BASQUE CENTRE
FOR CLIMATE CHANGE
Klima Aldaketa Ikergai

The DICER Model: Methodological Issues and Initial Results

Ramon Arigoni Ortiz, Alexander Golub,
Oleg Lugovoy, Anil Markandya and James Wang

July 2010

BC3 WORKING PAPER SERIES

2010-11

The Basque Centre for Climate Change (BC3) is a Research Centre based in the Basque Country, which aims at contributing to long-term research on the causes and consequences of Climate Change in order to foster the creation of knowledge in this multidisciplinary science.

The BC3 promotes a highly-qualified team of researchers with the primary objective of achieving excellence in research, training and dissemination. The Scientific Plan of BC3 is led by the Scientific Director, Prof. Anil Markandya.

The core research avenues are:

- Adaptation to and the impacts of climate change
- Measures to mitigate the amount of climate change experienced
- International Dimensions of Climate Policy
- Developing and supporting research that informs climate policy in the Basque Country

The BC3 Working Paper Series is available on the internet at
http://www.bc3research.org/lits_publications.html

Enquiries (Regarding the BC3 Working Paper Series):

Roger Fouquet

Email: roger.fouquet@bc3research.org

www.bc3research.org

Note: If printed, please remember to print on both sides. Also, perhaps try two pages on one side.

The DICER Model: methodological issues and initial results

Ramon Arigoni Ortiz[1], Alexander Golub[2], Oleg Lugovoy[3], Anil Markandya[4] and James Wang[5]

This paper introduces DICER, a model for the integrated assessment of climate – economy interactions within an optimal growth framework developed upon the structure of the DICE2007 model. We present the methodological differences introduced so far in DICER and some preliminary results of its deterministic version. We observe interesting results when comparing to other IAMs, such as (i) lower peak temperatures; (ii) radiative forcing differences; (iii) differences in control rates; and (iv) sensitivity of results to parameters such as climate sensitivity. A further innovation of this work has been to account for uncertainty and risk through an application of option pricing. The method allows for a simple representation of the risks through measures of volatility in the damages and abatement costs and shows that taking these factors into account lowers maximum mean temperatures by about 0.5°C. We also present some methodological issues that need to be dealt with in the near future in DICER.

Keywords: Climate change, Integrated Impact Assessment Model (IAM), damage function

JEL Classification: Q54, C61

Cite as: Ortiz, R. A.; A. Golub; O. Lugovoy; A. Markandya and J. Wang (2010) *The DICER model: methodological issues and initial results*. BC3 Working Paper Series 2010-11. Basque Centre for Climate Change (BC3). Bilbao, Spain.

[1] Basque Centre for Climate Change (BC3). Alameda Urquijo 4 – 4 – 1a derecha, 48008 Bilbao, Spain. E-mail: ramon.ortiz@bc3research.org.

[2] Environmental Defense Fund (EDF). 1875 Connecticut Avenue Northwest Washington DC, USA. E-mail: agolub@edf.org.

[3] Environmental Defense Fund (EDF). 1875 Connecticut Avenue Northwest Washington DC, USA. E-mail: olugovoy@edf.org.

[4] Basque Centre for Climate Change (BC3). Alameda Urquijo 4 – 4 – 1a derecha, 48008 Bilbao, Spain. E-mail: anil.markandya@bc3research.org.

[5] Environmental Defense Fund (EDF). 1875 Connecticut Avenue Northwest Washington DC, USA. E-mail: jwang@edf.org.

1 Introduction

This paper reports initial results of a new model for the integrated assessment of climate – economy interactions within an optimal growth framework. The Basque Centre for Climate Change (BC3) and the Environmental Defense Fund (EDF) investigated the instruments currently used in analyzing the interactions between the economy and climate change and identified points that are not addressed sufficiently or not addressed at all in existing models and that would contribute to reducing the uncertainties involved in the application of these models. These include: the inclusion of risk aversion and uncertainty in selecting the optimal path for the economy in the presence of climate change; allowing a direct feedback of climate change on welfare; providing a regional specification that allows for the damage functions and climate feedbacks to vary; and modelling the option for adaptation as a response that is included in the damage function.

EDF and BC3 thus started to develop an Integrated Impact Assessment Model (IAM) with a view to addressing the points mentioned above. We developed our model, taking as a point of departure the structure of the DICE2007[6] model and named the resulting model as DICER or DICE-Regional. This paper aims to describe the methodological changes introduced so far in DICER and to present some initial results of the model´s calibration. The main differences to DICE2007 so far include the regional specification; a modified climate model; updated damage functions; updated abatement cost functions; and a user-friendly interface. The current version of DICER is deterministic in the sense that it does not include uncertainty and associated probabilistic distributions of key parameters of the model, a feature that we understand will be implemented in future versions of DICER. This paper is organized as follows: section 2 presents a brief literature review focusing on the characteristics and limitations of some of the most used IAMs, which we intend to address in the DICER model; i.e. it highlights some reasons why we believe we need another IAM. Section 3 shows the main features of the DICER model as it currently stands and highlights where we differ from DICE2007. Section 4 presents some initial results obtained with the calibration of DICER, and section 5 discusses some outstanding issues and conclusions.

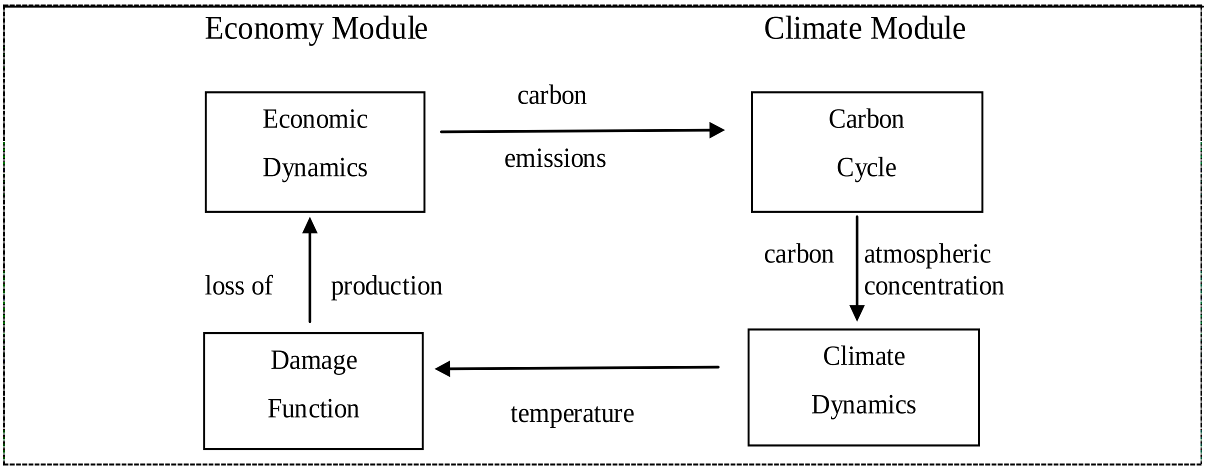
2 Literature Review

By definition, integrated assessments seek to understand the linkages or interactions and feedbacks among complex systems. Integrated Impact Assessment models of climate change are motivated by the need to balance the dynamics of carbon accumulation in the atmosphere and the dynamics of de-carbonization of the economy (Nordhaus, 1994). The interaction between the economy and climate systems can be drawn as in Figure 1. According to Toth (2005), IAMs have

[6] We are grateful to Williams Nordhaus for transparency and making the model´s code public for other researchers.

become recognized instruments for policy makers providing useful information and scientific insights for climate policy. These models can be classified as (i) policy evaluation - simulation models that take user-defined assumptions about a course of future policy and calculate the implications of the specified policy for all variables of interest of the police-maker; and (ii) policy optimization models, which summarize the relevant boundary conditions in a set of defined parameters in a scenario, separate key policy variables that control the evolution of the climate change problem and determine the value of these policy variables in an optimization procedure (Toth, 2005). Stanton *et al.* (2008) separate IAMs into (i) welfare optimization models; (ii) general equilibrium models; (iii) simulation models; and (iv) cost minimization models. However, these authors recognize that most classifications of IAMs found in the literature allow for some overlap between sub-groups of IAMs, since there are models that fit into more than one classification.

Figure 1: Interactions Between Economic and Climate Systems



Source: Edwards *et al.*, (2005)

Several IAMs, policy evaluation or computable general-equilibrium (CGE) models have been used in the climate policy debate. Each of these models has its characteristics, strengths and weaknesses, in general associated with the focus that the particular model puts in specific aspects of the analysis. We reviewed a number of these models in order to identify such characteristics and determine which aspects we would like DICER to be focused on. A summary of these models is provided in Table 1. The list of models presented here is not exhaustive; a large number of other models can be found in the literature but the main issues of all models are covered in what is reported.

The Dynamic Integrated model of Climate and the Economy (DICE) comprehends a set of climate-economy models developed at Yale University for the investigation of climate change. Its latest version available by the time we started to develop DICER, DICE2007 (Nordhaus, 2007), incorporates a number of methodological developments and data to its previous versions, for example, DICE99 (Nordhaus, 1994; and Nordhaus and Boyer, 2000). Other models of the DICE family include the multi-region version, RICE (Regional Integrated model of Climate and the Economy – Nordhaus and Yang, 1996), and a version that introduces endogenous technology changes, ENTICE-BR (Popp, 2006). According to Nordhaus (2007, 2008), one of the main advantages of DICE2007 is that the basic trends and tradeoffs of the economy can be captured rather accurately, and the underlying model is much more transparent and easily modified by researchers. However, some of its limitations are also well known. For example, Nordhaus (2007) observes that the climate module embedded in DICE tends to over predict the historical temperature change given estimates of emissions and radiative forcings (although our own analysis suggests that DICE underestimates the forcings for the future); and the damage functions are the major source of modelling uncertainty in the DICE2007 model. Another shortcoming of the DICE2007 model, which presents a globally aggregated approach, is that it cannot calculate the costs and benefits of impacts and mitigation on individual regions and countries. These issues have been addressed in DICER and constitute the major differences from DICE2007[7].

Other IAMs have been constructed as advancements from the DICE family of models, but focusing on different methodological aspects. For example, Buchner *et al.* (2005) describe the FEEM-RICE model as an extended version of the RICE model, which incorporates endogenous technical change (in addition to induced technical change) in order to respond to climate-change policies as well as to other economic and policy incentives. The fundamental driver of technical progress in FEEM-RICE is R&D investment, which induces knowledge accumulation and experience in emission abatement, and these variables move technology towards a more environmentally-friendly dynamic path (Bosetti *et al.*, 2006). Along the same lines, the World Induced Technical Change Hybrid (WITCH) model includes an energy input specification that operates as a bottom-up model. It is based on a development of the FEEM-RICE model (Bosetti *et al.*, 2007). An important distinction of WITCH is that energy demand is not exclusively defined by electricity consumption, as in DEMETER and MIND (Edenhofer *et al.*, 2006). The optimal path of the control variables is determined within a game-theory framework where each region plays a non-cooperative Nash game in a dynamic setting that yields to an Open-Loop-Nash equilibrium. The equilibrium solution is obtained such as each region´s choice is the best response to all other regions´ best response to its behaviour (Bosetti *et al.*, 2007). In DICER we obtain the optimal solution via maximizing (i) the sum of average regional utilities of consumption per capita as well as (ii) the average utility across regions (or the utility of aggregated regional consumption)[8].

[7] We started to develop the DICER model in January 2009. However, in August 2009 a new version of the RICE (RICE2009) and DICE (DICE2009) models were made available to the research community and also cover some of these issues (e.g. Nordhaus, 2009).

[8] Other regional IAMs treat global utility as the Negishi weighted sum of regional utilities (e.g. RICE2009 and AIM). However, Negishi welfare weights constrain possible solutions to those which are consistent with the existing distribution of income, imposing the assumption that human welfare is more valuable in richer parts of the world, therefore, eliminating the global welfare gain from income redistribution (Stanton *et al.*, 2008). We plan, however, to investigate in DICER different forms of aggregating regional utility and their impact on our results.

Table 1: General characteristics of selected IAMs and CGE models

Model	Regional or global	GHG gases	Number of economic sectors	Time span
DICE2007 Nordhaus, 2008	Global: aggregate of 12 regions	CO_2	1 single product (sector)	10-year periods up to 2200
FEEM-RICE Bosetti *et al.*, 2006	Regional: 10 regions	CO_2	1 single product (sector)	10-year periods up to 2200
WITCH Bosetti *et al.*, 2007	Regional: 12 regions	CO_2	1 single product (sector)	5-year periods; for 100 years
MERGE Manne *et al.*, 1995	Regional: 5 regions	CO_2, CH_4, N_2O	Energy products (electric and non-electric)	10 years from 1990 to 2050; 25 years from 2050 to 2200.
ICAM Dowlatabadi, 1998	Regional: 17 regions	CO_2	----	5-year periods; from 1975 to2100
MIND Edenhofer *et al.*, 2006	Global: 1 region	CO_2 and SO_2	1 aggregate production sector	5-year periods; from 1995 to 2300
DEMETER Gerlagh, 2006	Global	CO_2	3 sectors: final consumption good; energy based on fossil fuels, and energy based on carbon-free technologies	5-year periods; for 150 years
FUND Tol, 1997	Regional: 9 regions	Industrial CO_2	----	1-year periods; from 1950 to 2200
PAGE2002 Hope 2006	Regional: 8 regions	CO_2, CH_4, SF_6	----	10-year (1990-2000); 20-year (2020-2100) and 25-year (2125-2200)
E3MG Barker *et al.*, 2006	Global	CO_2	Energy and export demand	10-year periods; 2000 to 2100
DNE21+ Sano *et al.* 2006	Regional: 77 regions	CO_2	Energy sector	5-year (2000-2030); 10-year (2030-2050) and 25-year (2050-2100)
GET-LFL Hedenus *et al.*, 2006	Global	CO_2	3 end-use energy sectors: electricity, transportation and heat	30 years
GTAP-E Wang and Nijkamp 2007	Regional: up to 113 regions	CO_2	37	---
Imaclim-R Crassous *et al.*, 2006	Regional: 5 regions	CO_2	10	1-year period; from 1997 to 2100
AIM Masui *et al.*, 2006	Regional: 6 regions	CO_2	9	5-year period from 1995 to 2000; 10-year periods from 2000 to 2100
EPPA Yang *et al.*, 2005	Regional: 16 regions	CO_2, CH_4, N_2O, HFC, PFC, SF_6	---	5-year period; from 2000 onwards

Another relevant IAM used for policy evaluation is the MERGE model, described by Manne *et al.*, (1995), which consists of three modules or sub-models: (i) Global 2200, a fully integrated applied general equilibrium model that is used to assess the costs of alternative emission constraints at the regional and global level; (ii) the climate module; and (iii) the damage assessment module. One recognized weakness of MERGE is its treatment of uncertainty: the authors recognize that it needs to provide the capability to replace point estimates with probability distributions reflecting the full range of possible outcomes (climate-related risks). We have plans to introduce an explicit uncertainty treatment in future stages of the development of DICER.

The Climate Framework for Uncertainty, Negotiation and Distribution (FUND) is a policy optimization model that advices policy makers what an optimal policy looks like, given a specific scenario, rather than evaluating the economic and climate consequences of proposed policies (Tol, 1997). This is because FUND is not a CGE-type of model. All variables used in the model are either directly or indirectly determined by exogenous scenarios[9]. As a result, the costs associated with emission reduction policies are weighted against the avoided damage of climate change by using the criteria of comparing the net present value of average utility. FUND´s damage module, however, is more detailed than the other IAMs. The most relevant difference is that impacts of climate change in FUND depend to a large extent on the rate of climate change (benchmarked at 0.04^{o}C/year), the level of change (benchmarked at 2.5^{o}C) and on vulnerability, which is a function of per capita income. We have incorporated in DICER´s damage function some aspects of FUND´s damage functions (e.g. intangible damages).

Policy Analysis for the Greenhouse Effect, PAGE, is a computer simulation model for use in decision making within the European Commission. For a given set of policies, the PAGE model is run repeatedly using a random sample of uncertain input parameters (from a set of parameters defined by expert opinion), building up an approximate probability distribution for each model output covering: temperature rise, climate change damages, adaptive and preventative costs. This enables decision makers to perform a risk analysis and select the policy that balances the costs of intervention against the benefits of mitigating potential impacts (Plambeck *et al.*, 1997). PAGE emphasizes on the climate model; the economic module is restricted to estimating the damage cost associated with the risen temperature. The level of damage depends on the rate at which temperature rises as well as on the magnitude of increase. In this regard, PAGE95 takes an enumerative approach in which the total damage of climate change is the sum of damages in individual sectors. Plambeck *et al.*, (1997) recognize that this approach for estimating the damage costs of climate change leads to lower valuation of impacts than the more traditional general equilibrium approach used in other IAMs, which can account for higher order of interactions such as the impact of changes in agricultural output on the food industry. However, the authors believe that using highly aggregated damage estimates from the literature allows PAGE95 to capture interaction effects implicitly.

Impacts are assumed to occur only for temperature rise in excess of a tolerable rate of change or temperature changes above a tolerable plateau. Adaptation policies can increase the tolerable level of temperature rise. However, PAGE95 computes damages based on temperature increase, not GHG concentrations. The damage function in PAGE95 is calibrated to agree with a linear damage function for a benchmark temperature increase (2.5^{0}C) above the tolerable level. Hope (2006) presents the advances incorporated in the PAGE95 model for a more recent version of the

[9] Exogenous scenarios refer to the rate of economic and population growth; autonomous energy efficiency improvements; the rate of de-carbonization of the energy use; methane and nitrous oxide emissions.

PAGE model, PAGE2002. The main structural changes in PAGE2002 are the introduction of a third GHG (SF_6, Sulfur Hexafluoride), the incorporation of possible future large-scale discontinuities into the impact calculations of the model, in addition to the updated values for parameters (mostly taken from the IPCC Third Assessment Report) and the inclusion of an extra region of the world. The discontinuity issue relates to the modeling of climatic change impacts in each analysis year as a polynomial function of the regional temperature increase in that year above the time-varying tolerable level of temperature change.

3 The DICER Model

This section aims to describe the main features of DICER. We describe its major building blocks, how they differ from DICE2007 and why we think they were necessary changes from the original model. As it would be expected, the equations and description of DICER rely on the description of the DICE2007 model as in Nordhaus (2007).

As in DICE2007, the DICER model views the economics of climate change from the perspective of the neoclassical economic growth theory, in which economic agents invest in capital, education and technology in order to increase consumption in the future. DICER is a regional model that aggregates countries into regions with one output per region, which aggregates its capital stock, technology and emissions (natural capital). Global aggregates are estimated from data including all major countries from eight regions using PPP exchange rates. The regions[10] are assumed to have their preferences defined by a social welfare function that ranks different paths of consumption that are constrained by both economic and geophysical relationships. The welfare function (1) is the discounted sum of the population-weighted utility of per capita consumption, and is increasing in (per-capita) consumption of each generation, with diminishing marginal utility of consumption. The only commodity that represents the economy can be used for consumption and investment. The ´generalized´ consumption flow of consumption over time; i.e. policies are chosen to maximize the social welfare function (exogenous variables are in bold):

$$W_r = \sum_{t=1}^{Tmax} U_r[c_r(t), L_r(t)].(1+\rho)^{-t} \qquad (1)$$

$$U_r[c_r(t), L_r(t)] = L_r(t).\left[\frac{c_r(t)^{1-\alpha}}{1-\alpha}\right]$$

$$c_r(t) = C_r(t)/L_r(t)$$

[10] Most regional models separate the regions according to some mix of economic, geographical and GHG emission criteria (also an economic criterion). Some of the most important players in the climate change arena are always kept separately as a single region. In all models the authors seem to look for a compromise between policy relevance and modeling tractability. Thus, our regions were defined as: US (USA, Puerto Rico and the US Virgin Island); OECD-EU; China (and Hong Kong); India; OECD-non-EU (Australia, Canada, Japan, Korea, Mexico, New Zealand, Turkey); FOREST (Brazil, Indonesia, DR Congo and Malaysia); FSU_EE; and Rest of the World (143 more countries).

Where:

W_r	Welfare function of region (r);
U_r	Utility function of region (r);
$C_r(t)$	Consumption of goods and services (trillions of US$);
$c_r(t)$	Per capita consumption of goods and services (US$ per person);
$\boldsymbol{L_r(t)}$	Population and proportional to labour inputs (millions);
$\boldsymbol{\rho}$	Pure rate of social time preference (per year);
$\boldsymbol{\alpha}$	Elasticity of marginal utility of consumption;
$\boldsymbol{T_{max}}$	Length of estimate period for model (1 period = 10 years);
$\boldsymbol{t}$	Time (decades from 2008-2018; 2018-2028…);
$\boldsymbol{R(t)=(1+\rho)^{-t}}$	Social time preference discount factor (per time period);

Two major decision variables in DICER are the savings rate for physical capital accumulation and the emissions control rate for GHG. Capital accumulation is endogenously determined by optimizing the flow of consumption over time. Each region is endowed with an initial stock of capital and labour, and an exogenous region-specific level of technology. Technological changes are of two forms: economy-wide and carbon-saving, which is modelled as reducing the ratio of CO_2 emission to output. Output is determined with a constant-return-to-scale Cobb-Douglas production function in capital, labour and energy, which takes the form of either carbon-based or non-carbon-based fuels. Carbon fuels are limited in supply and fuel substitution over time from carbon-based to non-carbon-based is possible as carbon-based fuels become more expensive due to exhaustion or policies. In mathematical form, the global aggregate is given by:

$$Q_r(t) = [1 - \Lambda_r(t) - D_r(t)].A_r(t).K_r(t)^{\gamma}.L_r(t)^{1-\gamma} \tag{2}$$

$$D_r(t) = CAP_r.\left[1 - \frac{1}{1+\left\{a_r.\left(\frac{To_r+\Delta T(t)+\sqrt{(To_r-\Delta T(t))^2+0.001}}{2}+c_r\right)^2+d_r\right\}}\right] \tag{3}$$

$$\Lambda_r(t) = \Psi_r(t).\theta_{r_1}(t).\%GHG(t)^{\theta_{r_2}} \tag{4}$$

$$K_r(t) = I_r(t) - \delta_K.K_r(t-1)$$

$$Q_r(t) = C_r(t) + I_r(t)$$

$$\Psi(t) = \varphi(t)^{1-\theta_2}$$

Where:

$Q_r(t)$	Net output of goods and services, net of abatement and damages (trillions US$);
$D_r(t)$	Damage function in region (r) (climate damages as a fraction of world output);
$\boldsymbol{CAP_r}$	The highest percentage of GDP allowed as climate change damage;
$\boldsymbol{T0}$	The temperature at which the climate damage is no longer negative;
$\boldsymbol{a_r,b_r,c_r}$	Parameters of the damage function;
$\Lambda_r(t)$	Abatement cost function (as a fraction of world output);

A_r (t)	Total factor productivity (productivity units);
K_r (t)	Capital stock (trillions of US$);
I_r (t)	Investment (trillions of US$);
γ_r	Elasticity of output with respect to capita (pure number);
Ψ_r	Participation cost mark-up (abatement cost with incomplete participation as fraction of abatement cost with complete participation);
φ_r (t)	Participation rate (fraction of emissions included in policy);
$\theta_{r1}(t)$, θ_2	Parameters of the abatement cost function;
δ_K	Rate of depreciation of capital (per period);
$T_{AT}(t)$, $T_{LO}(t)$	Global mean surface temperatures, temperature upper ocean and lower oceans (^oC from 1990) – further discussed below;

The damage function, equation (3), assumes that damages are functions of global mean temperature change and limited to a maximum potential GDP loss. Another assumption is that the damages of climate change are likely to be larger for poor, small and tropical countries than for rich and larger countries in mid-latitude. The damage curves are derived from estimates of the damage for eight regions of the world, obtained in the pertinent literature[11]. For some regions we could only identify one estimate per temperature change and in this case the choice of estimates was obvious. In other cases where several estimates were available for the same temperature change and region we selected the central estimate of the interval. Initially, we decided to follow the literature and derive our regional damage functions as an exponential damage function of the form $D(t) = a.\Delta T(t)^b$. This worked well for positive estimates of damages and the results showed considerable different powers across regions. For example, the estimated function for India was $D_4(t) = 0.017\Delta T(t)^{1.15}$ while for region 8 (RoW) the damage function was $D_8(t) = 0.001.\Delta T(t)^{4.10}$. The result for group ´Forest´ (Brazil, Indonesia, Malaysia and DR Congo) was almost linear: $D_6(t) = 0.017.\Delta T(t)^{1.01}$.

However, some damage estimates available at the regional level are given for ΔT equal to 1^oC, which may correspond to negative damage estimates (benefits from climate change) in certain regions. This fact forced us to assume a different functional form for the damage function: a translated parabola suggested in Roughgarden and Schneider (1999) in the form: $D_r(t) = a_r.(\Delta T(t) + c_r)^2 + d_r$. We have also introduced a limit or a cap to the percentage of damage accepted for each region; a region-specific damage cap according to the general expectation in the literature. For example, damages in Africa are widely expected to be higher than in the US for any given positive temperature change.

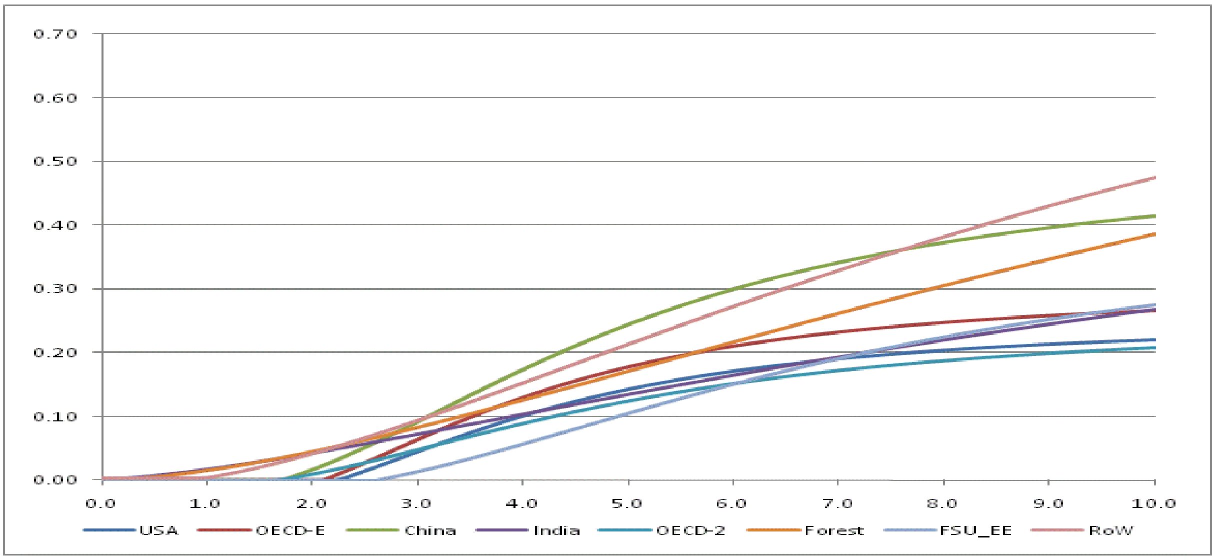
Attempts to calibrate DICER using region-specific translated-parabola damage functions were not successful because of the non-monotonic feature of some of our damage functions; i.e. for regions where some benefits of climate change are expected for a small increase in average atmospheric temperature our damage functions are decreasing between zero (no climate change) and

[11] Tol and Frankhauser (1998) observed that the monetization of damages is in general based on a small number of studies, mostly developed to the USA, a trend still in practice (Ortiz and Markandya, 2009).

1°C. In order to overcome such limitation we assumed "zero damage" where our damage functions predicted negative damages, on the basis that we have also ignored in our model ancillary benefits of mitigations that could to some extent over-compensate the positive impact of mild temperature increase. Figure 2 shows the curves.

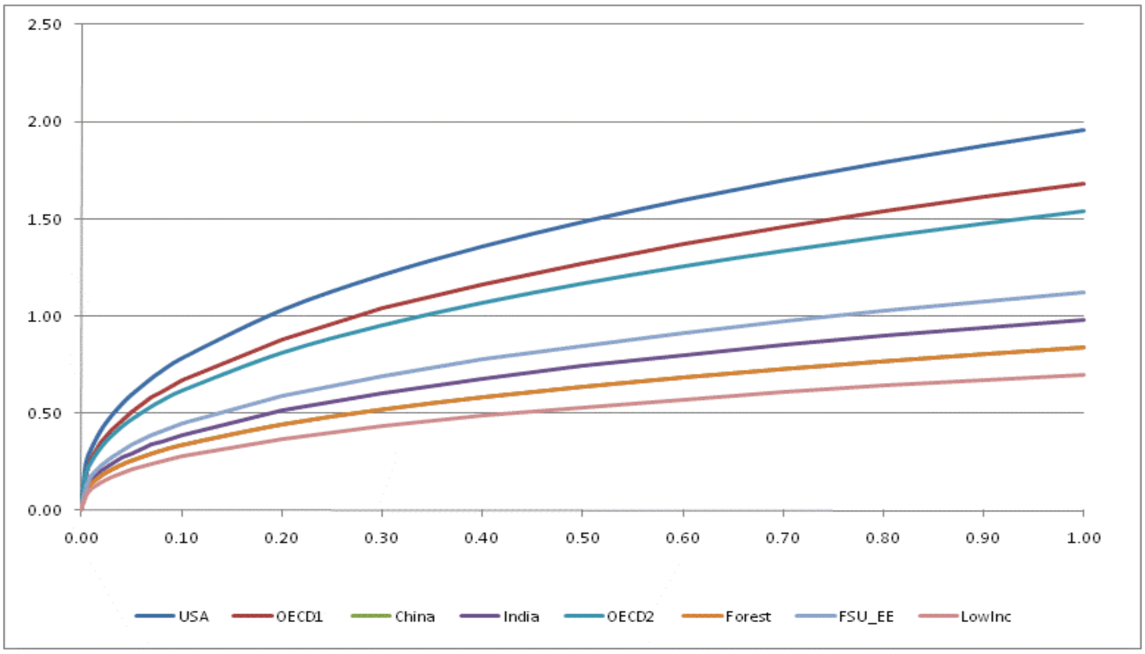
The family of abatement cost curves, represented by equation (4), assumes that the abatement costs are proportional to global output and to a polynomial function of the emissions-reduction rate. We started by estimating an abatement cost curve of the general form: $P = \alpha.\%GHG^{\beta}$, using data for the US (Paltsev *et al.;* 2007), who used the MIT-EPPA model to assess several cap-and-trade policies for the US under several scenarios. These policies specified emission reductions to be reached by year 2050 for several GHG gases. Using their results on GHG emissions and social cost of carbon at years 2015 to 2050 for the reference case and three core scenarios (167, 203 and 287 billions of metric tons) we obtained three points with which to fit an abatement cost function.

Figure 2: Damage functions used in DICER



We then used our estimated US abatement cost curve for year 2050 as a benchmark in order to calibrate cost functions for all other regions, by adjusting parameter alpha while keeping constant parameter beta. We took information found in the pertinent literature: for example, that abatement costs in Japan and Europe are potentially higher than in the US; that developing countries have comparative advantage to their developed counterparts, although these advantages tend to diminish over time, leading to lower costs of emissions´ abatement. Figure 3 shows the shape of the obtained curves. We believe that our marginal abatement cost functions form an envelope of current estimates derived from bottom-up models.

Figure 3: Marginal abatement cost curves (2050)



Note: Estimated by the authors using an estimated US MAC and expert opinion; %GHG reduction (horizontal axis); the abatement cost is given as %GDP (vertical axis).

Similarly to DICE2007, DICER introduces the natural capital of the climate system as an additional type of capital stock; i.e. GHG concentration is seen as a negative natural capital and emissions reductions as investments that lower the stock of negative natural capital. In this framework, the economic agents substitute consumption in the present for preventing climate change in the future and increasing future consumption possibilities. DICER includes a backstop technology[12] for non-carbon-based energy, which allows the complete replacement of all carbon fuels at a relatively high price that is decreasing over time.

The only GHG directly subject to controls in DICER is industrial CO_2. Emissions from land-use change are specified as an exogenous trend, as in DICE. We treat other climate forcing agents, including other well-mixed GHGs, tropospheric ozone, and warming and cooling aerosols, differently from DICE, which specifies an exogenous future trajectory for total non-CO_2 radiative forcing that we found to be unrealistically low compared to scenarios in the literature – rising from slightly negative at the present to slightly positive after 2020 and staying low thereafter. We therefore developed a formula in which the total non-CO_2 forcing is scaled to the CO_2 forcing calculated by the model. This scaling is a simple linear relationship derived from linear regression that we calculated for a number of future emission scenarios in the literature (specifically, IIASA´s MESSAGE reference

[12] Backstop technology is defined as a technology that produces a substitute to an exhaustible resource by using relatively abundant (no scarcity) production inputs and turns the reserves of the exhaustible resource obsolete. It provides resources at a constant marginal cost for an indefinitely long time (Dasgupta P. and G. Heal, 1979), *Economic Theory and Exhaustible Resources*, Cambridge: Cambridge University Press).

and mitigation scenarios and an "equal quantile walk" scenario from Meinshausen[13]). A linear relationship between non-CO_2 and CO_2 forcing makes intuitive sense, as emissions of non-CO_2 GHGs and aerosols tend to be higher when CO_2 emissions are higher, and are abated when CO_2 is abated.

Emissions are projected as a function of (i) total output; (ii) an emission-output ratio that varies over time estimated for all regions; and (iii) an emission control rate determined by the climate-change policy under examination. Uncontrolled industrial CO_2 emissions, $E_{Ind}(t)$, are given by a level of carbon intensity, $\sigma_r(t)$, times world output. Actual emissions are then reduced by the emissions-reduction rate, $\mu(t)$. DICER assumes that incremental extraction costs are zero and that carbon fuels are optimally allocated over time by the market, producing the optimal Hotelling rents. Equation (6) imposes a limitation on total resources of carbon fuels.

$$E_r(t) = E_{rInd}(t) + E_{rLand}(t)$$

$$E_{rInd}(t) = \sigma(t).[1-\mu(t)].A_r(t).K_r(t)^{\gamma}.L_r(t)^{1-\gamma} \quad (5)$$

$$CCum \leq \sum_{t=0}^{T_{max}} E_{rInd}(t) \quad (6)$$

Where:

$E_r(t)$	Total carbon emissions (billion metric tons C per period);
$\boldsymbol{E_{rLand}(t)}$	Emissions of carbon from land use (billion metric tons C per period);
$E_{rInd}(t)$	Industrial carbon emission (billion metric tons C per period);
$\mu(t)$	Emissions control rate (fraction of uncontrolled emissions);
$\boldsymbol{\sigma_r(t)}$	Ratio of uncontrolled industrial emissions to output (metric tons C per output);

DICER, similar to DICE2007, includes several geophysical relationships – a carbon cycle model (7); radiative forcing equation (8); climate-change equations (9); and climate-damage relationship – that link the economy and the factors affecting climate change. Accumulations of GHG is assumed to be linked to temperature rising through increases in radiative forces, this relationship being derived from empirical measures and existing climate models (e.g. MAGICC, 2007). The geophysical equations (the climate module) are as follows:

$$M_{AT}(t) = E(t) + \phi_{11}.M_{AT}(t-1) + \phi_{21}.M_{UP}(t-1) \quad (7)$$

$$M_{UP}(t) = \phi_{12}.M_{AT}(t-1) + \phi_{22}.M_{UP}(t-1) + \phi_{32}.M_{LO}(t-1)$$

$$M_{LO}(t) = \phi_{23}.M_{UP}(t-1) + \phi_{33}.M_{LO}(t-1)$$

$$F(t) = \eta.\left[log_2\left(\frac{M_{AT}(t)}{M_{AT}(1750)}\right)\right] + F_{EX}(t) \quad (8)$$

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1.[F(t) - \xi_2.T_{AT}(t-1) - \xi_3.[T_{AT}(t-1) - T_{LO}(t-1)]]$$

[13] Meinshausen's analysis using SIMCaP – Simple Model for Climate Policy Analysis (www.simcap.org).

$$T_{LO}(t) = T_{LO}(t-1) + \xi_4 . [T_{AT}(t-1) - T_{LO}(t-1)] \quad (9)$$

Where:

$M_{AT}(t)$	Mass of carbon in reservoir for atmosphere (billions of metric tons C, beginning of period);
$M_{UP}(t)$	Mass of carbon in reservoir for upper oceans (billions of metric tons C, beginning of period);
$M_{LO}(t)$	Mass of carbon in reservoir for lower oceans (billions of metric tons C, beginning of period);
ϕ_{11}, ϕ_{21}	Parameters of the carbon cycle (flow per period);
ϕ_{22}, ϕ_{23}	Parameters of the carbon cycle (flow per period);
$\phi_{32}, \phi_{12}, \phi_{33}$	Parameters of the carbon cycle (flow per period);
$F(t)$	Total radiative forcing (Watts per square meter from 1990);
$F_{EX}(t)$	Non-CO_2 radiative forcing (Watts per square meter from 1990);
η	Temperature-forcings parameter (^{o}C per Watts per meter square);
ξ	Parameters of climate equations (flows per period);

User interface and other data issues

A user-friendly interface was developed using Excel in order to facilitate the model´s runs and data management. The interface links the data and parameters used in DICER with the model´s codes developed in GAMS and the output interface in which the results of each run are shown. All the necessary data for DICER was gathered for year 2008, at the country level when possible, and aggregated according to our selection of regions. This characteristic allows us to easily run the model with different redefined regions if necessary. In addition, any parameter used in DICER can be corrected or updated without the need of changing the model´s codes, reducing the risk of errors.

General macroeconomic data per country were obtained in the World Economic Outlook (WEO) database of the International monetary Fund (IMF). Data for the countries that eventually were not in the WEO database were obtained in other sources (e.g. national statistics organizations). The forecasts of population per country in years 2100, 2200 and 2300 were given by the United Nations publication (UN ´World Population 2300´, 2004). Carbon emissions were obtained with the US Energy Information Administration (EIA - World Carbon Dioxide Emissions from the Consumption and Flaring of Fossil Fuels, 1980-2006). Emissions from land use and land use change data were obtained in the UNFCCC database (Annex-I countries). Carbon concentration in the atmosphere was given in the Earth System Research laboratory, NOAA. Estimates of the total amount of fossil fuel available in the world were produced based on data provided in the BP Statistical review of World Energy (2008).

4 Main Results

This section describes some initial results obtained with the calibration of the DICER model in its deterministic version, for an optimal policy scenario (i.e. full participation in emission control schemes) in which climate change policies maximize global economic welfare. These results represent only the optimization process in which we maximize the utility of aggregated regional consumption. Whenever possible we compare our results with similar results obtained with other IAM´s, mainly DICE2007 and RICE2009 (Nordhaus, 2009).

Some relevant results are shown in Figure 4 through Figure 10. Atmospheric concentration of CO_2 peaks at approximately 500ppm around year 2068 (Figure 4) whereas in RICE2009 the maximum concentration is between 500 and 550ppm by year 2085. This result is likely to be driven by our changes in the climate module of DICER involving higher non-CO_2 radiative forcings. As a result, total radiative forcings in DICER peaks at 4.4 Watts/m^2 (Figure 6) while in RICE2009 it peaks at 3.8 Watts/m^2. Atmospheric temperatures in DICER (Figure 5) peak at 2.6^{o}C around year 2078; the equivalent in DICE2007 is 3.5^{o}C in year 2185 and 2.4^{o}C around year 2115 in RICE2009.

Figure 4: CO_2 atmospheric concentration (ppm)

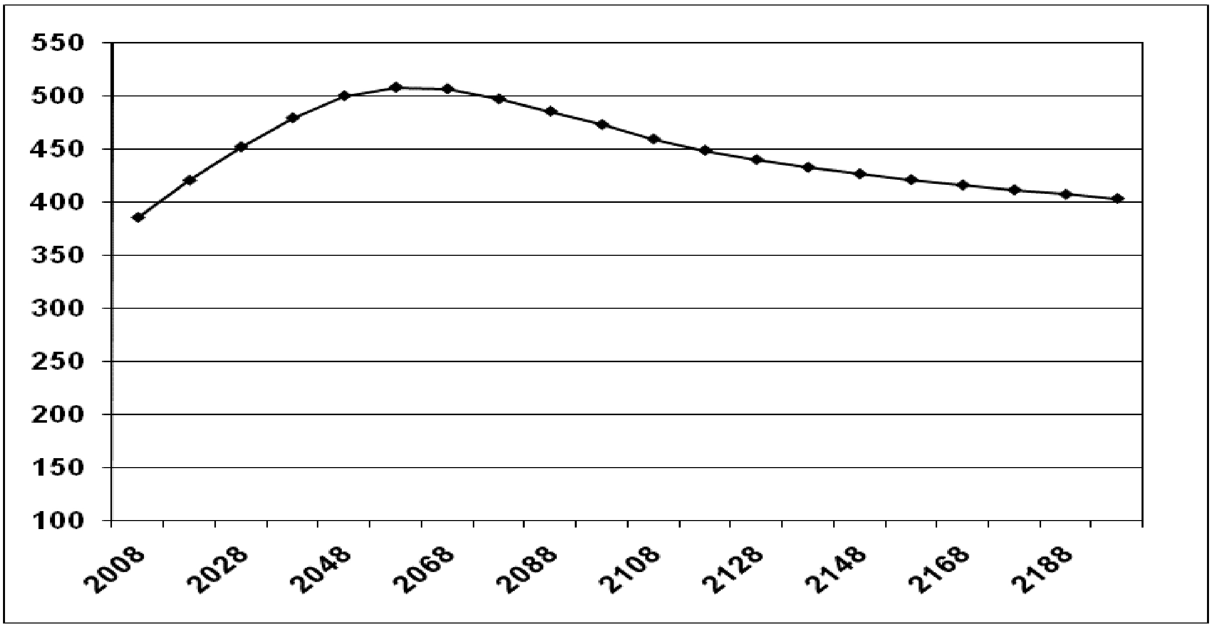


Figure 5: Atmospheric temperature (^{o}C)

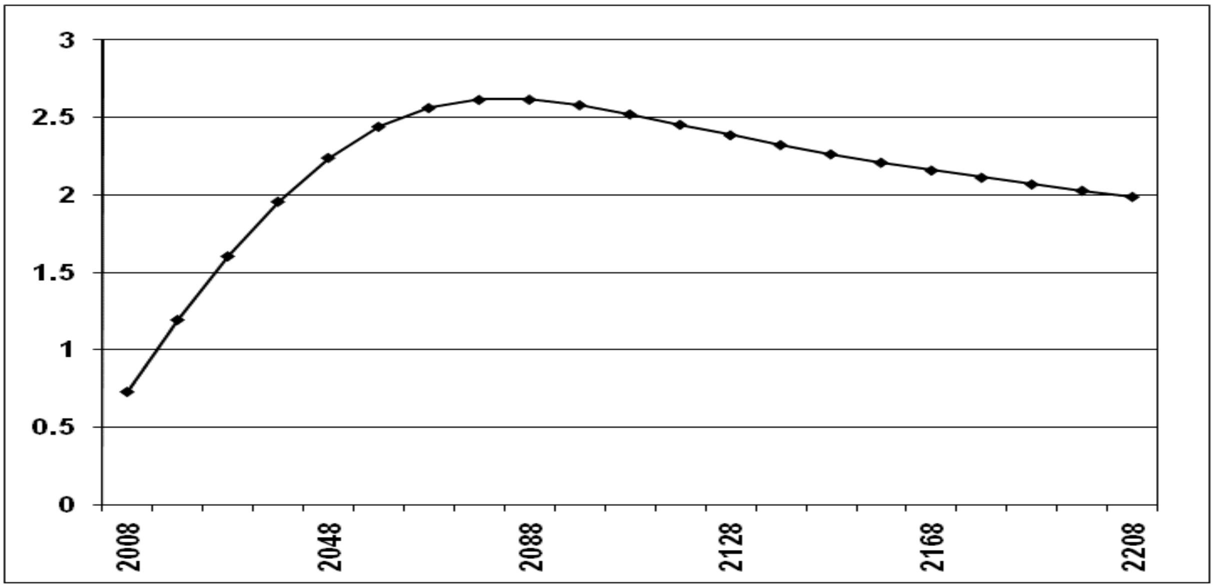
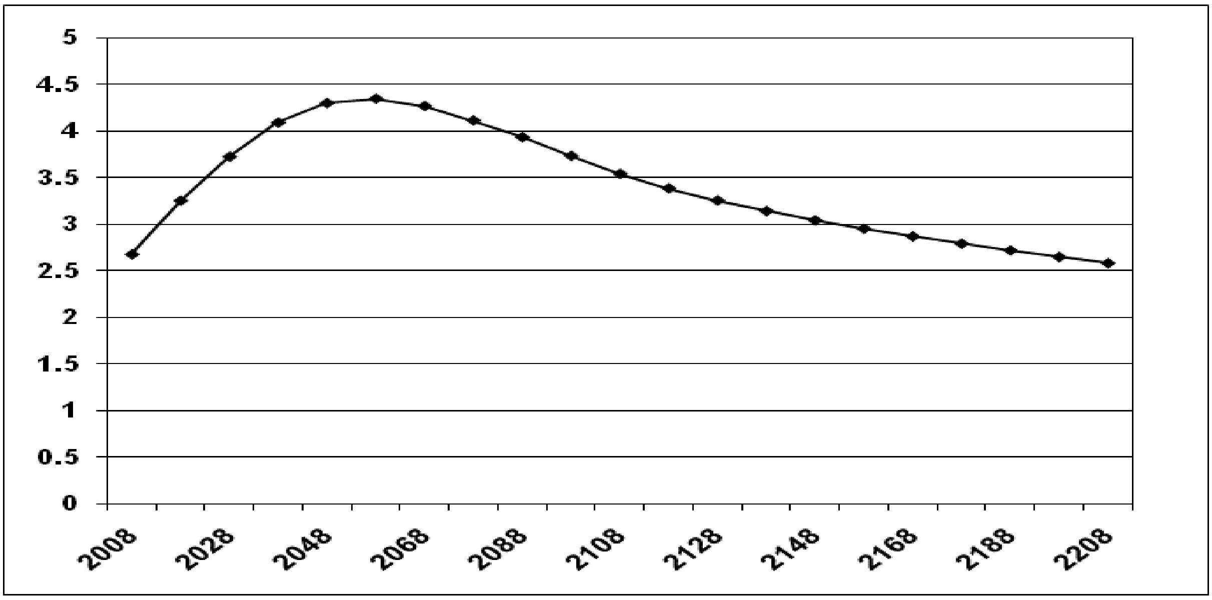


Figure 6: Radiative forcings (Watts/m^{2})



The results in Figure 7 suggest that by the beginning of the next century all regions would reach 100% of emission control rate, the extent to which GHG emissions are reduced from their 'reference levels' or the levels that would prevail with no climate policies. In DICE2007, the control rate is 44.3% around the same period in time. Thus with the plausible changes we made we get a much more rapid reduction in emissions than DICE2007, something that is of importance in policy terms.

Our estimates of the social cost of carbon (Figure 8), or the present value of contemporaneous and future economic damages caused by an additional ton of carbon emission, are higher than those presented in Nordhaus (2008) for the optimal policy scenario in DICE2007. We should also note that our estimate compares to some specific (more restrictive) policy scenarios in Nordhaus (2008), such as limiting temperature increases to 1.5°C or limiting GHG concentration to 1.5 times the preindustrial level.

Figure 7: Emission control rate GHGs (%)

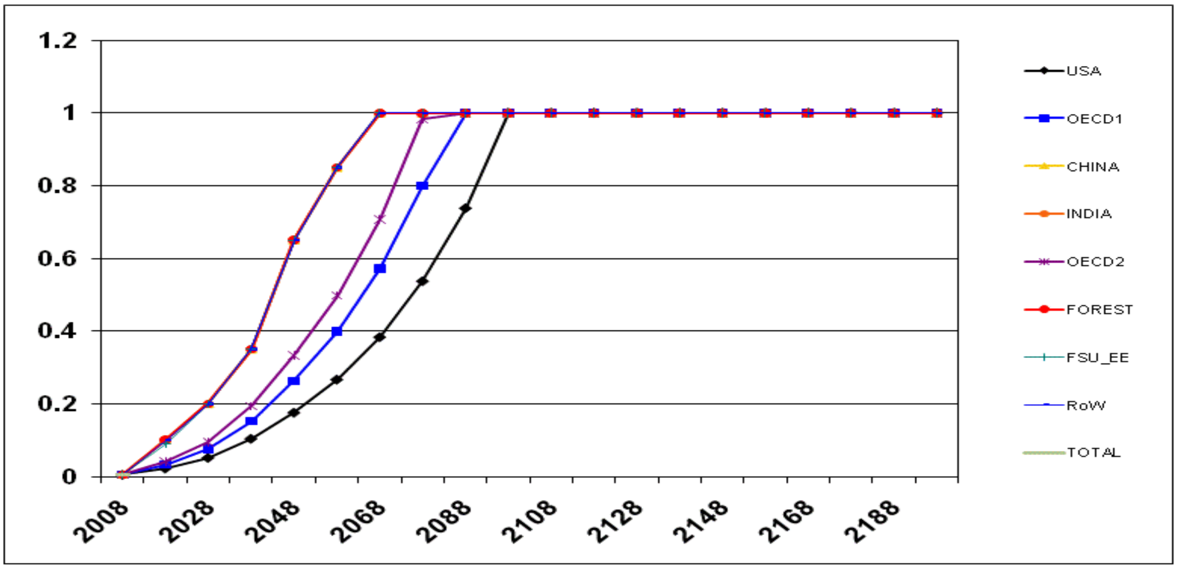
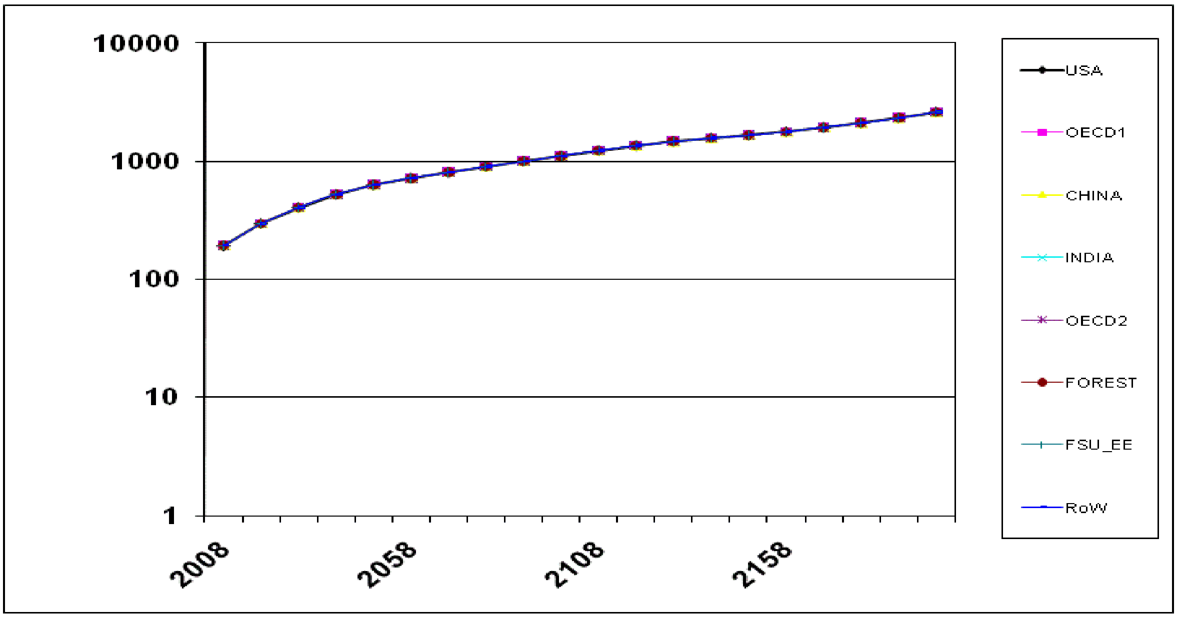


Figure 8: Social Cost of Carbon ($/tC)



Note: In an optimal policy regime, the social cost of carbon equals the optimal carbon tax.

Emission abatement costs estimated in DICER (Figure 9) are crescent-shaped in all regions until the second half of this century, when they start to decline sharply in most regions (in the US it starts to decline at the end of this century). These results compare to those presented in RICE2009, although Nordhaus (2009) only presents results until year 2045. Figure 10 presents total damage costs per region as estimated in DICER. The peak values correspond to our peak temperature change equal to 2.6°C around the second half of this century, and to the percentage of GDP estimated in our damage functions.

Figure 9: Abatement costs (%GDP)

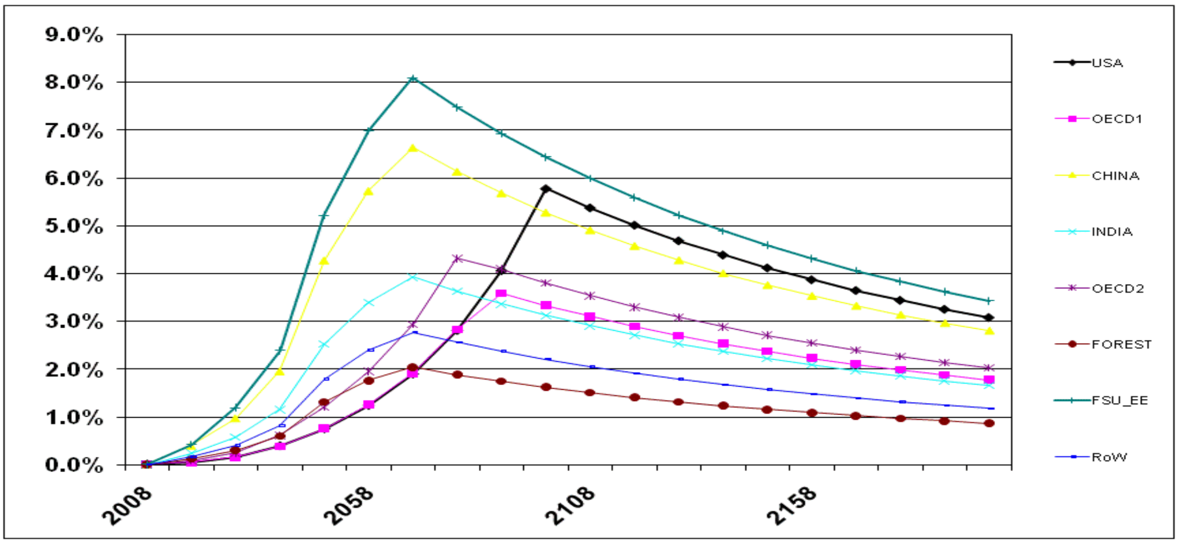
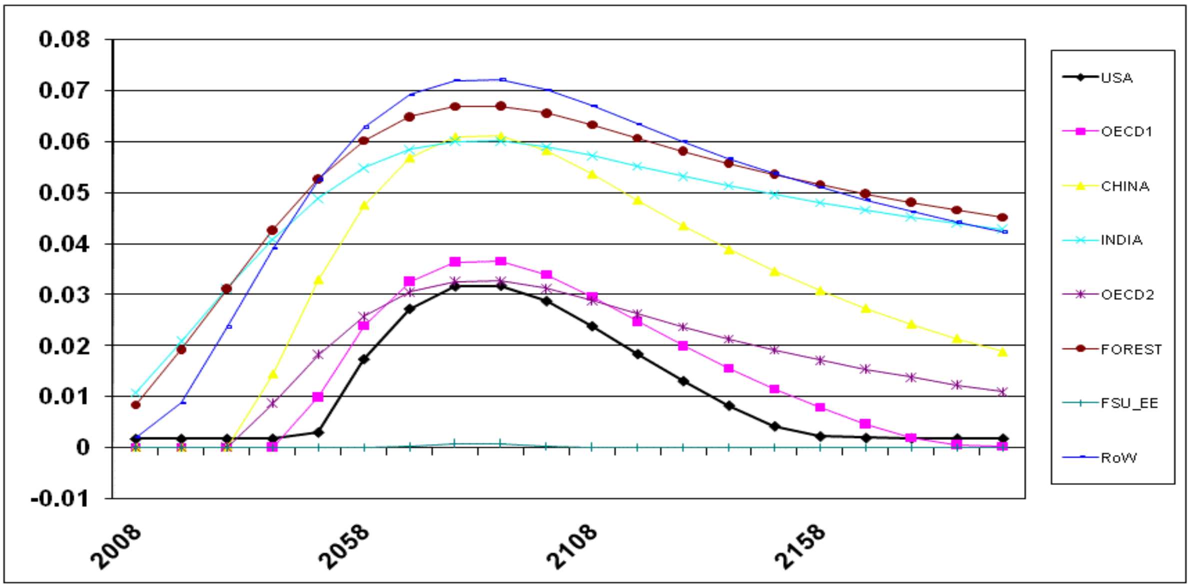


Figure 10: Damage costs (%GDP)



Monte Carlo simulations

We have performed Monte Carlo simulations in order to assess how our results are affected by uncertainty in a number of parameters in DICER. As an initial step towards treating uncertainty in DICER, we ran the model 1000 times randomly assigning values of each key parameter from an interval of possible values established in accordance with an assumed distribution for each parameter.

For this purpose, climate sensitivity was assumed to follow a log-normal distribution with parameters equal to 1.09 (ln mean) and 0.4 (ln std). Most other exogenous variables were assumed to have a triangular distribution with minimum and maximum values assumed around their observed initial value (see Annex). These (deterministic) DICER runs show us how the optimal strategy in DICER depends on exogenous parameters, in case the planner has full information about the future.

Figure 11 to Figure 13 show some examples of how atmospheric temperatures vary in DICER when we assume different random values for the climate sensitivity parameter and the economic exogenous variables (horizontal axis represents time periods of 10 years; i.e. T=10 represents 100 years). As can be seen, optimal policy is very much impacted by the climate sensitivity compared to business as usual (no participation in climate policy). Peak temperatures vary between 1.8^{o}C and 4.3^{o}C under optimal policy, depending on the assumed value of climate sensitivity (initial value equal to 3^{o}C) (Figure 11). The reduction relative to the business as usual is around 0.5 ^{o}C at the lower bound and 0.8 ^{o}C at the upper bound. Optimal policy is not so impacted with respect to economic variables, peak temperatures, varying between 2.2^{o}C and 2.6^{o}C under optimal policy but the reduction relative to business as usual is greater at the upper round – around 3 ^{o}C (Figure 12). The variation is even less impacted with respect to discount rate Figure 13. Future versions of the DICER model will include the treatment of uncertainty explicitly, aiming to produce a dynamic stochastic version of DICER.

Figure 11: Atmospheric temperature: (climate sensitivity randomly assigned; lognormal distribution)

Optimal Policy | Business as usual

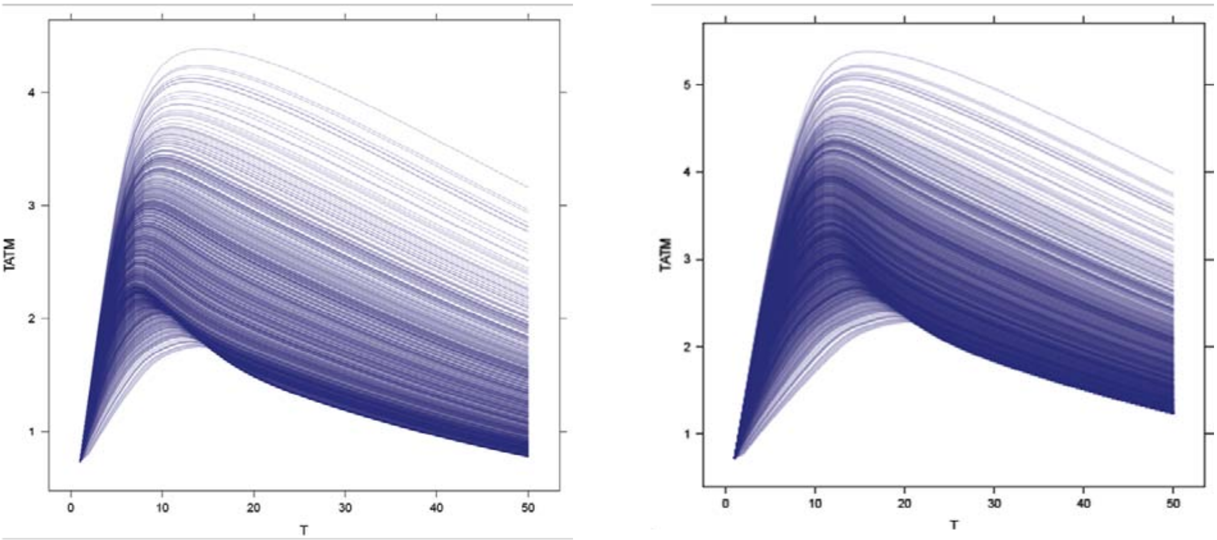


Figure 12: Atmospheric temperature: (all ´economy´ group randomly assigned; Triangular distribution)

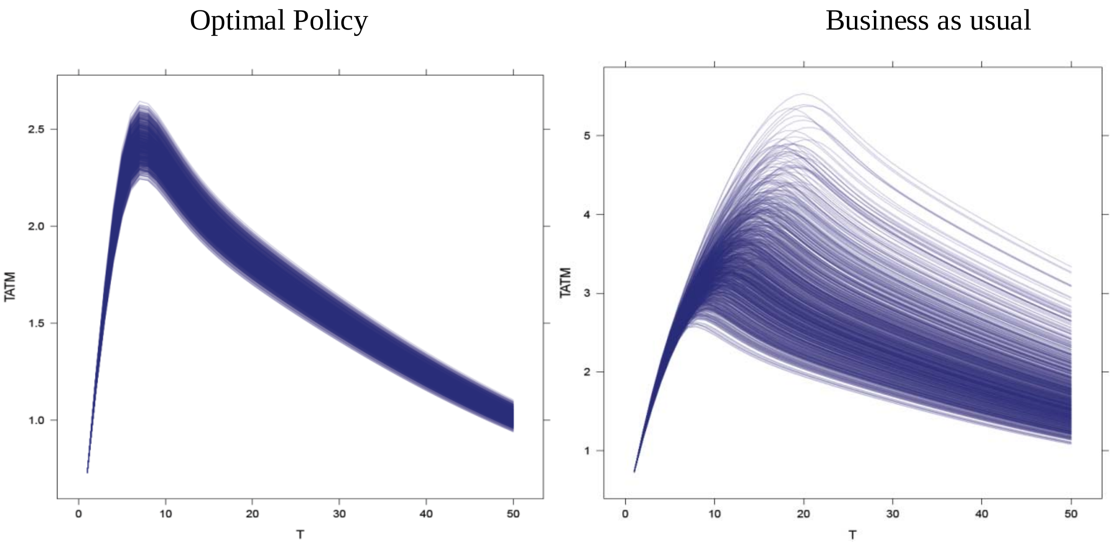
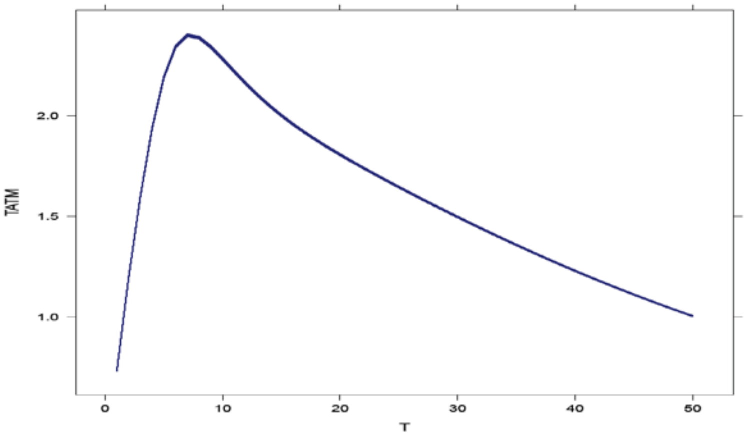


Figure 13: Atmospheric temperature: (discount rate – triangular distribution)



Risk-adjusted cost-benefit analysis of climate policy

We propose an alternative method to address uncertainties in DICER in the absence of running the fully stochastic dynamic version of DICER. This involves estimating some important properties of the optimal stochastic solution and then incorporating these into the deterministic run of DICER as an approximation to a stochastic solution. The key idea is to separate deterministic and stochastic analyses. Anda et al. (2009) provide the rationale for the suggested approach to dealing with irreversibility and the quantification of uncertainties in IAMs, which we summarize below.

The application of IAMs requires a single aggregate objective function, thus avoiding an otherwise complex multi-criteria optimization which would significantly complicate its computation.

Furthermore, this single criterion is a function aggregated overtime and, consequently, its value is sensitive to the rate of time preference. In addition, the criterion also is aggregated across different outcomes and appears in IAMs in a form of an expected value. As a result, the model relies on the aggregated estimation of various outcomes of climate policy over time, weighted and averaged by probabilities. The variance, skeweness, and kurtosis are important characteristics of uncertainties and risk associated with a climate policy, but can be easily lost in aggregation. A way round this is to use real option analysis (ROA), which explicitly accounts for the expected value of the underlying assets but also considers the shape of distribution and therefore factors in the variance of the expected value, as well as crucial moments of the distribution.

We start with an example of the simple case when decision regarding emission target should be taken now and considered to be fully irreversible over a given period. As in Gollier and Weitzman (2009), we assume two periods: period zero when decision on selection or rejection of the 450ppm target should be made[14] and period one (2010-2100) when the true cost and benefits of climate policy will be revealed. We can think of this in terms of a ´climate asset´ that corresponds to 450ppm. Holding this asset is like holding a share that has a cost now but its value is expected to drop in period one. The holder of this share can sell his/her right now and get the spot price that is equal to the avoided expected cost of climate policy. But if the owner of the share continues to hold it, the share may increase in value, and its owner would get benefits beyond the cost of holding. Lost benefits of trading this share now could be estimated as an option value -- i.e. the amount that the shareholder loses in period one. The lost value is calculated in terms of ´upsides vs. downsides´. Downsides are fixed: they are the negative expected value of climate policy while upsides could be calculated as the out-of-money option value.

The application of option pricing formulas is just a technical method to calculate upsides. The most direct and precise way of making the calculation would be the estimation of upsides during Monte-Carlo simulation. Upsides are equal to the expected value of benefits greater than the costs of the climate policy. The application of the Black-Sholes formula is one way to approximate this value. The option value is a function of the asset value (expected benefits of climate policy), implementation cost or strike price (expected cost of climate policy), volatility and risk-free interest rate. In the ´classical´ Black-Sholes formula the value of an asset is described by a differential equation that should be solved with respect to time. Dynamics of this value is a random walk and the underlying asset would gain and lose in value over time. In case of the climate asset, the central differential equation should be solved with respect to different outcomes of climate policy. For a given concentration target there is only one outcome which is unknown to the regulator at time zero and will

[14] Simplicity is helpful for a better understanding of core elements of ROA. For a more detailed analysis we could relax several assumptions. First of all, we could split period one by segments when we think climate policy could be adjusted. Selection of target should be a continuous process. All of that could be done in a modified IAM framework. However, each step of solving the model will be solving an option like the one described in this example albeit through a slightly more complicated process (option on option).

be revealed in the future when it is too late to change the policy. The cost of climate policy is uncertain too and therefore may exceed its expected level. Acceptance of climate policy in period zero means rejection of an option to save on mitigation costs. In contrast to the climate asset that has negative expected value but significant potential for upsides, the hypothetical asset that imitates savings on mitigation cost has immediate positive value but relatively lower chances for upsides that could be estimated as a value of in-the-money option.

In more general terms, in the model we substitute in-the-money option on sunk cost of the climate policy, and out-of money option on avoided damage from climate change. Instead of a fixed target we now consider an emission trajectory estimated in DICER. This optimal trajectory now maximizes the criteria taking into account risk adjusted cost and benefits of climate policy. In time period zero the planner is looking for an emission trajectory that maximizes the welfare function but costs and benefits functions are slightly modified to take into account risks. The planner applies his/her best knowledge to take into account risks associated with selected emission pathways and selects the pathway that balances risks and expected cost. There is no learning in optimization procedure, so it has no value for computing a near-term policy. Nevertheless, it may be the best we can do, giving that the learning process is uncertain too.

Formally, there is a good approximation of the Black-Sholes formula for at-the-money option. Roughly, $ROV \approx 0.4\sigma$, where σ stands for the standard deviation of the underlying asset (see Anda et al., 2009). Numerical experiments with DICE 2007 demonstrated that both damage and abatement costs of climate policy exhibit the same volatility over different emission pathways. Then we can apply the following expression for standard deviation: $\sigma = vE$, where v denotes volatility and E stands for the expected value of the underlying parameter. The existence of a simple expression for at-the-money option unfortunately covers the narrow situation when the planner breaks-even with climate policy. In the more general case, we need to take into account the expected cost and expected damage associated with a particular emission target. We add the expected value of damage and abatement cost parameters to two at-the-money options. Now adjusted cost has a form: $\tilde{Z} = \overline{Z}(1 + v_Z)$ and expected damage: $\tilde{D} = \overline{D}(1 + v_D)$ where $\overline{Z}$ denotes expected cost and $\overline{D}$ stands for the expected damage. The last complication is related to the non-linearity of cost and damage functions. In case of permanent shocks, expected value is higher than median as long as damage and abatement costs are convex functions. In summary, our suggested approach includes:

- Running Monte-Carlo simulations to estimate the moments of distribution of the parameters of the abatement cost and damage functions;
- Multiplying expected damage and abatement cost by the specific correction coefficients that reflects volatility of the underlying parameters; i.e. $\tilde{Z} = \overline{Z}(1 + v_Z)$ and $\tilde{D} = \overline{D}(1 + v_D)$

Figure 14 to Figure 17 present some results obtained when using the proposed approach to incorporate uncertainty in the climate policy analysis. It can be seen that temperatures and emissions are systematically lower under the optimal policy scenario when we adjust the parameters of the abatement cost and damage functions to consider uncertainty. The rationale for such result relies on the fact that volatility of the climate change damage is much higher than the volatility of the abatement costs, reflecting the current higher uncertainty involving climate change damages than the foreseen technologies and measures to mitigate climate change.

Figure 14: Risk-adjusted atmosphere temperature (C°)

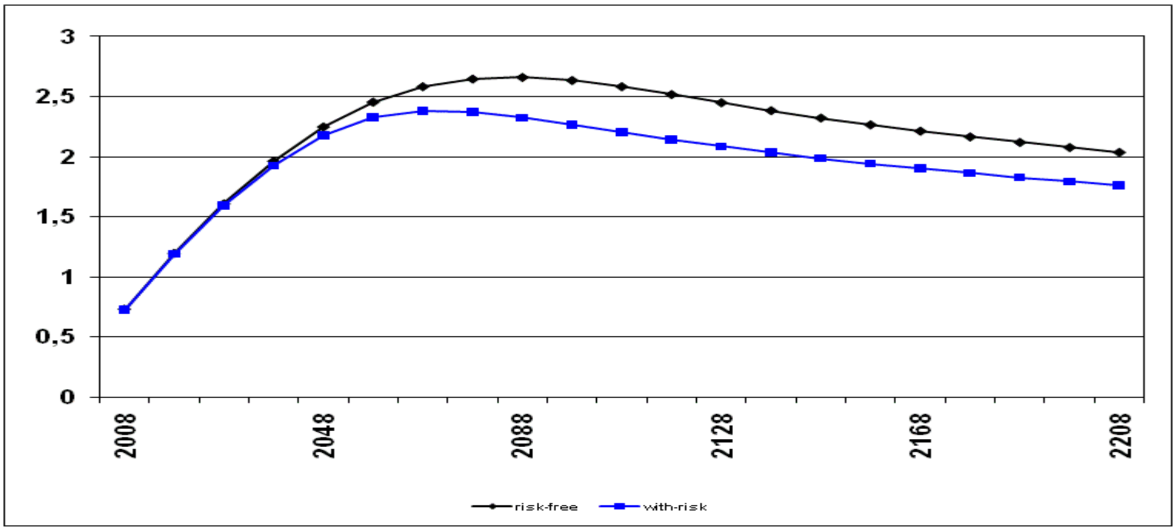


Figure 15: Risk-adjusted ocean temperature (C°)

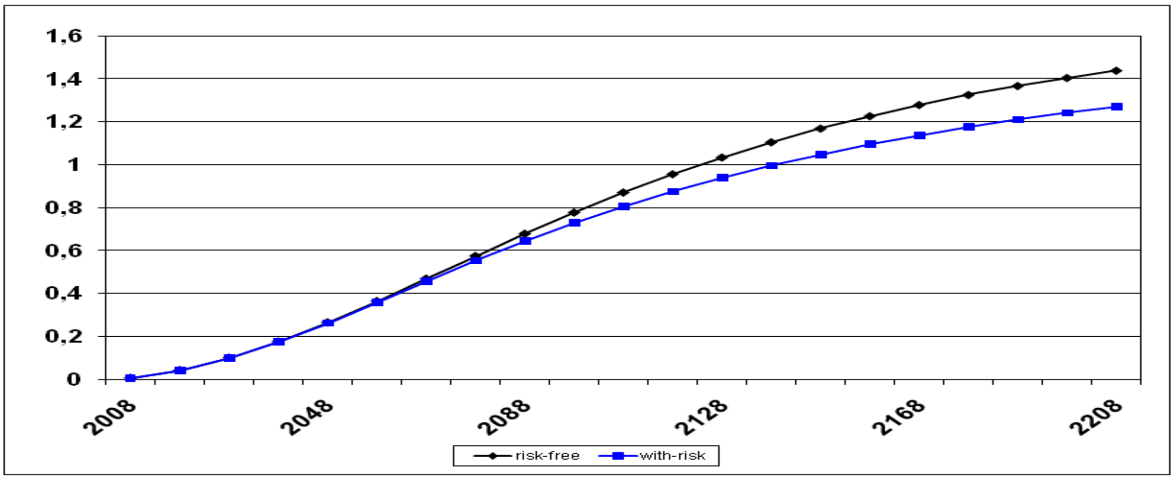


Figure 16: Risk-adjusted Emissions per region – 2028 (GtC)

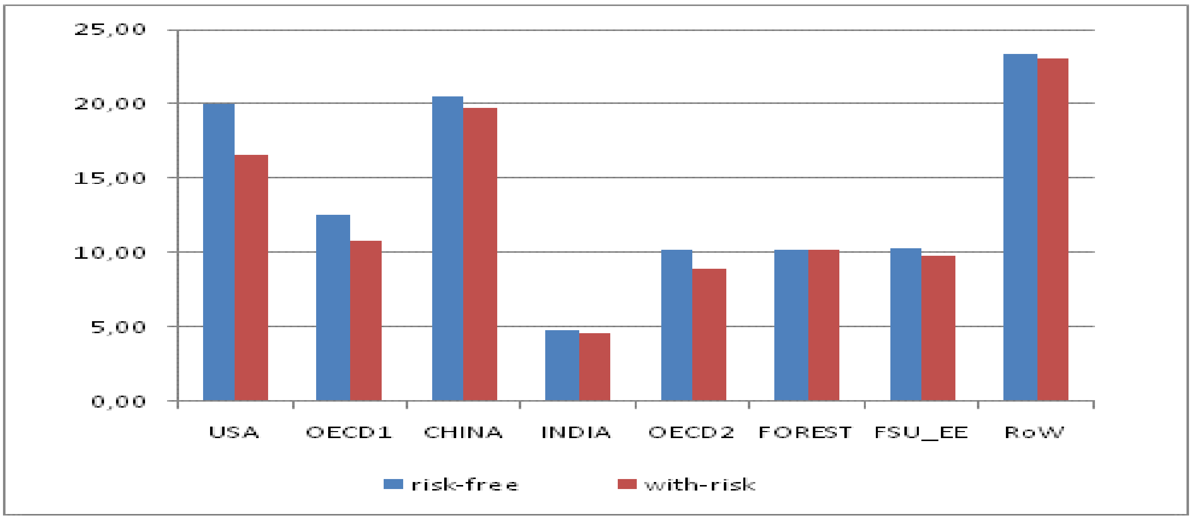
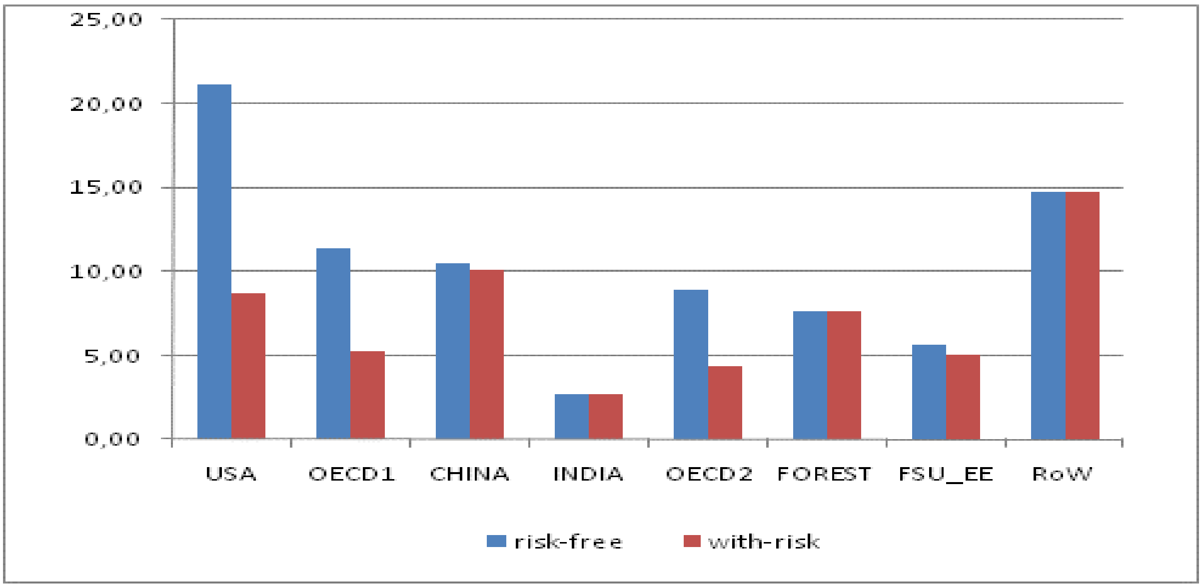


Figure 17: Risk-adjusted Emissions per region – 2048 (GtC)



5 Conclusions

The DICER model, as described in previous sections, is in its initial stages of development. It benefits from the platform of the DICE family of models, an open source and very useful set of tools for climate policy evaluation. The choice of DICE as a platform to our model was motivated by its transparency and simplicity in representing the relationships among the different parts of the economic and climatic systems, which facilitates sensitivity analysis of parameters. More complex IAMs; i.e. models containing more economy sectors, more GHGs or more energy sources – impose extra difficulties in understanding the effect of uncertain key parameters upon results. Our main objective with DICER is to develop a tool for sensitivity analysis of several key parameters in the climate policy debate; i.e., an educational tool focused on treating uncertain parameters that are currently used in most IAMs. The current stage of DICER has only incorporated a few methodological changes to the DICE2007 model (regionalization; modified climate module, damage and abatement cost functions) and more recent data. It has been calibrated to reflect the state of the world´s economy. Even with these few changes, however, we observe important new results such as (i) lower peak temperatures; (ii) radiative forcing differences; (iii) differences in control rates; and (iv) sensitivity of results to key parameters such as climate sensitivity.

A further innovation in this work has been to account for uncertainty and risk through an application of option pricing. The method allows for a simple representation of the risks through measures of volatility in the damages and costs of abatement and shows that taking these factors into account lowers maximum mean temperatures by about 0.5 ^{o}C.

As we have noted there is considerable further work to be done. A number of methodological and estimation problems that have arisen need to be addressed. One relates to the choice of the welfare maximization process, which needs further discussion. Regional IAMs found in the literature use different approaches in aggregating utility of consumption across regions. Another limitation in the current version of DICER regards the utility function used, which does not allow for intangible damages to directly affect utility. This has already been pointed out as a limitation of DICE (e.g. Tol, 1996). We aim to formulate and test different functional forms of the utility function that explicitly accommodate intangible damages of climate change. Further developments in DICER will include (i) the modeling of endogenous technological change; as in DICE2007 technological changes are represented through carbon-saving parameters such as the decreasing ratio of CO_2 emission to output; and (ii) tuning the carbon cycle parameters (or adding various carbon cycle feedbacks) since the carbon cycle derived from DICE does not simulate atmospheric CO_2 accurately – it tends to overestimate it in the near term and underestimate it in the long term.

Our objective in this paper is modest: to introduce the DICER model, its methodological differences to previous models and some preliminary results of its deterministic version. In addition, we indicate some issues where further analysis is required and the main improvements we foresee in DICER. Our aim is to develop a stochastic model where uncertainty of key parameters can be formally introduced in the model and these uncertainties reflected in climate policy evaluation.

References

Anda, J.A.; A. Golub and E.Strukova (2009), "Trade-offs between expectations and uncertainties: applying real options methodology to climate policy analysis", in A. Golub and A. Markandya (eds) Modeling Environment – improving technological innovations under uncertainty, London: Routledge.

Barker, T.; H. Pan; J.Kohler; R. Warren and S. Winne (2006), "Decarbonizing the Global Economy with Endogenous Technological Change: scenarios to 2100 using E3MG", *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Bosetti, V.; E. Massetti and M. Tavoni (2007), "The WITCH Model: structure, baseline and solutions", Nota di Lavoro, 10.2007, FEEM – Fundazione Eni Enrico Mattei, available online at http://www.feem.it/Feem/Pub/Publications/WPapers/default.htm

Bosetti, V.; C. Carraro and M. Galeotti (2006), "The Dynamics of Carbon and Energy Intensity in a Model of Endogenous Technical Change", *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Buchner, B.; C. Carraro; I. Cersosimo and C. Marchiori (2005), "Back to Kyoto? US participation and the linkage between R&D and climate cooperation", in A.Haurie and L.Viguier (eds.), *The Coupling of Climate and Economic Dynamics*, Amsterdam: Springer.

Crassous, R.; J-C Hourcade and O.Sassi (2006), "Endogenous Structural Change and Climate Targets Modelling Experiments with Imaclim-R", *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Dowlatabadi, H (1998), "Sensitivity of climate change mitigation estimates to assumptions about technical change", *Energy Economics*, 20(5), p.473-493.

Edenhofer, O.; K.Lessmann and N.Bauer (2006), "Mitigation Strategies and Costs of Climate Protection: the effects of ETC in the hybrid model MIND", *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Edwards, N.; H.Grepin; A.Haurie and L.Viguier (2005), "Linking Climate and Economic Dynamics", In *The Coupling of Climate and Economic Dynamics: Essays on Integrated Assessment*, eds. Alain Haurie and Laurent Viguier, Amsterdam: Springer.

Gerlagh, R. (2006), ITC in a Global-Climate Model with CCS: the value of induced technical change for climate stabilization". *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Gollier, C. and M.L. Weitzman (2009), "How Should the Distant Future be Discounted When Discount Rates are Uncertain?" available online at http://idei.fr/doc/by/gollier/discounting_long_term.pdf

Hedenus, F.; C.Azar and K.Lindgren (2006), “Induced Technological Change in a Limited Foresight Optimization Model”. *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Hope, C. (2006), “The Marginal Impact of CO_2 from PAGE2002: an integrated assessment model incorporating the IPCC´s five reasons of concern”, *The Integrated Assessment Journal*, 6(1), p.19-56.

MAGICC (2007), “Model for the Assessment of Greenhouse-gas Induced Climate Change”, available online at http://www.cgd.ucar.edu/cas/wigley/magicc/index.html.

Manne, A.; R. Mendelsohn and R. Richels (1995), “MERGE: A model for evaluating regional and global effects of GHG reduction policies”, *Energy Policy*, 23(1), p.17-34.

Masui, T.; T.Hanaoka; S.Hikita and M. Kainuma (2006), “Assessment of CO_2 Reductions and Economic Impacts Considering Energy-Saving Investments”. *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Nordhaus, W.D. (2009), “New Estimates of Efficient Approaches to the Control of Global Warming”, Cowles Foundation Discussion Paper, 1716, August 2009.

Nordhaus, W.D. (2008), A Question of Balance: weighting the options on global warming policies. New haven: Yale University press,

Nordhaus, W.D. (2007), *The Challenge of Global Warming: Economic Models and Environmental Policy*, available online at http://nordhaus.econ.yale.edu/dice_mss_072407_all.pdf, last visited 29/10/2008.

Nordhaus, W.D. (1994), Managing the Global Commons: The Economics of Climate Change, Cambridge: MIT Press.

Nordhaus, W.D. and J. Boyer (2000), *Warming the World: Economic Models of Global Warming*, Cambridge, MA: MIT Press.

Nordhaus, W.D. and Z. Yang (1996), “A Regional Dynamic General-Equilibrium Model of Alternative Climate Change Strategies”. *American Economic Review*, 886, p.741-765.

Ortiz, R.A. and A. Markandya (2009), "Integrated Impact Assessment Models of Climate Change: a literature review", *BC[3] Working Paper Series*, 2009-06, available online at http://www.bc3research.org/working_papers/view.html.

Paltsev *et al.* (2007), "Assessment of US cap-and-trade proposals", MIT Joint Program of on the Science and Policy of Global Change, Report 146, available online at http://mit.edu/globalchange/www/MITJPSPGC_Rpt146.pdf

Plambeck, E.L.; C. Hope and J. Anderson (1997), "The PAGE95 model: integrating the science and economics of global warming", *Energy Economics*, 19, p.77-101.

Popp, D. (2006), "Comparison of Climate Policies in the ENTICE-BR Model", *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

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

Sano, F.; K.Akimoto; T.Homma and T.Tomoda (2006), "Analysis of Technological Portfolios for CO_2 Stabilizations and Effects of Technological Changes". *Energy Journal*, Endogenous Technological Changes and the Economics of Atmospheric Stabilization Special Issue, 2006.

Stanton, E.A.; F. Ackerman and S. Kartha (2008), "Inside Integrated Assessment Models: four issues in climate economics", *Stockholm Environment Institute Working Paper*, WP-US-0801.

Tol, R.S.J. (1997), "On the optimal control of carbon dioxide emissions: an application of FUND", *Environmental Modeling and Assessment*, 2, p.151-163.

Tol, R.S.J. (1996), "The Damage Costs of Climate Change Towards a Dynamic Representation", *Ecological Economics*, 19, p.67-90.

Toth, F.L (2005), "Coupling Climate and Economic Dynamics: recent achievements and unresolved problems", In *The Coupling of Climate and Economic Dynamics: Essays on Integrated Assessment*, eds. Alain Haurie and Laurent Viguier, Amsterdam: Springer.

Wang, S. and P. Nijkamp (2007), "Impact Assessment of Clean Development Mechanisms in a General Spatial Equilibrium Context", in: Cooper, R., K. Donaghy and G. Hewings (eds) *Globalization and Regional Economic Modelling*, Springer, Berlin.

Yang, T.; J. Rilley and S.Paltsev (2005), "Air Pollution Health Effects: towards an integrated assessment", In *The Coupling of Climate and Economic Dynamics: Essays on Integrated Assessment*, eds. Alain Haurie and Laurent Viguier, Amsterdam: Springer.

Annex

Selection of exogenous variables in DICER and distributions for Monte Carlo simulation (2008 values)											
	USA	OECD1	CHINA	INDIA	OECD2	FOREST	FSU_EE	RoW	Distribution	Max value	Min value
Pop. Growth per decade %	0.1043	0.0410	0.0642	0.1746	0.0830	0.1566	-0.0217	0.2368	Triangular	+10%	-10%
Initial TFP growth	0.0756	0.0778	0.0978	0.1199	0.0801	0.0987	0.0848	0.1013	Triangular	+10%	-10%
TFP decline rate	0.0015	0.0013	0.0011	0.0015	0.0012	0.0011	0.0011	0.0011	Triangular	+10%	-10%
Depreciation of K	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	Triangular	0.2	0.05
Elasticity of K	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	Triangular	0.1	0.5
Growth rate of emissions	-0.073	-0.073	-0.073	-0.073	-0.073	-0.073	-0.073	-0.073	Triangular	+10%	-10%
Decline rate of emissions	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	Triangular	0.01	0.001
Abatement cost exponent	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	Triangular	1.2	1.8
Abatement cost function alpha	0.6	0.65	0.5	0.4	0.65	0.4	0.25	0.2	Triangular	+20%	-20%
Limit of fossil fuel	1324.99	169.44	623.18	306.06	513.19	99.43	1479.81	1483.90	Triangular	+10%	-10%
Elasticity of marginal utility of consumption	2	2	2	2	2	2	2	2	Triangular	2.5	1.5
Social rate of discount	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	Triangular	0.03	0.01
Equilibrium temp impact of CO2 doubling (climate sensitivity)	3	3	3	3	3	3	3	3	Lognormal	1	10
Forcings of equilibrium at CO2 doubling	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	Lognormal	3.5	4.2
Maximum damage as a share of GDP	0.25	0.3	0.5	0.6	0.25	1	0.4	1	Triangular	+20%	-20%

Note: Triangular distribution assumes mode = current values. Lognormal distribution assumes mean = current values.

BC3 WORKING PAPER SERIES

Basque Centre for Climate Change (BC3), Bilbao, Spain

The BC3 Working Paper Series is available on the internet at the following addresses:

http://www.bc3research.org/lits_publications.html

http://ideas.repec.org/s/bcc/wpaper.html

BC3 Working Papers available:

2009-09 Julia Martin-Ortega and Anil Markandya: *The Costs of Drought: the Exceptional 2007-2008 Case of Barcelona*

2009-10 Elena Ojea, Ranjan Ghosh, Bharat B. Agrawal and P. K. Joshi: *The Costs of Ecosystem Adaptation: Methodology and Estimates for Indian Forests*

2009-11 Luis M. Abadie, José M. Chamorro, Mikel Gonzáez-Eguino: *Optimal Investment in Energy Efficiency under Uncertainty*

2010-01 Sara L. M. Trærup, Ramon Arigoni Ortiz and Anil Markandya: *The Health Impacts of Climate Change: A Study of Cholera in Tanzania*

2010-02 Mikel González-Eguino, Ibon Galarraga and Alberto Ansuategi: *Carbon leakage and the Future of Old Industrial Regions after Copenhagen*

2010-03 Roger Fouquet: *Divergences in the Long Run Trends in the Price of Energy and of Energy Services*

2010-04 Giacomo Giannoccaro and Julia Martin-Ortega: *Environmental Concerns in Water Pricing Policy: an Application of Data Envelopment Analysis (DEA)*

2010-05 Roger Fouquet: *The Slow Search for Solutions: Lessons from Historical Energy Transitions by Sector and Service*

2010-06 Ibon Galarraga, Mikel González-Eguino and Anil Markandya: *Evaluating the Role of Energy Efficiency Labels: the Case of Dish Washers*

2010-07 Luis M. Abadie, Mikel González-Eguino and José M. Chamorro: *Optimal Abandonment of Coal-Fired Stations in the EU*

2010-08 Dirk Rübbelke and Stefan Vögele: *Impacts of Climate Change on European Critical Infrastructures: The Case of the Power Sector*

2010-09 Roger Fouquet: *The Sustainability of `Sustainable´ Energy Use: Historical Evidence on the Relationship between Economic Growth and Renewable Energy*

2010-10 Karen Pittel and Dirk Rübbelke: *Energy Supply and the Sustainability of Endogenous Growth*

2010-11 Ramon Arigoni Ortiz, Alexander Golub, Oleg Lugovoy, Anil Markandya and James Wang: *The DICER Model: methodological issues and initial results.*