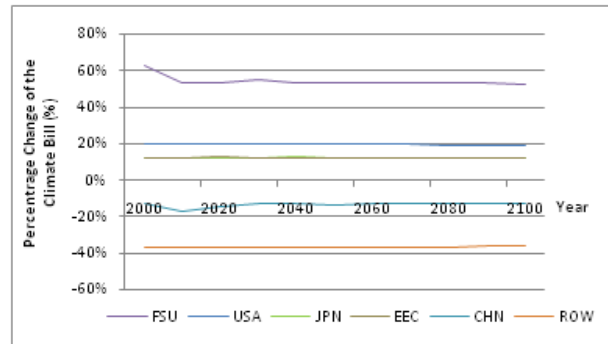


Figure 2.12: Percentage Change in the Regional Climatic Damage under Spatial Uncertainty w.r.t. Certainty Case

Spatial uncertainty influences both mitigation and adaptation decisions, but the impact on mitigation differs from that on adaptation.

Mitigation is a global public good, therefore total abatement effort is driven by total climate change damage. This effort is then distributed across regions in order to equalize marginal abatement costs, but these are not affected by spatial uncertainty. The consequence is that the (moderately) reduced total damage at the world level induces a roughly uniform moderate reduction of abatement effort in each region of the model (roughly -2% see Fig.2.13). Interestingly, all regions reduce their abatement effort irrespectively of the fact that expected damages in some of these regions can increase.

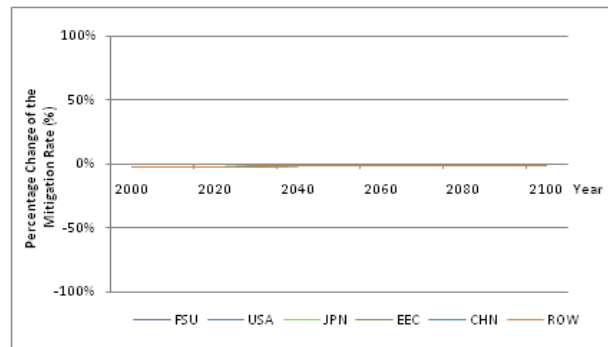


Figure 2.13: Percentage Change of the Mitigation Rates under Spatial Uncertainty w.r.t. Certainty Case

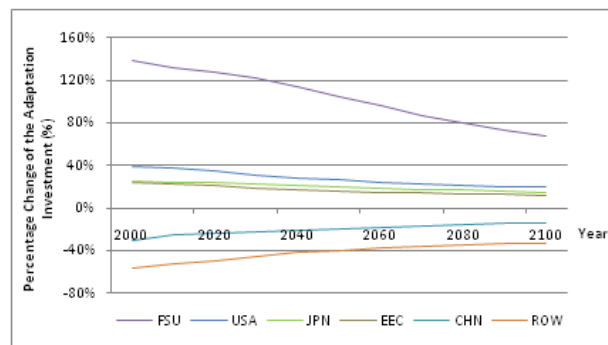


Figure 2.14: Percentage Change of the Adaptation Investments under Spatial Uncertainty w.r.t. Certainty Case

Adaptation, on the contrary, is a private good. It tackles local damages and benefits the

region that is adapting. Thus adaptation responds much more than mitigation to changes in regional damages. It increases when the expected damage increases and vice versa (see Fig.2.14). More specifically, expected damages are higher in FSU, USA, JPN, EEC and lower in CHN and ROW and this is mirrored by adaptive responses. Note also that changes in adaptation expenditure are larger than those in damages. This is the consequence of the interaction between mitigation and adaptation: under spatial uncertainty total mitigation effort is reduced and this pushes up adaptation.

Spatial uncertainty changes the damage distribution among the regions, hence changes the distribution of adaptation investments, which is implemented to reduce regional damages. In contrast, the expected damage at the global scale does not change as significantly as the regional damage, and the variation of the optimal mitigation rate is not as significant as that of adaptation investment.

This has also important policy implication. We cannot claim, as suggested by Lecoq and Shalizi (2007), that spatial uncertainty increases the cost-effectiveness of mitigation respect to that of adaptation, and the need for mitigation should be strengthened. In fact, spatial uncertainty can well increase considerably adaptation investment with respect to the certainty case, when there is a good probability to experience higher damages. Nevertheless we show clearly that optimal mitigation, designed to respond to global damages, is much less sensitive to spatial uncertainty than adaptation. Under this perspective mitigation offers a “safer” or more robust strategy to policy makers than adaptation. In other words, in a spatial uncertainty context a given mitigation policy can be expected to perform on average better, or to be revised less, than a given adaptation policy. This is an additional factor that should be considered, especially during international negotiation processes, in deciding mitigation efforts that can play in favor of mitigation compared to adaptation.

2.4 Sensitivity Analysis

In this section we are going to conduct series of sensitivity analysis to test the robustness of the results and the sensitivity of the outputs to key parameters.

2.4.1 *Discount Rate*

We used 3% as the social discount rate to weigh the welfare for different periods. It reflects our assumption that the interest of the next period is approximately 97% as important as the interest of one period earlier. However, the determination of an ideal social discount rate is highly debated in environmental economics for its moral implication. Here we choose other two levels to test the effect of social inter-generation unfairness on the policy choice.

Besides 3% we adopt another two with 50% higher (1.5%) and 50% lower (4.5%). We run the model under the policy scenario with both policies jointly implemented, in the light of event uncertainty. Because a lower social discount rate implies a higher concern for the interest of future generations, more cautious policies are taken to protect them from the damages. Therefore, as Fig.2.15 and Fig.2.16 show, higher mitigation rate and more adaptation investment are the optimal choices for lower social discount rate (Bosello, 2010). However, due to the delayed effect of mitigation, the increasing rate of mitigation is higher than adaptation to benefit more the future generations. Numerically the increasing rate is around 41% in average of mitigation comparing to 27% of adaptation. Figure.2.17 shows the elasticity of mitigation to adaptation. The elasticity is calculated as before, using the ratio of the changing rate of mitigation to adaptation, which is caused by the reduction of adaptation. The sensitivity analysis tests the robustness of the results we drew before: the negativity of the elasticity shows the substitution between the two policies. Furthermore, since mitigation takes effect later in the case of lower-discount rate, Fig.2.17 indicates that the higher weight on future generations (lower social discount rate) makes mitigation more responsive to the decreasing adaptation investment. However, since adaptation functions in a shorter period, the losses caused by the reduction of adaptation investment are similar among the cases with different social discount rate, so mitigation effort should be strengthened also by the similar rate. As it is shown in Fig.2.17, only after 70 years the elasticity starts to diversify.

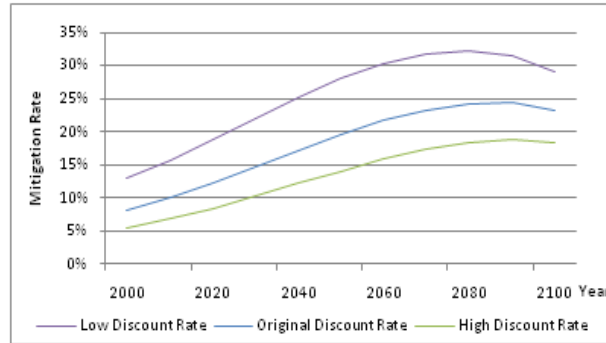


Figure 2.15: Effect of Discount Rate: Mitigation Rate under Event Uncertainty

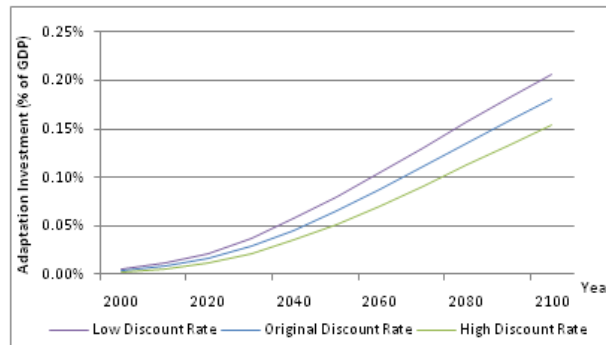


Figure 2.16: Effect of Discount Rate: Adaptation Investment under Event Uncertainty

2.4.2 Probability of the Catastrophic Happenings

For the calibration of the failure distribution function, we benchmarked the probability as 7% as the temperature increases by $3^{\circ}C$. Now we use the two extremes of the experts' opinion on this calibration point to conduct the sensitivity analysis, 4% and 75%.

Fig.2.18 and Fig.2.19 show that by higher probability of catastrophic happenings, it is optimal to implement more both policies. It is intuitive that the more probable catastrophic event will happen, the higher is the expected damage hence more adaptive actions are needed (adaptation) or more cautious the policy maker should be (mitigation). Additionally, we have already shown that mitigation does more than adaptation in the light of event

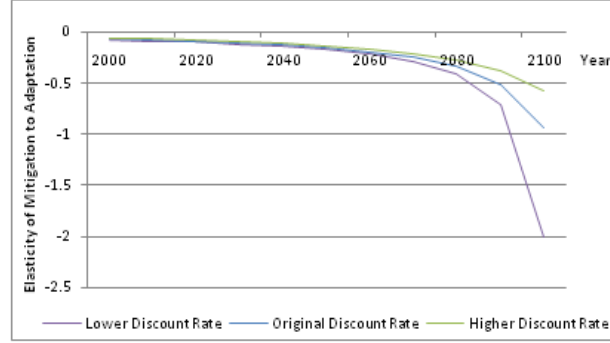


Figure 2.17: Effect of Discount Rate: Elasticity of Mitigation to Adaptation under Event Uncertainty

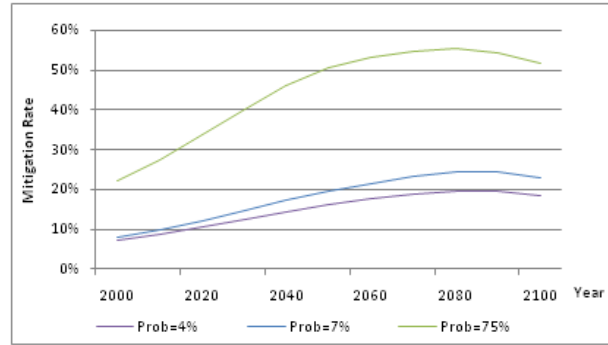


Figure 2.18: Effect of Probability: Mitigation Rate

uncertainty. Therefore, as the probability gets higher mitigation (adaptation) becomes even more (less) important. As the same amount of adaptation investment is decreased, less loss is induced in this case, thus less mitigation effort is needed to be substitution. By contrary, the same amount of mitigation reduction induces higher losses, so the adaptation investment increases more as a substitution. The elasticity between the two policies in Fig.2.20 and Fig.2.21 show the trends.

2.4.3 Damage Coefficient Re-shuffling

When we modeled spatial uncertainty, we reshuffled the damage coefficients among the six regions with the equal probability i.e. the six regions had the same chance (1/6) to get the six

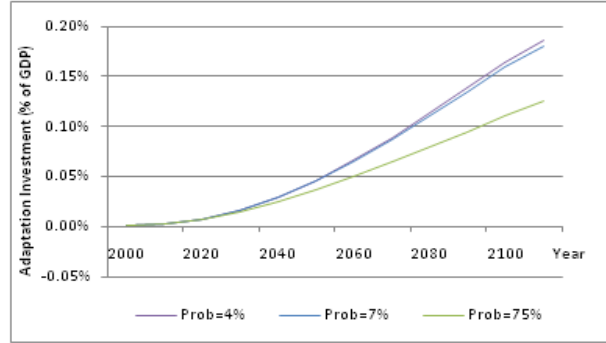


Figure 2.19: Effect of Probability: Adaptation Investment

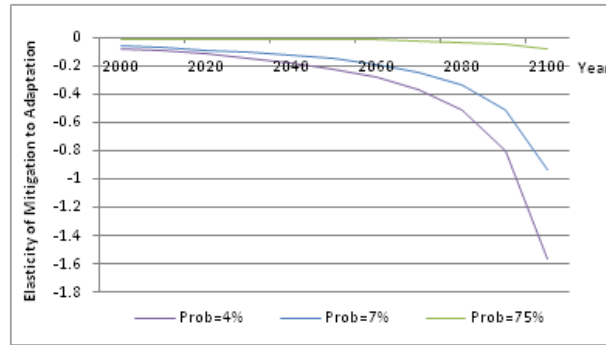


Figure 2.20: Effect of Probability: Elasticity of Mitigation to Adaptation under Event Uncertainty

damage coefficients. Now we test the robustness of the result by assuming a different degree of heterogeneity. The summed probability is still equal to 1. We decrease the probability of three regions by 25% consecutively and increase the other three by 25% consecutively i.e. three regions will be assigned the probability of $[(1/6) * (1 - 1/4)]$, $[(1/6) * (1 - 2 * 1/4)]$ and $[(1/6) * (1 - 3 * 1/4)]$ while the other three get $[(1/6) * (1 + 1/4)]$, $[(1/6) * (1 + 2 * 1/4)]$ and $[(1/6) * (1 + 3 * 1/4)]$. Re-running the model, we plot Fig.2.22 and Fig.2.23 accordingly.

Fig.2.22 and Fig.2.23 show the results qualitatively consistent with the one using the equal reshuffling probability: regional decision on mitigation rates is irresponsive to geographic uncertainty while adaptation is quite heterogeneous among the all.

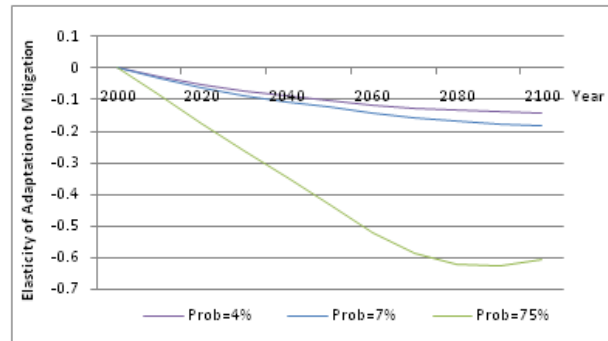


Figure 2.21: Effect of Probability: Elasticity of Adaptation to Mitigation under Event Uncertainty

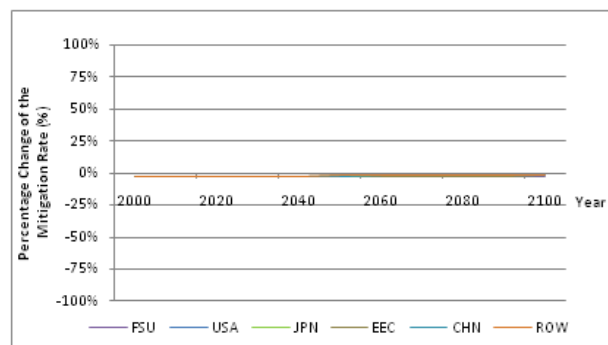


Figure 2.22: Damage Coefficient Re-shuffling: Percentage Change of the Optimal Mitigation Rate under Spatial Uncertainty w.r.t. Certainty Case

2.5 Concluding Remarks

Mitigation and adaptation are two strategies that support the policy maker in the struggle against climate change. While there is a broad consensus about the importance of both, there is still a significant knowledge gap in defining the effective optimal mix between mitigation and adaptation, their trade off and complementarities. Though a growing, albeit still thin literature, addressed this issue using economic-climate integrated assessment models, none of them explicitly included uncertainty in the picture. Our work fills this gap by introducing two sources of uncertainty into the analysis: event uncertainty i.e. the uncertain

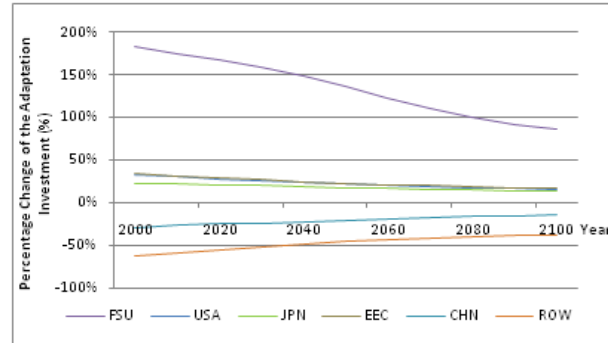


Figure 2.23: Damage Coefficient Re-shuffling: Percentage Change of the Optimal Adaptation Investment under Spatial Uncertainty w.r.t. Certainty Case

occurrence of a climate catastrophe triggered by temperature increase, and spatial uncertainty i.e. an imperfect knowledge on the geographic distribution of the climatic damage. We show that in both cases uncertainty works in the direction to make mitigation a more advantageous strategy over adaptation, but because of different causes.

When event uncertainty is concerned mitigation becomes relatively more important than adaptation because it helps to reduce temperature increase through reducing carbon emission and hence the probability of the occurrence of the event. Adaptation has no impact on this. Therefore, the optimal mitigation rate is increased under the event uncertainty, while the adaptation investment behaves insensitively. Actually the higher mitigation effort moderately decreases adaptation investment. Mitigation and adaptation remain economic substitutes under event uncertainty: more adaptation decreases the need to mitigate and more mitigation that to adapt. However, the crowding-out effect of adaptation to mitigation is weaker if compared to that in the certainty case, and of mitigation to adaptation is stronger. The results also show that the optimal mitigation responses are much less sensitive than adaptation responses to spatial uncertainty. While mitigation responds to global damage, adaptation functions to curb the regional-specific damages. Therefore, if the damage distribution is uncertain, mitigation which can effectively reduce the global climate risks helps policy makers commit fewer mistakes than adaptation. The consequence is that mitigation decisions under spatial uncertainty are much more stable than those related to

adaptation.

These results have important policy implications: in a world with climate-related catastrophic event uncertainty mitigation becomes the key policy variable as it is the only strategy able to reduce the probability of the catastrophic outcomes. As a consequence mitigation should be decided following precautionary considerations in the presence of discontinuity and irreversibility, and it should not, or not only at least, follow the standard cost benefit analyses performed in a smooth/continuous damage context. Then adaptation can be deployed to tackle the residual damage not accommodated by mitigation. Investing on mitigation has another advantage: considering the difficulty to assess ex-ante the economic dimension of region-specific damages, it endows the policy decision maker with a tool which is more robust to uncertainty than adaptation. Therefore the policy decision maker can be confident that by mitigating the probability of a planning mistake is somewhat smaller. All what said obviously applies in the context of a global policy which aims to internalize climate externalities. In a non-cooperative world adaptation will remain the preferred strategy.

Chapter 3

REDUCING UNCERTAINTY: THE EFFECT OF LEARNING ON CLIMATE POLICIES

Abstract

Climate policy is significantly impacted by various sources of uncertainty. The possible reduction of uncertainty, a step further, also imposes effects on the policy implementation. Groups of papers have been studying passive learning, i.e. reducing uncertainty through the observation of relevant outcomes and then updating knowledge accordingly, and its role in policy choice. However, theoretically speaking it is also possible to learn in an active way, that is, to reduce uncertainty by investing in the learning activities. So far active learning has not well-explored by the literatures. This chapter fills the gap between the theoretical possibility and the modeling exercise regarding active learning. We stick to the uncertainty of catastrophic happening and try to find the effect of learning catastrophic sensitivity (a parameter bridging temperature increase and occurrence of catastrophes) on policy decision. A two-stage sequential learning module is added to the modified version of RICE to approximate the policy making process with the knowledge updating, which is achieved by the investment in learning activities. The modeling exercise shows although it crowds out other investment option, the learning investment is worthwhile in improving knowledge and controlling climate damage by choosing more beneficial policies. The effect on policy decision is influenced by the productivity of learning, i.e. learning rate. A higher learning rate implies an earlier arrival of information, thus more quickly the policy choice approaches to the optimal.

3.1 Introduction and Background

Uncertainty has become an important and widely-recognized topic in the economics of climate change. A volume of literature in this area explored the effect of learning in reducing this uncertainty (see e.g. Kelly and Kolstad, 1999, Karp and Zhang, 2001, Leach, 2005, Webster et al., 2008 etc.). This dimension enriches the analysis of climate change policy because uncertainty itself becomes “uncertain” and possible to change. As time passes, more evidence about climate change will be revealed through observation; some actions may also be adopted to actively improve the knowledge through education and R&D programs. In either way, policy makers in the future will be more informed about the problems than policy makers today. Therefore, the climate policies might be more efficiently designed if they are planned according to the improved information.

Theoretical and empirical researches on learning are mainly trying to answer three questions: does information have any value? (Peck and Teisberg, 1993; Nordhaus, 1994; Bosello and Moretto, 1998) Due to the large uncertainty and the irreversibility in the context of climate change, is it worthwhile to wait for more knowledge in order to make the correct decision? (Arrow and Fisher, 1974; Henry, 1974; Freixas and Laffont, 1984; Ulph and Ulph, 1997) How to build up a framework for policy study, taking into account the effect of learning? (Kelly and Kolstad, 1999; Castelnovo et al., 2001; Karp and Zhang, 2001; Webster, 2002; Webster et al., 2008) The main results of these studies firstly quantify a positive value of information. It depends on the source of uncertainty, the different model settings, the way in which information is acquired and the time when the uncertainty can be reduced. Peck and Teisberg (1993) showed that the earlier learning takes place, the higher is the value of information; it could amount to \$56 billion for a learning anticipating knowledge by eight year. Bosello and Moretto (1998) estimated that the value of learning about climatic catastrophic events. It could vary from \$16.9 billion to \$465.1 billion under different modeling frameworks. Secondly, there are two kinds of counterbalancing irreversibility that could impact the climate change policy problem (Kolstad, 1996a): one referring to climate dynamics that cannot be reverted in practice, the other connected to the sunk cost of policy implementation. Whether it is optimal to wait for more information before making deci-

sions depends on which irreversibility prevails. If the economic irreversibility is stronger wait and then learn is a better strategy. The third question, analyzing policy making under uncertainty and learning, can be answered by following two approaches: active learning and passive learning¹. Active learning assumes that new information comes because of a dedicated investment in knowledge improvement; while passive learning assumes a sequential update of knowledge driven by simple observation. Until now passive learning has been the dominant approach. At first, passive learning was incorporated to study the value of information, and the information was assumed to arrive without any cost (Nordhaus and Popp, 1997). More recently, Bayesian statistics is introduced to represent a mechanism through which the knowledge updates by the observation of some relevant “signals”. A typical parameter to which passive learning is applied is climate sensitivity (CS) (see e.g. Kelly and Kolstad, 1999; Leach, 2005; Webster et al., 2008). CS functions as a link between GHG concentration and temperature increase. Therefore, the sequential observation of the GHG concentration and the temperature at the end of each period can be treated as the “signal” to update the knowledge about CS for the next period. Given that the stronger the signal is the faster the learning takes place, a paradoxical result is that in order to acquire more information, it is beneficial to emit more (control less). To control emission and to acquire more information constitute thus a pair of contradictory instances (Kelly and Kolstad, 1999; Webster et al., 2008). On top of that, Bayesian approach has other shortcomings and to some extent complicates the problem even more². On the other hands, active learning so far has not been developed by the empirical modeling literature.

In the second chapter uncertain catastrophic events and the policy responses to them have been discussed. In addition to the temperature level, the probability of the catastrophic outcome depends on the sensitivity of the climatic system in triggering such a catastrophe given certain level of temperature increase. This concept is embedded in the parameter φ of the catastrophic probability function. It can be considered a “catastrophic sensitivity” parameter and named as such hereafter. This parameter has been calibrated according to

¹For the precise definition, see Chapter 1.

²Refers to the Chapter 1 for the details.

the latest scientific evidence. However, there is still a huge uncertainty on this. As the research work on climate change continues, more information will be gained. How much should policy makers spend for the climate change research? Is the investment on those activities worthwhile? How is the learning activity able to affect the policy choice under the catastrophic risks? How is the balance between mitigation and adaptation likely to change? An exercise trying to shed light on these points will be interesting. Trying to avoid the shortcoming coupled with the Bayesian modeling approach, modeling active learning and its effect could be quite illuminative.

This chapter is going to provide insights about the effect of learning on climate policies when facing catastrophic risks. Furthermore, additional exercise is also conducted about the productivity of learning investment and how the different levels of productivity influence the decision making. To model active learning, ideas are borrowed from the literatures on induced innovation and R&D activities. In these literatures (Nordhaus, 2002; Papineau, 2006; Yu et al., 2009) R&D investment are made to help reduce the cost of technology, increase total factor productivity and indirectly the GDP growth. Similarly, learning investment in this exercise, e.g. on research program targeted at climate change, helps to improve the knowledge (or reduce the mistake) about the probability of the catastrophic event. The modified RICE framework is employed as Chapter 2, with learning module incorporated. Section 2 describes the model and its calibration to incorporate learning activities through investment. Section 3 displays the main results about the learning effect on policy choice, and further explores the learning effect under different circumstances through the sensitivity analysis. Section 4 provides the concluding remarks.

3.2 Modeling and Calibration

3.2.1 Modeling the Optimal Learning Path

The analytical framework used here to study learning effects is a further development of the model employed in Chapter 2. A learning module is embedded to describe how a dedicated investment is able to improve the knowledge about the true value of the catastrophic sensitivity. Initially policy makers have an idea about the catastrophic sensitivity, demonstrated

by parameter φ_0 , which is different from the true knowledge φ^* . This kind of knowledge is updated over time, denoted by $\varphi(t)$, through the accumulation of learning investment. We assume that the more capital is invested in learning, the closer will $\varphi(t)$ be to φ^* . To simplify, we assume that φ^* is higher than φ_0 . φ_0 is the value consistent with the lower bound of catastrophic probability given by the literature (4% for a doubling CO2 concentration), while φ^* is consistent with its upper bound (75%, the highest probability estimated by Arnell et al., 2005 for the collapse of THC). Besides, we also assume that catastrophic events will totally destroy the whole society, i.e. the post-catastrophic damage will decrease the utility to zero. The more policy makers invest on learning, the less the mistake they make, measured by the difference between the true state φ^* and $\varphi(t)$: $\Delta\varphi(t) = \varphi^* - \varphi(t)$, where $\Delta\varphi(0) = \varphi^* - \varphi(0)$. The smaller the difference, the closer their mitigation and adaptation strategies are to the optimal ones and the higher the utility. However investment in learning entails also a cost: it might crowd out other investment options in the budget constraint function.

The effect of learning on reducing $\Delta\varphi(t)$ is modeled by a learning curve, which resembles the experience curve explored firstly by Wright (1936) and recently applied to the energy and environmental sectors by e.g. Papineau (2006), Yu et al. (2009). The curve follows equation (3.1) saying that 1% increase of the learning index $X(t)$ brings about $|\beta|\%$ of knowledge improving (mistake reduction), $\beta < 0$ (Yu et al., 2009).

$$\Delta\varphi(t) = \Delta\varphi(0) * X(t)^\beta \quad (3.1)$$

Learning index $X(t)$, if put it in the context of learning-by-doing, was usually conceptualized as “experience”, demonstrated by the index related to the production or cumulative capacity at time t ; while in our setting, it is driven by the learning investment so we construct the index related to the cumulative learning capital made so far until time t $SIL(t)$.

$$X(t) = 1 + \alpha SIL(t) \quad (3.2)$$

Combining (3.1) and (3.2) together, we get the benefit of learning, described by the reduction of the mistakes equation (3.3). But practically the effective benefit of learning is

to have a higher utility when the policy portfolio, benefited by more information, is closer to the optimal one.

$$\varphi^* - \varphi(t) = (\varphi^* - \varphi_0) * [(1 + \alpha SIL(t))^\beta] \quad (3.3)$$

Accordingly when the learning capital stock is zero, $\varphi(t) = \varphi_0$ while when the capital stock goes to infinity, $\varphi(t) = \varphi^*$.

The cost of learning is represented by learning investment $IL(n, t)$, competing with physical capital investment, adaptation investment, mitigation expenditure and consumption in the income budget constraint. Following Nordhaus (2002) the opportunity cost of research activities in the environmental sector is set 4 times higher than other investment³. Therefore, the income budget constraint is now written as

$$Y_N(n, t) = C(n, t) + I(n, t) + IA(n, t) + 4 * IL(n, t) \quad (3.4)$$

The accumulation of learning investment, which decides the learning curve, is

$$SIL(t) = \sum^n [KL(n, t - 1) * (1 - \delta) + IL(n, t)] \quad (3.5)$$

(3.4) and (3.5) describe how learning accumulates. (3.3) – (3.5) build up the learning module that can be added into the basic framework of climate policy analysis employed in Chapter 2. The complete model is displayed completely in Appendix C.

3.2.2 Modeling Sequential Decision Making

The learning module above describes how the learning investment functions to improve the knowledge about the true state of the world. A technical problem is that by building up such a framework we are working with a perfect foresighted model. This implies that the decision made even at the first period is based also on the knowledge which will be got in all the subsequent periods. This of course is not consistent to what happens in the real world where decisions in every period can be based only on the knowledge effectively

³See Nordhaus (2002) for the details.

at hand. More specifically, considering the uncertain parameter φ , the decision about mitigation, adaptation and physical investment at time T can only be made according to the knowledge got updated so far, $\varphi(T)$. Therefore, we develop a sequential mechanism to mimic the decision making along with the process of knowledge updating. We follow here a two-stage approach to approximate this mechanism. To start the process, at the first stage a simulation is run producing an optimal learning path together with optimal path for all the decision variables throughout the whole simulation period. At the second stage the optimal learning investment and the updated value of $\varphi(t)$ for period 1 are stored as independent variables, and then the model repeats an optimization simulation from period 2 onward. This process is thus repeated t times. The number of iterations is consistent with the number of time periods. At each iteration, for example, the T^{th} , aggregated utility is maximized with the learning activity that takes place only before and at time T . In this way, all the policy variables follow the rule shown below, that is, Suppose that knowledge has been updated until time T , all the policy variables, generalized as $Var(n, t)$, are substituted with

$$Var(n, t) = \begin{cases} Var(n, t) & \text{when } t \geq T \\ Var_{level}(n, t) & \text{when } t < T \end{cases}$$

$Var_{level}(n, t)$ are the variables stored from the last iteration and used in the next as independent variables.

The sequential decision making process, which is the second stage of the mechanism explained above, is illustrated by Fig.3.1. Policy makers decide the policy variables at time T . TS stands for the iteration index, numerically it equals to t . To avoid index complexity, the regional index n is omitted. Learning investment $IL(t)$ is decided at the first stage. Thus the stock of learning investment at the first period $SIL(1)$ and $\varphi(1)$, the knowledge updated by investing in learning in the first period, are given as independent variables to maximize the aggregated utility in *Iteration 1* ($TS=1$). The policy variables derived from *Iteration 1* become the independent variables for *Iteration 2*, aggregated utility is maximized again to get the policy variables for *Iteration 3* and so forth. The algorithm terminates when the number of the iteration exceeds the maximum time period.

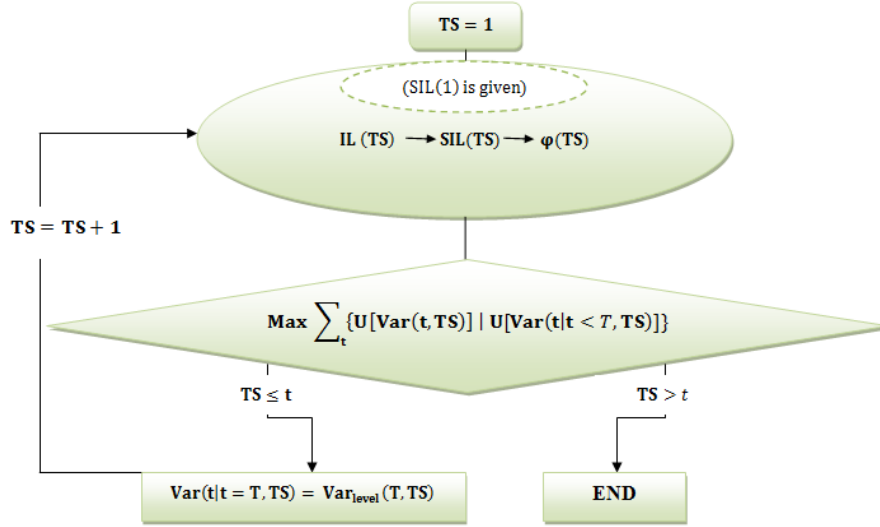


Figure 3.1: Algorithm of Sequential Decision Making Process

3.2.3 Calibrating the Learning Module

In the learning module, two parameters need to be estimated, the parameter α that decides the shape of the learning index $X(t)$ and β that decides the learning rate (LR), which implies the speed of learning. Two benchmarks are followed for the calibration.

First of all, empirical studies like IEA (2000) and Papineau (2006) defined LR as the percentage of cost reduction given the doubling of learning index. Here we follow this definition, and define LR as the mistake reduction when learning index $X(t)$ doubles. Thus LR is derived from eqn.(3.1) and written as $1 - 2^\beta$. Those literatures estimated that LR should be within the range of 5% – 35%, and β is calibrated here to fit this benchmark.

Secondly, there has been no literature so far defining the effect of learning climate change on mistake reduction in terms of policy making. So in order to calibrate α we choose as reference the effect of education expenditures on economic growth. The recent studies give the empirical evidence of this effect, that 1% increase of education investment brings about GDP growth by 0.03% – 0.23% (Sequeria and Martins, 2008; Beraldo et al., 2009). Here we benchmark our calibration within this range too and choose α to fit it.

<i>Catastrophic Outcome</i>	α	β	<i>Mistake Reduction by 1% Increase of Learning Investment</i>
25% Loss	0.8	-0.62	0.258%
50% Loss	0.3	-0.62	0.038%
100% Loss	0.3	-0.32	0.031%

Table 3.1: Calibration of the Learning Model: under Different Catastrophic Outcomes

If different levels of post-catastrophic outcome are assumed, the model needs to be recalibrated to fit the two benchmarks given above as α and β are both baseline dependent. Table 3.1 shows the parameters α and β calibrated for the cases of 100% loss, 50% loss and 25% loss, and also the effect of learning in terms of the mistake reduction. Note that under the scenario of 25% losses, compared to the other two, the learning effect displayed in the last column is much more significant (It is even slightly higher than the upper bound of the benchmark, therefore, in the main analysis conducted below, we will not stick to 25% loss scenario). It is because that the lower the catastrophic damage is, the less learning is needed in order to make the optimal policy and to avoid those damages. Thus the “threshold” by which learning starts to take effect is higher for lower damage scenario than the higher. In another word, the lower the catastrophic damage is, the more effective learning investment must be.

3.3 Results

3.3.1 Learning Investment

Based on the calibration above, Fig.3.2 shows the learning investment under the three catastrophic damage scenarios: respectively with the catastrophic loss of 100%, 50% and 25% of GDP. The learning investment ranges from 0.56% to 3.5% of GDP at the end of the century.

Recent literatures’ projections of optimal total R&D expenditure over GDP in the context of applied endogenous growth models are around 2.5% in 2100 (Nicita, et al., 2009; Massetti and Nicita, 2010). Our estimation of learning investments is lower than these

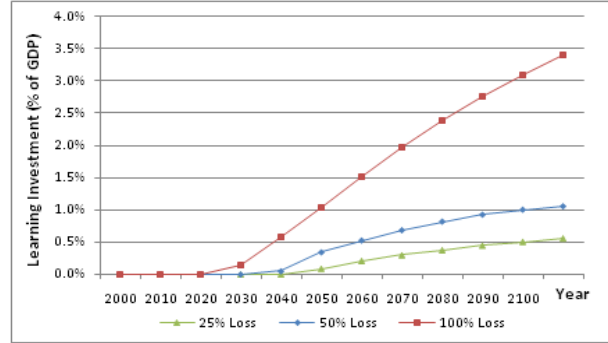


Figure 3.2: Optimal Learning Investments

values when the post-catastrophic damages are 50% or 25% of GDP. However this amount is quite high considering that the learning activity here only refers to the research, education and other expenditure related to climate change. For the case of 100% damages, the amount of investment dedicated to learning is far much higher than what is now presented in the existing literatures, which apparently did not take into account the possibility of total economic collapse.

What our simulation also suggests is that it would be worth to wait until 2030 to invest in climatic knowledge, and even later if the catastrophic damage is lower. As mentioned in the model description, learning benefits the utility under imperfect knowledge to approach the maximum under the full knowledge. Therefore, learning occurs whenever the utility is lower than the maximum. Due to the maximization of the aggregated utility over time, the temporal utility, however, is possible to be lower for the optimal case than the case under imperfect knowledge at least in the first several decades. For example, under the case of 100% damages, temporal utility only catches up at 2020, when it stays equal to the imperfect case. Therefore, learning takes place only at 2030, when the temporal utility starts to exceed.

	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Learning Investment (% of GDP)	0	0	0	0.15%	0.58%	1.04%	1.52%	1.97%	2.38%	2.76%	3.09%
Mistake (% Difference between $\varphi(t)$ and φ^*)	100%	100%	100%	100%	92.92%	76.16%	63.01%	53.52%	46.77%	41.72%	37.82%

Table 3.2: Effect of Learning on Mistake Reduction

3.3.2 The Effect of Learning

Hereafter, we stick to the case where catastrophic events bring the social utility down to zero (catastrophic damage is 100% losses of GDP) to look into the effect of learning. Dynamics are clearer in this case, and the results can be more easily to show comparing to the other two. The investment in learning takes effect on improving knowledge, and consequently helps to make more beneficial climate policy to reduce more climate damages.

Table 3.2 shows the effect of learning on knowledge improvement given the optimal learning investment. At the end of the century, the mistake will be reduced by 38%.

The benefit of those learning investment in terms of climatic damage reduction can be demonstrated by Figure 3.3. The reduction of residual damage is calculated by the percentage difference between the damage control under false knowledge and that under the updated knowledge. The lower the mistake is the more damage is controlled through a more beneficial policy portfolio. This point can be further illustrated by Figure 3.4 and Figure 3.5, where the climate policies are compared among the cases (a) under the perfect knowledge — true state-of-the-world (*TrueSOW*), (b) under the false-knowledge (*FalseKnw*) and (c) learning takes place (*Learning*). The policies under these three knowledge levels are hereafter mentioned as *optimal path*, *wrong path* and *learning path*. Following the wrong path, with the recognition that catastrophic events are less likely to happen, the policy choice is more optimistic – lower mitigation rate and higher adaptation expenditure – the results we have already shown in Chapter 2. As knowledge is updated, policy makers realize that the

state of the world is more pessimistic than previously expected. The policy portfolio should be tilted to mitigation to prevent the catastrophic happening. However, since the knowledge is sequentially updated decision makers can only adjust the policy gradually according to the information they have at hand. So an approach gradually being coincident to the optimal path is shown in the figures.

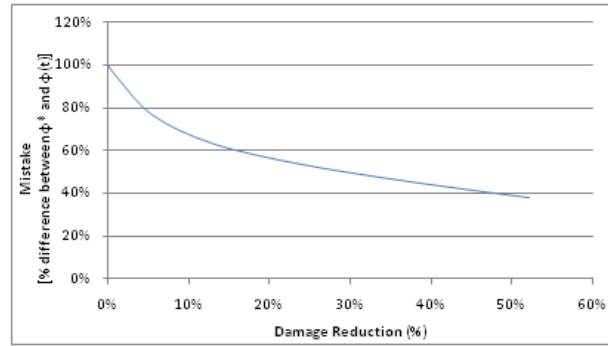


Figure 3.3: Benefit of Learning

Learning shifts the policy balance towards the direction that is consistent to the optimal path, but the adjustments of the two policies to the new balance follow different approaches. In Fig.3.4, the optimal mitigation rate with learning coincides with that under perfect information in 2060 when the knowledge about the catastrophic sensitivity is still 50% incomplete; moreover, an over-control occurs by 0.5% – 0.8% higher than the optimal path after 2060. This over-control behaviour helps to offset the previous excess emission (relative to the optimal path) due to the imperfect information. These trends however are not observed in the case of adaptation. As explained before, as far as policy makers realize that the knowledge they held previously was too optimistic, more stringent emission is implemented to compensate the losses caused by the insufficient mitigation effort. Therefore, as knowledge is updated, even if it is not fully improved to the perfect, mitigation rate roars up to catch up with the optimal path. In another word, the catastrophic penalization is enough to justify a very aggressive mitigation strategy. This compensation mechanism does not happen in the case of adaptation; the optimal adaptation investment is adjusted

following a smooth path, with every step of knowledge update. As a result, mitigation reacts more quickly than adaptation to approach to the optimal path.

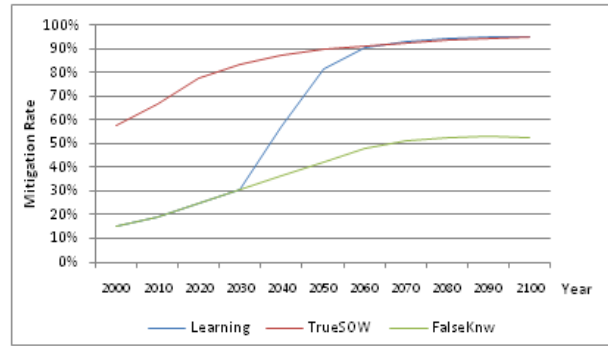


Figure 3.4: Mitigation Rate under Different Knowledge Levels

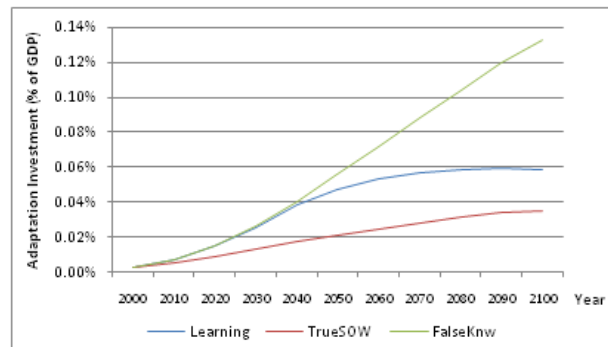


Figure 3.5: Adaptation Investment under Different Knowledge Levels

Learning takes place crowding out also other expenditures in the budget constraint. Figure 3.6 displays the comparison of physical investment before and after learning is introduced. It shows that the crowding out effect of learning investment on the physical investment does exist. At the end of the century, physical investment (calculated by the percentage of GDP) will be reduced by 13%.

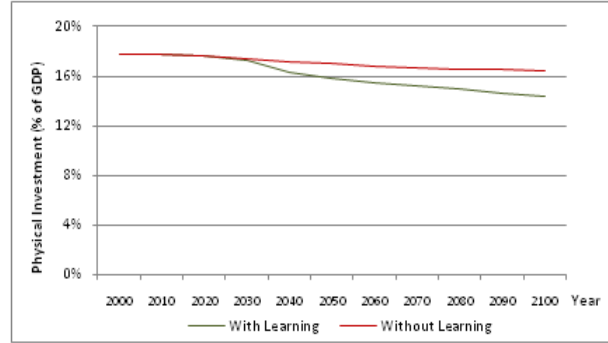


Figure 3.6: Crowding out Physical Investment

3.3.3 Sensitivity on the Learning Rate

Learning rate, defined as the percentage improvement of the knowledge by doubling the learning index, measures the productivity and the speed of learning. How efficient and how fast learning investment take effect influence the climate policies in the sense of timing and amount. Here we set five LRs according to its range given by literatures, 5%, 10%, 20%, 30%, 35%. Intuitively the higher the LR is the more productive learning could be. Figure 3.7 displays the benefit of learning under different LRs, demonstrated by the percentage reduction of the discounted & accumulated damage all over the century. Again the benefit of learning investment is given by the percentage reduction of residual damage compared to the case with wrong knowledge. Fig.3.7 shows that more effective learning investments brings about more damage reduction. A decreasing return to scale can also be found with respect to the learning rate. A higher LR induces higher motivation to invest in learning, however, theoretically speaking, at each level of LR, when the learning investment beyond certain threshold the updated knowledge becomes close to the perfect information. After that the continuously increasing investment will not bring about the benefit as much as the initial incremental capitals.

This “threshold” effect further functions for policy responses. Figure 3.8 and Figure 3.9 show the mitigation rate and adaptation investment corresponding to different LRs.

Of both mitigation rate and adaptation investment, more productive learning induces

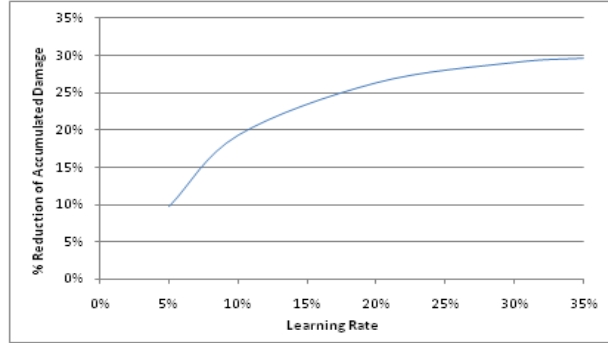


Figure 3.7: Benefit of Learning under Different LRs

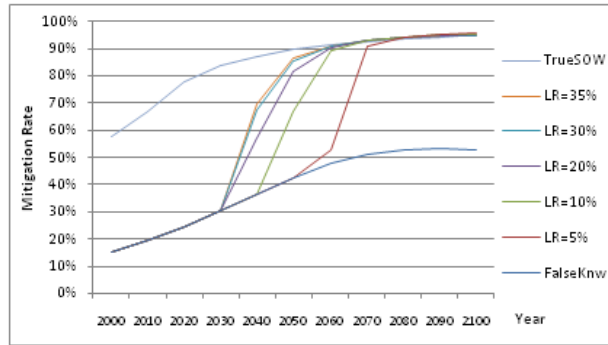


Figure 3.8: Mitigation Rate under Different LRs

the earlier arrival of the information, therefore the learning path approaches faster to the optimal path as LR increases. However, the change of the policy response is not linear to LR. Due to the decreasing return to scale, within the range of LR we gave from 5% to 35%, the first 5% increase (from 5% to 10%) induces stronger effect on both policies than the last 5% (from 30% to 35%). Particularly for the mitigation rate, the lower LR shows a higher over-control rate after the learning path crosses over the optimal path. The knowledge is updated more slowly, thus compared to the higher level of LR, lower LR allows more emission due to the under-estimation of the catastrophic risks; after more information is acquired, more damage need to be offset by a more strict mitigation policy. The highest over-control rate, relative to the optimal path, is listed in Table 3.3. It happens later to

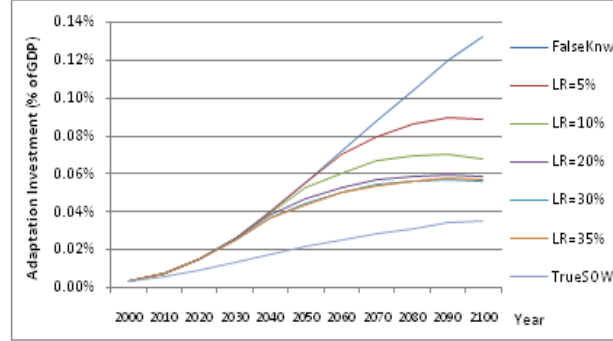


Figure 3.9: Adaptation Investments under Different LRs

LR	<i>Over-Control Rate</i>	<i>Time</i>
5%	1.2289%	2080
10%	0.9742%	2080
20%	0.8993%	2080
30%	0.7400%	2090
35%	0.6541%	2090

Table 3.3: The Highest Over-Control Rates of Mitigation

the lower LR than the higher LR due to the slower knowledge improvement, but the rate is higher.

3.3.4 Far-sighted and Myopic Policy Making

As a conclusion, it could be interesting to see, just for demonstrative purposes, what a far-sighted policy decision-maker would do. By far-sighted we mean a decision maker able to exploit since the beginning all the information available along all the simulation period. In another word, even though information update starts since 2030, it is embedded in the plan that starts since 2010. In fact this is the problem we had to overcome in order to simulate a more realistic policy making process, but we can draw some conclusion comparing the two behaviors of policy making.

Fig.3.10 shows the mitigation effort in far-sighted plan. Compared with the myopic plan in Fig.3.4, mitigation effort in the beginning of the century has already been strengthened and the learning path approaches faster to the optimal path. The far-sighted policy maker takes into today's consideration the knowledge update in the future, which in this case indicates that the true state of the world is expected to be more pessimistic than what is understood nowadays. In addition, the over-control rate in the far-sighted plan is even higher than the myopic plan, by around 2% at the end of the century, moreover it happens earlier by three decades. It is true that with higher mitigation rate less losses are caused in the far-sighted case. But the knowledge is still imperfect and the difference between the far-sighted and myopic policy makers is that their expectation of the future knowledge is different. The one who realizes earlier that the knowledge at present is too optimistic will adopt the more strict and earlier preventive policy.

The scale of adaptation investment, on the other hand shrinks for the far-sighted policy makers than the myopic ones as if more resources would be shifted to mitigation to alleviate the catastrophic risks.

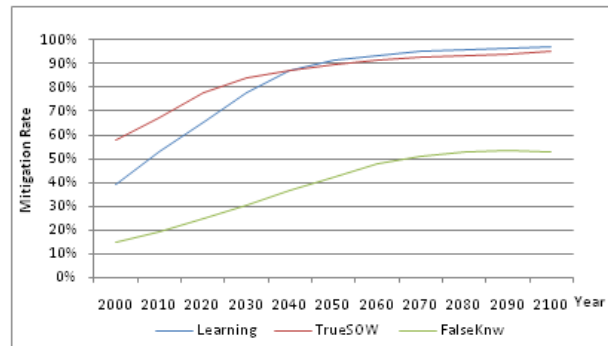


Figure 3.10: Mitigation Rate in a Far-sighted Plan

Last but not the least, the more beneficial policy portfolio makes the learning path closer to the optimal path, hence brings about higher level of the utility, as Fig. 3.12 displays the utility comparison between the myopic and the far-sighted.

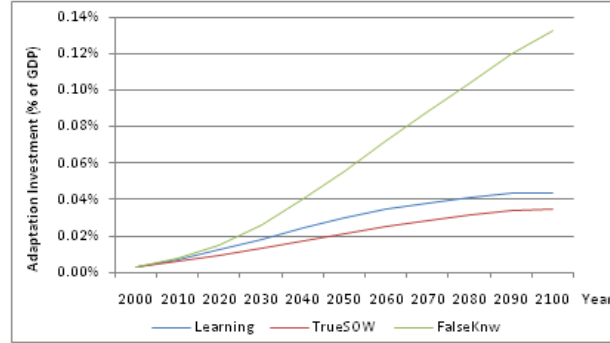


Figure 3.11: Adaptation Investment in a Far-sighted Plan

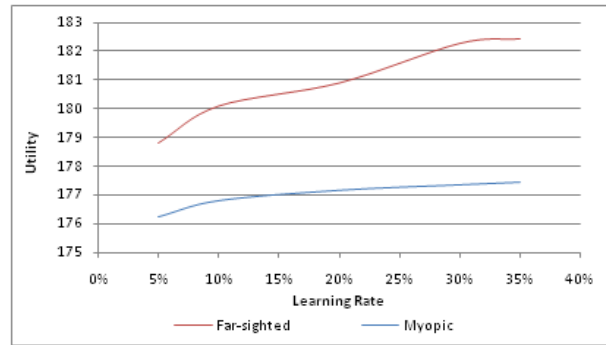


Figure 3.12: Utility Comparison: Far-sighted .vs. Myopic

3.4 Concluding Remarks

The possibility to reduce uncertainty adds another dimension to the economics of climate change. In a more dynamic environment, climate policy under uncertainty also takes into account the change of the uncertainty itself. Apart from the observation and the statistic approach, investing in research activities is another way to update knowledge and get closer to the perfect information. This chapter tries to incorporate those activities into the climate-economy integrated framework and study the effect of active learning on the policy choice when facing catastrophic risks. A parametric uncertainty, catastrophic sensitivity, is assumed to be reduced when research on climate change is carried on. A sequential

decision-making mechanism is developed to simulate a more realistic policy making process.

The exercise shows that learning investments helps to reduce the climatic damages since the policies will be made under the improving knowledge in this field. The optimal learning investment, considering about the wide range of the assumption of catastrophic outcome, accounts for 0.56% – 3.4% of GDP at the end of the century. The proportion learning investment takes in the budget plan is influenced by the outcome of the catastrophic event. If the total economic collapse is expected, the research investments on climate change alone even exceed the current projection of the R&D expenditure in 2100. Mitigation and adaptation are adjusted to compose a more beneficial policy portfolio if learning takes place. Both of them are following the path gradually approaching the optimal path that is under the perfect information, as learning keeps on carrying on. But the two policies are not adjusted synchronous in that mitigation reacts more quickly than adaptation to the new-arrived information. In addition, mitigation rate will experience an “over-control” to offset the damage caused by the less stringent emission control policy before enough information is gained. The learning investment crowds out the physical investment in the budget plan.

By sensitivity analysis, we also show that learning rate, a parameter that decides the productivity of learning, affects the speed in which policy choices converge to the optimal path. The higher the learning rate is, the more quickly the knowledge can be updated, and the faster the convergence can happen. In particular, the over-control rate of emission is higher for the lower learning rate to offset more damages caused before, but the over-control occurs later due to the slower knowledge improvement. In addition, the exercise also shows a decreasing return to scale of learning rate in terms of damage reduction. Analogously, as the learning rate increases, the learning effect on policy choices is weakened since information arrives earlier and the benefit of learning is “exhausted” earlier too. The exercise also compares the different types of policy makers, who are able to make decision in a far-sighted way or myopic way. By implementing a stricter mitigation plan, far-sighted policy makers are able to benefit the society with higher utility than the myopic ones.

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Appendix A

POLICY CHOICE UNDER THE UNCERTAINTY OF CATASTROPHIC EVENT: A THEORETICAL MODEL

In the theoretical model developed by Ingham et al. (2005), the probability of the catastrophic happening is related to the risk parameter and the mitigation effort. The higher the mitigation rate or the higher the risk, the more probable the catastrophic event will be materialized. They also assumed that the damage function is dependent on the adaptive action alone. However, there are two points missing in their assumptions if a more complete picture of the issue is required. First of all, since catastrophic damage happens only under certain probability, it is also possible that the damage happens only in the regular basis. This means that compared to the huge/discontinuous outcomes, climate change also causes the small, continuous damage that is not negligible. Secondly, mitigation, functions to reduce the GHG emissions, takes effect not only on the probability of catastrophic happenings but also on the damage reduction. Therefore, here we include these two additional assumptions in Ingham et al. (2005b)'s framework and further check the results about (1) the relationship between the two strategies; (2) the effect of uncertain catastrophic event on the policy choice.

Proposition 1 *Mitigation and adaptation are substitutes with the presence of the endogenous uncertainty of catastrophic events.*

Proof. Referring to Ingham et al. (2005), the endogenous uncertainty of catastrophic events can be modeled by including the probability of the catastrophic happenings in the cost minimization problem. But with two additional assumptions, our model includes the regular damage, which is proportional to the catastrophic damage following the definition of catastrophic events given by Nordhaus (1994b); we also assume that damage is not only controlled by adaptation but also mitigation. The minimization problem is as:

$$\min_{\{m,a\}} \pi(\rho, m) * 1.25 * D(m, a) + (1 - \pi(\rho, m)) * D(m, a) + M(m) + \alpha A(a) \quad (\text{A1.1})$$

where m and a represent the mitigation and adaptation investment; M and A are the cost of the policies. α is the positive parameter of the cost function of adaptation. D is the damage of climate change, which can be reduced through mitigation and/or adaptation. According to the definition of the catastrophic losses by Nordhaus (1994b), when catastrophe occurs, 25% of output will be lost - since the damage is proportional to the output, the post-catastrophic damage is 1.25 times of the regular damage suffered from climate change D . Here we take advantage of this setting. π is the probability of the occurrence of the catastrophic event, which is triggered by the GHG stocks in the atmosphere and hence influenced by the mitigation policy. π depends on the positive parameter ρ . The objective function above satisfies the condition as follows:

$$\frac{\partial D}{\partial m} = D_1 < 0; \frac{\partial D}{\partial a} = D_2 < 0 \quad (\text{A1.1-1})$$

$$D_{11} > 0; D_{22} > 0 \quad (\text{A1.1-2})$$

$$D_{12} = D_{21} \geq 0 \quad (\text{A1.1-3})$$

$$D_{11} \geq D_{12}; D_{22} \geq D_{12} \quad (\text{A1.1-4})$$

$$\frac{\partial \pi}{\partial \rho} = \pi_1 > 0; \frac{\partial \pi}{\partial m} = \pi_2 < 0 \quad (\text{A1.1-5})$$

$$\pi_{12} = \pi_{21} \leq 0 \quad (\text{A1.1-6})$$

$$\pi_{22} \geq 0 \quad (\text{A1.1-7})$$

$$M' > 0; M'' > 0; A' > 0; A'' > 0 \quad (\text{A1.1-8})$$

(A1.1-1) - (A1.1-4) are all conditions about the damage function, the value of which decreases when mitigation or adaptation is implemented, but the effect is diminishing. The own effect of either strategy alone is stronger than the cross effects of the two strategies. (A1.1-5) - (A1.1-7) are conditions about the probability of the catastrophic occurrence, which depends on the parameter ρ . Mitigation decreases the risk of catastrophes but the effect is diminishing. (A1.1-8) is the properties of the cost function w.r.t. mitigation and

adaptation. These conditions except (A1.1-7) are following Ingham et al.(2005). To minimize the cost function (A1.1), the following first order conditions should be satisfied:

$$1.25\pi_2 D + 1.25\pi D_1 - \pi_2 D + (1 - \pi)D_1 + M' = 0 \quad (\text{A1.2})$$

$$1.25\pi D_2 + (1 - \pi)D_2 + \alpha A' = 0 \quad (\text{A1.3})$$

The relationship between mitigation and adaptation can be derived by conducting the comparative static analyses for mitigation and adaptation with respect to the adaptation cost. Differentiating (A1.2) and (A1.3) with respect to α we get:

$$G_1 \frac{\partial m}{\partial \alpha} + G_2 \frac{\partial a}{\partial \alpha} = 0 \quad (\text{A1.3})$$

$$G_2 \frac{\partial m}{\partial \alpha} + G_3 \frac{\partial a}{\partial \alpha} + A' = 0 \quad (\text{A1.5})$$

It is easy to get that

$$\frac{\partial a}{\partial \alpha} = -\frac{1}{\Delta} G_1 A' \quad (\text{A1.6})$$

$$\frac{\partial m}{\partial \alpha} = \frac{1}{\Delta} G_2 A' \quad (\text{A1.7})$$

where

$$G_1 = 0.25\pi_2 D + 0.5\pi_2 D_1 + D_{11} + 0.25\pi D_{11} + M'';$$

$$G_2 = 0.25\pi_2 D_2 + 0.25\pi D_{12} + D_{12};$$

$$G_3 = D_{22} + 0.25\pi D_{22} + \alpha A'';$$

$$\Delta = G_3 G_1 - G_2^2.$$

der the same assumption as Ingham et al. (2005) that the cross effects is negligible, i.e. $\pi_2 D_2 = 0$, it is easy to find that $G_1 > G_2 > 0$ and $G_3 > G_2 > 0$, so that $\Delta > 0$. ■

Proposition 2 *With the presence of the endogenous event uncertainty, i.e. the occurrence of the catastrophic event is affected by GHG emissions, the optimal level of adaptation investment is non-increasing with the catastrophic risk while the optimal level of mitigation is non-decreasing.*

Proof. We conduct the comparative static analyses for mitigation and adaptation with respect to the catastrophic risk. Differentiating (A1.2) and (A1.3) with respect to risk parameter ρ that affect the probability of catastrophic happening, we get the following:

$$G_1 \frac{\partial m}{\partial \rho} + G_2 \frac{\partial a}{\partial \rho} = -0.25(\pi_1 D_1 + \pi_{21} D) \quad (\text{A2.1})$$

$$G_2 \frac{\partial m}{\partial \rho} + G_3 \frac{\partial a}{\partial \rho} = -0.25\pi_1 D_2 \quad (\text{A2.2})$$

Then it is easy to get the first derivative of m and a with respect to ρ by (A2.1) and (A2.2):

$$\frac{\partial a}{\partial \rho} = 0.25 * \frac{1}{\Delta} [\pi_1 (G_2 D_1 - G_1 D_2) + \pi_{12} D G_2] \quad (\text{A2.3})$$

Because $0 < G_2 < G_1$ and $D_1 \leq D_2 < 0$, which means that mitigation is more cost-effective than adaptation as far as the damage reduction is concerned (De Bruin et al., 2007; Bosello, 2008), it can be concluded that $\frac{\partial a}{\partial \rho} \leq 0$. (A2.2) tells that

$$G_1 \frac{\partial m}{\partial \rho} + G_2 \frac{\partial a}{\partial \rho} = -0.25(\pi_1 D_1 + \pi_{21} D) > 0 \quad (\text{A2.4})$$

It is easily to deducted that $\frac{\partial m}{\partial \rho} > 0$. When facing the uncertainty of catastrophic events, mitigation is enhanced but adaptation is unchanged even reduced ■

From the above, it shows that the two strategies are substitution, and the increased probability of catastrophic event will increase the investment on mitigation. Due to the substitution, the increase of the investment on one strategy cut down the other, so the increase of the mitigation investment decreases the adaptation investment.

Since the two strategies are substitution, to decide which one is more beneficial in dealing with the uncertain catastrophic happenings helps to see the effect of uncertainty on policy choice. By reducing GHG emissions and controlling the temperature increase, mitigation reduces the probability of a catastrophic outcome. Adaptation, on the other hand, can act only on the damage once materialized. Thus it can be expected that facing the possible occurrence of catastrophic event, mitigation becomes more radical and more mitigation effort should be paid. Due to the relationship of substitution, more mitigation also imply less or at least unchanged adaptive action, considering about the effect adaption also takes in reducing damage.

Appendix B

APPROACHES TO MODEL UNCERTAINTY IN IAM

To work with uncertainty in IAM framework means a three-step game: to know and recognize uncertainty, to play with uncertainty, and to resolve uncertainty. The three approaches for uncertainty study are the methods that correspond to each step. Studies can play either a single-step or multi-step game; hence some of them picked more than one approach in one paper. Table B gives the comparison among several integrated studies about methodologies and displays the selected findings. Literatures are classified by these three approaches. The method to conduct sensitivity analysis is similar across the existing literatures, so only two early ones are selected to be listed. In the uncertainty propagation approach, a series of papers are selected to represent different ways to quantify uncertainty. The papers selected for the sequential decision making approach are sub-categorized into the active learning and passive learning, the difference of which is whether learning takes place through some investment (R&D investment), which could take up part of the production. More literatures have been following the passive learning path – more precisely, no studies so far have taken the active learning path to study the reduction of uncertainty and the policy implication. The two papers quoted in the “active learning” rows both follow the integrated assessment approach coupled with endogenous technical progress, but neither of them deal with uncertainty by taking advantage of the knowledge investment. By quoting them we try to introduce a possible framework, which incorporates the module of endogenous technical change and can be applied for active learning in the future (Peterson, 2006).

Methodology	Literature	Quantifying Uncertainty	Main Findings
Uncertainty Propagation	Tol (1999)	1. Monte-Carlo simulation is conducted for 1000 runs. 2. The optimal emission path is being searched for with and without abatement policy s.t. uncertainty.	1. In the presence of uncertainty, mitigation effort is optimal to be higher. 2. Impact uncertainty has stronger effect and than the uncertainty of policy cost.
Uncertainty Propagation	Yohe (1996)	1. Characterize the catastrophic event by two uncertain parameters, climate sensitivity and the climatic damage. 2. Subjective probabilities are assigned accordingly to the states of the world. 3. Expected, discounted value of information is drawn from the comparison between the information got earlier and later.	1. Expected information value will fall if the economic cost of setting an incorrect policy is small. 2. Relatively modest short-term carbon abatement policy could be adopted to hedging against catastrophic event.
Uncertainty Propagation	Bosello and Moretto (1999) ["exogenous uncertainty" part]	1. A hazard rate function is estimated to relate probability of catastrophic event to the temperature increase in the same period.	1. Uncertainty of catastrophic event pulls up the mitigation rate.

		2. Expected utility over the utility before and after catastrophes is weighed by the hazard rate.	2. The value of the dynamic information is justified.
Sequential Decision Making	Bosello and Moretto (1999) ["endogenous uncertainty" part]	1. In the hazard rate function, the probability of catastrophic event is related not only to the temperature increase in the same period, but also the historical trend of the temperature increase, denoted by the rate of change of the temperature. 2. Value is estimated for the dynamic information through the comparison of utility under endogenous uncertainty and exogenous uncertainty.	3. RICE model shows the different reaction that less cautious action is taken when facing catastrophic risks, and the value of the dynamic information is negative.
Sequential Decision Making (Active Learning)	Castelnuovo et al. (2001)	1. Quantify the endogenous uncertainty using the same way as Bosello and Moretto (1998).	Uncertainty of catastrophic event decreases the non-environmentally-friendly research investment and drives down the price of the international carbon permit. The effect on the environmental R&D is the opposite.

		2. Incorporate the hazard function in the IAM with learning investment for knowledge accumulation. The IAM also includes the carbon permit demand to model the international carbon market. 3. Model is run to get the optimal policy choice.	
Sequential Decision Making (Active Learning)	Nordhaus (2002)	1. Uncertainty is not explicitly modeled but the improvement of the knowledge is incorporated into DICE model as the “induced innovation” by the research investment, which accounts for a proportion of the production. 2. The innovation possibility frontier (IPF) is added into the framework to describe how research investment improve the state of the knowledge. 3. IAM is run with the innovation function.	Induced innovation has small impact on the overall climate change path because the optimal learning investment accounts for a small proportion of production.

Sequential Decision Making (Passive Learning)	Kelly and Kolstad (1999)	1. An uncertain parameter, climate sensitivity, is treated as a random variable with unknown parameter in the distribution. 2. The random variable has a prior of certain distribution, and Bayes Rule is applied to update the prior consecutively according to the temperature and GHG concentration observed in the same period. 3. The model is run with the random variable (under updating) and gets the optimal policy choice.	1. The speed of learning is sensitivity to the noise in the temperature realization, and the noise can be reduced through more GHG emission. So there's a tradeoff between the speed of learning and emission control. 2. It is estimated that depending on the true value of the climate sensitivity, it needs longer time to resolve uncertainty than currently believed (90 – 160 years).
Sequential Decision Making (Passive Learning)	Karp and Zhang (2001)	1. A parameter in the damage function, as the slope of marginal damage, is unknown. Set it to be a random variable with unknown parameter in the prior distribution.	1. Learning leads to a very slight less stringent climate policy so the possibility to learn should not be the reason to delay the policy.

		2. Bayes Rule is applied for the random variable updated with the observed damage and GHG concentration. 3. 1&2 also applied for the unknown abatement cost shocks. 4. Two policy instruments: carbon tax and quota trade are compared. With carbon tax, a Bayesian regulator can update the knowledge of the abatement cost while quota trade doesn't enable her so. 5. Optimal policy is drawn through the saving cost maximization with the two uncertain but updating parameters. 6. Effect of learning is studied through the comparison of the initial belief and the true value.	2. Learning can be a quick process to get a parameter value close to the true one. 3. Tax is a better instrument than quota, which is lack of informative advantage.
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Sequential Decision Making (Passive Learning)	Leach (2007)	1. Set two uncertain parameters in the temperature equation, climate sensitivity and the inter-temporal coefficient of GHG concentration, each to be a random variable with prior containing unknown parameters. 2. Bayesian update takes place through 1000 Monte-Carlo runs for the two random variables at the same time. 3. Compare the updated process of climate sensitivity under two uncertain parameters and one.	1. When uncertainty is over two causes of certain observations, learning time might be extended to the order of century or millennium. 2. The data of certain observation don't provide sufficient information to learn if two causes are uncertain, using single set of observation in this case can lead significant errors.
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Table B.1: Approach to Model Uncertainty in IAM

Appendix C

STRUCTURE OF THE MODEL

VARIABLES

n : 1-5, regions, with reference to USA (the United States), EEC (the European Union), JPN (Japan), CHN (China), FSU (Former Soviet Nations), ROW (Rest of the World);

t : 1-12, time scale, 10 years as a unit; from 1990 to 2010;

Parameters

ω : utility weight for every regions;

R : discount rate;

γ : elasticity of output with respect to the capital stocks;

b_1, b_2, b_3 : parameters of the mitigation cost function;

a_1, a_2 : parameters of the damage function;

δ_K : depreciation rate of capital stocks;

δ_{IA} : depreciation rate of adaptation capital stocks;

c_1, c_2, c_3, c_4 : parameters of climatic equation;

λ : feedback parameter in climatic equation

σ : CO₂ emission/GDP ratio

ΔM : the removal rate of CO₂ stocks in the atmosphere;

θ : the retention rate of CO₂ stocks in the atmosphere;

η : parameter #1 of the hazard rate function of the catastrophic occurrence

φ : parameter #2 of the hazard rate function of the catastrophic occurrence

φ_0 : the initial value of the parameter #2 of the hazard rate function of the catastrophic occurrence

φ^* : the perfect knowledge about the parameter #2 of the hazard rate function of the catastrophic occurrence

Exogenous Variables

A : the Total Factor Productivity;

L : the population level;

F_o : the exogenous forces of the greenhouse gases other than CO_2 ;

Endogenous Variables

U : aggregated utility level

Y_G : gross output (trillion dollars);

Y_N : net output (trillion dollars);

Ω : damage parameter;

C : consumption (trillion dollars);

I : capital investment (trillion dollars);

K : capital stocks (trillion dollars);

IA : adaptation investment (trillion dollars);

SAD : adaptation investment stocks (trillion dollars);

IL : learning investment (trillion dollars);

SIL : learning investment stocks (trillion dollars);

μ : mitigation rate ($0 \leq \mu \leq 1$);

E : CO_2 emission to the atmosphere (hundred million tons);

M : CO_2 stocks in the atmosphere (hundred million tons);

T : atmospheric temperature ($^{\circ}C$);

T_o : oceanic temperature ($^{\circ}C$);

F : radiative force of the greenhouse gases in the atmosphere;

D : residual damage suffered from the climate change.

$\varphi(t)$: knowledge improvement in terms of parameter #2 of the hazard rate function of the catastrophic occurrence.

EQUATIONS

Aggregated Utility Equation

$$\begin{aligned}
U = & P(t) * \sum_{n=1}^n \sum_{t=1}^t \{ (1+R)^{10*(1-t)} * \omega(n) * L(n, t) * \log [0.75 * C(n, t) / L(n, t)] \} \\
& + (1 - P(t)) * \sum_{n=1}^n \sum_{t=1}^t \{ (1+R)^{10*(1-t)} * \omega(n) \\
& * L(n, t) * \log [C(n, t) / L(n, t)] \}
\end{aligned} \tag{C.1}$$

Economic Equations

$$Y_G(n, t) = A(n, t) * K(n, t)^\gamma * L(n, t)^{1-\gamma} \tag{C.2}$$

$$Y_N(n, t) = Y_G(n, t) * \Omega \tag{C.3}$$

$$\begin{aligned}
\Omega = & [1 - b_1(t) * b_2(n) * \mu(n, t)^{b_3(n)}] / \\
& \{ 1 + 1/[1 + SAD(n, t)^{1/2}] * a_1(n) * [T(t)/2.5]^{a_2(n)} \}
\end{aligned} \tag{C.4}$$

[No learning investment]

$$C(n, t) = Y_N(n, t) - I(n, t) - IA(n, t) \tag{C.5}$$

[With learning investment]

$$C(n, t) = Y_N(n, t) - I(n, t) - IA(n, t) - 4 * IL(n, t) \tag{C.6}$$

$$K(n, t) = (1 - \delta_K) * K(n, t - 1) + IA(n, t) \tag{C.7}$$

$$SAD(n, t) = (1 - \delta_{IA}) * SAD(n, t - 1) + IA(n, t) \tag{C.8}$$

$$SIL(t) = \sum_{n=1}^n [KL(n, t - 1) * (1 - \delta) + IL(n, t)] \tag{C.9}$$

Learning Equation

$$\varphi^* - \varphi(t) = (\varphi^* - \varphi_0) * [(1 + \alpha SIL(t))^\beta] \quad (C.10)$$

Climatic Equations

$$T(t) = T(t-1) + c_1 * [F(t) - \lambda T(t) - c_2 * (T(t) - T_o(t))] \quad (C.11)$$

$$F(t) = 4.1 * \frac{\ln(M(t)/590)}{\ln 2} + F_o(t) \quad (C.12)$$

$$E(n, t) = [1 - \mu(n, t)] * \sigma(n, t) * Y_G(n, t) \quad (C.13)$$

$$M(t+1) = 590 + \theta * \sum^n E(n, t) + (1 - \Delta M) * (M(t) - 590) \quad (C.14)$$

Uncertainty Equation

$$P(t) = 1 - e^{-\int_{T(0)}^T \varphi * \eta * (TE(t) - TE(0))^{\eta-1} dTE} \quad (C.15)$$

Damage Equation

$$\begin{aligned} D(n, t) = & P(t) * 0.25 * Y_N(n, t) + (1 - P(t)) * A(n, t) * K(n, t)^\gamma * L(n, t)^{1-\gamma} \\ & * \{1 - 1/[1 + 1/(1 + SAD(n, t)^{1/2}) * a_1(n) * (T(t)/2.5)^{a_2(n)}]\} \end{aligned} \quad (C.16)$$