A Cost-Benefit Analysis of Climate Change: Uncertainties and the Value of Information

Bob van der Zwaan[1,a,b] and Ari Rabl[c]

[a] vanderzwaan@ecn.nl, Energy research Centre of the Netherlands, Policy Studies Department, P.O. Box 37154, 1030 AD, Amsterdam, The Netherlands

[b] Columbia University, The Earth Institute, Lenfest Center for Sustainable Energy, 500 West 120th Street, New York, NY 10027, USA

[c] ari.rabl@gmail.com, Ecole des Mines, Centre Energétique et Procédés, 60 boulevard St. Michel, F-75272, Paris, Cedex 06, France

7 October 2007

Abstract

Even though climate change is a dynamic problem, we argue that its analysis in terms of steady-state conditions is instructive for policy purposes, analogous to often-cited targets for the stabilized global average temperature rise or atmospheric CO_2 concentration. We analyze climate change in a cost-benefit framework and specify CO_2 emissions as annual averages of the time-dependent emission profiles of Wigley *et al*. (1996) while relating these to stabilized atmospheric CO_2 concentrations and the corresponding global temperature increases. The resulting time-averaged model is simple enough to allow a fully transparent sensitivity study with respect to the uncertainties of all the damage and abatement cost parameters involved. Our result for the time-averaged optimal emission level E_o = 8.7 $GtCO_2$/yr (about a third of current emissions) turns out to vary by at most 2.3 $GtCO_2$/yr (or less than 30%) for the range of plausible parameter values. To assess the significance of uncertainties we focus on the social cost penalty, defined as the extra costs incurred by society relative to the overall social optimum if one makes the wrong choice of the time-averaged emission level as a result of errors in the estimates of the costs and benefits of CO_2 emissions abatement. In relative terms the cost penalty turns out to be remarkably insensitive to errors. For example, if the true damage costs are three times larger or smaller than the estimate, the total social cost of global climate change increases by less than 20% above its minimum at the true optimal time-averaged emission level. However, because of the enormous magnitude of the total costs involved with climate change (mitigation), even a small relative error implies large additional expenses in absolute terms. To evaluate the benefit of reducing cost uncertainties, we plot the cost penalty as function of the uncertainty in relative damage and abatement costs, expressed as geometric standard deviation and standard deviation respectively. Suppose continued externality analysis reduces the geometric standard deviation of relative damage cost estimates from 10 to 5, the benefit is 0.5% of Gross World Product (about 250 billion €). If further research reduces the standard deviation of relative abatement costs from 1 to 0.5, the benefit is 0.06% of Gross World Product (some 30 billion €).

Key words: climate change, carbon dioxide, damage cost, abatement cost, social cost, cost penalty, information value, uncertainty reduction

JEL classification: H21, D58, C61, O33, Q40

[1] Corresponding author.

1. Introduction

Even if a comparison of costs and benefits may not be the only relevant criterion for the design and implementation of environmental policy, it is a crucial input. For the case of climate change it is thus advisable to quantify the costs and benefits of CO_2 emissions abatement as much as possible, as done in the landmark Stern Review (Stern *et al*., 2006). The usefulness of cost-benefit analysis (CBA) for assessing environmental policy like relating to climate control has been questioned, given that usually notoriously large uncertainties are involved. In earlier work, however, we showed, for several pollutants including CO_2, that the cost penalty incurred by making the wrong abatement choice because of uncertainties in the estimates for the costs and benefits of environmental policy is remarkably small (Rabl *et al*., 2005). Hence, CBA can be useful despite large uncertainties.

This paper extends our earlier cost-benefit study to a non-linear model for climate change damage costs, which is more realistic than the linear model presented there. Indeed, for damage costs resulting from greenhouse gas emissions a combination of linear and quadratic terms seems most appropriate. The reasons lie in both the non-linearity of the impacts and that of the corresponding costs. There is growing consensus that non-market damages (such as biodiversity impacts) are non-linear, while for market damages (like agricultural losses) linearity may today be a good approximation (but likely not farther in the future), and that the share in total climate change damage costs of the former is significantly larger than that of the latter. Especially for non-market damage costs, however, uncertainties are high, which justifies a careful inspection of their importance in climate change CBA. We therefore present a detailed sensitivity study regarding the contribution of our CBA input parameters and modeling assumptions to the uncertainty in the optimal emission level.

We define E_o as the optimal time-averaged CO_2 emission level that minimizes the total cost $C_{tot}(E)$, that is, the sum of the damage cost $C_{dam}(E)$ and the abatement cost $C_{ab}(E)$, as function of the total global time-averaged emission level E:

$$C_{tot}(E) = C_{dam}(E) + C_{ab}(E)\,. \qquad (1)$$

To perform this optimization, mathematical expressions are needed for both $C_{dam}(E)$ and $C_{ab}(E)$ and their derivatives. Ideally one should use a detailed dynamic top-down or bottom-up integrated assessment model fit for comparing the costs and benefits of climate change policies over time. For a systematic analysis of the main uncertainties in climate change CBA, however, we consider such models too complicated and their detail too great, as a result of which our findings would become opaque. Instead, our analysis is much more concise, is based on time-averaged relations, and possesses only few parameters that express the key features of the problem. Thus we can carry out a CBA that is fully transparent and shows clearly the role of each of the major factors involved. Our work is complementary to that of many, notably to recent publications like DEFRA (2004, 2005) and Tol (2005), in which overviews are given of estimated climate change damage costs under a specified increase in the concentration of atmospheric CO_2 or the average global temperature. We, on the other hand, allow in principle for a large range of possible optimal values of the time-averaged emission level E or the corresponding global average temperature increase ΔT.

Even though omitting time in this study may appear a radical approximation, we argue that the results of our CBA are realistic and provide good guidance for policy making. In reality there is of course time-dependence in at least three key elements of the problem: the relation between CO_2 emissions and temperature rise, the evolution of damage costs, and the profile of abatement costs. As far as the first is concerned, we use the time-dependent relationship between CO_2 emissions and concentrations published by Wigley *et al*. (1996) to derive a relation between time-averaged emissions and concentrations. This relation is an exact representation of the steady-state conditions in the Wigley *et al*. (1996) model. We then couple this relation to the expression employed by Caldeira *et al*. (2003) relating CO_2 concentrations with global average temperature rises ΔT. As damage cost relation we use the standard formulation of most integrated assessment models (see references in Table 1), in which the damage cost increases quadratically with ΔT. Being based on the stabilized temperature rise ΔT, these models possess a strong time-independent foundation, much like our analysis. Thus we obtain an expression for the steady-state damage cost as function of steady-state emissions.[2] As for the third time-dependent element, we replace it by a time-independent relation for the marginal abatement cost as function of E. Marginal abatement costs are expected to decrease over time as a result of technological progress. We account for this phenomenon implicitly, by adopting abatement cost curves that are significantly lower, especially as low emission levels are reached, in comparison to the cost curves currently determined that apply to abatement during the forthcoming decade (see e.g. Klaassen *et al*., 2005).

With these three stylized time-independent assumptions our model is a realistic representation of stabilized conditions. The result from our CBA for the optimal CO_2 emission level also proves to be a realistic estimate of the relevant long-term policy goal. Being time-independent our model does not indicate the profile or rate at which one should reduce emissions towards that long-term goal. That question can be answered through the numerous dynamic studies that have analyzed the time-dependent relation between emission scenarios and climate impacts (see, notably, Baker, 2005; Heal and Kriström, 2002; Keller *et al*., 2004; Kolstad, 1996; Nordhaus and Popp, 1997; Peck and Teisberg, 1993).

Whereas the uncertainties of CO_2 abatement costs are large, especially when projected far into the future (varying by typically a factor of 3), those of the damage costs are significantly larger (diverging over a range of as much as an order of magnitude). We therefore first provide, in section 2.1, a concise summary of some of the recent literature reporting estimates for aggregated climate change damage costs. We subsequently develop our expressions for $C_{dam}(E)$ and $C_{ab}(E)$, in sections 2.2 and 2.3 respectively. In section 3 we present the solution for the optimal emission level E_o as function of our model's key input parameters. To evaluate the consequences of damage and abatement cost uncertainties, we calculate in section 4 the cost penalty, defined as the extra social cost incurred relative to the social optimum, as function of the error in the estimates of relative damage and abatement costs. We also estimate the value of reducing these uncertainties through further research, by plotting the cost penalty as function of the geometric standard deviation of the relative damage cost distribution (assumed lognormal) and the standard deviation of the relative abatement cost distribution (assumed normal). In section 5 we summarize our main results, compare these with those of the Stern review (Stern *et al*., 2006), and give recommendations for climate change research and policy making.

[2] Note that understanding the steady state of environmental indicators is relevant for policy making, because the notion of sustainability possesses a strong connotation with stabilized conditions.

2. Damage and abatement costs

2.1. Review of damage cost estimates

A large number of integrated assessment models have been developed to assess climate change damage costs and their evolution over time.[3] Some are based directly on the impact of ΔT on Gross Domestic Product (GDP) or Gross World Product (GWP). Others, in particular FUND (Tol, 1995) and PAGE (Plambeck and Hope, 1996), attempt to simulate climatic impacts in more detail, according to the categories or economic sectors to which they apply. Quite generally, most of the reported damage cost estimates do not cover all climate change impacts, as they usually exclude possibilities like major disastrous events or socially contingent effects, as well as many of the non-market impacts. For the economic assessment of catastrophic climate change impacts, for example, CBA as used in these models, and the one we present below, pose strong limitations, so that it is preferable to apply other types of analysis instead (see Weitzman, 1997a and Yohe, 1996). Damage costs estimated through these models strongly depend on the time discounting method used, assumptions regarding equity weighting, and the supposed risk aversion or willingness-to-pay to avoid damages, important subjects that we will not address in this paper.[4]

One of the pioneering models in this field was DICE (Nordhaus, 1991 and 1994). DICE optimizes the trade-off between the costs of climate change and the costs of restricting CO_2 emissions. The damage cost simulation of DICE is based on the assumption that a 3 ˚C warming induces a 0.25 % loss of GDP in the USA, based on estimates of market damages such as crop loss, forestry impact, and shoreline erosion. This value is raised to 1 % to account for all probable damages, especially non-market ones that are generally hard to quantify. In order to render DICE applicable globally the relative loss is further increased to 1.3 % of GWP, as many less developed countries are more dependent on e.g. agriculture and have as such a more limited ability to adapt to the effects of climate change. Furthermore, Nordhaus recognizes that for temperature rises higher than 3 ˚C disproportionally large damages are likely to result, so that the use of a quadratic function is appropriate. Most of the subsequent climate-economy models have adopted a similar climate change damage cost formulation.

Another widely used climate policy assessment model is MERGE, a multi-region Ramsey-Solow optimal growth model including greenhouse gas emissions and a global climate module (Manne and Richels, 2004). It can be operated in a cost-benefit mode, in which a time path is chosen for emissions that maximizes the integrated discounted utility of consumption, after making allowance for the disutility associated with climate change. Whereas MERGE includes both market and non-market damages, it focuses on the latter, as they are considered the largest. In particular, market and non-market damages are assumed to be linear and non-linear with temperature increases, respectively, and follow the type of assumptions made in DICE (Nordhaus, 1994). Thus, the loss resulting from climate change, possibly even climatic catastrophe, is supposed to increase disproportionally (in this case again

[3] Most of them are essentially based on a comparison of future consumption trajectories in the expected utility framework as originally developed by Mirrlees and Stern (1972).

[4] Weitzman (1997a) points out that the influence on CBA of large catastrophic damages with small probabilities may outweigh the importance of discounting. This supports the focus of our analysis on (damage and abatement) cost uncertainties rather than on the nature of the CO_2 emissions time-profile.

quadratically) if mankind passes beyond an average atmospheric temperature increase of a few ˚C. While different numerical assumptions are made for different regions in the world, Manne and Richels (2004) presume that for a ΔT of 2.5 ˚C an economic loss of 2 % of GDP is incurred in high-income countries (in other words, the willingness-to-pay to avoid such a temperature increase is 2 % of GDP).[5] At the basis of simulations performed with models like FUND and PAGE, and of the other modeling exercises referred to below (Cline, 1992; Fankhauser, 1995; Titus, 1992), are damage cost assumptions similar to those made in DICE and MERGE, in some cases detailed per sector and/or region.[6] The parameter choices and corresponding specific quantifications of damage costs, however, and thus the numeric way the quadratic temperature dependence is introduced in these models, often vary substantially, as shown in the next section.

Two recent studies have produced an overview of an important part of the climate change damage literature and made a comparison of two modeling exercises determining the marginal damage cost dC_{dam}/dE of CO_2 and its uncertainties (DEFRA, 2004 and 2005). They report central estimates for six points in time from 2000 to 2050. As an indication of the uncertainties they show a set of lower and upper central estimates as well as a lower and an upper bound (corresponding to 5% and 95% confidence intervals). We quote some of their results, using an exchange rate conversion of 1.5 €/£, to allow for later comparison. Their central estimate is 23 €/tCO_2 in 2000, increasing to 59 €/tCO_2 in 2050. The reported lower and upper central estimates for 2000 are 14 €/tCO_2 and 53 €/tCO_2, respectively. The lower bound is 4 €/tCO_2 (5% bound of PAGE) and the upper bound 90 €/tCO_2 (average of the 95% bounds of FUND and PAGE). Even though the range from lower to upper bound is enormous, it does not fully capture all published estimates. Indeed, some negative values for dC_{dam}/dE have been reported (implying net climate change benefits rather than costs) as well as values a couple of times higher than the upper bound. Tol (2005) also reviews a large number of climate change impact studies, and combines over 100 estimates for the marginal damage cost of CO_2 to form an overall probability density function. The uncertainty proves to be strongly right-skewed, with a median of \$3.8/tCO_2, a mean of \$25.4/tCO_2, and a 95% CL of \$95/tCO_2. According to Tol (2005), under standard assumptions of time discounting, equity weighting, and risk aversion, the marginal damage cost is unlikely to exceed \$14/tCO_2, and is probably smaller. This value is significantly lower than the \$85/tCO_2 reported by the widely publicized Stern Review (Stern *et al*., 2006), on which we will comment in the conclusion.

2.2. Damage cost as function of emissions

Most of the integrated assessment modeling studies (see references in Table 1) on energy, climate change, and the economy, use a damage cost function with the shape:

[5] For low-income countries, like China and India, the 'hockey-stick'-parameter they use in MERGE is smaller than 1. This means that at a per capita annual income between \$5,000 and \$50,000 a region is only willing to pay 1 % of GDP to avoid a 2.5 ˚C temperature rise, and at \$5,000 or below basically nothing. At \$50,000 or above the 2 % of GDP willingness-to-pay applies.

[6] Differences may exist though in assumptions on the tolerable temperature rise, defined as the ΔT below which no climate change damage is expected. While most models suppose a tolerable temperature of 0 ˚C, Manne and Richels (2004) assume it to be the temperature level in 2000 (which was about 0.7 ˚C higher than the average pre-industrial value) and Plambeck and Hope (1996) 2 ˚C.

$$C_{dam} = \rho(\Delta T_{stab})^{\theta}, \qquad (2)$$

in which C_{dam} is the damage cost expressed as fractional loss of GWP, ΔT_{stab} the global average temperature change with respect to the pre-industrial atmospheric temperature in stabilized conditions, i.e. when equilibrium is reached of the climate system, and ρ and θ coefficients characterizing the shape of the damage function. Central to our analysis is the definition of ΔT_{stab} as the stabilized global average temperature change obtained after a specified emission profile leads to new equilibrium values of the atmospheric CO_2 concentration and the corresponding increase in atmospheric temperature. Time lags exist both between the CO_2 emissions level and the stabilized CO_2 concentration, and between this new atmospheric CO_2 concentration and ΔT_{stab}, typically in each case of at least several decades up to a century. The very concept of stabilized temperature change is a time-independent summary of a dynamic process; it is of great practical importance because for policy applications one needs quantities that are easy to understand and communicate while preserving the key information. That justifies the formulation of integrated assessment models in terms of ΔT_{stab}.

Uncertainties about the parameters ρ and θ abound. The function of Equation 2 is usually assumed to be quadratic, so that θ is 2. Roughgarden and Schneider (1999) investigate values of θ other than 2 (both $1<\theta<2$ and $\theta>2$) on the basis of a set of expert views. They conclude, however, that a quadratic damage function is most plausible: while $\theta=2$ is not a necessity – the damage function may e.g. be somewhere in between linear and quadratic or perhaps even cubic – differences of opinion on climate damage costs show up primarily in the coefficient ρ of the damage function, rather than in its exponent. Roughgarden and Schneider (1999) argue that allowing for views from experts of different scientific disciplines – who have differing opinions on especially the likelihood of extreme climate events – implies variations of ρ by as much as an order of magnitude, but in most of the literature one finds values for ρ that typically lie between 0.001 and 0.004. Table 1 summarizes the values of the coefficient ρ as obtained from a survey of some of the most widely used integrated assessment models of climate change.

Formulated slightly differently, Manne and Richels (2004) assume in MERGE the relation:

$$C_{dam} = \left(\frac{\Delta T_{stab}}{\Delta T_{cat}}\right)^2, \qquad (3)$$

in which ΔT_{cat} is the catastrophic temperature change at which all economic activity, hence the entire GWP, is supposed to be wiped out. Combining Equations 2 and 3 one finds the ΔT_{cat} implicit in the models behind the references listed in Table 1.

Table 1. Parameter values for ρ and corresponding ΔT_{cat} as assumed in several widely employed integrated assessment models of climate change.

Source	$\boldsymbol{\rho}$	$\boldsymbol{\Delta T_{cat}}$ **(˚C)**
Cline (1992)	0.0023	20.7
Fankhauser (1995)	0.0028	19.0
Manne and Richels (2004)	0.0032	17.7
Nordhaus (1991, 1994)	0.0015	26.0
Plambeck and Hope (1996)	0.0028	19.0
Titus (1992)	0.0021	21.9
Tol (1995)	0.0032	17.7

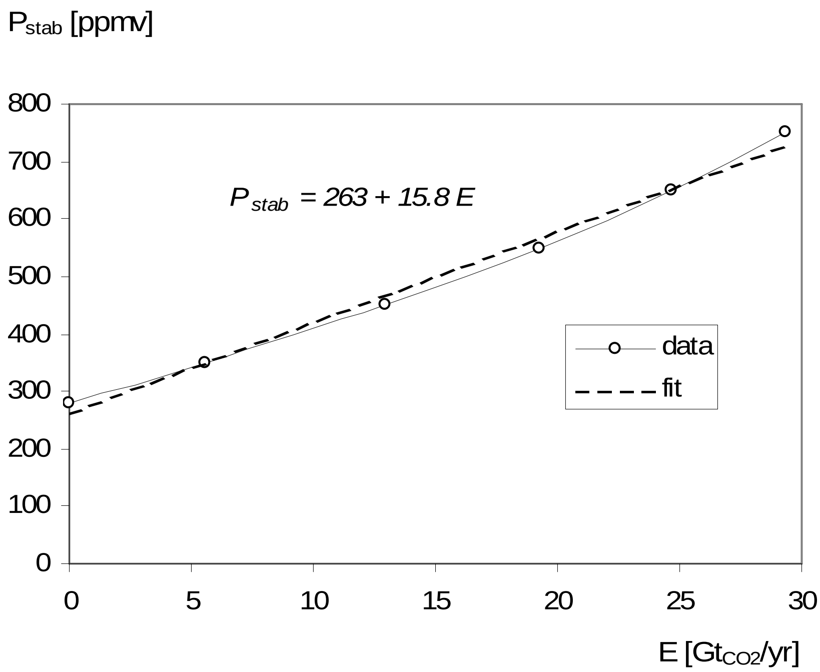
N.B. Most of these authors report damages relative to GDP in the USA for one temperature increase level only, typically as associated with a doubling of the atmospheric CO_2 concentration. Roughgarden and Schneider (1999) apply Nordhaus' assumptions to the figures adopted by them in order to obtain expressions for the damage function of Equation 2 consistent with DICE.

Since for our analysis we need to express C_{dam} as function of E, we first relate ΔT_{stab} to the atmospheric CO_2 concentration P by recalling that a roughly logarithmic relation exists between this concentration and global temperature increase (Houghton *et al.*, 1996). More precisely, the stabilization level of atmospheric CO_2 concentration, P_{stab}, can be related to ΔT_{stab} by (see Caldeira *et al.*, 2003):

$$\frac{P_{stab}}{P_{280}} = 2^{\left(\frac{\Delta T_{stab}}{\Delta T_{2X}}\right)}, \tag{4}$$

in which P_{280} is the pre-industrial CO_2 concentration of about 280 ppmv, and ΔT_{2X} the climate sensitivity, defined as the temperature change ΔT_{stab} resulting from a doubling of the atmospheric CO_2 concentration. Hence, a stabilization concentration target for atmospheric CO_2 increases exponentially with the ratio of the stabilization temperature change and the climate sensitivity. As before, neither ΔT_{stab} nor ΔT_{2X} are instantaneous temperature changes, but global mean surface temperature changes attained if CO_2 concentrations are held constant long enough to reach stable average climate conditions. ΔT_{2X} is thought to lie in a range of about 1.5 to 4.5 ˚C. Recent empirical studies (based on e.g. ice core measurements) indicate that there is significant likelihood that ΔT_{2X} lies above this canonical range (see for a recent overview of possible values of ΔT_{2X} and implications, for example, van der Zwaan and Gerlagh, 2006). A most likely value of 3 ˚C for ΔT_{2X} may thus still be considered conservative. In order to derive a simple time-independent relationship between P_{stab} and E, we employ the curves of Figure 1 in Wigley *et al.* (1996) representing a set of time-dependent emission profiles for the period 1990 – 2300 calculated for different values of P_{stab}. We take for each value of P_{stab} the corresponding annual emission level E averaged over this time frame. The data and a linear fit are shown in Figure 1.

Figure 1. Time-independent relationship between P_{stab} and E based on the data of Wigley et al. (1996), obtained by setting E equal to the annual average of their 1990-2300 emission profiles. The data points show E for P_{stab} = 280, 350, 450, 550, 650, and 750 ppmv. The straight line is our linear regression.



Let E_s be the current emissions value of about 25.7 $GtCO_2$/yr. By using P_{280} and E_s as reference levels we represent the linear fit of Figure 1 in dimensionless form:[7]

$$\frac{P_{stab}}{P_{280}} = \varepsilon + \delta \frac{E}{E_s} \qquad \text{with } \delta = 1.45 \text{ and } \varepsilon = 0.94. \tag{5}$$

Combining Equations 2, 3 and 5, and assuming $\theta = 2$, we get for the first term of the RHS of Equation 1:

$$C_{dam}(E) = \rho \left[\Delta T_{2X} \ln(\varepsilon + \delta \frac{E}{E_s}) / \ln 2 \right]^2 . \tag{6}$$

This relation is shown as a dashed line in Figure 3. We have also carried out a Monte Carlo analysis, using the CrystalBall software and assuming that the parameters characterizing the damage cost curve are normally distributed.[8] The resulting distribution of marginal damage costs is highly right-skewed, although fairly different from a lognormal distribution, with a geometric standard deviation of about 3.5. It is easy to get higher or lower values for the geometric standard deviation by making different assumptions on the distributions of the parameters. On balance we feel that a geometric standard deviation in the range of 4 to 5 is reasonable for current estimates of the marginal damage cost of climate change.

[7] This choice for E_s is arbitrary and has no effect on our final results.

[8] For the means and standard deviations we assumed, respectively, δ: Normal (1.45, 0.10); ε: Normal (0.94, 0.05); ρ: Normal (0.0020, 0.0005); ΔT_{2X}: Normal (3, 1.2).

2.3. Abatement cost as function of emissions

Like in Rabl *et al*. (2005), we assume that the marginal CO_2 abatement cost takes the functional form:

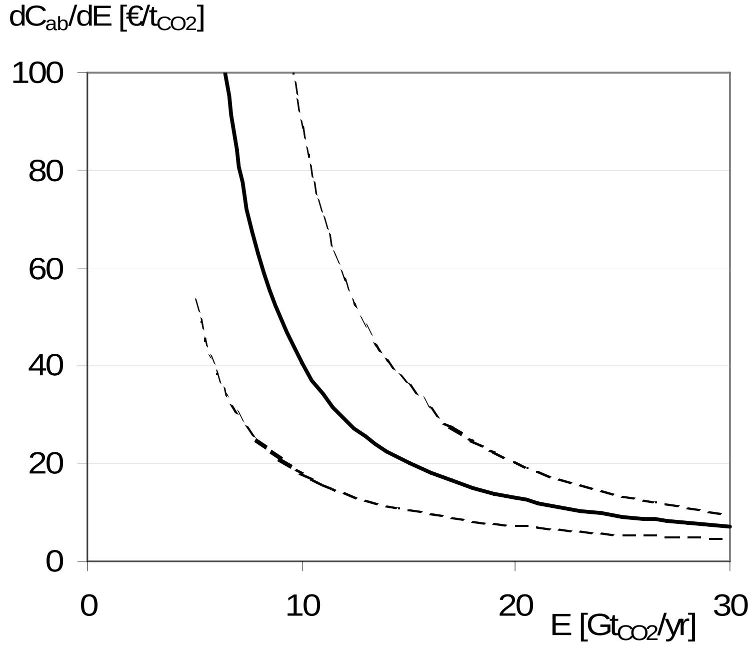
$$\frac{dC_{ab}}{d(-E)}=\frac{1}{G}\alpha\left(\frac{E-\beta}{E_s}\right)^{\gamma}, \tag{7}$$

in which C_{ab} is the globally aggregated abatement cost as fraction of GWP (abridged to G in this formula), E and E_s (both in $GtCO_2$/yr) are as before, and α (in €/tCO_2), β (in $GtCO_2$/yr) and γ are coefficients characterizing the non-linear convex form of the abatement cost function. The factor G is added to the relation used in Rabl *et al.* (2005) in order to stay consistent with the way damage costs are expressed in Equation 2 and because in the present analysis we find it convenient to express all costs as fraction of GWP. For GWP we adopt today's value of approximately 50 trillion €/yr. We choose the signs in Equation 7 so that dC_{ab} is positive for a reduction of E. The parameters α, β, and γ may be determined by least squares regression if cost data are available as a function of the abatement level. Alternatively, they may be estimated on the basis of energy technology assessments or energy systems modeling. Here we choose the marginal abatement cost curves depicted in Figure 2, based on an evaluation of published integrated assessment modeling results (see notably Goulder and Mathai, 2000; Goulder and Schneider, 1999; van der Zwaan *et al*., 2002; Yohe, 1996).[9] Figure 2 contrasts with near-term abatement cost curves obtained through detailed engineering energy technology analyses, like with the GAINS model up to 2020 (Klaassen *et al*., 2005). Over such a short time frame the potential for deep reductions is limited or exceedingly costly, because many of the technological options available require long installation lead times or have costs that are unacceptably high at the present time. In the long run, however, major cost reductions are to be expected as a result of technological progress and learning-by-doing. Thus, our abatement cost assumptions concern the long run and should not be interpreted as realistic short-term policy goals.[10] Note, however, that our model does not represent the phenomenon of learning, as function of time or cumulative installed capacity, explicitly.

[9] These references typically report shadow carbon prices, which we associate with the efforts needed to achieve carbon emission reductions or, alternatively, carbon abatement costs.

[10] Figure 2 shows marginal abatement costs only down to E = 5 $GtCO_2$/yr, as below this reduction level they become much higher than marginal damage costs, such that effectively no mitigation takes place. Also, below this abatement level the cost uncertainties are too extreme to be of real significance.

Figure 2. Our choice for the marginal abatement cost curve (solid line) and lower and upper bounds (dashed lines). The coefficients are α=7.5, β=3, and γ=−1.3 for the central curve, α=5, β=2, and γ=−1.1 for the lower limit, and α=10, β=4, and γ=−1.5 for the upper limit.



The cost of reducing CO_2 emissions from starting point E_s to level E is the integral of the marginal abatement cost equation of Equation 7:

$$C_{ab}(E)=\frac{1}{G}\frac{\alpha E_s}{\gamma+1}\left[\left(\frac{E_s-\beta}{E_s}\right)^{\gamma+1}-\left(\frac{E-\beta}{E_s}\right)^{\gamma+1}\right] \qquad \text{for } \gamma\neq\text{-}1. \tag{8}$$

This is the E-dependent expression for the second term of the RHS of Equation 1.[11] We have also carried out a Monte Carlo analysis, using the CrystalBall software and assuming that the parameters of the abatement cost curve are normally distributed.[12] The resulting distribution of marginal abatement costs is approximately normal, except when the emission level drops below about 8 $GtCO_2$/yr. The ratio of standard deviation and damage cost is about 0.15 at E = 25 $GtCO_2$/yr, increasing to about 0.25 at E = 10 $GtCO_2$/yr. We are now in a position to solve our optimization problem.

3. Cost-Benefit Analysis: Solution

Since E_o minimizes $C_{tot}(E)$, the sum of the marginal abatement cost and the marginal damage cost is equal to zero at this optimal emission level, so that:

$$-\frac{\alpha}{G}\left(\frac{E-\beta}{E_s}\right)^{\gamma}+\frac{2}{\ln 2^2}\rho\Delta T_{2X}^2\frac{\ln(\varepsilon+\delta E/E_s)}{\varepsilon+\delta E/E_s}\frac{\delta}{E_s}=0 \qquad \text{at } E=E_o. \tag{9}$$

---

[11] Note that we only consider values of γ < -1, since these provide a sufficiently broad abatement cost uncertainty range.

[12] For the means and standard deviations we assumed, respectively, *α*: Normal (7.5, 1.0); *β*: Normal (3, 0.5); *γ*: Normal (-1.3, 0.1).

Unlike the case with linear damage costs, there is no analytical solution to this relation. We thus use the FindRoot function of Mathematica® to obtain a numerical solution.[13] Table 2 lists the central values, $p_{central}$, of all parameters of the optimization problem, as well as their ranges, [p_{min}, p_{max}], considered for the uncertainty analysis. For the central values of these parameters the optimal emission level is found to be E_o = 8.7 $GtCO_2$/yr, about one third of the current emission level E_s. The marginal damage and abatement costs at E_s are about 77 €/tCO_2 and 9 €/tCO_2, respectively, while at the optimum they are equal to approximately 54 €/tCO_2. Figure 3 shows the abatement, damage, and total costs expressed as percentage loss of GWP as function of emission level E. At today's emissions the damage cost clearly dominates, which highlights the need for major reductions.

Table 2. Central values and ranges of parameters p for the damage and abatement costs in the optimization problem.

Parameters *p*	p_{min}	$p_{central}$	p_{max}
Damage cost $C_{dam}(E)=\rho\left[\Delta T_{2X}\ln(\varepsilon+\delta\frac{E}{E_s})/\ln 2\right]^2$			
δ	1.15	1.45	1.75
ε	0.74	0.94	1.14
ρ	0.0005	0.0020	0.0035
ΔT_{2X} [ºC]	1	3	5
Abatement cost $C_{ab}(E)=\frac{1}{G}\frac{\alpha E_s}{\gamma+1}\left[\left(\frac{E_s-\beta}{E_s}\right)^{\gamma+1}-\left(\frac{E-\beta}{E_s}\right)^{\gamma+1}\right]$			
α [€/tCO_2]	5.0	7.5	10
β [$GtCO_2$/yr]	2	3	4
γ	-1.5	-1.3	-1.1

[13] All numerical results presented in this paper have been calculated with Mathematica.

Figure 3. Damage, abatement, and total costs expressed as percentage loss of GWP as function of emissions level E.

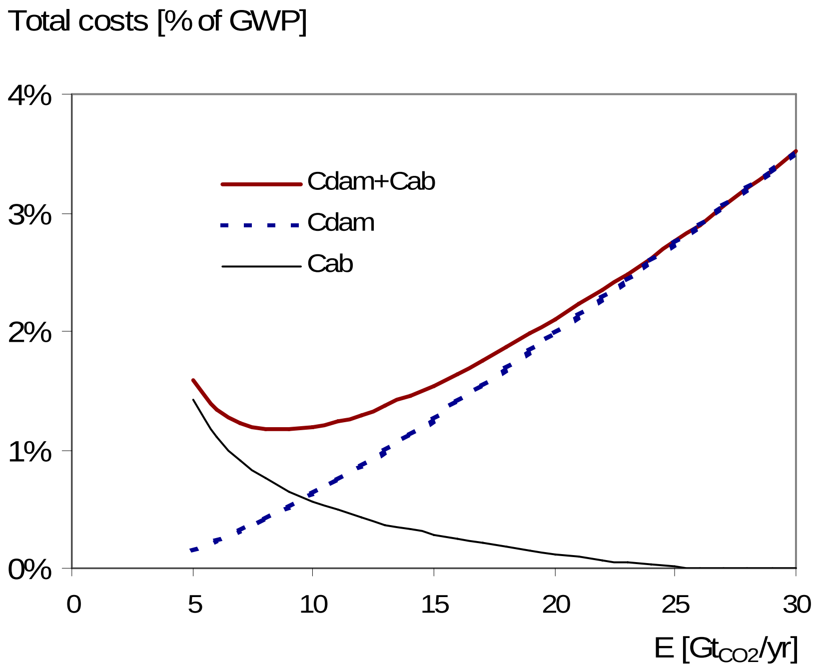
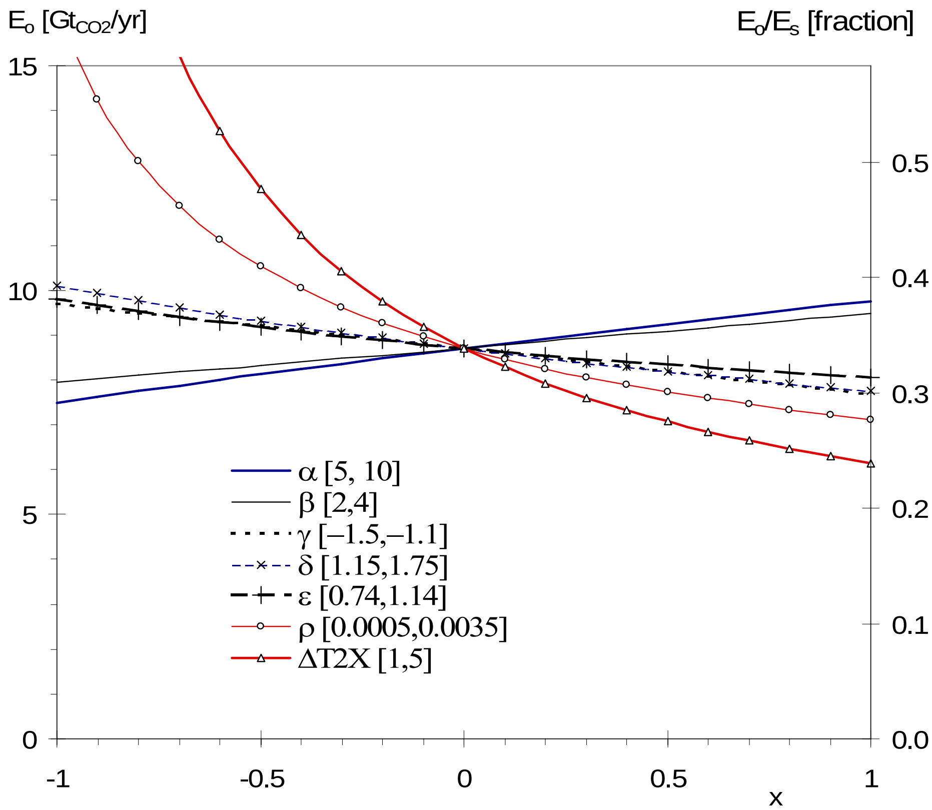


Figure 4 shows our results regarding the dependence of the optimal emissions level E_o on the parameter assumptions of our optimization problem. Since G and E_s are known with sufficient precision – their uncertainties are essentially negligible – they do not need to be subjected to a sensitivity analysis. We vary each parameter p over the range $[p_{min}, p_{max}]$ as listed in Table 2, wide enough to span any reasonable possible value of p. To show results in a compact format we choose to represent p in non-dimensional form as $x = (2p - p_{max} - p_{min})/(p_{max} - p_{min})$. The central value $p_{central}$ equals $(p_{max} + p_{min})/2$, corresponding to x=0. For the large uncertainty range chosen for the parameters α, β, γ, δ, and ε, we find that E_o varies by less than 20% in most cases.

The largest error margins derive from changes in the climate sensitivity, ΔT_{2X}, and the main parameter used to express climate change damage costs, ρ. Especially for values of x close to -1, for these two parameters, E_o could be much larger. For ΔT_{2X}, however, we find it reasonable not to consider values below 2 °C, given the high likelihood that the climate sensitivity is higher than this level. For ρ, we consider 0.0010 a generous lower bound, as it lies significantly below the minimum of values listed in Table 1. Since we abstract from the time-dimension of the cost-benefit problem, we cannot explicitly consider the effect of variations in the discount rate. Indirectly, however, we assume it is included in changes of ρ. Thus, limiting ourselves for ΔT_{2X} and ρ down to values of x=-0.5 but up to x=1, corresponding to a broad uncertainty range, we find that the optimal emission level E_o = 8.7 $GtCO_2$/yr varies by no more than 2.3 $GtCO_2$/yr or less than 30%.

Figure 4. Dependence of the optimal emissions level E_o (in $GtCO_2/yr$ and as fraction of current emissions E_s) on parameters α, β, γ, δ, ε, ρ, and ΔT_{2X} of the optimization problem. Each curve shows the effect of varying the parameter under consideration while keeping the others fixed at their central value. The x-axis shows the variation of each parameter p in non-dimensional form as $x = (2p - p_{max} - p_{min})/(p_{max} - p_{min})$.



4. Cost penalty and value of research

In our cost minimization problem the optimal emission level may well be determined incorrectly as a result of uncertainties in damage and abatement costs. Consequently, the real cost borne by society when establishing a desirable CO_2 emission level is larger than at the social optimum. Of course, various political processes may also preclude the choice of the optimal emission level, but here we are interested in errors in E_o resulting from erroneously estimated damage and abatement costs. In particular, we examine by how much the total social cost increases above the optimum due to damage and abatement cost estimation errors. Rather than looking at the uncertainty in each of the parameters of Table 2, as we did in the previous section, we here take a simplified approach by considering overall errors in respectively the damage and abatement cost.

Suppose that damage costs have been estimated as $C_{dam,est}(E)$, while the true damage cost is $C_{dam,true}(E)$. Likewise, we assume that the abatement cost has been guesstimated as $C_{ab,est}(E)$, whereas it is really $C_{ab,true}(E)$. The optimal emission level corresponding to the estimated costs is $E_{o,est}$, instead of the true optimum $E_{o,true}$. We represent damage and abatement cost uncertainties by random variables, x_{dam} and x_{ab}:

$$x_{dam} = C_{dam,\,true}(E) \,/\, C_{dam,\,est}(E), \tag{10}$$

and

$x_{ab} = C_{ab,\,true}(E) / C_{ab,\,est}(E).$ (11)

We look at variations of x_{dam} and x_{ab} separately because their magnitudes and probability distributions are fundamentally different. Uncertainties in the abatement cost function are much smaller than those in the damage cost. Also, for the former a normal distribution seems most plausible. We therefore characterize the distribution of x_{ab} by a Gaussian with mean 1 and standard deviation σ_{ab}. Since for large σ_{ab} a significant portion of the Gaussian corresponds to negative values of x_{ab}, i.e. negative abatement costs, we truncate the Gaussian at zero and replace it by a normalized distribution that is proportional to the Gaussian at positive x_{ab}.

For uncertainties in the damage cost function we assume a lognormal distribution. A variable has a lognormal distribution if the distribution of the logarithm of the variable is Gaussian. The lognormal distribution is strongly skewed, with a long tail of high values with low probability. It is usually characterized in terms of its geometric mean μ_g and its geometric standard deviation σ_g. Its geometric mean μ_g is equal to the median. If a quantity with a lognormal distribution has a geometric mean μ_g and a geometric standard deviation σ_g, the probability is approximately 68% for the true value to be in the interval $[\mu_g/\sigma_g,\ \mu_g\ \sigma_g]$ and 95% for it to be in the interval $[\mu_g/\sigma_g^2,\ \mu_g\ \sigma_g^2]$. Thus the confidence intervals of the lognormal are multiplicative, in contrast to the additive ones of the Gaussian.[14]

The highly skewed distribution of damage cost estimates in the literature (DEFRA, 2004 and Tol, 2005) is fairly consistent with a lognormal function, even though a few studies claim negative damages. Indeed, global climate change probably produces both winners and losers, at least at moderate temperature increases, but we do not believe that the net world-wide damage cost could be negative for any increase of the atmospheric CO_2 concentration. As representation of the estimates found in the literature we therefore take a lognormal distribution, and choose for its parameters a median μ_g = \$3.8/tCO_2 and upper limit $\mu_g\ \sigma_g^2$ = \$95/tCO_2, that is, $\sigma_g = 5$.[15] In view of the limitations of currently available studies – notably the fact that especially some of the most troubling potential impacts, such as a change in the thermohaline circulation, rapid non-linear ice-sheet disintegration, or methane release from permafrost melting, have not yet adequately or hardly at all been taken into account – we realize that the uncertainty range may well be larger than $\sigma_g = 5$.

Since we focus in this section on variations in x_{dam} and x_{ab}, we use these variables as arguments of the true optimal emission level $E_{o,true}(x_{dam},x_{ab})$ as well as of the difference $\Delta C(x_{dam},x_{ab})$ between the total cost at $E_{o,est}$ and that at $E_{o,true}$:

$$\Delta C(x_{dam},\, x_{ab}) = [C_{dam,true}(E_{o,est}) + C_{ab,true}(E_{o,est})] - [C_{dam,true}(E_{o,true}) + C_{ab,true}(E_{o,true})]. \quad (12)$$

$\Delta C(x_{dam},x_{ab})$ is the cost penalty due to errors in the damage and abatement cost functions. The results in this section are complementary to those of Figure 4. We here cover a wider range of uncertainties than considered there, but present less detail

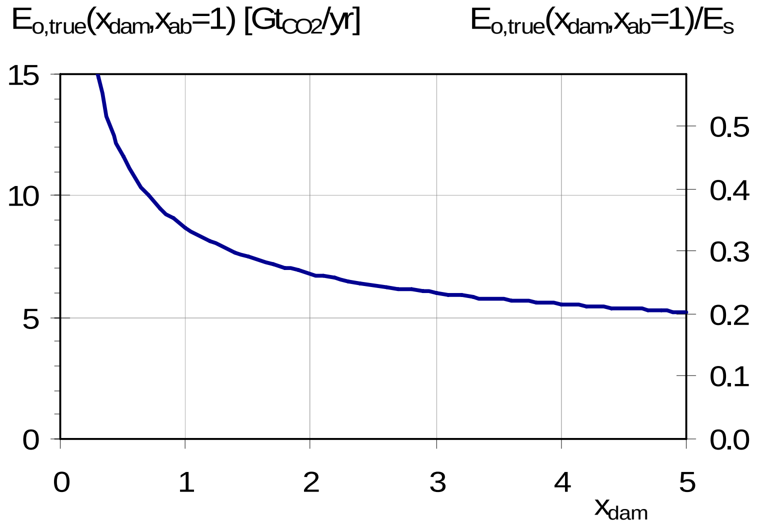
[14] See Spadaro and Rabl (2007) for more information on the use of lognormal distributions for the uncertainty analysis of environmental damage costs.
[15] This median is the one reported in the review by Tol (2005) and the upper limit the 95% confidence interval in this reference.

about the specific role of individual parameters. Starting from the quantities $C_{dam,est}(E)$, $C_{ab,est}(E)$, and $E_{o,est}$ as calculated with the central values of the parameters in Table 2, the corresponding true quantities are obtained by incorporating the factors x_{dam} and x_{ab} in our analysis. As can be seen from an inspection of Equations 6 and 8, the variation of x_{dam} is equivalent to variations in ρ and $(\Delta T_{2X})^2$, while the variation of x_{ab} is equivalent to a variation in α.

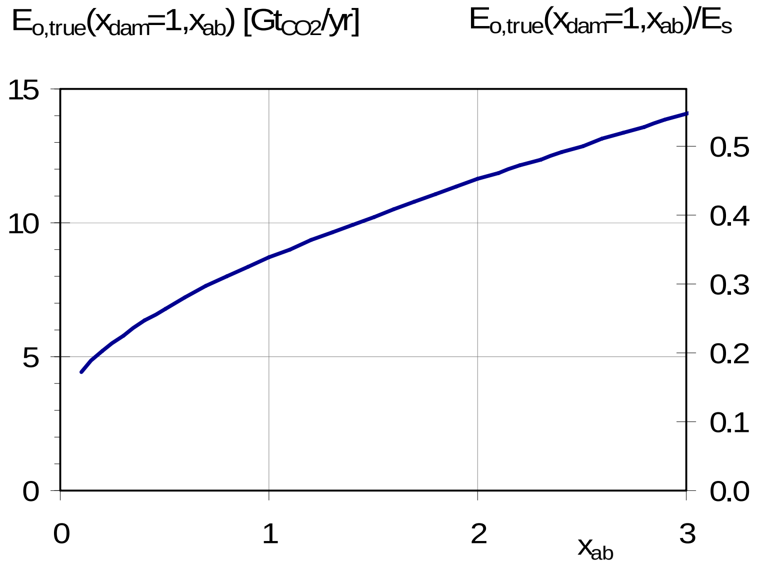
The variation of the true optimal emission level $E_{o,true}(x_{dam},x_{ab})$ is plotted in Figure 5, in part a) as function of x_{dam}, keeping $x_{ab} = 1$, and in part b) as function of x_{ab}, keeping $x_{dam} = 1$. Since we think that the abatement cost uncertainty is smaller than the damage cost uncertainty, the depicted range of x_{ab} is smaller than that of x_{dam} (up to a maximum of 3 and 5, respectively). As expected, both graphs of Figure 5 confirm our central result of $E_o = 8.7$ $GtCO_2$/yr, reached in this representation when both $x_{dam} = 1$ and $x_{ab} = 1$. These plots also include our finding that the uncertainty range of this optimal emission level amounts to at most 2.3 $GtCO_2$/yr, or less than 30%, but furthermore depict the dependence of E_o on a larger scope of damage and abatement cost uncertainties than the ones we considered before, that is, parameter values beyond what we regard generous minimum and maximum boundaries. In addition, through the relative units used for the y-axis on the right, Figure 5 points out that even if the damage or abatement costs are estimated wrongly by as much as a factor of 3, the optimal emission level still amounts to about half the present-day emissions of CO_2. Yet such an error by a factor of 3 could also imply that today's emissions should be reduced by almost 80%, rather than the suggested central reduction value of 67%. These findings strengthen our analysis' case for realizing a deep cut in CO_2 emissions.

Figure 5. Effect of uncertainties on the optimal emission level $E_{o,true}(x_{dam},x_{ab})$.
a) True optimum if true damage cost is x_{dam} times larger than the estimate, keeping x_{ab} = 1.
b) True optimum if true abatement cost is x_{ab} times larger than the estimate, keeping x_{dam} = 1.

a)



b)



The cost penalty $\Delta C(x_{dam},x_{ab}=1)$ resulting from damage cost errors is shown in Figure 6 as function of x_{dam}, keeping x_{ab} = 1. To get a sense for the magnitude of the cost penalty with respect to the total costs incurred at the optimum, it is instructive to complement the cost penalty in absolute terms (solid line and left hand scale) with that in relative terms as ratio $\Delta C/C$ (dashed line and right hand scale), with in this case $\Delta C=\Delta C(x_{dam},x_{ab}=1)$ and $C=C(x_{dam},x_{ab}=1)$. Analogously, the cost penalty $\Delta C(x_{dam}=1,x_{ab})$ due to abatement cost errors is shown in Figure 7, again both in absolute and in relative terms (left and right hand scales, respectively). Like for Figure 6, given that the uncertainty range for abatement costs is probably smaller than for damage costs, we think it justified to depict a smaller x-axis span for x_{ab} than for x_{dam}.

Figure 6. The cost penalty $\Delta C(x_{dam},x_{ab}=1)$ if the true damage cost is a factor x_{dam} times the damage cost estimate, in absolute terms (solid line, left scale) and in relative terms as fraction of the total cost $C(x_{dam},x_{ab}=1)$ at the optimum (dashed line, right scale).

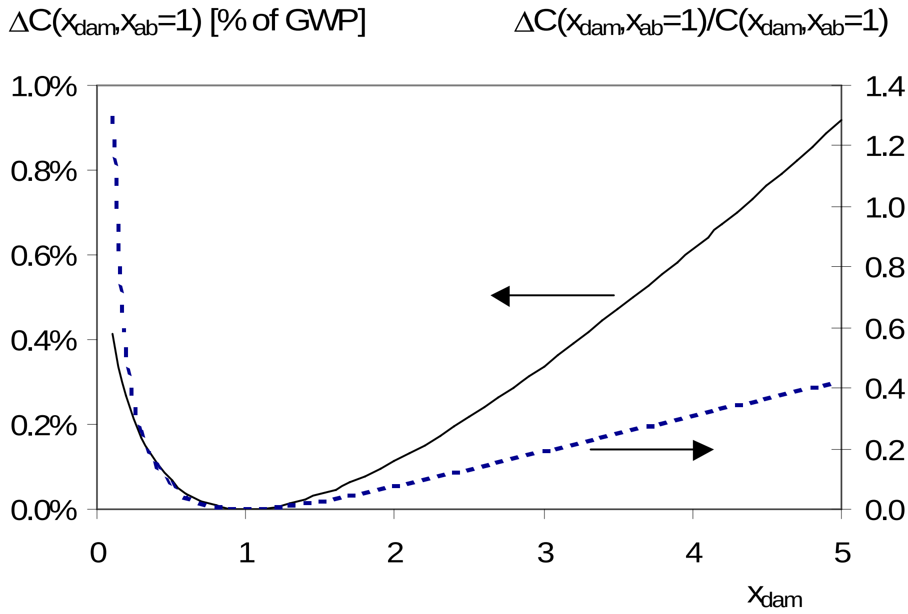
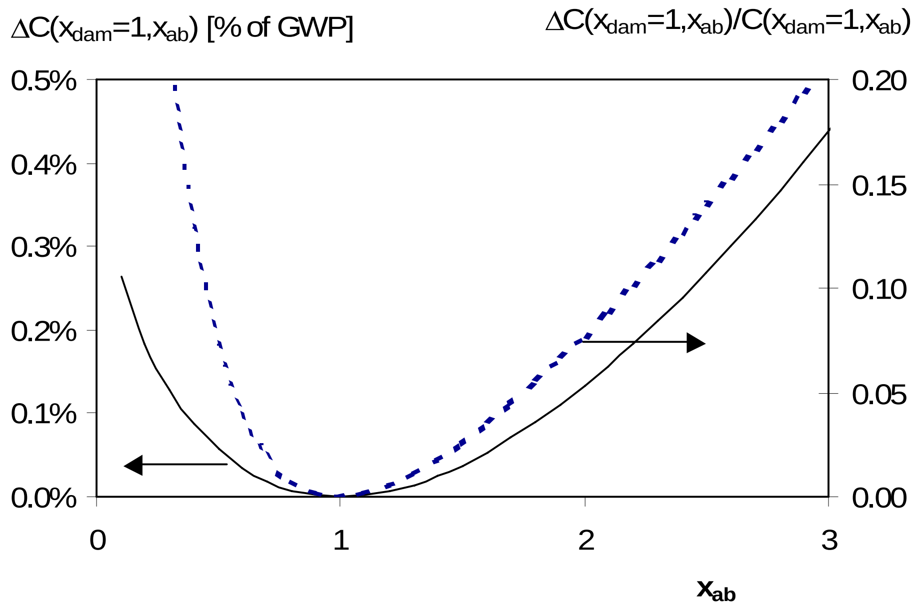


Figure 7. The cost penalty $\Delta C(x_{dam}=1,x_{ab})$ if the true abatement cost is a factor x_{ab} times the abatement cost estimate, in absolute terms (solid line, left scale) and in relative terms as fraction of the total cost $C(x_{dam}=1,x_{ab}=1)$ at the optimum (dashed line, right scale).

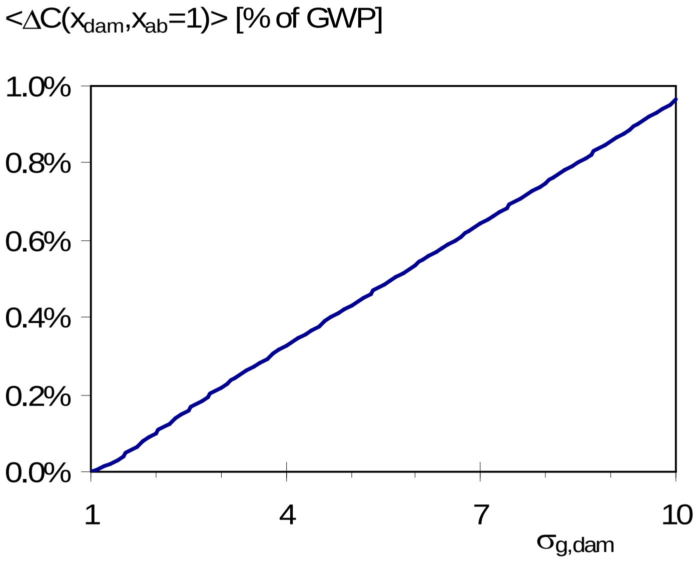


Like in Rabl *et al*. (2005), we find that the cost penalty is relatively small near the optimum, or, in other words, the optimum is fairly broad. Only when the damage and abatement cost errors get large, the cost penalty becomes substantial. Figures 6 and 7 show that when the true damage costs are 5 times the estimated ones, the relative cost penalty amounts to about 40%, and that when the true abatement costs are 3 times the estimated ones, the relative cost penalty amounts to about 20%. These relative changes may still be considered modest, but in absolute terms the cost penalty can become really enormous. The explanation is that the stakes involved in global climate change, i.e. the costs both at the damage and abatement side of the problem, are simply very high. For example, for x_{dam}=5 and x_{ab} = 3, the cost penalty reaches values nearing 1% and 0.5% of GWP, respectively, close to the total costs of 1.2% of GWP involved in the climate change problem at the optimum (see also Figure 3).

Uncertainties in damage and abatement costs can be reduced by further research. To assess the value of such research we calculate the expectation value $<\Delta C(x_{dam},x_{ab}=1>$ as function of the geometric standard deviation σ_{gdam} of the damage cost, with x_{dam} characterized by a distribution *Lognormal(1,*σ_{gdam}*)*. Likewise, we determine the expectation value $<\Delta C(x_{dam}=1,x_{ab})>$ as function of the standard deviation σ_{ab} of the abatement cost, with x_{ab} characterized by a distribution *Normal(1,*σ_{ab}*)*. Even though abatement options exist with negative costs, we do not believe that on a global scale total abatement costs could be negative. We therefore truncate the normal distribution at x_{ab} = 0. The results are shown in Figure 8.

Figure 8. Expectation value of the cost penalty: a) $<\Delta C(x_{dam}, x_{ab}=1>$ *as function of the geometric standard deviation* $\sigma_{g,dam}$ *of the damage cost; b)* $<\Delta C(x_{dam}=1, x_{ab})>$ *as function of the standard deviation* σ_{ab} *of the abatement cost.*

a)



b)

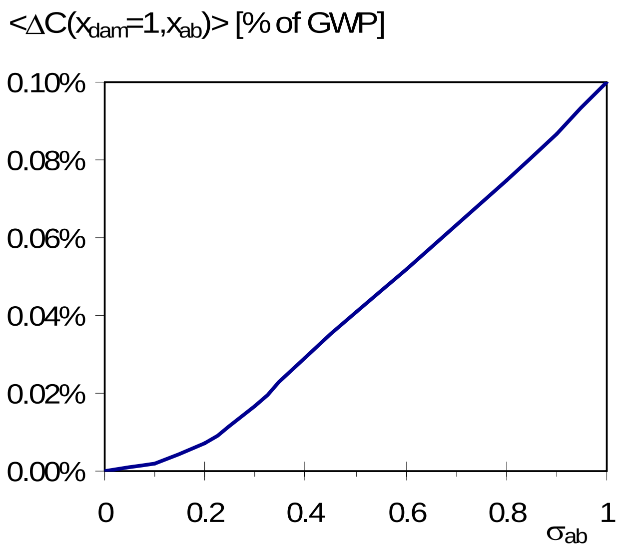


Figure 8 provides an indication of the value of improved information on the damage and abatement costs. For example, if research reduces the geometric standard deviation $\sigma_{g,dam}$ of the relative damage cost estimates from 10 to 5, the expectation value of the cost penalty decreases from around 0.9% to some 0.4% of GWP. Hence the value of such research is about 0.5% of GWP. In relative terms less than half a percent benefit may seem negligible, but in absolute terms this reduction of the cost penalty corresponds to an amount of about 250 billion €. In a similar way, if further research reduces the standard deviation of relative abatement cost estimates from 1 to 0.5, the benefit is about 0.06% of GWP, that is, about 30 billion €. We thus conclude that research to reduce the uncertainty of damage and abatement cost estimates can be extremely cost-effective. We also observe that the possible gains from continued climate change damage cost analyses (i.e. climatic externality studies) may be significantly higher than those obtainable by increasing our understanding of the nature of abatement technologies and their prospected costs. The reason is the small likelihood for extreme climate events with high impacts, that is, the lognormal distribution of the damage cost function. Note that the change of slopes in Figure 8 b) around $\sigma_{ab} = 0.2$ is a reflection of the truncation at $x_{ab} = 0$. Such details should not be taken too literally, however, since the probability distributions are not known sufficiently well.

5. Conclusions and recommendations

We have carried out a cost-benefit analysis of climate change mitigation, with a focus on the uncertainties associated with both sides of the problem: the damage costs of CO_2 emissions and abatement costs of CO_2 emission reductions. To keep the analysis transparent we have introduced several major simplifications, especially by assuming a time-independent relation between CO_2 emissions and atmospheric CO_2 concentrations, arguing that they do not affect the validity of our conclusions. Based on a review of the literature, we have formulated elementary approximations for the damage and abatement cost functions. For the most plausible choice of the model parameters, we find that the 'climatic social optimum' corresponds to an emission level $E_o = 8.7$ $GtCO_2$/yr, about a third of CO_2 emissions today.

Varying the model parameters over a wide range, we evaluate the sensitivity of E_o and find that our central result is surprisingly robust. For most of our parameter tests, E_o changes by less than 20%. Varying the climate sensitivity parameter ΔT_{2X} and the scaling factor ρ of the damage cost function, on the other hand, has a stronger effect. For ΔT_{2X} we assume a central value of 3°C, a lower bound of 2°C and an upper bound of 5°C. For ρ we adopt a margin broader than the proportionality factors found in the literature, by supposing a central value of 0.0020, a lower limit of 0.0010, and an upper limit of 0.0035. On the basis of the corresponding parameter changes we find that E_o varies by no more than 2.3 $GtCO_2$/yr, i.e. less than 30% from E_o as found under our central parameter assumptions. This finding both confirms and narrows down the result of the more rudimentary cost-benefit analysis by Rabl *et al.* (2005), who calculate that the optimal CO_2 emission level lies between one third and three quarters of the current emission level under a wide range of parameter choices. Interestingly, our results imply that the optimal emission level is unlikely to be lower than E_o = 6.4 $GtCO_2$/yr, i.e. about one quarter of current CO_2 emissions, the explanation for which is that the abatement costs become too high at this mitigation plateau.

Ultimately it is not only the optimal emission level and its uncertainty that matters, but also the cost penalty, i.e. the extra social cost incurred due to an erroneously chosen E_o. Since it proves the optimum is broad, the cost penalty is relatively small even for large errors in the estimation of relative damage and abatement costs. For example, if the true damage cost is three times larger or smaller than the estimate used in our cost-benefit analysis, the total social cost of climate change increases by less than 20% above its minimum at the true optimal emission level. Because of the magnitude of the total costs involved with global climate change, however, even a fairly small relative error implies a large cost difference in absolute terms, amounting typically to hundreds of billions € in the case of damage cost uncertainties. We have therefore calculated the benefit of reducing these uncertainties. For example, if research reduces the geometric standard deviation of the relative damage cost estimate from 10 to 5, the expectation value of the cost penalty decreases from around 0.9% to some 0.4% of GWP. Clearly, the value of information brought forward by increased climate change damage research can be enormous.

With E_o = 8.7 $GtCO_2$/yr as optimal central emissions level and an uncertainty range of 2.3 $GtCO_2$/yr, we derive from Figure 1 an optimal CO_2 concentration of approximately $P_{stab,o}$ = 400 ppmv and a possible variation of some 40 ppmv. This result deviates from the recommendation of Stern *et al*. (2006), who claim that the optimal climate stabilization concentration is around 500 ppmv CO_2 (equivalent) with an error margin of about 50 ppmv. The discrepancy between their and our results is unlikely to be explainable by the fact that Stern *et al*. (2006) aggregate all greenhouse gases, while we only consider the most important contributor to climate change, CO_2. While receiving support from most scientists for its clear message to undertake action to reduce greenhouse gas emissions, the Stern review has also been criticized for several reasons (Dasgupta, 2006; Nordhaus, 2006; Weitzman, 2007b): while some focus on the low discount rate it employs, others indicate that the damage costs it reports are too high or the abatement costs too low. In the present paper we confirm the observation made by others that, despite the Stern review's high damage and low abatement costs, it arrives at an inexplicably high stabilization concentration. We strongly agree with the Stern review's overall conclusion that a deep cut in CO_2 emissions is required to avert the risk of global climate change. Like others, however, we also question certain aspects of the analysis leading to this result, as well as the precise outcome. In particular, in addition to our suggested CO_2 concentration level (400 +/- 40 ppmv) being significantly lower than that of the Stern review (500 +/- 50 ppmv), we find in our analysis that the marginal damage costs (77 €/tCO_2 at E_s and 54 €/tCO_2 at E_o) are below those quoted in the Stern review (85 €/tCO_2). The optimal emissions level we calculate (E_o = 8.7 +/- 2.3 $GtCO_2$/yr) is also significantly lower than figures quoted in recently professed policy statements by several G8 and EU countries, who aim at reducing their CO_2 emissions by half in 2050, that is, to about 13 $GtCO_2$/yr.

From the above climate change cost-benefit analysis, and the description of the uncertainties involved, it is evident that much more work is required in the field of CO_2 damage and abatement cost calculations. Especially climate change damage research really has only barely started off. In order to reduce damage cost uncertainties and exploit the value of the corresponding information, it is particularly important to perform detailed analyses of regional climatic impacts and associated economic costs. These are needed to complement the highly aggregated studies produced so far, like the one presented in this paper. We thus agree with the recommendation by DEFRA (2004) that the disaggregation and valuation of damage costs by sector and region should be forcefully pursued. Determining the possible physical impacts of CO_2 emissions in all areas of economic and social activity should be vigorously continued, since the ensuing findings can effectively profit long-term policy making. The classical challenges of mitigation timing, social discounting, equity weighting, and risk aversion remain on the agenda, as well as the question how policy makers should confront the uncertainties associated with climate change damage and CO_2 abatement costs. To the latter, this article has attempted to contribute a step forward. As in the future more understanding on all the above fields emerges, the type of analysis presented here should be revisited. For the moment at least our study has shown how drastic the CO_2 emission reductions are that need to be reached. We hope our analysis convinces policy makers that these cuts are even deeper than previously suggested: rather than continuing on the business-as-usual path that within decades may generate twice the amount of today's CO_2 emissions, the energy technologies should urgently be implemented capable of reducing these emissions to on average one-third of present-day levels, with uncertainty bounds of only one-fourth and two-fifths of the current figure of 25.7 $GtCO_2$/yr, i.e. in any case well below the proclaimed one-half reduction. The more time we take not reaching the average one-third goal, the deeper are the emission cuts required subsequently. Since in this paper we abstract from questioning the time profile of future emission reductions, but rather focus on damage and abatement cost uncertainties, we have performed our analysis in terms of the average emissions required over the coming three centuries. Consequently, whereas our results do not allow determining the transition path to reduce CO_2 emissions from 25.7 to 8.7 $GtCO_2$/yr, they do suggest that not being able to return to an emission level of below e.g. 20 $GtCO_2$/yr during the 21st century necessitates a decrease down to at least 3 $GtCO_2$/yr on average during the two following centuries.

Acknowledgements

This work has been supported by the EC DG Research under the CASES (Cost Assessment for Sustainable Energy Systems) project of the ExternE series (Contract no. 518294). We would like to thank Erin Baker, Jae Edmonds, Geoffrey Heal, James Mirrlees, Jos Sijm, and Richard Tol, as well as the CASES project members, for providing us with their expertise, opinions, and suggestions.

References

Baker, E., 2005, "Uncertainty and Learning in a Strategic Environment: Global Climate Change", *Resource and Energy Economics*, 27, 19-40.

Caldeira, K., A.K. Jain, M.I. Hoffert, 2003, "Climate sensitivity uncertainty and the need for energy without CO_2 emission", *Science*, 299, 5615, 2052-2054.

Cline, W.R., 1992, "The economics of global warming", Institute for International Economics, Washington D.C.

Dasgupta, P., 2006, "Comments on the Stern Review's Economics of Climate Change", mimeo, see www.econ.cam.ac.uk/faculty/dasgupta.

DEFRA, 2004, "The Social Costs of Carbon (SCC) Review - Methodological approaches for using SCC estimates in policy assessment", Department for Environment, Food and Rural Affairs, London.

DEFRA, 2005, “Social Cost of Carbon: A closer look at uncertainty”, Department for Environment, Food and Rural Affairs, London.

ExternE, 1998, ExternE: Externalities of Energy, European Commission, DG-XII, Science Research and Development, http://ExternE.jrc.es/publica.html.

Fankhauser, S., 1995, Valuing climate change: the economics of the greenhouse, Earthscan, London.

Goulder, L.H., S.H. Schneider, 1999, “Induced technological change and the attractiveness of CO_2 abatement policies”, *Resource and Energy Economics*, 21, 211-253.

Goulder, L.H., K. Mathai, 2000, “Optimal CO_2 abatement in the presence of induced technological change”, *Journal of Environmental Economics and Management*, 39, 1-38.

Heal, G., B. Kriström, 2002, “Uncertainty and Climate Change”, *working paper*, Columbia Business School, New York.

Houghton, J.T., *et al*. (Eds.), 1996, Climate Change 1995: The Science of Climate Change, Cambridge University Press, UK.

Keller, K., B. M. Bolker, D.F. Bradford, 2004, “Uncertain Climate Thresholds and Optimal Economic Growth”, *Journal of Environmental Economics and Management*, 48, 723-741.

Klaassen, G., C. Berglund, F. Wagner, 2005, “The GAINS Model for Greenhouse Gases, version 1.0: Carbon Dioxide”, IIASA Interim Report IR-05-53, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Kolstad, C.D., 1996, “Learning and Stock Effects in Environmental Regulation: the case of greenhouse gas emissions”, *Journal of Environmental Economics and Management*, 31, 1-18.

Manne, A.S., R.G. Richels, 2004, MERGE: an integrated assessment model for global climate change, www.stanford.edu/group/MERGE.

Mirrlees, J.A., N.H. Stern, 1972, “Fairly Good Plans”, *Journal of Economic Theory*, 4, 2, 268-288.

Nordhaus, W.D., 1991, “To slow or not to slow: the economics of the greenhouse effect”, *The Economics Journal*, 101, 920-937.

Nordhaus, W.D., 1994, *Managing the Global Commons*, MIT Press, Cambridge, Massachusetts.

Nordhaus, W.D., D. Popp, 1997, “What is the Value of Scientific Knowledge? An Application to Global Warming Using the PRICE Model”, *The Energy Journal*, 18, 1, 1-45.

Nordhaus, W.D., 2006, “The Stern Review on the Economics of Climate Change”, mimeo, see http://nordhaus.econ.yale.edu.

Peck, S.C., T.J. Teisberg, 1993, “Global Warming Uncertainties and the Value of Information: an analysis using CETA”, *Resource and Energy Economics*, 15, 1, 71-97.

Plambeck, E.L., C.W. Hope, 1996, “PAGE-95: an updated valuation of the impacts of global warming”, *Energy Policy*, 24, 9, 783-794.

Rabl, A., J.V. Spadaro, B.C.C. van der Zwaan, 2005, "Uncertainty of Air Pollution Cost Estimates: to what extent does it matter?", *Environmental Science and Technology*, 39, 2, 399-408.

Roughgarden, T., S.H. Schneider, 1999, "Climate change policy: quantifying uncertainties for damages and optimal carbon taxes", *Energy Policy*, 27, 415-429.

Spadaro, J.V., Rabl, A., 2007, "Estimating the Uncertainty of Damage Costs of Pollution: a Simple Transparent Method and Typical Results", *Environmental Impact Assessment Review*, in press.

Stern, N., *et al*., 2006, *The Economics of Climate Change: The Stern Review*, Cambridge University Press, Cambridge, UK.

Titus, J.G., 1992, "The cost of climate change to the United States", in: S.K. Majumdar et al. (Eds.), Global Climate Change: implications, challenges, and mitigation measures, Pennsylvania Academy of Science, Easton, PA.

Tol, R.S.J., 1995, "The damage costs of climate change: towards more comprehensive calculations", *Environmental and Resource Economics*, 5, 353-374.

Tol, R.S.J., 2005, "The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties", *Energy Policy*, 33, 16, 2064-2074.

van der Zwaan, B.C.C., R. Gerlagh, G. Klaassen and L. Schrattenholzer, 2002, "Endogenous Technological Change in Climate Change Modelling", *Energy Economics*, 24, 1.

van der Zwaan, B.C.C., R. Gerlagh, 2006, "Climate Sensitivity Uncertainty and the Necessity to Transform Global Energy Supply", *Energy*, 31, 14, 2235-2251.

Weitzman, M.L., 2007a, "The Role of Uncertainty in the Economics of Catastrophic Climate Change", working paper.

Weitzman, M.L., 2007b, "The Stern Review of the Economics of Climate Change", *Journal of Economic Literature*, forthcoming.

Wigley, T.M.L., R.G. Richels, J.A. Edmonds, 1996, "Economic and environmental choices in the stabilization of atmospheric CO2 concentrations", *Nature*, 379, 6562, 240-243.

Yohe, G., 1996, "Exercises in hedging against extreme consequences of global change and the expected value of information", *Global Environmental Change*, 6, 2, 87-100.