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The Contribution of Economics to the Analysis of Climate Change and Uncertainty: A Survey of Approaches and Findings

by

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Abstract:

There is a general agreement that (a) climate change is one of the most serious environmental problems, that (b) the analysis of climate change is confronted with a large degree of uncertainty and (c) that these uncertainties need to be taken into account to arrive at meaningful policy recommendations. The main contribution of economics to this interdisciplinary task is to provide formal frameworks and techniques for analyzing climate policy in the context of uncertainty. The aim of this paper is to give a comprehensive survey of existing approaches and findings and thus to give a broad picture of what economics has contributed and can contribute to the debate.

Keywords: Climate change, uncertainty, survey, modeling

JEL classification: Q54, C60, D81, D83

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1 Introduction

There is a general agreement that (a) climate change is one of the most serious environmental problems, that (b) the analysis of climate change is confronted with a large degree of uncertainty and (c) that these uncertainties need to be taken into account to arrive at meaningful policy recommendations. Yet, many economic, environmental and integrated assessment (IA) models are deterministic and there is no clear concept of the implications of the uncertainties for practical policy making.

Climate change and uncertainty is clearly an issue for interdisciplinary research. The main contribution of economics is to provide formal frameworks and techniques for analyzing climate policy in the context of uncertainty (Samstad & Greening 1998). The aim of this article is to give a comprehensive overview of these frameworks and techniques. This is not a trivial task, not only since there is a long tradition of economics in analyzing decision making under uncertainty, but also because there are quite different strands of literature dealing with climate change and uncertainty. This paper thus tries to extract and structure the most important approaches and their findings. As most models are constructed to analyze very specific situations, the aim is to give a broad picture of what economics has contributed and can contribute to the debate[1] and to discuss the policy relevance of the findings, rather than to describe any theoretical approaches and models in detail.

The next section starts with a taxonomy of the uncertainties associated with the analysis of climate change in order to derive the potential role of economics. Section 3 than discusses different issues and approaches that are associated with optimal policymaking under uncertainty and that are discussed in the economic literature. Section 4 tries to summarize the findings relevant for policy purposes. Section 5 concludes.

[1] The article by Heal & Kriström (2002) has a comparable goal. While Heal & Kriström though discuss the scientific background and different economic modelling approaches in detail, this article wants to focus more on the general issues and approaches, adding also some applied modelling approaches and decision theory that go beyond the review of Heal & Kriström.

2 Taxonomy of uncertainties

There are two broad dimensions of the uncertainty problem: *Parametric uncertainty*, which arises due to imperfect knowledge and s*tochasticity*, which is due to natural variability in certain processes. A third, additional category of uncertainty, is the uncertainty about values such as e.g. the discount rate (Kelly & Kolstad 1999; Kann & Weyant 2000).

Parametric uncertainty includes uncertainty about relevant model parameters but also about the general model structure. Thus, it includes uncertainty about what are relevant parameters and relevant linkages and what are appropriate functional forms (e.g. of a damage function of climate related damages). Parametric uncertainty is not constant over time and can be expected to diminish with further research.

Stochasticity results from phenomena that affect the economic or physical process and that are not or cannot be modeled. Zapert et al. (1998) talk in a broader sense about uncertainty caused by random effects that combine stochastic phenomena external to the system and internal unpredictable climate processes. Stochastic phenomena that are not captured by climate models are e.g. volcanic eruptions and sunspots. Future values of many economic and technology processes are also stochastic because if the future were known, the consumers would act on that knowledge in ways, which change the future. Internal climate variability factors include the El Nino effect and variable cloud cover. Stochastic effects can have a cumulative effect on the overall model uncertainty and may contribute to larger part of outcome uncertainty (Zapert et al. 1998).

A different taxonomy of uncertainties stems from the 3-stage process that is at the heart of an economic analysis of climate change and associated with the following questions (Heal & Kriström 2002):

(1) What will the climate be?

(2) What does any given climate change mean in economic terms?

(3) What is the optimal policy to choose to control emissions over the coming decades?

The first question is concerned with the future emissions path and its impact on the climate parameters such as temperature, precipitation or the sea level. The second question implies a translation of climate changes into climate damages. The third question is about the costs of CO_2 reductions and the effectiveness of instruments. This 3-stage process leads to four categories of uncertainties, which can be broadly defined as:

(1) Uncertainties about the emissions path.

(2) Uncertainties about what the climate will be.

(3) Uncertainties about the impacts of climate change.

(4) Uncertainties about optimal policies.

Different authors denote these categories differently or further disaggregate some of them. As regards the uncertainties about what the climate will be (sometimes also denoted as ecological or scientific uncertainties) the IPCC, for example, distinguishes between responses of the carbon cycle, the sensitivity of the climate to changes in the carbon cycle and regional implications of a global climate scenario. The German National Committee on Global Change Research distinguishes between calculating the concentration of GHG in the atmosphere, determining the climate sensitivity and simulating future climate. Gjerde et al. (1999) disaggregate the uncertainties about optimal policies into uncertainties about the costs of emissions reductions and uncertainties about the effectiveness of different policy instruments. Many authors talk about costs and benefits of emission reductions. The costs are part of optimal policy strategies, while the benefits are determined by the avoided damage resp. impacts of climate change. Table 1 summarizes some of the different classifications. In general, uncertainties rise when moving through these stages.

<table>
<tr><th colspan="5">Table 1: Cascade of Uncertainties</th></tr>
<tr><th></th><th>IPCC (1995)</th><th>Heal & Kriström (2001)</th><th>Molander (1994)</th><th>Sausen (2003)</th></tr>
<tr><td>1</td><td>Emission scenarios (anthropogenic GHG emissions)</td><td>Emission scenarios</td><td rowspan="4">Basic physical uncertainties
Incomplete empirical data on current emission and absorption rates</td><td>Choice of the emission scenario</td></tr>
<tr><td rowspan="3">2</td><td>Responses of the carbon cycle</td><td rowspan="3">Ecological uncertainty
What will the climate be?</td><td>Calculating the concentration of GHG</td></tr>
<tr><td>Sensitivity of the climate to changes in the carbon cycle</td><td>Determining the climate sensitivity</td></tr>
<tr><td>Regional Implications of a global climate scenario</td><td>Simulating future climate</td></tr>
<tr><td>3</td><td>Possible range of impacts on human societies</td><td>Impacts
What does given climate change mean in economic terms?</td><td>Effects of a potential climate change on ecosystems</td><td>Interpreting the results</td></tr>
<tr><td>4</td><td></td><td>Policies</td><td>Uncertainties that affect policy measures
Costs & benefits of slowing climate change</td><td>Perception of results</td></tr>
</table>

Turning to the question of the potential contribution of economics, economics *cannot* contribute to solving the problem of ecological uncertainties. In the cascade of uncertainties economics *can* contribute to the quantification, assessment and resolution of uncertainties concerning

- emission scenarios as they depend to a large degree on economic development
- the economic impacts of climate change
- the costs of slowing climate change

Besides quantifying and resolving the existing uncertainties the main contribution of economics is to analyze the distributional and allocative impacts of given climate polices and to determine optimal reduction strategies in the presence of uncertainty. In this context, there are also a number of other relevant issues that are discussed in the next section.

3 Optimal climate policies in the presence of uncertainties – questions and approaches

The ultimate goal of an analysis of climate change and uncertainty is **how to formulate optimal climate policies** under uncertainty. Following Kann & Weyant (2000) an ideal uncertainty analysis includes:

(A1) Probability weighted values of the output variables

(A2) Optimal decisions in the light of imperfect knowledge

(A3) A measure of risk or dispersion about the outcome, and

(A4) The value of information for key variables.

A2, the question of optimal policy decisions, can then be broken down further, as e.g. done by Baranzini et al. (2003) or Carraro & Hourcade (1998):

(A2-1) How much to reduce? (abatement level)

(A2-2) When to reduce? (timing)

(A2-3) How to reduce? (measures/ policies)

(A2-4) Who should reduce resp. where to reduce? (distribution among countries/sectors)

Economic analysis and theory has contributed to different aspects of all questions. The largest contribution of economics to the issue of climate change and uncertainty has come through the use of **theoretical** as well as **applied, numerical economic or economic-environmental models** of climate change and climate policy. In addition, there are other areas of economics such as decision theory and analysis**,** game theory or portfolio analysis that have been applied to analyze climate policy under uncertainty.

3.1 Uncertainty in economic models of climate change

There are two broad categories of models: **policy evaluation models** that evaluate given policy scenarios and tend to be rich in physical detail and **optimizing models** that optimize over key decision variables to achieve a certain objective, such as cost minimization of welfare maximization (IPCC 1996). To incorporate uncertainties into these models or to use these models for uncertainty analysis there are three broad approaches (Kann and Weyant 2000).

The most simple approach, which is not a real uncertainty analysis but can be used as a tool to identify which model parameters should be treated stochastically, is a **sensitivity analysis.** It answers the question of how sensitive model outputs are to changes in model inputs and involves varying input parameters that are not known with certainty. In a simple single-value deterministic sensitivity analysis only one parameter is varied keeping the other parameters at their base values. When there are dependencies between variables, varying several parameters jointly can produce more accurate measures of output sensitivity.

More demanding, but still relatively simple, is what is termed **uncertainty propagation**. In this case, there are uncertain parameters in the model, but the agents in the model do not account for them. This implies that there is no learning. The simplest implementation of uncertainty propagation involves specifying a joint distribution on selected input parameters and then propagating this uncertainty through to the model output. Finally, one can for instance take expectations of the output. A more complex implementation involves modeling certain variables as stochastic processes. Uncertainty propagation can generally not be used to determine optimal decisions under uncertainty. This is only the case if certainty equivalence holds, which means that the optimal action under uncertainty (for example maximizing expected utility) is equivalent to the expected value of the actions under each realization of the uncertain parameters with certainty (Kelly & Kolstad 1999). However, as Kelly and Kolstad note, certainty equivalence does not hold under risk aversion. Furthermore, uncertainty propagation offers no model of learning. Nevertheless, this approach provides the decision maker with a sense of the risk associated with the outcome and with a distribution of output variables. It is thus associated with probability-weighted values of the output variables (question A1) and measures of risk or dispersion about the outcome (question A3). In addition, it can be used to obtain measures for the relative importance of different input variables on the outcome (question A4). For computational purposes propagation of uncertainty usually involves sampling from a joint distribution using mostly the Monte Carlo method or, if this is still computationally to expensive, reduced Monte Carlo simulations for example on Latin Hypercube sampling (see e.g. Nordhaus 1994).

The most demanding approach accounts for learning and can be termed **sequential decision-making under uncertainty**. This implies that models determine optimal policies at more than one point in time, taking into account the available information in each period. Models in this category range from simple two-period decision analysis to an infinite-horizon stochastic optimization. There are three main types of learning: **active learning** whereby the effect of policy choices on certain key variables (e.g. the effects of emissions on the economy and the climate system) is observed for the purpose of obtaining information about uncertain parameters**, purchased learning** e.g. from R&D and **autonomous learning** where the passage of time reduces uncertainty (Kelly and Kolstad 2000). The first two types of learning imply **endogenous technological change**, which is also an important issue in the context of climate change (see e.g. Carraro & Hourcade 1998). Most existing models though, use autonomous learning and not more than two decision periods. Models of sequential decision-making under uncertainty are used to determine optimal policies under different aspects of uncertainty and learning. This is discussed below in section 3.2.

Altogether, uncertainty analysis is very complex and computationally intensive. Most existing models are deterministic and, if at all, most modelers have only performed very basic types of uncertainty analysis. Table 2 summarizes the three approaches. Some of the outcomes are discussed in the next subsection. For detailed information on different implementation techniques and problems in policy evaluation models and optimizing models see Kann & Weyant (2000).

3.2 Irreversibilities, catastrophes and the value of information

Large parts of the literature focus on four features of the natural and economic environments that influence optimal policy decisions under uncertainty. These are (see e.g. Fisher & Narain 2003 or Heal & Kriström 2002)

(1) A non-degradable or irreversible stock of greenhouse gases

(2) Sunk, irreversible abatement capital

(3) Potentially catastrophic damages and

(4) Future learning about the nature of damages

The first two features are two different types of **irreversibilities** that are relevant in the context of optimal climate policies. These are on one hand irreversible changes in the climate system and in the natural environment driven by climate change that generally depends on the stock of greenhouse gases in the atmosphere. Following Kolstad (1996) such irreversibilities are also denoted stock effects and are modeled as non-degradability of the stock of greenhouse gases (Fisher & Narain 2003). The rational behind this is that climatologists claim that some part of the stock of GHG cannot be reduced through abatement and does not decay naturally so that the atmospheric concentration of carbon is not expected to return to its pre-industrial level but to reach a new equilibrium. On the other hand, there is also irreversible abatement capital that is sunk in the sense that it cannot be converted to other forms of capital or to be used for consumption.

Table 2: Uncertainty in economic models

	Sensitivity analysis	Propagation of uncertainties	Sequential decision making under uncertainty
Description	Varying uncertain input parameters to determine the sensitivity of the output reaction	Specify a joint distribution/stochastic processes on selected input parameters and then propagate this uncertainty through to the model output	Determine optimal policies at more than one point in time taking into account learning
Practice	Very simple Can be carried out with every model Some models directly offer the user the possibility to evaluate different future scenarios	Still relatively simple Monte-Carlo Method or Latin Hypercube sampling Often used in large numerical/applied models	Most demanding Existing models mostly involve autonomous learning and two decision periods. Used in rather small, simple, aggregated (growth) models, and rather in theoretical than applied models
Outcome	Determine which parameters should be treated stochastically Give a first feeling for the uncertainty of the model output	Gives a sense of the risk associated with the outcome resp. a distribution of output variables Measures for the relative importance of different input parameters on the outcome	Optimal decisions under uncertainty Optimal hedging strategies Role of irreversibilities Determine expected value of information
Shortcomings/ Problems	Not possible to model stochastic variability Does not measure or detect specification errors	Difficult to specify joint distributions due to significant correlations between parameters. Impractical for computationally intensive models Different results for optimization models (learn now then act) vs. policy evaluation models (act then learn). Parameters can contribute to uncertainty but be irrelevant for decisions.	Difficult for optimizing models Can only be performed for a very limited set of uncertainties in optimizing models due to computational complexity Infinite stochastic optimization causes many problems

The next question is then how uncertain damages, and the (low) endogenous or exogenous probability of an extreme, catastrophic event influences optimal policy choices. Finally, there is the question of how uncertainty is resolved over time. The potential of future learning together with the irreversibilities has lead to the concept of an (**quasi**) **option value.** Independently of each other, Arrow & Fisher (1974) and Henry (1974) demonstrated that there is a premium on policies that maintain flexibility. Originally, the work focused on irreversible environmental effects that imply a precautionary principle, as there is a real value associated with preserving the present climate regime. Sunk abatement capital on the other hand has the opposite effect and suggests that it is optimal to avoid costly abatement measures requiring irreversible investments until we are sure that they are needed. Different authors have emphasized one or the other or both of these effects (see e.g. Fisher & Narain 2003 for a summary).

Altogether, this strand of literature thus focuses on the question of how to reduce (A2-3) and the **optimal timing of policies, which** implies a consistency between short run and long run policy strategies. Such a strategy that balances the risk of waiting with those of premature action is also called optimal **hedging** strategy. The models used for these kinds of analysis are simple growth models or models of optimal investment that differ with respect to the included irreversibilities, the distribution of damages and the endogeneity of risk.

Another approach related to the issue of learning is to evaluate the **value of "early knowledge"** i.e. the economic value of resolving uncertainties about climate change sooner rather than later. As Nordhaus & Popp (1997) formulate it: "If natural and social scientists succeed in improving their understanding, what will be the payoff in terms of improved economic performance?" What is generally done to determine the value of information is to compare an "act then learn" strategy with a "learn than act" strategy that differs in the time at which the information about uncertain variables (such as damages) becomes known.

To illustrate the basic idea assume here a simple two period model where decisions about emission abatement are taken in two points of time t=1,2. The objective is to minimize total climate costs $TC(s,x_1,x_2)$ that comprise abatement costs and damages and that depend on the uncertain state of the world *s* and the chosen emission level x_1 and x_2 in both time periods. There are now three possibilities for resolving uncertainties about the state of the world. In the first case, the uncertainties are not resolved at all (no learning NL). In the second case, the uncertainties are resolved before the second period so that the decision on the emission level in t=2 can be made under certainty. This framework is denoted act then learn (ATL). Finally, the uncertainties can be resolved upfront. We then have a “learn then act” (LTA) framework. The decision sequence and the resulting objective function are illustrated in Figure 1.

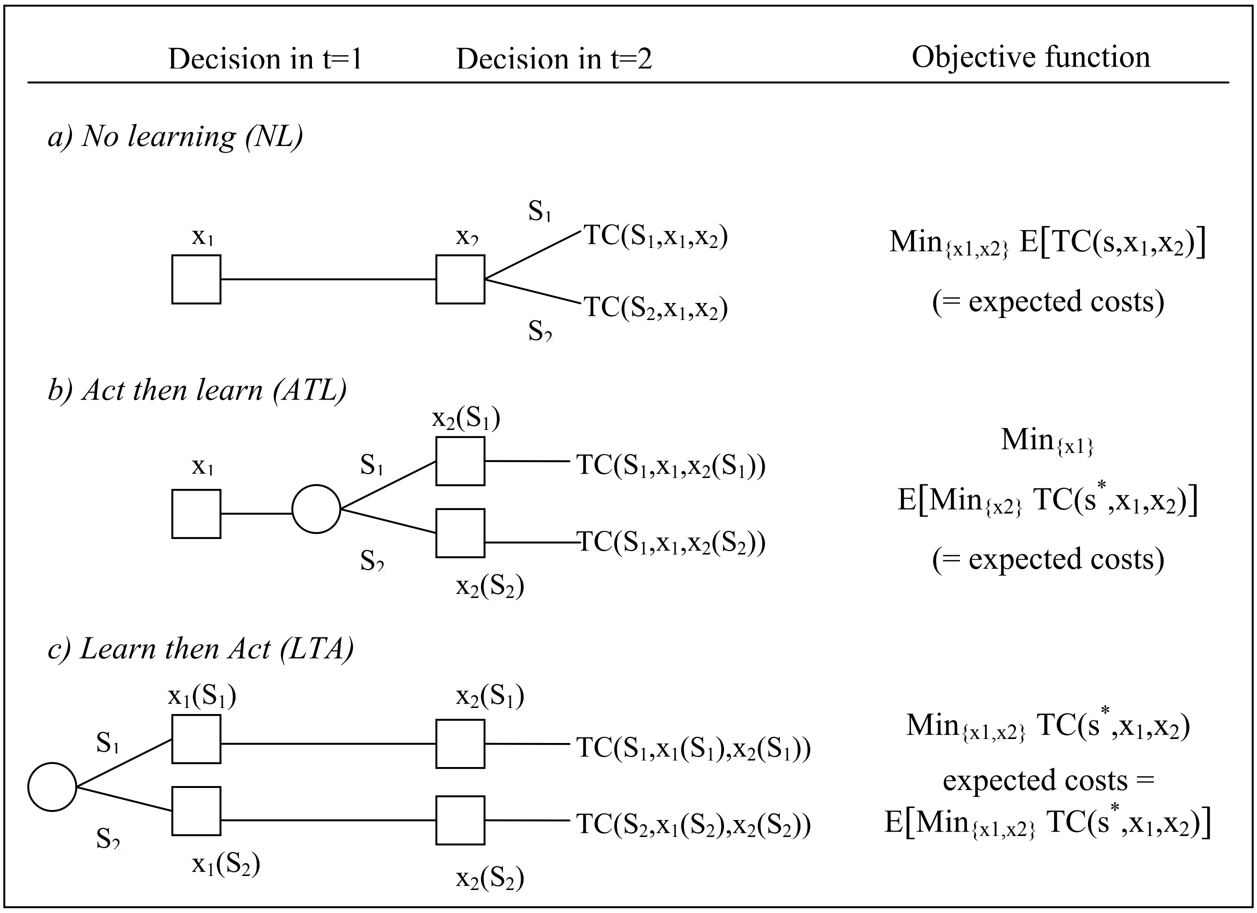

Figure 1: Policy choice as two-period decision with and without learning

This framework can now be used to derive the value of information comparing the expected costs of policy choices in different situations. Manne & Richels (1992) for example compare the expected costs under ATL and LTA in a two period model and denote the difference as **expected value of perfect information** (EVPI). Peck & Teisenberg (1993) and Peck & Wan (1996) define the EVPI in a single period decision-making model as the difference between NL and LTA. Ha-Duong (1998) defines for given first period policies the **expected value of future information** EVFI as the difference between NL and ATL. Nordhaus & Popp (1997) compare the expected costs for LTA and ATL where the uncertainty is resolved in different years.

In addition, the example can be used to demonstrate the concept of option values. Assume that there are two different policy strategies in period 1: H (high abatement) and L (low abatement). The following table is an extended version of the table in Ha-Duong (1998) and shows the expected costs when choosing over all policy strategies as in figure 3 and also for given policy choices in period 1.

The last row compares the expected costs of policies H and L. If the opportunity cost of H is positive it is optimal to chose L and vice versa. Comparing the opportunity costs (OC) in the scenario without learning (one-shot decision) and the scenario with learning in the second period (sequential decision) reveals the effects of irreversibilities. Assume without loss of generality that $OC_L(NL) > 0$ so that under a decision that does not account for potential learning it is optimal to chose policy H. If $OC_L(ATL) > OC_L(NL)$ the effects of irreversibility support the one-shot decision. In other words, conventional cost-benefit analysis even underestimates the opportunity costs of L. If H is “high early abatement“, this would suggest that the environmental irreversibilities dominate. If OC_L (ATL) = OC_L (NL) there is no irreversibility effect and the results of a one-shot analysis and a sequential decision are the same. If finally $OC_L(ATL) < OC_L(NL)$ the irreversibility effects decrease the advantages of H in the one-shot analysis. If $OC_L(ATL) > 0$ these effects do not change the optimal decision. If $OC_L(ATL) < 0$ the irreversibility effect now leads to an optimal decision of L. In this case the sunk costs dominate. Against this background the option value of L is defined as OV(L) = $OC_L(ATL) - OC_L(NL)$. If OV(L) is positive, this implies that the irreversibility effects that are relevant in the case of learning are in favor of H. If the irreversibility effects support the one-shot decision or revise it completely, a positive option value of a policy strategy indicates that this is the optimal strategy. In the case where the irreversibility effects work in a different direction than the one shot decision but do not revise it (e.g. if $0 > OC_L(ATL) < OC_L(NL) > 0$) the option value of a strategy may be positive even though even under sequential decision making this strategy is not optimal. The increased costs of the strategy only decrease under sequential decision-making relative to one-shot decision-making.

Table 3: Option value and expected value of information				
Exp. Costs	**NL**	**ATL**	**LTA**	**Value of information**
Total	$C_T(NL)= Min_{\{x1,x2\}} E[TC(s,x_1,x_2)]$	$C_T(ATL)= Min_{\{x1\}}E[Min_{\{x2\}} TC(s^*,x_1,x_2)]$	$C_T(LTA)= E[Min_{\{x1,x2\}} TC(s^*,x_1,x_2)]$	Exp. value of perfect info. EVPI = $C_T(ATL)$ resp. $C_T(NL) - C_T(LTA)$
Policy H: x_1^*	$C_H(NL)= Min_{\{x2\}} E[TC(s,x_1^*,x_2)]$	$C_H(ATL)= E[Min_{\{x2\}} TC(s^*,x_1^*,x_2)]$		Exp. value of future info. EVFI(H) = $C_H(NL) - C_H(ATL)$
Policy L: $\underline{x}_1$	$C_L(NL)= Min_{\{x2\}} E[TC(s,\underline{x}_1,x_2)]$	$C_L(ATL)= E[Min_{\{x2\}} TC(s^*,\underline{x}_1,x_2)]$		Exp. value of future info. EVFI(L) = $C_L(NL) - C_L(ATL)$
Opportu-nity cost OC	$OC_L(NL) = C_L(NL)–C_H(NL)$	$OC_L(ATL) = C_L(ATL)–C_H(ATL)$		**Option value OV(L)** = EVFI(L) – EVFI(H) = $OC_L(NL) – OC_H(ATL)$

Note: In this context certainty equivalence means that the expected costs under NL and ATL are the same thus that $Min_{\{x1,x2\}} E[TC(s,x_1,x_2)] = E[Min_{\{x1,x2\}} TC(s^*,x_1,x_2)]$.

Another question that is linked to the value of information are the payoffs in different areas or in other words the **relative importance of different uncertainties**. In the simple model described above it is assumed that when uncertainty is resolved that the state of the world is completely known. As there are many uncertainties associated with climate change, it is also possible that only some uncertainties in some parameters are resolved at some point in time. Comparing the expected costs (or welfare) under no learning and partial learning at some point in time gives the expected value of information for a specific variable. Comparing these values for different uncertain variables provides information on the relative importance of different uncertainties.

From a conceptional point of view, most authors use relatively simple two period decision models in which the objective is to maximize utility or to minimize the sum of damages and abatement costs (= total climate costs) by choosing optimal emission levels. Costs and damages are usually uncertain and can often be only in two different states. In some models, the probability of high damages (or catastrophes) is endogenous and depends on the stock of greenhouse gases. In others, it is exogenous. An important determinant of the outcome is also the choice of the utility function and whether agents are risk averse.

Most of the analysis ignore that there is more then one decision maker in the context of climate policy. In particular, there are different nations with different emission paths and damages. **Game theoretic approaches** take into account the strategic interaction between different actors. Most models including such game theoretic approaches are deterministic, but there are some models that account for different aspects of uncertainties. Ulph & Ulph (1996) and Barker (2003) look at the impact of learning, irreversibilities and uncertain damages in a two period model with two players choosing emissions to maximize their utility taken the emissions of the other player as given.

Finally, the analysis of option values is closely related to **Portfolio analysis** which is concerned with creating an optimal composition of assets characterized by different returns and different levels of risk under a given budget constraint (Toth 2001). The design of GHG abatement policy has similarities to a portfolio selection problem. In both cases, the decision maker faces a number of investment projects with an incomplete known payoff, in a generalized sense (Molander 1994). So far, the applications to climate change have been limited. One example is Molander (1994).

3.3 Further issues & approaches

An approach that is different from calculating optimal decisions in a more or less sophisticated model is to support decision makers in making good abatement and investment decisions under uncertainty with the help of decision analytic tools. **Decision analysis** in general can be defined as a formal quantitative technique for identifying "best" choices from a range of alternatives (Toth 2001). In particular, this strand of literature tries to extract optimal decisions starting from a set of given (or to be constructed) alternatives that are characterized by one or more properties called attributes that can have different (uncertain) values. As some of the general assumptions that underlie an decision analysis (for example single decision makers, complete and consistent utility valuation of decision outcomes) are hardly met for climate change the IPCC report from 1995 concludes that decision analysis can not serve as the primary basis for international climate change decision making. Nevertheless, elements of the technique are seen to have considerable value in framing the decision problem and identifying its critical features (IPCC 1995).

One study in this area is the study by Willows & Connell (2003) that wants to help decision makers including governments, regulatory bodies, executives in national and international corporations and individual citizens to identify good adaptation options. This means to account for the risk and uncertainty associated with climate variability and future climate change and to identify and appraise measures to mitigate the impact or exploit the opportunities presented by future climate. At the core of the study is a general 8-stage decision process as it has been developed in the field of decision analysis. These steps are then one by one discussed in the context of climate adaptation discussing key issues, questions and tools and techniques.

Another example is the study of Greening & Bernow (2004) that gives an overview **of multi-criteria decision-making** (MCDM) - a sub-area of decision theory and analysis - in energy and environmental polices. It also includes examples of greenhouse gas control and a discussion on MCDM tools and Integrated Assessment models. Greening & Bernow conclude that ".. the current evolution of IA tools to include elements of physical science and economics provides a mean of utilizing MCDM methods for the development of integrated environmental and energy policies. […] In many cases, more than one analytical method from this family may be used to analyze a problem, and ranges of uncertainty may be exhaustively identified".

Decision analytic elements can also be combined with other types of analysis. Lange (2003) for example combines expected utility and the maximin criterion for decision under uncertainty (maximize the minimal worst case outcome) in a two period model of optimal emissions. In the ICAM model of Dowlatabadi et al. (Dowlatabadi & Morgan 1993, Dowlatabadi et al. 1998) it is possible to choose between different decision rules that also include expected costs and the maximin criterion. Cohen et al. (1994) couple their deterministic model with a decision tree system that organizes relevant information about the decisions and uncertainties stemming from different assumptions in the deterministic model. In addition, the framework of learn then act versus act then learn and the decision trees described in the last section stem from formal decision analysis.

There are also a few further issues and approaches in the context of climate policy and uncertainty. One question concerns the advantages and disadvantages of different **policy instruments** in the presence of uncertainties. The starting point of the few existing analysis is the article by Weitzman (1974). Weitzman showed that that if the damage function of environmental damages is relatively more uncertain than the abatement cost function, taxes are preferable to quotas to reach a certain environmental goal and vice versa. Pizer (1997) and Nordhaus (1994) using IAMs have come to the result, that in the case of climate change, damages are indeed more uncertain and that thus taxes are more efficient under uncertainty than rate controls. Taxes also dominate quotas in a model where damage and cost uncertainties are multiplicative (Hoel & Kart 2001).

Lecocq & Crassous, (2003) ask a different the question and look at whether quota allocation rules are robust to uncertainty. They use a partial equilibrium model of the international GHG market to determine the consequences of existing Post-Kyoto allocation rules and whether these consequences are sensitive to uncertainties in population, emission and economic growth. While allowance prices and abatement costs are sensitive to uncertainties, the least-cost rules turn out to be relatively robust.

Another question is behavior on the international carbon market. Haurie &Viguier (2003) use a two-player stochastic equilibrium model to look at the possible competition of China and Russia on the global emission market if the entry of the developing countries represented by China is uncertain.

An approach taken by Hawallek (2003) is called Meta analysis. The idea here is to take the results from different models to obtain information about the uncertainty of the outcome.

3.4 Quantifying uncertainties

All reviewed approaches work with uncertain parameters or events. Quantifying the uncertainties surrounding the issue of climate change and climate policies is one of the most demanding tasks. To enhance the development of a consistent but unrestrictive style of describing the source and character of uncertainties is one of the goals for the fourth assessment report of the IPCC. Wherever possible, uncertainties should be quantified but it is also recognized that there is the need to obtain semi-quantitative, verbal assessments of uncertainties. One approach is for example to use terms like very high (95% or greater), high (67-95%), medium (33-67%), low (5-33%) and very low (5% or less). For more information on this extensive discussion, see Manning & Petit (2003).

To conduct numerical studies a verbal assessment of uncertainty is not sufficient and it is necessary to assign probability distributions to the uncertain parameters and events. In most studies these distributions are constructed by a mixture of guessing, literature review and estimation – thus they can be termed “guestimates”. In many cases, there are only low, medium and high values that are assigned probabilities (3 point distributions). In other cases, 5-point distributions are used. Sometimes the probabilities and values are derived from literature, sometimes they are rather chosen for illustrative purposes. Other authors chose specific probability distributions or stochastic processes and specify the necessary parameters by guestimates. The most sophisticated studies are probably those by Nordhaus & Yohe (1983), Edmonds et al. (1983), Nordhaus (1994), and Pizer (1997). Pizer uses US Post war data to estimate a joint distribution of six parameters. Normally the different uncertain parameters are assumed independent of each other. Only few studies look at correlations and joint distributions. Examples are Edmonds et al (1983) and Pizer (1997). Altogether, it is hard to evaluate the methods used in the different papers. Some studies seem to apply sophisticated estimation procedures based on real data, but when describing how the probabilities are derived most papers refer to earlier, more detailed publications, which are hard to obtain.

4 Main findings

Some findings were already included in the last section. In addition, the tables in the appendix summarize the main findings of economic models. Though only covering a (subjective) choice of all existing models, they should give a good overview of the covered topics and main findings. As most models are build for very specific situations and assumptions, it is not easy to derive the main results. This section turns back to the four parts of an uncertainty analysis and tries to summarize the main results of the approaches outlined in the last section.

4.1 Optimal decisions in the light of uncertainty

From the four questions that were mentioned in the last section (How much to reduce? When to reduce? How to reduce? and Who should reduce resp. where to reduce?) research accounting for uncertainty so far has mainly focused on the first two questions.

How much to reduce?

Even though there are exceptions where uncertainties do not markedly affect optimal abatement levels (Manne & Richels 1995) or even lead to lower abatement (Pindyck 2000), most modeling results show that there is **optimally more emission abatement** if uncertainties in parameters or the possibility of catastrophic events are considered (Bosello & Moretto 1998, Castelnuovo et al. 2003, Nordhaus 1994, Nordhaus & Popp 1997, Pizer 1999, Tol 1999). Pizer (1997) for example finds that while the optimal rate of CO_2 reduction accounting for uncertainty is only slightly higher then the rate obtained when ignoring uncertainty and taking best guess values in the beginning, it grows over time. By the end of the next century, the rate is almost doubled. According to Nordhaus (1994) roughly speaking, the optimal carbon tax doubles when uncertainty is taken into account, and the optimal control rate increases by slightly less than half.

When to reduce?

Concerning the timing of the abatement, the results are less clear. There is some agreement that (under certain, not unrealistic conditions) the possibility of learning about uncertain values in the future has some effect on the timing of emission abatements A relative large number of studies shows that the probability of irreversible environmental damages leads to higher early abatement (Bosello & Moretti 1998, Gjerde et al. 1999, Ha-Duong 1998, Heal 1984). Nevertheless, there is also the sunk cost effect and studies that consider both kinds of irreversibilities find that it is optimal to emit more in the short run if learning about uncertainties is possible (Baranzini et al. 2003, Fisher & Narain 2003, Kolstad 1996, Ulph & Ulph 1997). One policy recommendation that can be drawn is that in any case it makes sense to invest in flexible abatement measures that do not imply a large amount of sunk and irreversible investment.

How to reduce?

Concerning the third question there has been some research on the advantages and disadvantages of policy instruments, comparing in particular carbon taxes and permit trading. Most authors conclude that in the light of climate damages that are much more uncertain than abatement costs, taxes are preferable to quotas resp. emissions trading (Nordhaus 1994, Pizer 1999). In the study of Pizer, the welfare gain of using a tax compared to a rate instrument is 13$ per person. One study looking at investment incentives for firms though finds that those are larger under emission trading than under emission taxes (Zhao 1998).

Where to reduce?

Even fewer studies have looked at regional distribution of abatement and emission under uncertainty. There are some results on the optimal policy from the view of a single nation assuming non-cooperative behavior (Barker 2003, Ulph & Ulph 1996). In such a setting, the results of an analysis with a single decision maker maybe revised if countries differ, especially in climate damages. If e.g. damages are negatively correlated the more we expect to learn, the lower emission should be. In addition, while a single decision maker is always better of under learning, countries can be worse of.

4.2 Uncertainty of model outcomes and relative importance of uncertain input parameters

The first and the third issue of an uncertainty analysis as outlined in section 3 (the probability weighted values of the output variables and a measure of risk or dispersion about the outcome) can be subsumed under the uncertainty of the model outcomes. This issue has been mainly analyzed using numerical climate-economy models with uncertainty propagation. An early work on uncertainty and climate change is the study by Nordhaus & Yohe (1983) who systematically examined the influence of key economic, demographic, and technological parameters on CO_2 emissions. This was followed by an extended analysis of Reilly et al. (1987) including nearly 80 uncertain parameters. Newer studies include Hope et al. (1993), Plambeck & Hope (1996), Nordhaus (1994), Nordhaus & Popp (1997), Scott et al. (1999).

All studies evaluate the variability of certain target model outcomes (or combinations of target outcomes) as a result of uncertain input parameters. Typical target variables are emissions, costs of emission reductions and damages. Other studies also look at the uncertainty range of other variables such as atmospheric carbon concentrations, temperature, output or optimal carbon reductions (see Table 4). The studies then try to assess which of the uncertain input parameters contributes most to the output uncertainty or which uncertain input parameters have the highest value of information.

Table 4: Relative importance of different input uncertainties in selected studies			
Study	**Uncertain inputs**	**Target variable(s)**	**Most relevant input uncertainties**
Nordhaus & Yohe (1983)		Carbon emissions	Price induced substitution between fossil and non-fossil fuels Labor productivity Labor-energy trade offs
Reilly et al. (1987)	79 uncertain parameters; mainly resource, cost & population parameters	Carbon emissions	Labor productivity Exogenous energy efficiency Income elasticity of demand in developing countries
Dowlatabadi & Morgan (1993)	Over 120 uncertain parameters	Cost of climate policies as loss in GDP	The significance of the uncertain parameters varies by policy and region; Uncertainties in abatement cost play minor role, uncertainties in market damages play major role for outcome uncertainties.
Hope et al. (1993) Plambeck & Hope (1996) PAGE model	84 uncertain parameters including scientific, cost of control, cost of adaptation and damage parameters. 3-point probability distributions	Mitigation cost Climate damage	For damages: Global temperature sensitivity to doubling of CO_2 Global warming response to change in forcing Weight of impacts in agriculture, service & manufacturing sector.
Nordhaus (1994) DICE model	Sensitivity analysis of 24 parameters to chose the most important 8 parameters (see last column) 5-point probability distributions	Per capita consumption Output Optimal emission reduction Atmospheric carbon concentration Temperature Optimal carbon tax Index of overall uncertainty as weighted average	Index of overall output uncertainty: Population growth Productivity growth Pure rate of time preference Decline inoutput-CO_2 ratio Climate Damages Climate-GHG sensitivity Mitigation cost Atmospheric retention of CO_2

Table 4 continued			
Study	**Uncertain inputs**	**Target variable(s)**	**Most relevant input uncertainties**
Yohe & Wallace (1996) Connecticut Model	9 parameters 3-point distributions	Carbon emissions	Population Technological change in energy supply Depletion factor in fossil fuel price Interfuel elasticity of substitution
Nordhaus & Popp (1997) DICE Model	8 parameters from Nordhaus (1994)	Temperature Optimal carbon tax	Highest value of information: Climate damages Mitigation cost (Climate feedback) (Population growth)
Scott et al. (1999) MiniCAM 1.0	74 uncertain parameters including climate and economic variables (Subjective probability distribution?)	Carbon emissions Atmospheric carbon concentration Temperature Damages	Source of overall uncertainty: Future demand for energy in the developing world Labor productivity Technological change in energy production

The different studies are difficult to compare, as the input parameters that are treated as uncertain depend on the modeling approach and vary across model. Parameters that are included in one model do not exist in another and the same parameter may be an input in one model and a target in another. Table 4 tries to summarize the main findings of the most known studies. Among the most important uncertainties are uncertainties in climate damages, in labor productivity and in some kind of change in energy efficiency.

In addition, Nordhaus & Popp (1997) find that the value of anticipating knowledge by 50 years, range from $45 to $108 billion. Manne & Richels (1992) find that the payoff to reducing climate related uncertainties could be more than $100 billion for the US alone.

5 Conclusions

As this paper has shown, there have been quite some contributions of economics to the question of climate change and uncertainty. Large parts of the literature though are conceptual rather than policy orientated using stylized models and focusing on theoretical issues rather than on realistic numerical simulations. As a result, there is now some agreement on the role of learning, irreversibilities and the impacts of extreme low probability events. Simulations with a few numerical climate-economy models provide a first feeling about the relevance of different uncertain input parameters and the resulting variation in emissions, mitigation costs and damages. There are also a growing number of attempts to include uncertainty in all kinds of analyses on climate policy, such as game theoretic approaches for coalition forming or the advantages and disadvantages of different policy instruments under an uncertain setting. Yet, the research so far only provide small pieces of a broad picture and it is not always clear how these different pieces fit together. Especially, there is a lack of practical policy implications of the research on uncertainty. Only few large economy-climate models include uncertainty analysis and if this is the case, the distributions are chosen rather ad hoc ignoring correlations between different parameters. In future, it is necessary, to become more policy orientated and to improve the existing models to include more sophisticated treatment of uncertainties. This includes the specification of realistic joint distribution functions as well as a broader inclusion of uncertainty in the numerous existing economy-climate models, which will enable a comparison of different models.

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Table A-1a: Models with sequential decision making & learning that analyze the stringency of optimal policies in the case of uncertainty

Author & Model	Underlying Model Type	Special features & issues	Type of uncertainties & derivation of distribution	Key Results
Baranzini et al. (2003)	Cost Benefit Model	Costs & benefits are stochastic processes	Cost benefit ratio as stochastic process with guestimated parameters	Uncertainty modifies the policy recommendations from classical CB analysis. Since waiting processes are now valuable, policies that were optimal under traditional CB should now be delayed. The possibility of catastrophic events increases the probability of implementing abatement strategies.
Baker (2003)	2-period 2-region game-theoretic model of optimal abatement	Strategic interaction between two decision makers	Damages Stochastic shift parameter of deterministic damage function; no numerical parametrization	Optimal policy depends on the correlation of damages across countries. If damages are negatively correlated the policy is reversed for the single decision maker: the more we expect to learn the lower emissions should be.
Bosello & Moretto (1999) RICE, CETA, MERGE	IAM Growth Models Optimization	Hazard rate function; effects of catastrophes Exogenous & endogenous uncertainty	Probability of catastrophic events depends on temperature change Utility change after catastrophe Hazard rate function; calibrated to results of expert panel	Probability of high-consequence irreversible outcomes leads to lower optimal emissions Models react differently: CETA and MERGE depict sudden emission decrease below the no-uncertainty case, RICE shows less prudent behavior in the short run.
Castelnuovo et al. (2003) RICE-ET	Growth Model Optimization	Hazard rate function; effects of catastrophes Role of technology	Same as Bosello & Moretto (1999)	When environmental uncertainty is modeled, the behavior of the agents is more cautious. If R&D is not environmental-friendly, R&D is optimally reduced. With environmental-friendly R&D uncertainty stimulates to undertake more R&D in order to reduce the emissions-output ratio.

Dowlatabadi (1998) ICAM	IAM Simulation model	Various decision rules	Up to 25 parameters Decision rules & metrics Model structure	Optimal decision depends on the decision rule. None of the policies are stochastically dominant.
Fisher & Narain (2003)	2-period optimal investment model	Irreversibilities: sunk abatement costs and GHG stock effects	Endogenous risk of catastrophe / distribution of damages Expert panel to specify risk function	1^{st} period investment is negatively related to degree of sunkness of capital, if the coefficient of risk aversion is less then one and the coefficient of intertemporal substitution is greater then one. The lower the degradability of the stock of GHG in the numerical model, the greater 1^{st} period investment. The investment irreversibility effect is substantially larger than the climate irreversibility effect.
Gollier et al. (2000)	2-period optimal consumption model	Bayesian framework Only theoretical model	Damage Only small numerical example	Learning only induces earlier prevention effort, if prudence is twice as large as absolute risk aversion Discussion of sufficient conditions that guarantee that more uncertainty in the future generate more conservative action today.
Grubb (1997) DIAM	Optimization		Stochastic stabilization limit Guestimated distribution	Possibility of low levels of stabilization limits has large influence on optimal path. Even though this occurs with low probability, the large cost assigned to the constraint drives the outcome. Consideration of impact costs leads to different time profiles than optimization under a stabilization constraint (fixed or stochastic)
Ha-Duong (1998)	2-period optimal investment model	Irreversibilities: sunk abatement costs and GHG stock effects	Only high damages with probability of 0.1 and low with probability 0.9; calibrated to EMF guidelines and expert panel	Option value of early abatement are positive for most values Option value is about 50% of the cost.

Heal (1984)	Growth model Optimal depletion model		Level of GHG stock at which there will be a discrete irreversible change in the productivity of the capital stock	Optimal rate of fossil fuel declines more rapidly relative to the situation with no climate change. Index of risk aversion is important for results.
Kolstadt (1996)	Finite horizon discrete Ramsey type growth model Optimization	Continuous, exog. learning Irreversibilities: sunk abatement costs and GHG stock effects	Climate damage	The irreversibility of investment capital has a stronger effect than irreversibilities in climate change. Thus uncertainty and learning tend to bias emission control downward relative to the case of uncertainty but no learning.
Lange (2003)	2-period optimal stock-pollutant model	Combining expected utility and maximin	Climate damage	Larger weight on the worst case can lead to higher emissions. The effect of learning is not clear in general, there is the possibility of a negative value of learning.
Manne & Richels (1995) **MERGE 2.0**	Growth model Optimization		High damage with probability of 0.5 and low damage scenario	With small chance of high damages, hedging strategy departs only slightly from low damage case Hedging strategy is sensitive to when uncertainty is resolved.
Nordhaus (1994) **DICE**	Optimization Growth model	Sensitivity analysis to find most relevant uncertainties Monte Carlo Analysis (using representative scenarios); Choice of instruments	Productivity growth Population growth Discount rate GHG-output ratio Damage function Climate-GHG sensitivity Mitigation cost funct. intercept Atmospheric detention rate Distributions guestimated from results in the literature; 5 point estimates for quintiles	Optimal control rates do not differ markedly from best-guess models. The optimal carbon tax is much higher than in the best-guess analysis, but the major reason is the introduction of uncertainty itself rather than the timing of the resolution of uncertainties. Carbon tax might be a more efficient instrument in the light of enormous uncertainties. Carbon tax is more invariant across resolution of uncertainties than optimal GHG control rate.

Nordhaus & Popp (1997) PRICE	Optimization Growth model	Value of Information about uncertain parameters Value of Early Information	8 uncertain parameters (same as DICE); Monte Carlo + Latin Hypercube sampling to arrive at 5 states of the world	The optimal policy under uncertainty tends to raise control rates Climate impacts and costs of reducing GHG emissions are most important. Resolving their uncertainty would contribute 75% of the value of improved knowledge. Considerable value of information Efficient carbon taxes under perfect knowledge vary by a factor of 1000.
Peck & Teisberg (1993) CETA	Growth model Optimization	Decision making under uncertainty with discrete possible outcomes Value of information	Warming per CO_2 doubling Damage function 3-point estimates for 5, 50 & 95 percentils 2 point estimates for uncertainty in 2 parameters simultaneously	If an optimal policy is used, the benefits of resolving uncertainty is high, but resolving uncertainty now vs. in 20 years is not worth much. If an arbitrary political policy is used, and if resolving uncertainty now would imply that an optimal policy would be used then there is a high premium on resolving uncertainty now vs. later.
Scott et al. (1999) MiniCAM 1.0	IAM	Monte Carlo + Latin Hypercube sampling Act then learn then act then … scenario Value of information	Several uncertain model parameters Subjective probability distributions which are not described	Most important uncertainties are future demand for energy in the developing world, labor productivity and technological change in energy production. Act then learn more cost effective then any other tested policy response
Ulph & Ulph (1997)	Theoretical 2-period utility maximizing model and numerical model	GHG stock irreversibilities only Conditions for existence of irreversibility effect	High, low, medium climate damage; High damage with prob. ph = 0.1 and 0.6. Probability low = 0.25*(1-ph); prob. Medium = 0.75*(1-ph)	Irreversibility effect cannot be assumed to apply as a matter of principle Empirical evidence find little support for irreversibility effect. Optimal current emission abatement is lower if we learn about future damages in the future.

Ulph & Ulph (1996)	2-period 2 country game-theoretic model of optimal abatement	Strategic interaction between two decision makers	Utilities and damages (high and low)	In situations where a single decision-maker would delay cutting emissions under learning, strategic interactions can cause countries to accelerate the cutting of emissions. While a single decision maker is always better of when there is the possibility of learning, countries can be worse off. One source for this are asymmetries between countries
Yohe & Wallacce (1996)	Growth model Optimization	Monte Carlo simulations with 9 uncertain variables to determine most relevant uncertainties (see next column) and representative scenarios	Population growth Technological change in energy supply Depletion factor in fossil fuel price Interfuel elasticity of substitution Others that play less significant roles in the distribution of emissions Always high, medium and low value with prob. 0.25, 0.5, 0.25.	Little or no emissions reduction is warranted over the near term even as a hedge against the possibility of having to met severely binding concentration levels in the not too distant future. Modest emissions reduction can be supported when hedging against high consequences/low probability events across a wide range of emissions futures. Hedging to achieve "tolerable windows" proposed by the German advisory Board on Climate Change would require significant, costly near term emissions reductions.
Webster (2002)	2-period model with objective of minimizing total climate costs.		Climate costs (= abatement costs + damage costs) High, medium and low values; distributions calibrated to expert panel	Whether there is a learning effect on the fist period decision depends on the existence of an interaction between periods. For most parameter distributions the optimal emission control today is independent of whether or not learning will occur.

* Part of the table is taken from the table in the appendix of Kann & Weyant (1999).

Table A-1b: Stochastic simulation models using uncertainty propagation

Author & Model	Underlying Model Type	Special features & issues	Type of uncertainties & derivation of distribution	Key Results
Dowlatabadi & Morgan (1993) **ICAM-1**	IAM	Different decision rules	Over 100 uncertain variables	Choice of the decision rule plays a key role in the selection of mitigation policies The significance of the uncertain parameters varies by policy and region; Uncertainties in abatement cost play minor role, uncertainties in market damages ply major role for outcome uncertainties.
Gjerde et al. (1999)	IAM Dynamic Optimization	Hazard rate function; effects of catastrophes Importance of time preference	Probability of catastrophic event depends on temperature change Utility change after catastrophe Hazard rate function; calibrated to results of expert panel	Probability of catastrophe leads to higher early emission abatement. Optimal abatement is sensitive to probability of catastrophe and pure rate of time preference.
Hope et al. (1993) **Plambeck & Hope (1996)** **PAGE**	Policy evaluation	Partial Rank Coefficients between inputs and outputs	80 uncertain parameters ♦ Scientific ♦ Costs of control ♦ Costs of adaptation ♦ Valuation of impacts Triangular guestimated probability distributions	Important factors come from all four groups of inputs to the model. Most important parameters are preventive costs of CO2 and temperature sensitivity.

Lecocq & Croussos (2003)	Partial equilibrium model of the international GHG market	Are Post Kyoto quota allocation rules robust to uncertainty?	Population Emissions Economic growth	Allowance prices and abatement costs are sensitive to uncertainties. The least-cost rules are relatively robust
Pizer (1998) (version of DICE)	Stochastic growth model Optimization	Choice of instruments Monte Carlo analysis	Endogenous labor productivity & population growth are random walks Utility, cost & technology parameters, parameters describing the development of CO_2 in the atmosphere (19 uncertain parameters) Estimated joint distributions for 5 parameters; distributions taken from Nordhaus (1994)	Productivity slowdown encourages stricter optimal regulation Short run responses are rather similar whether or not uncertainty is introduced. Taxes are preferable to emissions trading Preferences are most important source of uncertainty
Pindyck (2000)	Cost-benefit analysis	Monte-Carlo analysis	Future costs and benefits are modeled as stochastic processes with guestimated parameters.	Less abatement with increasing uncertainty
Reilly et al. 1995) **IEA/ORAU**	Economy-energy model	(Monte Carlo + Latin Hypercube sampling Assessment of relative importance of different uncertain parameters	79 uncertain model parameters 5 point guestimates with continuous contributions between values	Overall uncertainty in the emission rate is considerable. To bracket 90% of 400 random scenarios +3 to –1.4% change per year. Most important determinants of the variation are labor productivity, energy efficiency growth and income elasticity of demand for energy in the developing world.

Tol (1999). FUND	Optimization/simulations	Monte Carlo analysis	Selected parameters including ♦ Socio-economic drivers ♦ Carbon cycle/climate ♦ Climate change impacts ♦ Emission reduction Distributions, means and spread taken from literature	The baseline scenario leads to an unbounded loss when uncertainty is included (though the divergence is slow). This does no occur with the emission reduction scenarios. Optimal emissions reduction is more strict under uncertainty than under certainty.
Zapert et al. (1998) IMAGE	IAM Policy Evaluation		Initial state and/or stochastic noise are modeled for 155 uncertain parameters (mostly physical climate descriptors)	Even conservative uncertainty estimates result in scenario overlap of several decades during which the consequences of any actions affecting the environment could be difficult to identify with sufficient level of confidence. In general, the stochastic fluctuation contribute more to the uncertainty than the initial state measurements.
Zhao (2003)	Rational expectations general equilibrium model of permit market Optimizing	Tradable permits vs. taxes Investment incentives for firms	Abatement cots	Firm's investment incentives decreases in cost uncertainties, but more so under emission charges than under tradable permits

* Part of the table is taken from the table in the appendix of Kann & Weyant (2000).