DICER: a Tool for Analyzing Uncertainties in Climate Policy Analysis

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Abstract

Modeling the economy and the planet’s climate involves a great number of variables and parameters, some of them very uncertain given the current stage of knowledge regarding technology and the science of climate. The DICER model (or DICE-Regional) is a recently developed IAM, based on the structure of the DICE family of models, which was developed to be an instrument for the analysis of uncertainties in climate policy. This paper aims to describe the deterministic version of DICER in which future developments addressing uncertainty in climate policy analysis will be based. Our results suggest a few interesting conclusions when compared to other IAMs: (i) under a plausible set of assumptions and parameters we used in DICER an optimal global climate policy would imply higher costs of climate change in the short run but a faster (and more expensive) decarbonization process in all regions, resulting in a faster stabilization of the climate; (ii) lower peak temperatures observed earlier in time; (iii) sensitivity of results to key parameters such as climate sensitivity, but lower than expected sensitivity of results to the social discount rate.

Key words: Climate change; Integrated Impact Assessment Model;

JEL classification codes: Q54; C61;
1 Introduction

Integrated assessment models of climate change (IAM) are important tools for evaluating the linkage between the economy, greenhouse gases (GHG) emissions and climate change. Examples include PAGE (Plambeck et al., 1997); DICE (Nordhaus, 1994; 2007; 2008; Nordhaus and Boyer, 2000); RICE (Nordhaus and Yang, 1996); MERGE (Manne et al., 1995); WITCH (Bosetti et al. 2007); ICAM (Dowlatabadi, 1998); MIND (Edenhofer et al., 2005); and FUND (Tol, 1997). Most IAMs consist of (i) an economy module in which the interactions among economic sectors and agents are represented; (ii) a climate module representing the relationships between GHG concentration and temperature changes; and (iii) pre-determined relationships between both modules; i.e. damage functions representing the impact of temperature changes in the economy, and abatement cost functions summarizing the available climate change mitigation options. The level of details employed in each of these components characterizes and differentiates the existing models.

Modeling the economy and the planet’s climate involves a great number of variables and parameters, some of them very uncertain given the current stage of knowledge regarding technology and the science of climate. For example, the climate sensitivity parameter, defined as the temperature variation resulting from a doubling of atmospheric CO$_2$ concentration compared to pre-industrial years (280 ppm), is believed to lie in the range 2.0°C to 4.5°C, with its most likely value to be approximately 3°C (IPCC 4th AR, 2007). Besides uncertainty on the climate science, analysts face uncertainties inherent to the economic science (e.g. the adequate social discount rate to be used for climate policy analysis) as well as models’ uncertainties (e.g. the shape and parameters of the damage and abatement cost functions). Therefore, undertaking risk analysis is important when using IAMs for climate policy analysis. Critical issues for risk analysis include the irreversibility of climatic change and the existence or not of a threshold for catastrophic damage. Recent works dealing with uncertainty of climate policy modeling include Pindyck (2009), Ackerman et al. (2010) and Ikefuji et al. (2010).

The DICER model (or DICE-Regional) is a recently developed IAM, based on the structure of the DICE2007 model, which addresses some of the issues mentioned above. It is designed to be an instrument for the analysis of uncertainties in climate policy. For that purpose, we aim to: (i) account for uncertainty and risk through an application of option pricing, in which we obtain a simple representation of the risks through measures of volatility in the damages and abatement costs, which 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; and (ii) develop a fully stochastic model where uncertainty of key parameters can be formally introduced in the model and these uncertainties reflected in climate policy evaluation. These are, however, not addressed in this document but subject of forthcoming papers.

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1 The list of IAMs and Computable General Equilibrium (CGE) models used in climate policy analyses is long. The reader can refer to Ortiz and Markandya (2009) and Stanton et al. (2008) for a literature review of some of these models.

2 The word “likely” is used in a general sense rather than in a specific calibrated sense. No calibrated confidence assessment is provided in the TAR Technical Summary Chapter 9 (IPCC 4th AR, 2007).

3 We thank Prof. Williams Nordhaus at Yale University for making the DICE2007 model’s code public for other researchers.
This paper aims to describe the basic version of DICER on which the approaches described above will be based; its methodological characteristics and results obtained with different policy scenarios. It is organized as follows: section 2 presents the main features of the DICER model; section 3 presents some results obtained with DICER for a business as usual (BAU) and optimal scenarios and for a policy in which a limit of 2°C average atmospheric temperature increase is allowed. Section 4 presents a sensitivity analysis of our results undertaken by the means of a Monte Carlo simulation of key parameters, while section 5 discusses some outstanding issues and conclusions.

2 The DICER model

This section aims to describe the main features of DICER. It does not lay out all model’s equations, which can be found in Ortiz et al. (2010), but emphasizes key aspects of the model. As DICER is built upon the structure of DICE2007, its general aspects are identical to those of DICE2007 (Nordhaus, 2008): the model views the economics of climate change from the perspective of 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 natural capital (emissions). Global aggregates are estimated from data including all major countries from eight regions using PPP exchange rates. The regions 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 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. As in DICE2007, the only commodity that represents the economy can be used for consumption or investment.

The 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 labor, and an exogenous region-specific level of technology. Technological changes are of two forms: economy-wide and carbon-saving, which is modeled as reducing the ratio of CO₂ emission to output. Output is determined with a constant-return-to-scale Cobb-Douglas production function in capital, labor 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 encouraged as carbon-based fuels become more expensive due to exhaustion of supply or to increases in the price of fossil fuels.

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).
Damage functions

The damage function used in DICER assumes that economic (tangible and intangible) damages are dependent on global mean temperature change and limited to a maximum potential GDP loss (damage cap). 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 climate change-related impacts for eight regions of the world, obtained from the pertinent literature. The studies in which we obtained region-specific damage estimates include Tol (2002, 2005), Pearce et al. (1996), Mendelsohn et al. (1998), Nordhaus and Boyer (2000).

Initially, we decided to follow the literature and derive our regional damage functions as an exponential damage function of the form \( D_{r,t} = a_r . \Delta T_t^{br} \), where \( D_{r,t} \) represents the damage in region (r) as a fraction of the region’s output in period (t), and \( a_r \) and \( b_r \) are region-specific parameters of the damage function. This functional form worked well for positive estimates of damages and the results showed considerable different powers “\( br \)” 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 \( D_{8,t} = 0.001 . \Delta T_t^{4.10} \). Additionally, 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 \( \Delta T \) equal to 1°C, and in some regions in the north hemisphere they corresponded to negative damage estimates (or benefits from climate change). This fact forced us to assume a different functional form for the damage function: a translated parabola, suggested in Roughgarden and Schneider (1999), which presents the form: \( D_{r,t} = a_r . (\Delta T_t^c + c_r)^2 + d_r \). 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 benefits increase in average atmospheric temperature our damage functions are decreasing between zero (no climate change) and 1°C. In order to overcome such limitation we assumed “zero damage” for the temperature range where our damage functions predicted negative damages. Given the relatively small benefits from climate change over this interval we believe that the errors in ignoring them will not qualitatively affect the results in this model. We also note that the model overestimates the costs of mitigation at low temperature increases because it does not account for ancillary benefits from those reductions in GHGs. Thus, overestimating the costs of making small reductions in temperature increase is cancelled out to some extent by overestimating the damages caused by these increases. Equation 1 shows our final functional form adopted in our damage functions while Figure 1 shows the curves.

\(^5\) We introduce a region-specific limit or damage cap to the percentage of damage from climate change accepted for each region, based on the relevant literature. For example, damages in Africa are widely expected to be higher than in the US for any given positive temperature change. We acknowledge that these damage caps were chosen rather arbitrarily but a sensitivity analysis of these parameters showed that our results do not vary significantly when damage caps varied by up to 20% from their initial values (see annex).

\(^6\) 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).

\(^7\) The final functional form was suggested by an anonymous participant at a discussion forum of GAMS’ users and modelers.
\[ D_{r,t} = CAP_r - \frac{CAP_r}{1 + \left( a_r (\Delta T_{r,t}^* + c_r)^2 + d_r \right)} \]  

(1)

Where:

- \( D_{r,t} \), The damage function in region \( r \) as a fraction of the region's output;
- \( CAP_r \), The highest percentage of GDP allowed as climate change damage;
- \( T0_r \), The temperature at which the climate damage starts to become positive in region \( r \);
- \( a_r, c_r, d_r \), Region-specific parameters of the damage function;
- \( t \), Time (decades from 2008-2017; 2018-2027; ...);
- \( \Delta T_{r,t}^* \), Global temperature growth adjusted to regional damage pattern:

\[
\Delta T_{r,t}^* = \begin{cases} 0, & \Delta T_t \leq T0_r \\ \Delta T_t, & \Delta T_t > T0_r \end{cases}
\]

For computational purposes \( \Delta T_{r,t}^* \) is approximated with the functional form:

\[
\Delta T_{r,t}^* \approx \frac{1}{2} (T0_r + \Delta T_t) + \frac{1}{2} \sqrt{(T0_r - \Delta T_t)^2 + \delta}
\]

Where

- \( \delta \), Small positive constant (\( \delta = 0.001 \));
- \( \Delta T_t \), Global temperature increase observed at period \( t \).

Figure 1: Damage functions in DICER
Regarding the shape of damage functions, we believe that IAMs must consider the threshold effect of climate change; i.e. the existence of a temperature change above which catastrophic damage is observed. Thresholds for catastrophic damages are viewed in the literature as the proper way to communicate the magnitude of climatic changes and its negative impact on the economy. It is mostly agreed that the explicit introduction of such events into the model would justify very aggressive climate policies. Unfortunately, the most common quadratic damage function (e.g. DICE2007) does not capture this threshold. Alternative shapes such as those assuming infinite damage are also not realistic. But what if climate change damage is controllable? To account for this we introduced an exogenous cap or upper limit on climate change damage. As can be seen in Figure 1, our damage functions implicitly build in a threshold temperature change at temperature increases around 2-3°C, in addition to damage caps based on expert opinion.

Abatement Cost functions

The family of abatement cost curves assumes that the abatement costs are proportional to global output and to a polynomial function of the emissions-reduction rate. The functions used have the form \( P_r = a_r \%GHG^2 \), where \( P_r \) is the abatement cost in terms of percentage of GDP; \%GHG is the reduction in emissions and \( a_r \) is the region-specific parameter (backstop technology price). Figure 2 shows the shape of the obtained curves. These are similar to those used in RICE2010 (Nordhaus, 2010). However, by checking some of the latest available literature on the cost of abatement from the Energy Modeling Forum (EMF22 – Clarke et al., 2009) we decided to re-calibrate the parameters of the MACs used in the RICE2010 model in order to reflect the average abatement costs given in EMF22. In summary, our aim was to choose the MACs – functional form and parameters – that better represent the available data on abatement costs. The calibration involved using higher backstop technology prices, about 50% higher than those used in the RICE2010 model. Our MACs have the form shown in Figure 2.

Climate module

Similarly to DICE2007 and RICE2010, 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 flows 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. The only GHG directly subject to controls in DICER is industrial CO₂. Emissions from land-use change are specified as an exogenous trend.

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8 USA = 1.7; OECD1 and OECD2 = 2.65; China = 1.32; India = 2.08; Forest = 2.46; FSU_EE 1.13; and RoW = 2.27.

9 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).
Figure 2: Marginal abatement cost curves

Note: Estimated by the authors using RICE2010 MACs but assuming higher costs of backstop technologies; %GHG reduction (horizontal axis); the abatement cost is given as %GDP (vertical axis).

However, we treat other climate forcing agents, including other well-mixed GHGs, tropospheric ozone, and warming and cooling aerosols, differently from DICE2007, 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\(_2\) radiative forcing is scaled to the CO\(_2\) forcing calculated by the model. This scaling is a simple linear relationship derived from linear regression that was based on a number of future emission scenarios in the literature (specifically, IIASA’s MESSAGE reference and mitigation scenarios, and an "equal quantile walk" scenario from Meinshausen\(^\text{10}\)). In essence, we have re-estimated (or scaled-up) the parameter corresponding to the CO\(_2\) radiative forcing in order to account for the non-CO\(_2\) radiative forcing. A linear relationship between non-CO\(_2\) and CO\(_2\) radiative 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 are given by a level of carbon intensity times world output. Actual emissions are then reduced by the emissions-reduction rate. As in DICE2007, DICER assumes that incremental extraction costs for fossil fuels are zero and that carbon fuels are optimally allocated over time by the market, producing the optimal Hotelling rents.

The model includes several geophysical relationships – a carbon cycle model; a radiative forcing equation; climate-change equations and climate-damage relationship –

\(^{10}\) Meinshausen’s analysis using SIMCaP – Simple Model for Climate Policy Analysis (www.simcap.org).
that link the economy and the factors affecting climate change. Accumulation of GHG is assumed to be linked to temperature increase through increases in radiative forces, this relationship being derived from empirical measures and existing climate models (e.g. MAGICC, 2007).

We believe that our climatic block better represents the response of climatic system than previous versions of the DICE model. In addition, many IAMs underreport irreversible changes of the climatic system. Temperature that initially increases in response to GHG accumulation, declines back "very easily" (e.g. see optimal trajectory in the DICE2007 model). With the changes included in DICER’s climatic block, the reduction of average temperature as a function of GHG accumulation is not as sharp as in other IAMs, so we believe that we better capture the irreversibility of climate damage.

User interface and data

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 for changing the model’s codes, thus 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 from 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 (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).

3 Results of the deterministic version

This section describes key results obtained with the DICER model in its present version, for an optimal policy scenario (i.e. full participation in emission control schemes) in which climate change policies maximize global economic welfare; the business-as-usual (BAU) scenario (i.e. no participation in emission control schemes); and a hypothetical scenario where average temperature increase is limited to 2°C. These results use the optimization process in which we maximize the utility of aggregated regional
consumption\textsuperscript{11}. Whenever possible, and to highlight the impact of the changes introduced so far in DICER, we compare our results with similar results obtained with RICE2010\textsuperscript{12} (Nordhaus, 2010).

An initial assessment of our main changes introduced in DICER suggests that our results for the optimal scenario show a faster increase in GHG emissions, atmospheric concentrations and temperature than observed in other IAMs. On the other hand, our results show faster and earlier stabilization of CO\textsubscript{2} concentration. This result is driven by our changes in: (i) the climate module of DICER (non-CO\textsubscript{2} radiative forcings), which implies faster temperature increase than in DICE/RICE, for example; (ii) in the functional form for damages, which implies no damage at low temperature increases but a steep increase in damages after temperature increases higher than a region-specific threshold (around 2\textdegree C in the north hemisphere); and (iii) the abatement cost function parameters, which foresee higher costs of abatement than in DICE/RICE. Since in the optimal policy scenario action is taken when the marginal cost of abating equals the present value of expected marginal damage of climate change, we can expect that under our assumptions action would tend to be delayed as a result of introducing a region-specific threshold. On the other hand, the fast temperature increases move the model in favor of earlier stabilization. The net effect of these opposing forces is to produce a higher impact of climate change under the optimal scenario in the short-term, but a faster stabilization process.

Figure 3 shows CO\textsubscript{2} atmospheric concentration under the three scenarios used in DICER. As can be seen, CO\textsubscript{2} concentration peaks at approximately 500 ppm around year 2088 in the optimal case, and around 450 ppm in year 2048 under the 2\textdegree C policy. The same results in RICE2010 (Figure 4) show that CO\textsubscript{2} maximum concentration is approximately 600 ppm by year 2108 in the optimal case and around 500 ppm in year 2068 in the 2\textdegree C policy.

Figure 5 shows CO\textsubscript{2} emission paths of selected regions under the optimal scenario. A relatively fast decarbonization process can be seen in China and the US, whilst OECD1 region needs three extra periods (30 years) for full decarbonization of the economy. This result is driven by our assumption of higher costs of backstop technology in OECD countries. The Forest region (Brazil, Indonesia, DR Congo and Malaysia) takes much longer to reduce emissions due to both higher prices of backstop technologies and to the fact that reductions in emissions from land use change take longer to bring about\textsuperscript{15}.

\textsuperscript{11}We have investigated different forms of aggregating regional utility and their impacts on our results. We tested DICER by: (i) maximizing utility of the average world consumption per capita; (ii) maximizing the sum of regional utility of consumption; and (iii) using Negishi welfare weights as in RICE2009 and AIM, which treat global utility as the Negishi weighted sum of regional utilities. Maximizing regional sum of utility does not guarantee an optimal solution at the global level since the set of regional optimal solutions may not correspond to the optimal at the global level; and 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). Our preferred maximization process, therefore, is given by (i).

\textsuperscript{12}Note that all results of RICE2010 are given for an initial period in year 2005. We considered these results starting in year 2008 in order to facilitate the comparison with our results.

\textsuperscript{13}As in DICE2007, DICER assumes a constant reduction rate of emission from land use change.
Figure 3: CO₂ atmospheric concentration (ppm)

Figure 4: DICER x RICE2010: CO₂ atmospheric concentration (ppm)
Figure 5: CO2-equivalent emissions (GtC)

Atmospheric temperatures in DICER (Figure 6) peak at 2.6°C between years 2108 and year 2118 under the optimal policy scenario; the equivalent in RICE2010 (Figure 7) is 3°C in year 2138. Uncontrolled emissions would correspond to atmospheric temperature increases up to 6.3°C in two hundred years, according to our model.

Figure 6: Atmospheric temperature (°C)
Regarding ocean temperature, the uncontrolled emissions scenario (BAU) corresponds to 2.8°C increase in 2208, while the ocean temperature increase is 1.4°C under the optimal policy scenario and 1.2°C in the 2°C policy scenario. The corresponding figures in RICE2010 are: 2.4°C (BAU), 1.6°C (optimal policy) and 1.2°C (2°C policy scenario). Total radiative forcings in DICER peak at 4 Watts/m² in year 2088 while in BAU it peaks at 3.3 Watts/m² in year 2048 under the 2°C policy scenario. As expected given our assumptions about non-CO₂ forcings, RICE2010 presents a different pattern in all policy scenarios. Radiative forcing peaks at 4.4 Watts/m² in year 2108 under the optimal policy scenario and at 3.1 Watts/m² in year 2058.

The results in Figure 8 suggest that, under an optimal policy scenario, by mid 2100’s 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.
Our estimate of the social cost of carbon (Figure 9), or the present value of contemporaneous and future economic damages caused by an additional ton of carbon emission in a certain period of time, equals 57.8 US$/tC in the initial period (2008) under the optimal policy scenario, and 85.3 US$/tC in the 2°C policy scenario. The equivalent figures in DICE2007 (Nordhaus, 2008, page 82) are 27.3 US$/tC (optimal) and 45.3 US$/tC (2°C). The carbon taxes induced by the policies in DICER are equal to the social costs of carbon until the fourth period 4 (2038), after which the carbon taxes are higher than the SCC for the equivalent policy. The induced carbon tax in DICE2007 was 33.8 US$/tC (optimal) and 60.2 US$/tC (2°C). Our higher carbon taxes suggest that the changes introduced in DICER induce more restrictive climate policy than other IAMs in the DICE family of models suggest.
Emission abatement costs estimated in DICER under the optimal policy scenario (Figure 11) are crescent-shaped in all regions until the end of this century (except for FSU and China, which peak before the end of the century). In the beginning of the next century the abatement costs start to decline sharply in most regions. The higher abatement costs presented in China and FSU are determined by our preferred maximization process and the assumption of cheaper abatement opportunities (e.g. backstop technology) in these regions. Since we maximize utility of the world’s aggregated per capita consumption, the efficient choice of abatement is done in the region where it is cheapest to abate, regardless of the level of climate change damage of the region. In our case, FSU presents very low damage (Figure 13) but FSU and China still present cheaper abatement opportunities (e.g. coal substitution). This result has an important implication for policy since eventual compensation schemes among regions should be considered if an optimal climate policy is to be negotiated. As expected, abatement costs are higher and incurred earlier in all regions if a stricter climate policy is implemented, such as the 2°C policy (Figure 12).

Figure 11: Abatement costs (%GDP): optimal policy scenario

Figure 12: Abatement costs (%GDP): 2°C policy scenario
Figure 13 shows the climate change damages observed in all regions under the optimal policy scenario. As it could be anticipated, developing regions (in our model regions Forest, RoW, China and India) will bear the bigger share of the costs, which will peak approximately in the beginning to the 22nd century. RoW, which includes Africa, looses approximately 7% of the region’s GDP, followed by the countries with tropical forests (6.5%), India (5.9%) and China (5.8%).

**Figure 13: Damage costs (%GDP)**

4 Sensitivity Analysis

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. In every DICER run we used the utility maximization process in which we aggregate global per capita consumption for the optimal policy scenario. The list of variables, probability distribution and parameters used is given in the Annex. For example, climate sensitivity was assumed to follow a log-normal distribution with parameters equal to 1.1 (location or log mean) and 0.4 (scale or log standard deviation). Most other exogenous variables were assumed to have a triangular distribution with minimum and maximum values assumed around their observed initial value. These DICER runs show us how the optimal strategy in DICER depends on exogenous parameters, in case the planner has full information about the future. We show the results only for atmospheric temperature paths in order to facilitate the comparison of results across randomly assigned parameters of the model. Horizontal axes represent time periods

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14 We also see this sensitivity analysis as a “navigation tool” for further calibration improvements of DICER.

of 10 years; i.e. T=20 represents 200 years from 2008. Vertical axes are temperature changes in °C.

Figure 14 shows how atmospheric temperature varies in DICER when we assume different random values for the climate sensitivity parameter; Figure 15 when we vary discount rates; Figure 16 refers to changes in damage caps; and Figure 17 shows the results of temperature changes when we allow the parameters of the abatement cost function to vary randomly. As can be seen in Figure 14, atmospheric temperature under optimal policy is very much impacted by the climate sensitivity parameter, as expected. Peak temperatures vary between 1.9°C and 4.1°C depending on the assumed value of climate sensitivity. In our base case, climate sensitivity equals to 3°C and maximum atmospheric temperature peaks at 2.6°C.

A rather surprising result suggests that atmospheric temperature under an optimal policy in DICER is relatively not so impacted with respect to social discount rates where peak temperatures vary between 2.4°C and 3.2°C (Figure 15). This result was observed also in previous versions of the DICER model (Ortiz et al., 2010), and suggests that the degree of uncertainty introduced in IAMs through the social discount rate is lower than the uncertainty surrounding the parameter climate sensitivity, although higher than damage cap (Figure 16) and abatement cost (Figure 17).

Figure 14: Atmospheric temperature: climate sensitivity randomly assigned
Figure 15: Atmospheric temperature: discount rate randomly assigned

Figure 16: Atmospheric temperature: damage cap randomly assigned
Figure 17: Atmospheric temperature: abatement cost function parameters randomly assigned

5 Conclusions

The DICER model 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., a tool focused on treating uncertain parameters that are currently used in most IAMs. We incorporated in DICER 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.

In this paper we describe the main features of the deterministic version of DICER, and some results obtained for different climate policy scenarios. Our results suggest a few interesting conclusions when compared to other IAMs: (i) under the plausible set of assumptions and parameters we used in DICER an optimal global climate policy would imply higher costs of climate change in the short run but a faster (and more expensive) decarbonization process in all regions, resulting in a faster stabilization of the climate; (ii) lower peak temperatures observed earlier in time; (iii) sensitivity of results to key parameters such as climate sensitivity, but lower than expected sensitivity of results to social discount rate. Future developments in DICER include checking whether these results are consistent across different utility maximization criteria.
There are at least two major issues that need further investigation. To begin with we note that IAMs do not deal with the question of how individual countries will be persuaded to support the optimal solution. It is clear that the participation of all countries is essential, especially the emerging economies of China and India. But we have not determined that the reductions demanded of them result in an increase in their welfare. This requires further research, which can then determine what wealth redistribution will be needed to ensure that the optimal path is also a Pareto Improvement (i.e. one that all countries benefit from).

The other major factor is of course uncertainty. While we have identified which parameters are the ones to which the optimal solution is most sensitive, we have not determined how much that uncertainty should influence the optimal policy – i.e. how much of a cost are we willing to bear to reduce the risk of potentially high climate impacts. That will be the work of the follow-up paper, which looks at solutions that are fully stochastic, as well as ones that approximate the full stochastic solution through instruments such as options pricing.

6 References


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


### 7 Annex

**Table 1: Exogenous variables and distributions for Monte Carlo simulation**

<table>
<thead>
<tr>
<th></th>
<th>USA</th>
<th>OECD1</th>
<th>CHINA</th>
<th>INDIA</th>
<th>OECD2</th>
<th>FOREST</th>
<th>FSU_EE</th>
<th>RoW</th>
<th>Distribution</th>
<th>Max value</th>
<th>Min value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abatement cost exponent</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>Triangular</td>
<td>3.36</td>
<td>2.24</td>
</tr>
<tr>
<td>Abatement cost function alpha</td>
<td>1.70</td>
<td>2.65</td>
<td>1.32</td>
<td>2.08</td>
<td>2.65</td>
<td>2.46</td>
<td>1.13</td>
<td>2.27</td>
<td>Triangular</td>
<td>+20%</td>
<td>-20%</td>
</tr>
<tr>
<td>Social rate of discount</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>Triangular</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Equilibrium temp impact of CO2 doubling (climate sensitivity)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>Lognormal</td>
<td>Mean 1.1</td>
<td>S.D 0.4</td>
</tr>
<tr>
<td>Maximum damage as a share of GDP</td>
<td>0.25</td>
<td>0.3</td>
<td>0.5</td>
<td>0.6</td>
<td>0.25</td>
<td>1</td>
<td>0.4</td>
<td>1</td>
<td>Triangular</td>
<td>+20%</td>
<td>-20%</td>
</tr>
</tbody>
</table>

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