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Identifying parametric controls and dependencies in integrated assessment models using global sensitivity analysis

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ABSTRACT

Integrated assessment models for climate change (IAMs) couple representations of economic and natural systems to identify and evaluate strategies for managing the effects of global climate change. In this study we subject three policy scenarios from the globally-aggregated Dynamic Integrated model of Climate and the Economy IAM to a comprehensive global sensitivity analysis using Sobol' variance decomposition. We focus on cost metrics representing diversions of economic resources from global world production. Our study illustrates how the sensitivity ranking of model parameters differs for alternative cost metrics, over time, and for different emission control strategies. This study contributes a comprehensive illustration of the negative consequences associated with using *a priori* expert elicitations to reduce the set of parameters analyzed in IAM uncertainty analysis. The results also provide a strong argument for conducting comprehensive model diagnostics for IAMs that explicitly account for the parameter interactions between the coupled natural and economic system components.

1. Introduction

Climate change is one of the most challenging issues confronting the scientific and policy communities. The National Research Council (NRC, 2009) has called for advances in climate change decision support that facilitate a "deliberation with analysis" approach to the problem. A key aspect of "deliberation with analysis" is the need for frameworks that aid in identifying the key uncertainties influencing the trade-off between near-term carbon dioxide (CO_2) mitigation costs and long-term risks posed by climate change. A large body of literature has emerged seeking to better characterize this trade-off using integrated assessment models (IAMs) (Parson and Fisher-Vanden, 1997; Kelly and Kolstad, 1999). IAMs seek to inform our understanding of the coupled natural and economic systems that shape mitigation and adaptation decisions. More formally, Kelly and Kolstad (1999) define an IAM as "… any model which combines scientific and socio-economic aspects of climate change primarily for the purpose of assessing policy options for climate change control". For evaluating climate mitigation strategies, IAMs must incorporate important aspects of the climate system and the global economy, and yet be sufficiently transparent to be useful for decision support (Kelly and Kolstad, 1999; Stanton et al., 2009). For IAMs to be useful they need to advance our understanding of the linkages between economic activities, greenhouse gas emissions, the carbon cycle, climate and damages (Parson and Fisher-Vanden, 1997; Courtois, 2004; Stanton et al., 2009; Weyant, 2009). Broadly there are two classes of IAMs (Stanton et al., 2009): (1) inter-temporal optimization models, and (2) simulation models. Inter-temporal optimization models seek to identify a best future course based on global/regional welfare or cost optimization. Optimality is typically defined in this class of IAMs subject to an assumption of perfect foresight and the IAM modeler's expected state-of-the-world (SOW). Simulation (or evaluation) models, instead, play out specific policy scenarios over time without explicitly defining or seeking optimality. Both of these

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classes of IAMs are nonlinear and require large numbers of externally-specified (exogenous) parameters to abstract the economic and natural systems being modeled.

IAMs are now garnering significant roles in shaping climate change impact projections and in the formulation of alternative mitigation policies (IPCC, 1996; Stern, 2007; EPA, 2010, 2013; UNEP, 2010, 2011; NRC, 2011; Rogelj et al., 2011, 2013a,b). Many agencies (EPA, 2009; EU, 2009) recommend that all models used for policy development and analysis, including IAMs, be rigorously evaluated. The challenges of evaluating IAMs, as has been reviewed over two decades (Risbey et al., 1996; Stanton et al., 2009; Schwanitz, 2013), include the potentially high degrees of model complexity, the degree of integration and resolution of model components, and incomplete knowledge of underlying processes and data. Efforts to model the inherently unknown future behavior of complex, interrelated systems have led to a focus on the uncertainties associated with framing possible futures. This is often done in the context of community model inter-comparison exercises (e.g., Clarke et al., 2009). Our study builds on additional guidance from broader environmental modeling communities for improving diagnostic assessments of complex environmental modeling systems (e.g., Jakeman et al., 2006; Gupta et al., 2008; Gudmundsson et al., 2012; Kelly (Letcher) et al., 2013; Baroni and Tarantola, 2014).

Recently, Schwanitz (2013) outlines an evaluation framework specifically for the IAM community. Included as one of the tools in this evaluation framework, global sensitivity analysis has the potential to attribute the uncertainty in an IAM's projections to its parameters, both individually and collectively (Saltelli et al., 2008). To date, sensitivity analyses of IAMs focused on specific functions or modules within a given model (Keller et al., 2004; Gillingham et al., 2008; Ackerman et al., 2010) or on exploiting expert elicitations to reduce the set of parameters to be analyzed with a local sensitivity analysis (Peck and Teisberg, 1993; Prinn et al., 1999; Toth et al., 2003). Recent studies that have applied global statistical sampling to IAMs still confine sensitivity testing to a small subset of parameters within a limited Monte Carlo sampling (Pizer, 1999; Scott et al., 1999; Goodess et al., 2003; Campolongo et al., 2007; Nordhaus, 1994, 2008; Kypreos, 2008; Johansson, 2011). Overall these analyses overlook the potential for multiple parameters in an IAM to interactively influence the outcomes and, consequently, may lead to incorrect inferences as to which parameters or factors most strongly influence key uncertainties (Saltelli and D'Hombres, 2010).

We focus our sensitivity analysis on the globally-aggregated IAM, the Dynamic Integrated model of Climate and the Economy (DICE) (Nordhaus, 1994; Nordhaus and Boyer, 2000; Nordhaus, 2008), and extend the uncertainty and sensitivity analysis reported in Nordhaus (2008). Our purpose is to demonstrate that for IAMs, i.e., non-linear models with many exogenous parameters, the uncertainties of model outputs can arise from complex parameter interactions. DICE presents a simple, yet comprehensive, representation of the world where alternative economy-climate scenarios can be tested without having to explicitly model the complexities of the global system. There are multiple potential foci when designing a global sensitivity analysis of an inter-temporal optimization IAM. The choice of the appropriate experimental approach depends on the overall policy question to be answered. For example, one question that might be explored is, *how do scenario pathways for a given stabilization goal change across alternative SOWs?* This problem is reflective of the majority of IAM studies where the primary focus is on comparing the resulting optimized policy scenario outcomes. Alternatively, we pursue in this study the question, *how vulnerable are specific optimized DICE policy scenarios to uncertainties in the exogenous assumptions?* By isolating the policy scenarios from the optimization process, we are exploring which exogenous parameters (e.g., population growth, technology efficiency, climate sensitivity) control deviations from the policy costs attained under the assumption of perfect information. We do not recalibrate the model to external data sources for each sampled SOW, do not re-optimize the model for each sampled SOW, and do not claim to assign likelihoods to exogenous parameter combinations. Rather we measure how exogenous parameters, individually and interactively, affect selected policy-relevant model outputs. For a deterministic, perfect foresight model such as DICE, it is arguably quite useful to know the vulnerabilities of a policy solution and to identify the key model parameters that control its performance over time. Our results could also inform subsequent calibration efforts or uncertainty analyses by giving an improved *a posteriori* understanding of complex, interactive parametric effects.

Here we use the cost benefit form (see Section 2.2 below) of the DICE model as described in Nordhaus (2008). In this form of the model a policy scenario outcome is characterized by the control variables, emission control rates and investment, which optimize the objective function, the sum of the discounted utility of consumption over time, given the constraints applied, such as available fossil fuel resources and limits to atmospheric temperature increases. Emission pathways are endogenous in this form of the model. A different (cost effectiveness) form of this model is employed for the use of pre-specified emission control pathways (Meinshausen et al., 2011a; Rogelj et al., 2012). See Appendix Fig. A.9 for an example of a DICE policy scenario and resulting emissions pathway.

For this study we construct a simulation version of DICE, called CDICE, which reproduces DICE model outcomes for a supplied policy scenario, given the reference values of all exogenous parameters. With this simulation model, we can explore the vulnerability of a fixed policy scenario to the uncertainty in the DICE model's exogenous parameters. We choose three distinctly different DICE policy scenarios to see how parametric sensitivities change for scenarios with different treatments of the trade-offs between climate damages and abatement costs. In this study, we apply the Sobol' method, a global variance-based sensitivity analysis method (Sobol', 2001; Saltelli et al., 2008), to CDICE simulations of each policy scenario. Using the Sobol' method, we choose model outputs (in this case, climate damages and abatement costs) for the analysis. We create ensembles of these model outputs by iteratively running the CDICE simulation model while simultaneously varying a selection of model parameters over specified ranges using Sobol' quasi-random sampling. The Sobol' method is used to decompose the variance of the damage and abatement cost outputs into portions contributed individually or interactively by the sampled parameters.

This exercise demonstrates the importance of understanding the non-separable, interactive parameter dependencies that control uncertain IAM projections. We also contrast our findings with the more typical local sensitivity analysis as performed in Nordhaus (2008). Our results illustrate the consequences of using *a priori* expert elicitations to reduce the set of parameters analyzed, especially within the context of a one-at-a-time (OAT) sensitivity analysis. The results of this global sensitivity analysis provide a strong argument for comprehensive model diagnostics for IAMs to explicitly account for the parametric interactions between their coupled natural and economic components. Moreover, this study illustrates how the sensitivity ranking of model parameters differs for alternative cost metrics, over time, and for alternative emission control strategies.

In Section 2 we describe the DICE IAM and the CDICE simulation model as well as the policy scenarios used in this study. Section 3 presents the methods used and descriptions of the computation experiments. Results and implications are discussed in Section 4, followed by conclusions in Section 5.

2. The integrated assessment model

2.1. The DICE model

Fig. 1 provides a schematic overview of the DICE IAM. In this study, we use version 2007.delta.8b, which is documented in detail in Nordhaus (2008), and was obtained from the author's website (http://nordhaus.econ.yale.edu) in February 2011. The model presents a neoclassical economic growth theory view of the economics of climate change (Nordhaus, 2008). This version of the DICE model builds on more than twenty years of development of a conceptually simple, yet complete, example of a fully coupled economic, carbon cycle, and climate model (Nordhaus, 1993, 1994; Nordhaus and Boyer, 2000). DICE is a highly aggregated model comprising a single global economy producing a single commodity. DICE couples a simplified representation of the economy with a 3-reservoir carbon cycle model and a 2-reservoir climate model. Industrial emissions are a by-product of production and contribute to atmospheric greenhouse gas concentrations, along with non-CO_2 greenhouse gases and emissions from land use change. The total atmospheric burden of greenhouse gases determines the radiative forcing and, ultimately, changes in atmospheric temperature. Global temperature increase has a negative impact on economic output through a simplified damages function. Climate damages can be mitigated in DICE by transitioning to carbon-free energy sources. The abatement costs for this transition also lower economic output, yielding a trade-off between the costs of current mitigation activities and the costs of future climate damages (Nordhaus, 2008). When solving the model in the Generalized Algebraic Modeling System (GAMS, GAMS Development Corporation, USA; GAMS Software GmbH, Germany) using a nonlinear programming, reduced-gradient solver (CONOPT3 from AKRI Consulting and Development), the DICE model produces a time series of industrial emission control rates and investment (the control variables) that maximize the sum of discounted utility of consumption over time (the objective function).

As an aggregated model abstracted from more detailed and complex models, DICE is driven by dozens of exogenous factors (shown in italics in Fig. 1). These factors include initial conditions, parameters for sub-model functions, and constraints. For example, the population/labor resources are determined by an initial population, a rate of population increase, and an assumed asymptotic upper limit of global population. The population trajectory is derived from these three parameters. Many of these exogenous factors are derived from calibrations to more comprehensive models. For example, the parameters defining the exchange of carbon between carbon reservoirs and the exchange of heat between climate reservoirs are calibrated to results from the Model for the Assessment of Greenhouse-Gas Induced Climate Change (MAGICC; Meinshausen et al., 2011b, and references therein). Details of the model calibration and choices for reference values of the exogenous (externally specified) parameters are documented in the DICE model accompanying notes (Nordhaus, 2007a). Results from a DICE model execution represent deterministic mitigation decisions over time assuming perfect foresight of both decisions as well as exogenous conditions (e.g., climate sensitivity, population, participation). Alternative mitigation policy scenarios are evaluated in DICE by adding constraints. For example, the 2 °C stabilization scenario used in this study is the result of a DICE run with a constraint that limits the increase in the atmospheric temperature over pre-industrial to 2 °C.

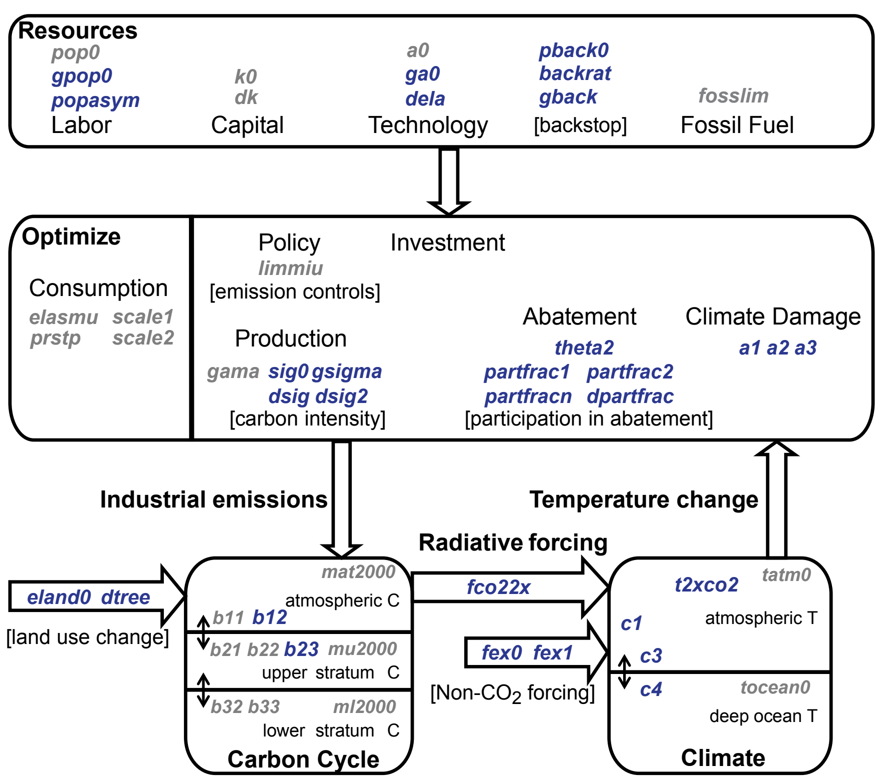

Fig. 1. Overview of the DICE Integrated Assessment Model. Exogenous parameters are shown in italics. Parameters tested as part of this global sensitivity analysis are in bold blue italics. Parameter names correspond to the DICE GAMS implementation (Nordhaus, 2008). Parameters are documented in Appendix B. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 2A shows the trajectories of emission control rates for the three policy scenarios included in our study. Each was generated from a DICE GAMS execution. We save the emission control rates and savings rates (investment as a fraction of production) from each scenario for use in the CDICE simulation model. These policy scenarios are: (1) a business-as-usual (BAU) or wait-and-see strategy that delays abatement efforts for more than 100 years, (2) an optimal strategy that balances the trade-off between climate damages and abatement cost impacts on global production, and (3) a 2 °C climate stabilization strategy that constrains global atmospheric temperature to increase no more than 2 °C above pre-industrial temperature with no overshoot permitted. In both the optimal and 2 °C climate stabilization strategy scenarios, the maximum temperature increase occurs around 2100. All policy scenarios assume that the transition to carbon-free energy sources is essentially complete by the mid-2200s. Fig. 2B shows the decadal climate damages and abatement costs for the DICE optimal policy scenario. Fig. A.9 in the Appendix shows the emission control rate, investment, and savings rate trajectories for the optimal policy scenario, which is characterized by a smooth ramp-up of emission reductions.

2.2. The CDICE model

In this study we have developed a time-stepped, deterministic simulation version of DICE, called CDICE, which we use to compare the sensitivities of the underlying DICE model across the three policy scenarios shown in Fig. 2A, independent of the optimization algorithm used by the GAMS version of DICE. We are careful to maintain the original model equations of DICE (Nordhaus, 2008) while imposing the deterministic emission control and savings rate trajectories from the DICE GAMS executions that produced each of the three policy scenarios. Given the DICE control variables and the reference values of all model parameters, the CDICE model yields results nearly indistinguishable from the DICE GAMS optimized execution. In this study, we focus in detail on the modeled climate damages and abatement costs as summarized in Equations (1)–(11) below and shown in detail in Nordhaus (2008, Appendix A). Fig. 2B shows, for example, the decadal policy costs from the DICE GAMS optimal policy solution with the corresponding CDICE results for the same policy and reference values of all model parameters. See Table 1 for definitions of the damages and abatement cost metrics.

The CDICE model runs in decadal time steps beginning in the year 2000. We use output from the first 200 years (or 21 time steps) in this study, and identify decadal results with mid-decade years (e.g., 2105). See Appendix B for descriptions of all of the exogenous parameters and sampling ranges used in this study. We begin the summary of pertinent model equations with the definition of global world production. Global production (in trillions of 2005 USD at time step t), $Q(t)$, net of climate damages, $\Omega(t)$, and abatement costs, $\Lambda(t)$, is defined in Equation (1).

$$Q(t) = \Omega(t)[1 - \Lambda(t)]A(t)K(t)^{\gamma}L(t)^{1-\gamma} \tag{1}$$

In Equation (1), $A(t)$ is the total factor productivity or assumed technology efficiency, $K(t)$ is capital stock input, and $L(t)$ is the population or labor input to production. The capital elasticity of production (also known as the value share of capital in production) is represented by the exogenous parameter γ. The product of total factor productivity and capital and labor shares in Equation (1) constitute gross production. Of the two modifying functions in Equation (1), climate damages, $\Omega(t)$, is defined in Equation (2), and the abatement function, $\Lambda(t)$, is developed in Equations (3)–(8) below. Each represents a fraction of gross world production diverted to the costs of damages or emissions abatements. In this study, we report climate damages and abatement costs as decadal values and in net present value terms (NPV) in trillions of 2005 USD.

$$\Omega(t) = 1\Big/\left[1 + a1\, T_{\mathrm{atm}}(t) + a2\, T_{\mathrm{atm}}(t)^{a3}\right] \tag{2}$$

In the climate damages function shown in Equation (2), $T_{\mathrm{atm}}(t)$ is the increase in atmospheric temperature since 1900 in °C. The coefficients $a1$ and $a2$ as well as the exponent $a3$ are exogenous parameters, calibrated so that a 2.5 °C increase in temperature results in a 1.77% decrease in output in 2105 (Nordhaus, 2007a).

Abatement cost in Equation (3) is a function of the emission control rate, $\mu(t)$, modified by factors representing the cost of incomplete participation in the abatement, $\pi(t)$, and the cost of substituting for carbon-based energy, $\theta_1(t)$. These factors are further described in Equations (4)–(8). The value of the exponent in

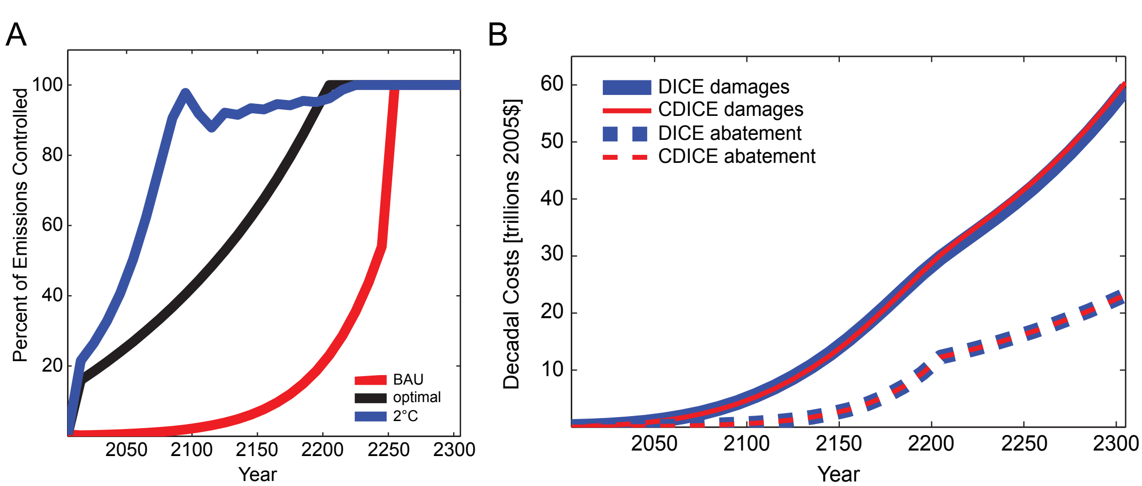

Fig. 2. **A** DICE emission control scenarios. Industrial emissions reductions, output from DICE runs for the business as usual (BAU) policy scenario (red), the optimal policy scenario (black), and the 2 °C climate stabilization scenario (blue). See also Appendix Fig. A.9 for a complete description of the optimal policy scenario. **B** Decadal policy costs for the optimal policy scenario. Climate damages (solid lines) and abatement costs (dashed lines). Blue lines are direct results from the DICE model. Red lines are from the CDICE model using the optimal policy scenario and reference values for all model parameters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Description of terms for cost metrics in this study.

Term	Description	Examples
Cost metrics		
Climate damages	Loss of production due to changes in global surface temperature	Reduced agricultural yields Loss of ecosystem services
Abatement costs	Loss of production due to efforts to reduce greenhouse gas emissions	Investments to increase industrial efficiency Costs of using less carbon-intensive fuels
Total costs	Sum of climate damages and abatement costs	
Temporal resolution		
Decadal costs	Snapshot of costs	Climate damages in 50 years (2050–2060) Abatement costs in 100 years (2100–2110)
NPV costs (net present value)	Sum of discounted decadal costs from 2000-2010 to 2300–2310 using modeled market return-on-capital discount rates	NPV of total costs

the abatement cost function, θ_2, is chosen so that the function is convex (i.e., the marginal cost of the control rises faster than the emission control rate).

$$\Lambda(t) = \pi(t)\theta_1(t)\mu(t)^{\theta_2} \tag{3}$$

The incomplete participation factor, $\pi(t)$, in Equation (4), also called participation markup (Nordhaus, 2008), is a function of the participation rate in Equation (5). The participation markup includes an adjustment based on the same exogenous exponent, θ_2, used in Equation (3).

$$\pi(t) = \phi(t)^{1-\theta_2} \tag{4}$$

The participation rates in the first two time steps (*part frac*1 and *part frac*2), a 'final' participation rate in time step 25 (*part fracn*), as well as the rate at which participation monotonically increases from the second to the final rate (*dpart frac*) determine the time series $\phi(t)$ or the fraction of the economy paying for the abatement at any time step as shown in Equation (5). In practice, the $\phi(t)$ function is either set to model complete participation or replaced with policy-specific participation scenarios (Nordhaus, 2008, Chapters 5–6). We do use the $\phi(t)$ function as defined in this study, but are careful with the bounds of individual parameters to avoid computational problems that arise if the final participation rate is below 50%.

$$\phi(t) = \begin{cases} partfrac1 & t = 1 \\ partfracn + (partfrac2 - partfracn) \times \exp(-dpartfrac \times (t-1)) & 1 < t < 25 \\ partfracn & t \geq 25 \end{cases} \tag{5}$$

The final component in Equation (3) is $\theta_1(t)$, the cost of substituting away from carbon-based energy. This cost is a function of the carbon intensity of production expressed in purchasing power parity terms, $\sigma(t)$. Equations (6) and (7) specify the rate of decline of carbon intensity over time. The exogenous parameters *gsigma*, *dsig*, and *dsig*2 are chosen so that this decline in carbon intensity mirrors historical trends.

$$gsig(t) = gsigma \times \exp\left(-10dsig\, t - 10dsig2\, t^2\right) \tag{6}$$

$$\sigma(t) = \sigma(t-1)/(1 - gsig(t)) \tag{7}$$

The cost of substituting away from carbon-based energy, $\theta_1(t)$ is defined in Equation (8) and is a function of the exogenous parameters *pback*0, *backrat*, and *gback*. This function introduces into the DICE model an unspecified 'backstop' technology as a substitute for carbon-based energy. The values of the exogenous parameters are set to represent an initially high cost of the backstop and a subsequent decline over time. The model is calibrated so that the marginal cost of abatement is equal to the backstop cost in the year when the emissions control rate reaches 100 percent (Nordhaus, 2008).

$$\theta_1(t) = [(pback0 \times \sigma(t))/\theta_2] \times [(backrat - 1 + \exp(-gback \times (t-1)))/backrat] \tag{8}$$

The endogenous emissions pathway is a sum of the industrial emissions and an exogenously specified contribution from land use change, E_{land}, shown in Equation (9). The industrial emissions are a function of gross world production modified by the carbon intensity of production, *sigma*(t), and the emission control rate, $\mu(t)$.

$$E(t) = \sigma(t)[1 - \mu(t)]A(t)K(t)^{\gamma}L(t)^{1-\gamma} + E_{\text{land}}(t) \tag{9}$$

Finally, Equations (10) and (11) describe the computation of the discount rate and discount factors as specified in the base model that are used to develop the net present value metrics reported in this study. In Equation (10), *rir*(t) is the real interest rate at decadal time step t, and δ_K is the capital depreciation rate. Net present value, as used in this study, is the sum of discounted decadal values through the first decade of the 23rd century. As a result of the discounting, discounted decadal values are very small by 2200.

$$rir(t) = [\gamma Q(t)/K(t)] - \left[1 - (1-\delta_K)^{10t}\right] \Big/ 10 \tag{10}$$

$$rdisc(t) = 1 \Big/ (1 + rir(t))^{10t} \tag{11}$$

2.3. A note about modeling choices

We have not sampled the pure rate of time preference (ρ) or the elasticity of marginal utility (α) in this study. These two parameters strongly influence the optimized mitigation trajectories that result from maximizing the sum of discounted utility of consumption over time in the DICE model. Since there exists substantial literature on the issue of discounting the future (e.g., Stern, 2007; Nordhaus, 2007b; Weitzman, 2007), we chose instead to focus our study on the specific model outputs of climate damages and abatement costs, and the net present value of these costs over 200 years, applying the discount factors described in Equations (10) and (11).

3. Methods and computational experiment

3.1. Methods

3.1.1. Sobol' sensitivity analysis

We apply a global sensitivity analysis based on the variance decomposition method proposed by Sobol' (2001) and described by Saltelli et al. (2008) to assess the sensitivity in CDICE of the DICE policy scenarios to (1) the exogenous model parameters identified as having the most influence on the model in Nordhaus (2008) and (2) an extended list of model parameters (see Section 3.2 for details). The Sobol' method (Sobol', 2001; Saltelli et al., 2008) decomposes the variance of model outputs from an ensemble of model executions. Portions of these variances are attributed to individual model parameters or factors as well as to interactions between those factors. Tang et al. (2007) showed that the Sobol' method performed well in comparison to other sensitivity analysis methods in the case of nonlinear hydrologic models. Their study compared local and global sensitivity analysis methods, including parameter estimation software (PEST), Regional Sensitivity Analysis (RSA) and analysis of variance using iterated fractional factorial design sampling (ANOVA). For additional details, see Tang et al. (2007). We note that there are other global sensitivity methods that can be used, especially when the model is computationally expensive. A recent example is the study of the DICE model in Anderson et al. (2013) using the sensitivity analysis method described in Plischke et al. (2013). There is a useful guide for practitioners in Saltelli et al. (2008, Table 6.9) for choosing a sensitivity analysis method suited to a specific analysis goal. We use the Sobol' method in our study to identify first-order sensitivity indices (the fraction of the variance that can be attributed to a single parameter), second-order indices (the fraction of the variance attributed to interactions of pairs of parameters), and total-order indices (sum of all first-order and higher-order effects). Our parameter sampling exploits quasi-random sampling (Sobol', 1967). The method provides an efficient and comprehensive coverage of the parameter space and enhances the convergence speed of variance decomposition (Saltelli, 2002). We assess the convergence and confidence of our global sensitivity indices using bootstrapping to compute confidence intervals (Archer et al., 1997) for the sensitivity indices.

Following Saltelli et al. (2008), we derive the sensitivity indices. We begin with a function f transforming the inputs $X_1, X_2, \cdots, X_n$ into model output Y as shown in Equation (12).

$$Y = f(X_1, X_2, \cdots, X_n) \tag{12}$$

The function f can be expanded into terms of increasing dimension as shown in Equation (13) (Saltelli et al., 2008). For example, $f_i = f_i(X_i)$ and $f_{ij} = f_{ij}(X_i, X_j)$.

$$f = f_0 + \sum_i f_i + \sum_{i<j} f_{ij} + \sum_{i<j<k} f_{ijk} + \cdots + f_{ijk\ldots n} \tag{13}$$

Sobol' (2001) suggests computing each of these terms using conditional expectations, as shown in Equations (14)–(16).

$$f_0 = E(Y) \tag{14}$$

$$f_i = E(Y|X_i) - f_0 \tag{15}$$

$$f_{ij} = E(Y|X_i, X_j) - f_i - f_j - f_0 \tag{16}$$

Sensitivity indices are assembled from the variances of these conditional expectations, normalized by the grand variance, such that they sum to 1. The larger the sensitivity index, the larger the contribution to the variance of the model output. The first order and second order indices are shown in Equations (17) and (18).

$$S_i = \frac{V[f_i(X_i)]}{V[Y]} = \frac{V[E(Y|X_i)]}{V[Y]} \tag{17}$$

$$S_{ij} = \frac{V\left[f_{ij}(X_i, X_j)\right]}{V[Y]} = \frac{V\left[E(Y|X_i, X_j)\right]}{V[Y]} - S_i - S_j \tag{18}$$

A total order index, shown in Equation (19), reflecting the total effects due to input X_i, is the sum of the first order effect S_i and all higher order effects in which X_i takes part.

$$S_i^T = 1 - \frac{V[E(Y|X_{\sim i})]}{V[Y]} \tag{19}$$

The notation $X_{\sim i}$ indicates all inputs except the i-th model parameter X_i.

3.1.2. One-at-a-time (OAT) sensitivity analysis

Prior sensitivity analyses of DICE have, for the most part, assumed linear separability and focused on the local OAT model parameter sampling approach. OAT analysis requires the user to choose model parameters for testing and vary one parameter at a time over a plausible range while measuring the impact on a given model output or metric. The parameters causing the most change, or steepest ascent (Box et al., 2005), are classified as important. The method can be used as a simple, qualitative method for ascertaining local sensitivities in linear models; however, it cannot detect parameter interactions. We use OAT sensitivity analysis to replicate a first step in parametric sensitivity analysis documented in Nordhaus (2008, Chapter 7), which seeks to identify the key DICE model parameters (the “expert set” as noted in Section 3.2). We replicate the OAT analysis (see Section 3.2.1) as a preliminary step in our sensitivity analysis to show that CDICE attains the same results and that these results serve as a baseline to demonstrate the consequences of using OAT analysis on nonlinear IAMs. We also use this method (see Section 3.2.3) to show results of an OAT analyses using an extended set of parameters.

3.1.3. Independent verification method

We employ an independent verification test of the OAT and Sobol' classifications of key parameters as suggested by Andres (1997), following the example of Tang et al. (2007). We choose an independent Latin Hypercube sample varying the full suite of 30 parameters over the bounds indicated in Appendix B. This sampled is referred to as Set 1 in the terminology of Andres (1997). We execute CDICE for each parameter combination in this Set 1 sample and save one or more of the metric outputs. We then adjust the Set 1 sample by fixing the least sensitive parameters for the given output metric to their constant reference values, leaving the sensitive or influential parameters randomly sampled. These adjusted samples, one for each metric, are referred to as Set 3 samples in the terminology of Andres (1997). We execute CDICE for each Set 3 sample, again saving the appropriate metric output. If our choice of sensitive parameters is correct, then the values of the metric in Sets 1 and 3 will be highly correlated.

3.1.4. Visual representation of sensitivity results

We display the results of the Sobol' sensitivity analyses in radial convergence diagrams (Lima, 2011). The sampled exogenous parameters are arranged in groups related to model component around a circle beginning with the socio-economic parameters at 3 o'clock and, proceeding counter-clockwise, with the climate-related, damage and abatement parameters. Individual parameter descriptions can be found in Appendix B in the same groupings. For the Sobol' variance decomposition analyses, the magnitudes of the first and total order Sobol' sensitivity indices are shown by the size of the nodes at the location of each parameter on the diagram. First order indices are filled circles and total order indices are hollow rings. Second order indices are lines of increasing shading and thickness connecting the interacting parameters. Large differences in the sizes of the first and total order index nodes are indicative of substantial higher order parameter interactions in the variance decomposition. Of the higher order interactions, we show explicitly only those of second order in these diagrams. Indices larger than a threshold of 1% of the variance are shown in the figures. We use the radial convergence diagrams to compare parametric sensitivities for the different parameters sets, for the different metrics, and for changes in the sensitivities of the metrics over policy scenarios and time.

3.2. Computational experiments

We conduct a number of experiments to determine the sensitivity of the damage and abatement cost outputs/metrics to sampled parameters using the CDICE simulation model. We identify two groups of parameters for testing: (1) a set of eight parameters designated as important (which we call the "expert set") in Nordhaus (2008) based on expert assessment and experience with a previous version of the DICE model (Nordhaus, 1994) and (2) a set of 30 parameters (the "extended set") that includes seven of the eight parameters in the expert set. The eighth parameter in the expert set is the upper limit of fossil fuel resources (*fosslim*), which serves as a constraint to the optimization in DICE. We configured CDICE to only report violations of this constraint. The parameters tested are listed in Appendix B in groups related to model component, along with the literature sources of information used to set the bounds for each parameter. The parameters in the expert set are shown in bold in the tables in Appendix B. For these parameters, we reference the standard deviations supplied in Nordhaus (2008, Table 7-1) in setting the bounds. In some cases, time series used in the main equations of the model are constructed from several related parameters. For these related parameters, we selected ranges for related parameters to constrain the overall bounds of the time series. See Appendix B for more detail.

3.2.1. Initial OAT analysis

To ensure that we have a valid replication of the DICE model in CDICE, we conduct the OAT sensitivity test described in Nordhaus (2008, Chapter 7) using the expert set of parameters and the BAU policy scenario. We varied each of these eight parameters one at a time over ± 6 standard deviations (Nordhaus, 2008, Table 7-1, Fig. 7-1) to measure the impact on the increase in atmospheric temperature in the first decade of the 22nd century. Fig. 7-1 of Nordhaus (2008) is adapted here as Fig. 3A. We have excluded values of parameters that are non-physical or cause model failure. Results are reported relative to the reference case, the atmospheric temperature increase in 100 years for the BAU policy scenario.

3.2.2. Verification test for expert set of important parameters

Examining the impact on 100-year atmospheric temperature increase, Nordhaus (2008) asserts that the expert set of parameters has "the largest impact on DICE model outcomes and policies." We attempt to verify this for two important net present value cost metrics (Table 1). We use our independent verification method (described in Section 3.1.3) for this experiment, which involves a pairwise comparison of two ensembles of CDICE computations for these two metrics. In the first ensemble (Set 1), parameter sets are created from a Latin Hypercube sample of the extended set of parameters (8192 parameter sets or SOWs in the ensemble). For the second ensemble (Set 3), we modify the Set 1 samples to use the reference values for all parameters except those in the expert set. This verification exercise tests the validity of the assumption that the parameters in the expert set have the largest impacts on model outcomes, including metrics and policy scenarios other than those shown in Nordhaus (2008).

3.2.3. OAT Analysis for the NPV of climate damages and abatement costs

In the next computational experiment, we conduct OAT analyses specifically focused on the NPV of climate damages and abatement costs output metrics. OAT sensitivity analysis has been used as an

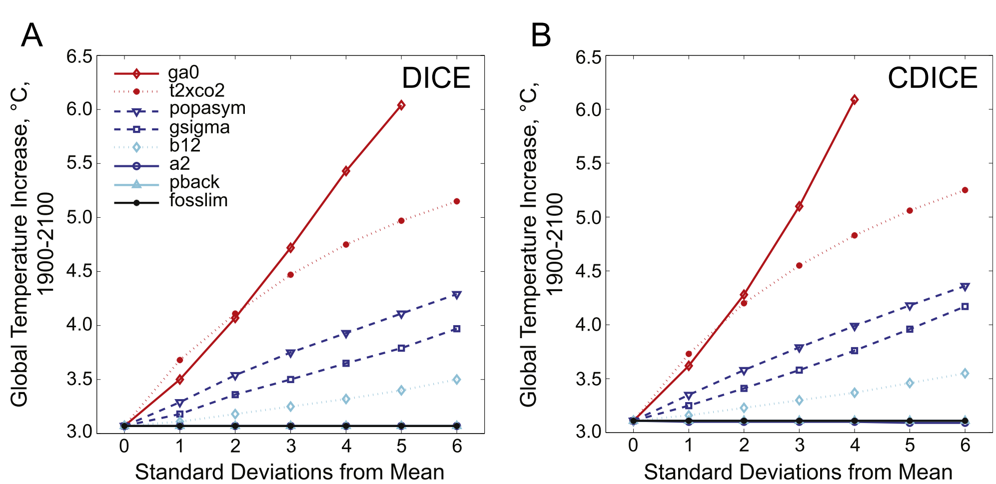

Fig. 3. Replication in CDICE of a DICE one-at-a-time (OAT) sensitivity analysis for the expert set of parameters for atmospheric temperature increase after 100 years using the BAU scenario. **A** Results from DICE, adapted from Nordhaus (2008, Fig. 7-1). **B** Results from CDICE. The order of importance of the sampled parameters is the same in both analyses.

initial step to identify important parameters to limit the computational demands of follow-on uncertainty testing (Nordhaus, 1994, 2008; Scott et al., 1999). We compute reference values $metric_{ref}$ using the DICE optimal policy scenario with all exogenous parameters at their reference settings, where *metric* is the NPV of climate damages or the NPV of abatement costs. We use the optimal policy scenario here as both the climate damages and the abatement costs are non-negligible. For each parameter p in the expert or extended set of parameters we compute two additional values of each NPV metric, one with the parameter at the low end of the range, $metric_{p,low}$, and one at the high end of its range, $metric_{p,high}$, using the bounds in Appendix B. We then compute the normalized deviation from the reference value for the parameter and metric using Equations (20) and (21).

$$deviation_{p,low} = \frac{\left|metric_{p,low} - metric_{ref}\right|}{metric_{ref}} \tag{20}$$

$$deviation_{p,high} = \frac{\left|metric_{p,high} - metric_{ref}\right|}{metric_{ref}} \tag{21}$$

We choose the larger of $deviation_{p,low}$ and $deviation_{p,high}$ for each parameter and metric, and then rank order the parameters in terms of the magnitude of this deviation. These rankings are posted in a table in percentage terms. Although we cannot detect possible effects of parameter interactions, we hypothesize that comparing the results with the two different parameter sets will show that there are influential parameters in the extended set that are not in the expert set.

3.2.4. Sobol' sensitivity analysis

We impose each of the policy scenarios in turn in CDICE and construct alternative SOWs by simultaneously varying parameters (7 in the expert set or 30 in the extended set) using Sobol' pseudo-random sampling (Sobol', 1967). First-order and total-order Sobol' sensitivity indices for each parameter and second-order sensitivity indices for each parameter pair in the set are computed in CDICE from the variance decomposition of the target cost metrics using the SOW ensemble. Results are reported here for sample sizes that result in bootstrap confidence intervals that are $\leq$10% of the total order indices for the leading indices. See Appendix C for an illustration of how Sobol' indices converge for increasing sample sizes for this experiment. For the expert set, we use 65,536 samples of each parameter for a total of 1,048,576 SOWs; for the extended set, there are 131,072 samples of each parameter and a total of 8,126,464 SOWs.

3.2.5. Verification test of Sobol' parameter rankings

As an additional test of the Sobol' sensitivity analysis identification of sensitive parameters within the extended set of parameters, we conduct another independent verification, as described in Section 3.1.3, in this case for the net present value of total costs (the sum of the NPV of climate damages and abatement costs) for the three different policy scenarios. Using the same Set 1 Latin Hypercube sample chosen in the earlier independent verification (Section 3.2.2), we compute in CDICE the NPV total cost metric for this ensemble of SOWs for the three policy scenarios. For each policy scenario, we modify the Set 1 parameter values, by fixing the insensitive parameters (Sobol' total order indices <0.1%) to their reference values, creating Set 3 parameter sets for each policy scenario. Pairwise comparison of the NPV total cost metrics from the Set 1 and Set 3 SOW ensembles for each policy scenario should be highly correlated if our designation of sensitive parameters is correct. We report a separate verification test for each of the policy scenarios, as the sensitive parameters could be different in the alternative scenarios.

4. Results

4.1. OAT Sensitivities of the CDICE model outputs

Fig. 3 verifies that we are able to match the Nordhaus OAT-based sensitivity rankings (Nordhaus, 2008, Chapter 7) for the parameters controlling the increase in atmospheric temperature in the first decade of the 22nd century in DICE (Fig. 3A) and CDICE (Fig. 3B) using the BAU policy scenario. The atmospheric temperature increase using reference values of all parameters is 3.2 °C for DICE (Nordhaus, 2008) and 3.1 °C for CDICE, illustrating that the CDICE simulation captures the atmospheric temperature OAT analysis of Nordhaus' selection of key DICE parameters (the expert set) and their rank order assuming their effects are linear and separable.

Fig. 4 provides the results of the independent verification (Section 3.2.2) used to determine whether the expert set parameters are the most important parameters for the NPV of climate damages and the NPV of abatement costs. These NPV metrics are discounted sums through the first decade of the 23rd century (Table 1), applying the real interest rate discount factors in Equations (10) and (11). The discount factors diminish at a rate that makes the contributions to the discounted sum very small beyond 200 years. As described in Section 3.2.2, the results in Fig. 4 were obtained using an initial Latin Hypercube sample (Set 1) that varied the parameters in the extended set of 30 parameters over the ranges in Appendix B. We computed the NPV of climate damages and abatement costs for each SOW in the Set 1 sample using the BAU policy scenario in CDICE. We then adjusted the Set 1 sample by fixing all parameters except those in the expert set to their reference values; this sample is called Set 3. The NPV of climate damages and abatement costs are computed in CDICE for the SOWs in Set 3 using the same BAU policy scenario. If the expert set of parameters is correctly specified and sufficiently controls the NPV cost metrics, then the pairwise plot of the unadjusted and adjusted ensembles in Fig. 4 should lie on the 45-degree (i.e., the perfect correlation) line. In Fig. 4, we see that this is not true and conclude that the NPV cost metrics must be sensitive to parameters not included in the expert set specified by Nordhaus (2008).

The core question that emerges from this analysis is, *what are the controlling parametric sensitivities of these important cost metrics?* At present within the integrated assessment community, expert-driven parameter selection coupled with OAT analysis is the primary method for a first assessment of model sensitivities (e.g., Scott et al., 1999; Nordhaus, 2008). This may be followed by a limited Monte Carlo sensitivity test of impacts of the parameters that pass the initial OAT screening. As a way to explore the consequences of this methodological approach and its implicit linear independence assumptions, we continue with the OAT analysis described in Section 3.2.3. Using the DICE optimal policy scenario we rank order the parameters in terms of their percentage effect on the NPV of climate damages and abatement costs. The top five parameters for each parameter set are shown in Table 2. We note first the agreement of both expert and extended parameter sets in the top-ranked parameter, $t2xco2$ or climate sensitivity, for the NPV of climate damages. Differences in the rank ordered lists are primarily in the effects of parameters in the extended set that are not sampled in the expert set. For example, of the parameters related to the climate damages function (Equation (2)), only $a2$, the coefficient on the nonlinear term, is in the expert set of parameters. The exponent of the nonlinear term, $a3$, and the coefficient on the linear term, $a1$, both have a larger individual effects that push $a2$ down in

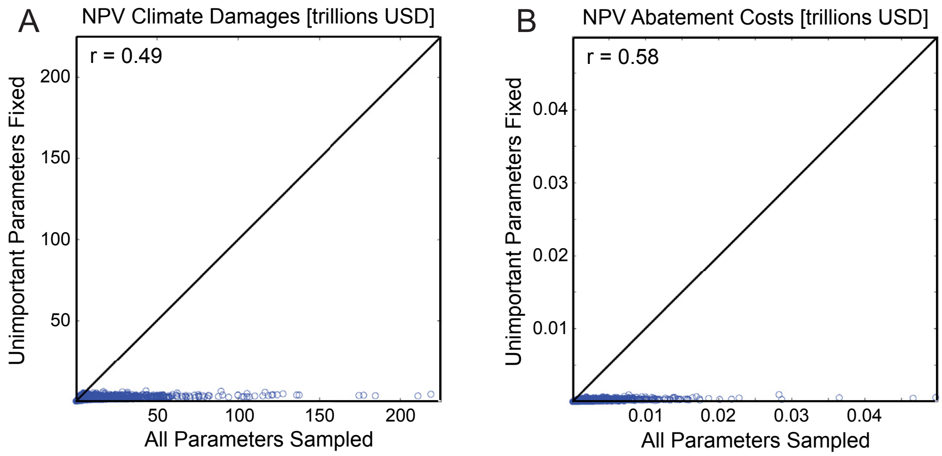

Fig. 4. Pairwise comparison of CDICE output metrics for ensembles with the extended set of parameters sampled (horizontal axis) and with all parameters except those from Fig. 3 fixed (vertical axis). Results are shown for **A** the net present value of climate damages and **B** the net present value of abatement costs. If the insensitive parameters from the atmospheric temperature increase experiment were also insensitive for these cost metrics, the pairwise comparisons would be highly correlated.

rank order for the NPV of climate damages. Parameters that affect the total factor productivity function (*dela*, a rate of decline, in the extended set and *ga*0, an initial growth rate, in both parameter sets) are high-ranked parameters for both of the NPV metrics. Total factor productivity, in the form of *ga*0, also ranked high for the 100-year temperature increase as seen in Fig. 3. That *dela* outranks *ga*0 in the extended set of parameters is a reflection of its role in the total factor productivity function. See Appendix B for details of how we chose bounds for these related total factor productivity parameters. The rankings for the extended set confirm that total factor productivity is important to both of the NPV cost metrics.

The highest ranking parameter for the NPV of abatement costs in the extended set is the fraction of the economy sharing the costs of the abatement in the 2010–2020 decade (*partfrac*2). None of the participation parameters are included in the expert set of parameters. Their common use in the DICE model is as pre-set values to model specific cost-sharing participation scenarios (see the discussion in Nordhaus, 2008, Chapter 6). Our DICE policy scenarios were created assuming an extremely optimistic 100% participation in the abatement. The magnitude of the effect shown in Table 2 is largely a result of the piece-wise participation function (Equation (5)). The OAT analysis assumes that the parameter effects are independent, which will not be true for the participation parameters. In a typical modeling exercise, the participation function is likely to be invoked as a whole or at the reference 100% setting. As this IAM is highly nonlinear and composed of coupled models, we can expect there to be significant parameter interactions. A global sensitivity analysis method, such as the Sobol' variance decomposition method used here, is required to identify these interactions.

Table 2
Top five ranked parameters for NPV metrics for expert and extended parameters sets for the optimal policy scenario. Parameters are ranked by their percentage effect (shown in brackets) as described in Section 3.2.3. Parameters are defined in Appendix B.

Rank order	NPV climate damages		NPV abatement costs	
	Expert	Extended	Expert	Extended
1	*t2xco2* [115]	*t2xco2* [115]	*pback0* [160]	*partfrac2* [1221]
2	*popasym* [37]	*a3* [88]	*ga0* [45]	*pback0* [160]
3	*a2* [21]	*dela* [40]	*gsigma* [36]	*dela* [83]
4	*gsigma* [14]	*popasym* [37]	*popasym* [18]	*ga0* [45]
5	*ga0* [14]	*a1* [24]	*t2xco2* [7]	*gsigma* [36]

4.2. Sobol' sensitivities of net present value cost metrics

Fig. 5 shows the result of the Sobol' sensitivity analysis for these NPV cost metrics for both the expert and extended sets of parameters under the BAU policy scenario. Fig. 5A and B show the variance decomposition of approximately 1 million SOWs created from global sampling of the expert set of parameters. Comparing the results of the BAU scenario for the expert set in Fig. 5A with Table 2, the top three rank order parameters from the OAT analysis for the NPV of climate damages again dominate, but note the high degree of interactions between them. The interaction between climate sensitivity (*t*2*xco*2) and the coefficient on the nonlinear term of the damages function (*a*2) accounts for 10% [confidence interval (CI) 1%] of the variance of the NPV of climate damages. Compared to the top three sensitive parameters in the OAT test, the total order sensitivity indices for the climate sensitivity (*t*2*xco*2), population limit (*popasym*) and the damage function coefficient (*a*2) parameters are 45% [1%], 11% [1%], and 59% [1%]. The interactions of the *a*2 parameter with other parameters makes its impact much greater than would be apparent in the OAT test. Fig. 5B shows that the top four rank order parameters from the OAT analysis for the NPV of abatement costs remain the leading sensitivities in the Sobol' analysis. However, here again the parameter interactions dominate, although the carbon intensity parameter (*gsigma*) now outranks the total factor productivity parameter (*ga*0) due to the interaction between the initial cost of the carbon-free energy substitute (*pback*0) and the carbon intensity parameter (*gsigma*) accounting for 3% [1%] of the variance of the NPV of abatement cost.

Fig. 5C and D illustrate the shortcomings and possible biases of limiting the parameters tested to those in the expert set. These figures show the variance decomposition of approximately 8 million SOWs created by the global sampling of the extended set of parameters. Table 3 lists the numerical values of the total-order indices supporting Fig. 5C and D in the columns for the BAU policy scenario. For the NPV of climate damages (Fig. 5C), the difference in first- and total-order indices shows that the parameter interactions dominate. The second-order interaction between climate sensitivity (*t*2*xco*2) and the exponent in the damages function (*a*3) accounts for 13% [1%] of the variance in the metric. An additional 7 parameter pair interactions each account for ≥1% of the variance. The total factor productivity parameter (*ga*0) in particular accounts for a larger total-order portion of the variance (27% [3%]) than could be inferred from the OAT analysis in Table 2.

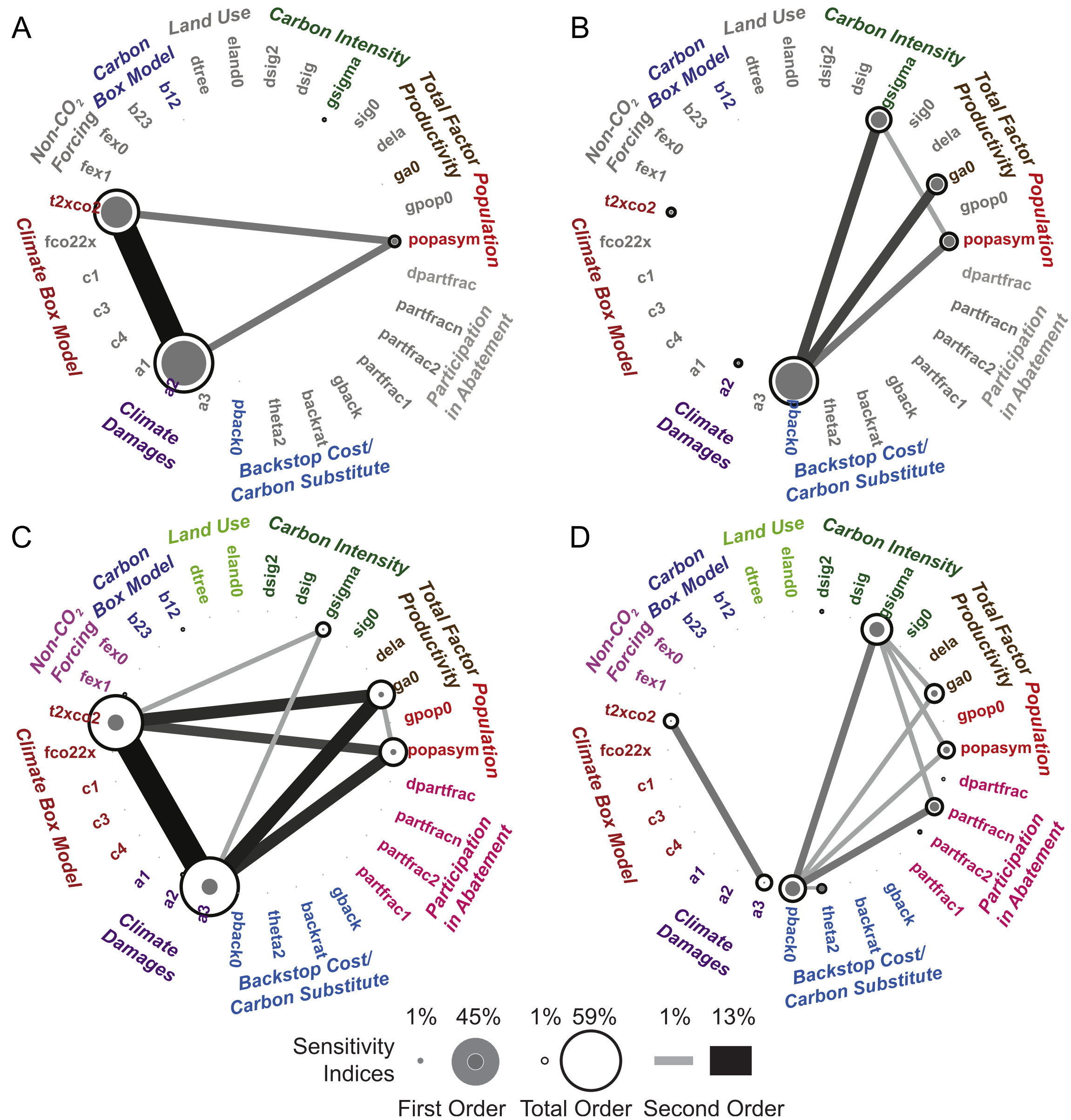

Fig. 5. Sobol' sensitivity results for the NPV of climate damages (**A** and **C**) and the NPV of abatement costs (**B** and **D**). **A** and **B** use the expert set of parameters. **C** and **D** use the extended parameter set. Filled nodes represent first-order sensitivity indices. Rings indicate the magnitude of the total-order indices. Shading and width of lines are the second-order indices. The legend indicates the minimum and maximum indices shown in the figure. Results are from the BAU policy scenario.

Of all the climate-related parameters, the NPV of climate damages is sensitive only to climate sensitivity (*t2xco2*) and not to any of the other climate box model, land-use change, carbon box model, and non-CO greenhouse gas forcing parameters. In Fig. 5D, we see that the NPV of abatement costs is more sensitive to the initial growth rate of the carbon intensity of production (*gsigma*) and the total factor productivity parameter (*ga0*) than we found in the OAT analysis in Table 2. The relatively small influence of the abatement participation parameters (only *partfracn* has a total-order index $>1\%$) is a reflection of the low abatement in the BAU policy scenario where most mitigation is deferred until after the 200 year horizon of the NPV cost metrics. This policy scenario tends to be dominated by climate damage costs.

Comparing the Sobol' analysis result for the NPV cost metrics between the expert and extended sets of parameters, we see significant differences in the rank ordering of the sensitive parameters in addition to the considerable increase in parameter interactions in the extended parameter set. The principal lesson here is that OAT analyses and the limited global analyses afforded by the expert set of parameters fail to accurately portray the controlling parametric sensitivities of the NPV of climate damages and abatement costs in this DICE model policy scenario. Moreover, if the OAT analysis were used to inform investments in further research related to the underlying uncertainties, key interdependencies between the exogenous parameters would likely be missed.

4.3. Sensitive parameters and interactions change with mitigation strategy and time

In Fig. 6, we introduce the Sobol' sensitivity analysis results for a composite metric, the NPV of total costs (the sum of the NPV of

Table 3
Total-order indices [confidence intervals] for NPV metrics by policy scenario. Bold values indicate sensitivity indices above a threshold value of 0.01 (or 1% of variance).

Model parameter	BAU		Optimal		2 °C stabilization	
	NPV Climate damages	NPV Abatement costs	NPV Climate damages	NPV Abatement costs	NPV Climate damages	NPV Abatement costs
popasym	**0.27 [0.05]**	**0.16 [0.02]**	**0.23 [0.03]**	**0.03 [0.00]**	**0.11 [0.01]**	**0.01 [0.00]**
gpop0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
ga0	**0.27 [0.03]**	**0.19 [0.02]**	**0.20 [0.02]**	**0.02 [0.00]**	**0.06 [0.01]**	0.00 [0.00]
dela	0.00 [0.01]	0.00 [0.01]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	**0.01 [0.00]**
sig0	**0.01 [0.01]**	0.00 [0.01]	**0.01 [0.01]**	**0.01 [0.00]**	**0.01 [0.00]**	**0.01 [0.00]**
gsigma	**0.14 [0.03]**	**0.31 [0.03]**	**0.09 [0.02]**	**0.14 [0.01]**	**0.03 [0.01]**	**0.13 [0.01]**
dsig	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
dsig2	0.00 [0.01]	**0.02 [0.01]**	0.00 [0.00]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]
eland0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
dtree	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
b12	**0.01 [0.01]**	0.00 [0.00]	**0.01 [0.01]**	0.00 [0.00]	**0.01 [0.00]**	0.00 [0.00]
b23	0.00 [0.01]	0.00 [0.01]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
fex0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
fex1	**0.02 [0.01]**	0.00 [0.00]	**0.03 [0.01]**	0.00 [0.00]	**0.04 [0.00]**	0.00 [0.00]
t2xco2	**0.55 [0.04]**	**0.14 [0.03]**	**0.53 [0.03]**	**0.01 [0.00]**	**0.62 [0.01]**	0.00 [0.00]
fco22x	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c1	0.00 [0.01]	0.00 [0.00]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c3	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c4	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
a1	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.01 [0.00]**	0.00 [0.00]
a2	**0.02 [0.01]**	0.00 [0.00]	**0.02 [0.01]**	0.00 [0.00]	**0.03 [0.00]**	0.00 [0.00]
a3	**0.59 [0.04]**	**0.15 [0.03]**	**0.47 [0.03]**	**0.03 [0.01]**	**0.31 [0.01]**	0.00 [0.00]
pback0	0.00 [0.00]	**0.26 [0.02]**	0.00 [0.00]	**0.45 [0.01]**	0.00 [0.00]	**0.48 [0.01]**
theta2	0.00 [0.00]	**0.08 [0.01]**	0.00 [0.00]	**0.02 [0.00]**	0.00 [0.00]	0.00 [0.00]
backrat	0.00 [0.00]	**1.00 [0.01]**	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
gback	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
partfrac1	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
partfrac2	0.00 [0.00]	**0.02 [0.01]**	0.00 [0.00]	**0.27 [0.01]**	0.00 [0.00]	**0.21 [0.01]**
partfracn	0.00 [0.00]	**0.17 [0.01]**	0.00 [0.00]	**0.17 [0.01]**	0.00 [0.00]	**0.17 [0.01]**
dpartfrac	0.00 [0.00]	**0.01 [0.01]**	0.00 [0.00]	**0.03 [0.00]**	0.00 [0.00]	**0.07 [0.01]**

climate damages and the NPV of abatement costs) to compare the parametric sensitivities of the three policy scenarios in our study (Fig. 2). The BAU policy scenario defers most abatement with only ~20% of emissions reduced at 200 years. The optimal policy scenario and the 2 °C stabilization scenario both impose controls on industrial CO_2 emissions immediately, reaching 100% reduction in the second half of the 22nd century. These two policy scenarios differ primarily in how quickly emission controls are implemented. We use these three scenarios to show how parameter sensitivities change when there are trade-offs of near-term abatement costs for future climate damages. In the deterministic runs for these three scenarios in DICE and in the CDICE simulation (using reference values of DICE's exogenous parameters), climate damages are similar for all three scenarios in the first half of the 21st century. In the 2 °C stabilization scenario, decadal abatement costs surpass decadal climate damage costs in the 2060s, and are within a few percent of each other at the end of the 200 year net present value horizon. For the optimal and BAU policy scenarios the decadal abatement costs are 40% and <1%, respectively, of the damage costs at the end of the 200 year net present value horizon. The Sobol' sensitivity analysis for the NPV of total costs for the BAU scenario in Fig. 6A closely resembles the analysis for the NPV of climate damages for the same scenario in Fig. 5C, underscoring how much the climate damages overwhelm the abatement costs over the 200 year NPV horizon for this wait-and-see policy scenario. The analysis for the optimal policy scenario in Fig. 6B is similar to the analysis for the BAU scenario, even with a ramp up of emission controls that is much closer to the 2 °C stabilization scenario. This reflects the higher fraction of the total costs from damages versus abatement. The aggressive strategy to stabilize the increase in atmospheric temperature below 2 °C, shown in Fig. 6C, presents a very different result for the NPV of total costs. More of the total costs in the early decades of the net present value horizon are attributed to abatement. The sensitivity to the damage-related parameters is minimal. The parameter interactions between the initial cost of the carbon-free energy alternative and the participation parameters dominate the metric variance reflected in Fig. 6C.

The aggregate net present value metrics explored to this point tell only part of the story: a picture of a limited future horizon from the perspective of current, perfect knowledge of the future. It is also informative to see how the sensitivities evolve over time. In Fig. 7, we show the results of Sobol' analyses of decadal abatement costs in snapshots at 50 years, 100 years and 200 years within the NPV time horizon. We use these snapshots of decadal costs as an example of how the sensitivities of model metrics can change over time as well as by policy scenario. We contrast the sensitivities of the decadal abatement costs in the BAU policy scenario (Fig. 7A, C and E) with the snapshots for the same decades for the 2 °C stabilization scenario (Fig. 7B, D and F). The BAU policy scenario imposes very little reduction in industrial emissions for the first 150 years, and consequently incurs minimal abatement costs during this time. In our ensemble of SOWs, the abatement costs in Fig. 7A and C are sensitive to the development of the cost of the carbon-free energy replacement technology parameters (*pback*0 and *theta*2). There is also the expected progression of sensitivities to the participation parameters over time as these sensitivities shift from the participation fraction in the second decade (*part frac*2) in Fig. 7A, to the final participation fraction (*part fracn*) and the rate at which it is achieved (*dpart frac*) in Fig. 7C, to the final participation rate alone in Fig. 7E. The relative sensitivities of the total factor productivity parameter (*ga*0) and the carbon intensity

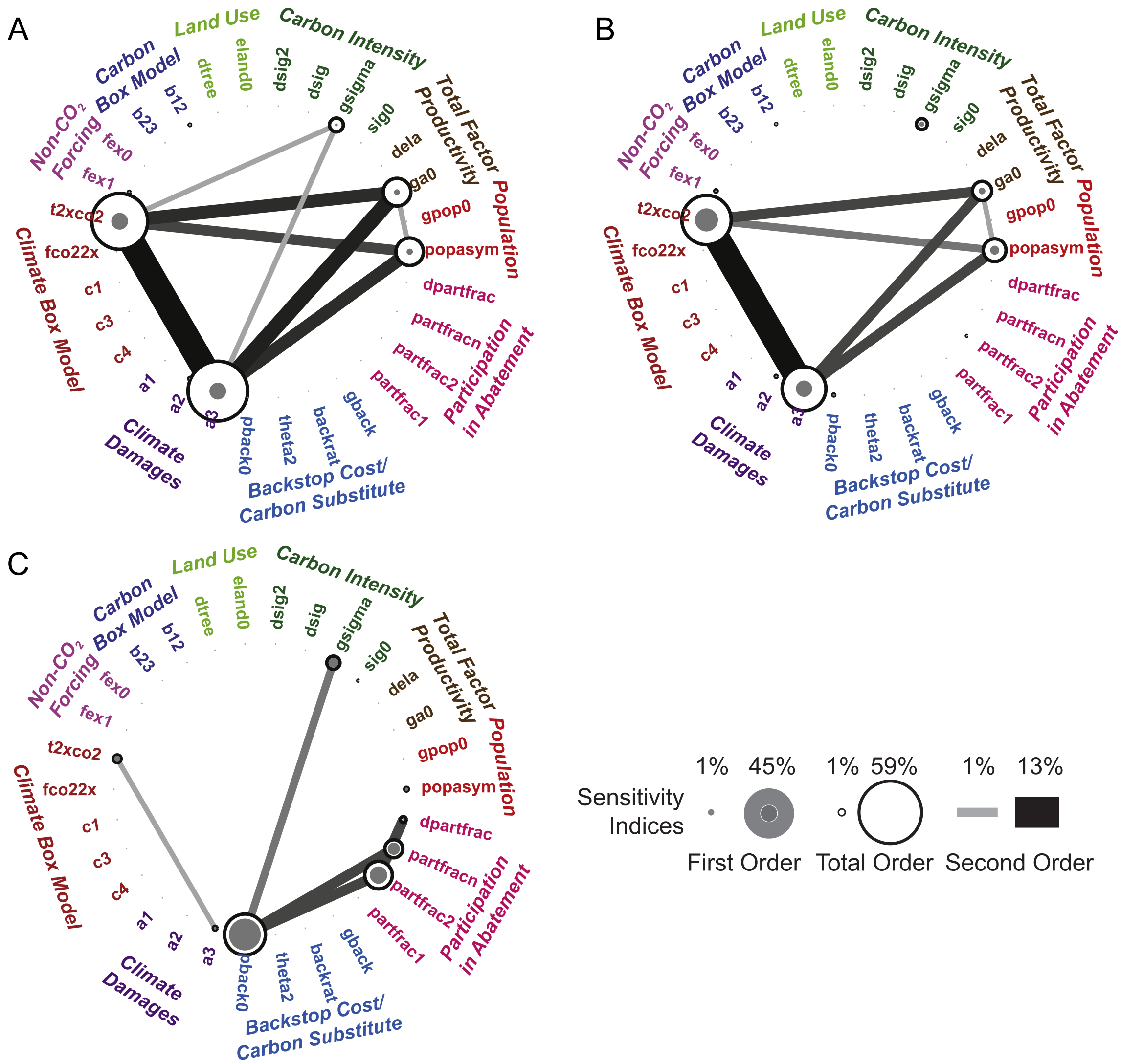

Fig. 6. Sobol' sensitivity results for the NPV of total costs by policy scenario. **A** BAU; **B** optimal; **C** 2 °C climate stabilization. The legend indicates the minimum and maximum indices shown in the figure.

parameter (*gsigma*) increase over time. The many parameter interactions illustrate a complex, evolving situation. The 2 °C stabilization scenario imposes abatement immediately, with strong sensitivities to the initial cost of the carbon-free energy substitute (*pback*0) and the abatement participation in the second decade (*part frac*2) in Fig. 7B. As in the BAU scenario, the sensitivities to the total factor productivity (*ga*0), carbon intensity (*gsigma*), population limit (*popasym*), and participation parameters evolve over time as seen in Fig. 7D and F. What is remarkable here is the resemblance of Fig. 7E and F. By the end of the NPV planning horizon, the parametric sensitivities are nearly identical in both scenarios. This convergence also holds for the optimal policy scenario (not shown).

4.4. Verification of the method for NPV total costs

As a final verification of the sensitive parameters for the NPV of total costs, we undertake a verification test of the Sobol' sensitivity rankings for the extended set of parameters as described in Section 3.2.5. Using the same Latin Hypercube sample from the earlier verification (Set 1 in Section 4.1), we make a Set 3 sample for each policy scenario. We fix the insensitive parameters (Sobol' total-order indices <0.1%) to their reference values and compute the NPV of total costs for each Set 3 sample in CDICE. Fig. 8 shows the pairwise comparisons of these samples. Again, a perfect identification of the insensitive parameters would result in each data point lying on the 45° line and a correlation score of 1.000. In Fig. 8 we see that sampling or not sampling the insensitive parameters makes very little difference in the values of the NPV of total costs metric, giving us confidence that we have identified both the insensitive and sensitive parameters correctly for each policy scenario. Fig. 8 also shows that the range of the NPV of total costs in the BAU policy scenario (Fig. 8A) is five times larger than in the 2 °C stabilization scenario (Fig. 8C). We also note that the NPV of total costs for the CDICE runs, assuming the reference values of all parameters, is ~2 trillion USD in each of these three policy scenarios. This is at the very low end of the distributions for all SOWs in each case, reflecting the influence of the choice of parameter values on the optimized results. The lesson here is that the more aggressive the control on emissions, the greater the dependence on the early existence and use of renewable energy sources and more efficient use of technology.

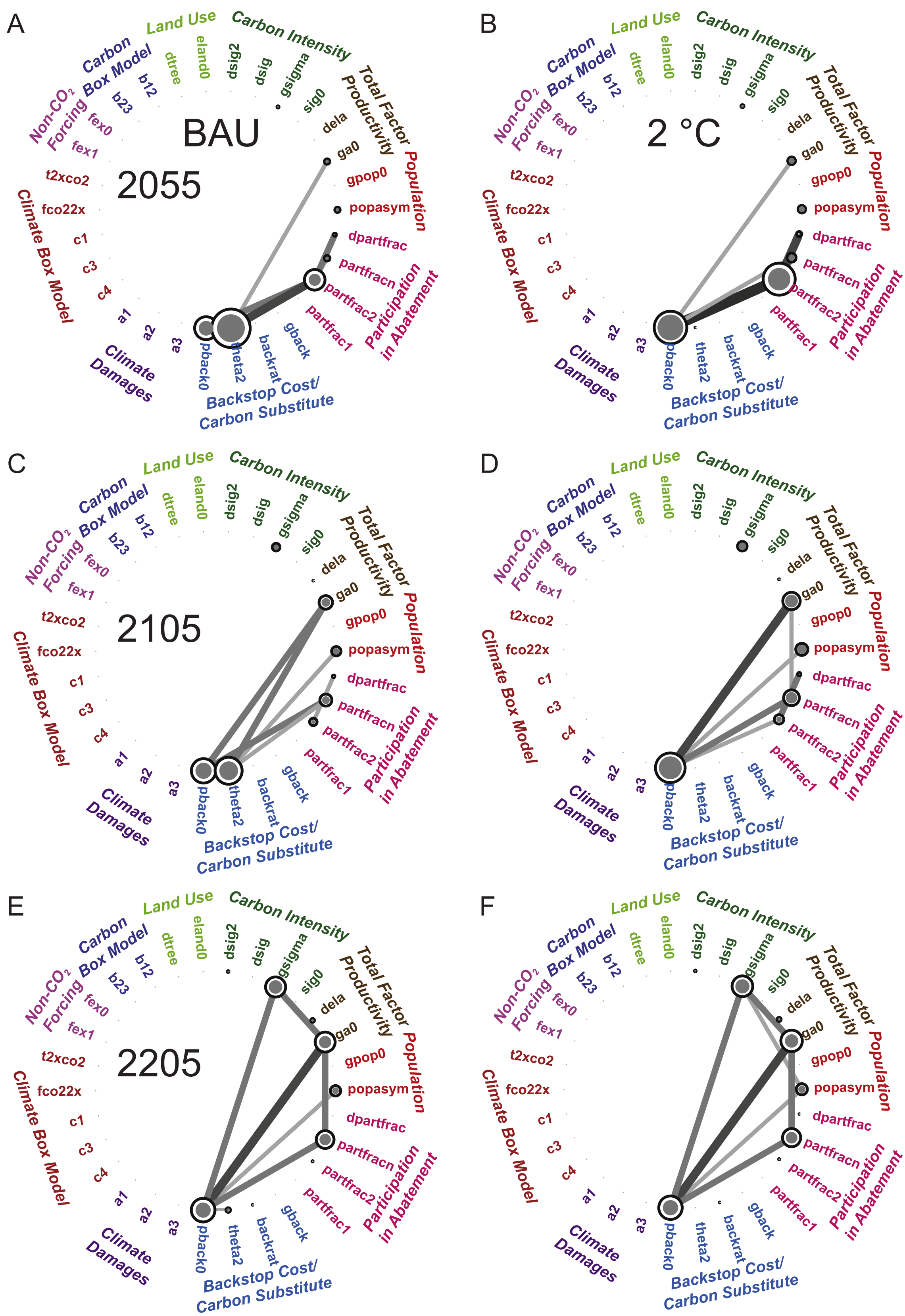

Fig. 7. Sobol' sensitivity results for decadal abatement costs at three snapshots in time for two policy scenarios: **A**, **C** and **E** for the BAU scenario; **B**, **D** and **F** for the 2 °C climate stabilization scenario. The dates indicate the middle years of the decades of the snapshots. See Fig. 6 for legend description.

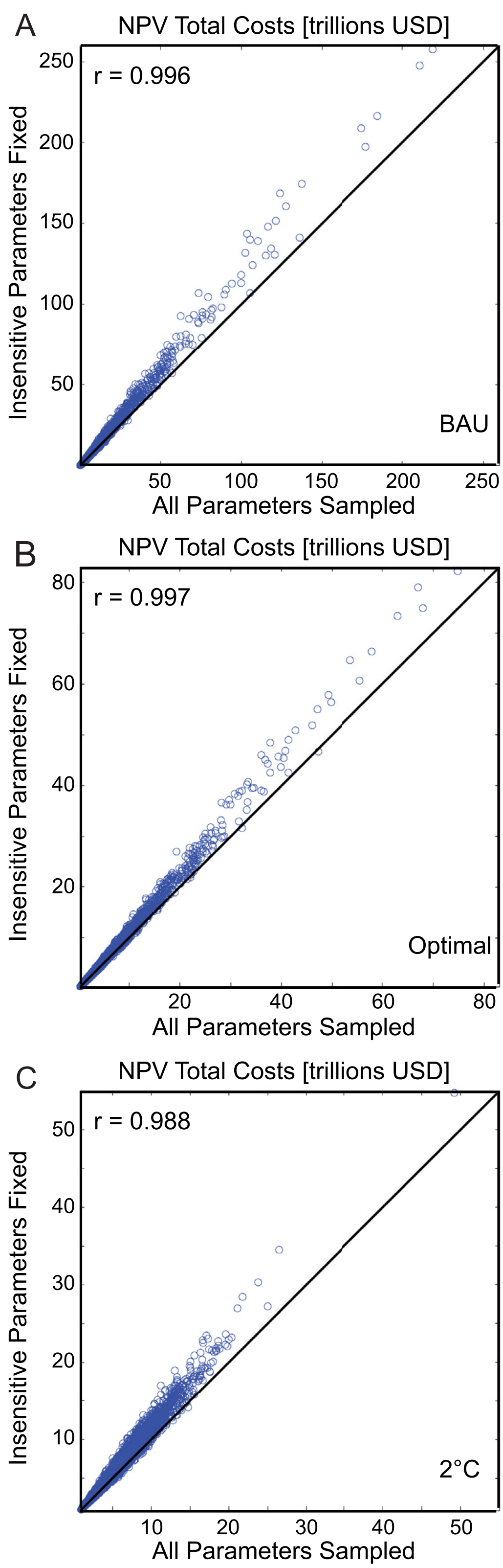

Fig. 8. Pairwise comparison of the NPV of total costs for **A** BAU, **B** optimal and **C** 2 °C climate stabilization scenarios. In each pairwise comparison, all parameters in the extended set are sampled on the horizontal axis. On the vertical axis, the ensemble is adjusted to fix the insensitive parameters to reference values for the scenario indicated as determined by the Sobol' total-order index <0.1%. Correlation indices between sets or results are noted in each figure.

5. Conclusions

This study contributes a detailed demonstration of the consequences of using expert elicitations to narrow the set of parameters used for sensitivity and uncertainty analyses of IAMs. We demonstrate how local approaches, such as OAT analysis with a small parameter set varied over a small part of the feasible parameter space, can mis-classify key sensitivities. As a result, research investments to reduce uncertainties guided by an OAT analysis could be biased, and early-warning signs of policy failures could be missed. Our results are based on an analysis of policy scenarios from the globally-aggregated DICE IAM. Our CDICE results strongly contrast with the DICE sensitivities described in Nordhaus (2008). Our findings provide an argument for comprehensive model diagnostics that explicitly account for the parametric interactions and dependencies between IAM coupled climate and economic components. Moreover, our study illustrates how IAM controls change with alternative metrics, over time, and with alternative emission control scenarios.

In our analyses, we chose three sample policy scenarios and contrasted the parametric sensitivities of the important cost metrics, the net present value of climate damages and abatement costs. Our CDICE results show that the assumption of 100% global participation in abatement costs overlooks the large variability in the mitigation costs with less than 100% participation. This is especially important in light of other recent studies (Clarke et al., 2008; Nordhaus, 2010; Rogelj et al., 2011) which find it unlikely that emission control targets can be reached with incomplete participation. We find that uncertainties in population estimates, future technology efficiency, carbon intensity of production, and the emergence of replacements for carbon-based energy sources are the most critical to these important cost metrics. These socio-economic trends are difficult to project, but should be taken into account in any risk assessment of potential emission control strategies.

With the exception of the climate sensitivity parameter, the climate damage and abatement costs are not sensitive to any of the climate-related parameters of the model, including land use change, non-CO_2 greenhouse gases, the carbon cycle model, and the climate model. This is in direct contrast to studies with other IAMs (for a recent example, see Rogelj et al., 2013b). Other IAMS in addition to DICE directly use, or are calibrated to, the MAGICC model (Meinshausen et al., 2011b). In a recent study using MAGICC, Bodman et al. (2013) attribute more importance to the carbon cycle in constraining atmospheric temperature increases than we find. Our findings in this case may be indicative of DICE and not IAMs in general, and may be due to the limited detail in the climate and carbon cycle components in DICE. The policy costs we find are demonstrated most simply in the industrial emissions function (Equation (9)). The nonlinear relationships between population, total factor productivity, and the carbon intensity of production in determining total emissions are carried forward in the parameter interactions for abatement costs for all three of the policies we studied.

To at least some extent our concerns with IAMs have not changed since Kelly and Kolstad (1999) identified the critical assumptions of IAMs to be the discount factor, the projected trajectories of population growth and technology growth (and how endogenous it is within the model), the response to control policy, and, finally, the degree of model aggregation. We acknowledge that, while the DICE model covers all of the important aspects of the climate-economy problem, it is a globally aggregated, highly abstracted model. As such, its specific sensitivities will likely not transfer to more complex IAMs which deal more completely with inter-regional trade, specific energy choices, emerging technological capabilities, and learning over time. There is a regional version of the DICE model, RICE (Nordhaus and Yang, 1996; Nordhaus and Boyer, 2000; Nordhaus, 2010) which addresses the aggregation problem. Nonetheless, uncertainties in the projections from higher complexity IAMs should be expected to be controlled by non-separable, highly interactive parameter groupings.

The reference deterministic policy formulations used in our analysis assume perfect knowledge of future SOWs and parameter values and neglect future learning (see, for example, Keller et al., 2007; Keller and McInerney, 2008). Additional uncertainties (e.g., about the pure rate of social time preference and the elasticity of marginal utility of consumption) are known to be important, but not tested here. While the median discounted utilities of our ensembles are within 10% of the DICE reference values for each of the policy scenarios in our analysis, the 90th percentile values of total climate damage and abatement costs are more than twice the DICE reference values (2–3 trillion 2005 USD). We hypothesize that a more comprehensive pre-calibration step to reduce the sampling of parameters at the tails of their ranges would reduce the uncertainties of these costs. However, based on our experience with the climate sensitivity parameter, we expect that this would not necessarily change the rank order of parameter sensitivities.

The Sobol' analysis we report here is one example of an evaluation of model structure and behavior as recommended in the IAM evaluation framework of Schwanitz (2013). IAM modelers are encouraged to consult that framework for additional evaluation practices. For parameter sensitivity analysis of more computationally expensive IAMs, an initial parameter screening (e.g., Morris, 1991) to discover total-order sensitivities can be accomplished with a fraction of the sample sizes we used in this study. This can be followed with a more detailed analysis with the most sensitive parameters to identify second-order parameter interactions. There is a need for the integrated assessment field to embrace rigorous model diagnostics that can account for uncertainties when seeking to advance our management of future climate change risks.

Acknowledgments

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Appendix A. Example emissions pathways for optimal policy scenario

The optimal policy scenario as determined by a DICE GAMS execution is shown in Panel A of Fig. A.9. It consists of the control variables from the GAMS optimization, which are the emission control and investment variables. The savings rate from the GAMS optimization is the investment fraction of global world production. The CDICE model accepts as a policy scenario the emission control and savings shown in the figure. Panel B of Fig. A.9 shows the endogenous emission pathway calculated in DICE (solid black line) as well as the distribution of emissions pathways calculated in CDICE using the optimal policy scenario and the ~8 million SOWs used in this study. The difference in the DICE emissions pathway and the median and mean CDICE pathways for this policy scenario are due to a modeling decision to constrain the total factor productivity trajectory within a range similar to earlier and later Excel versions of DICE (see Panel B of Fig. B.10). The DICE2007 total factor productivity reference values give a trajectory that increases the likelihood of model instability in decades beyond the net present value planning horizon used in this study.

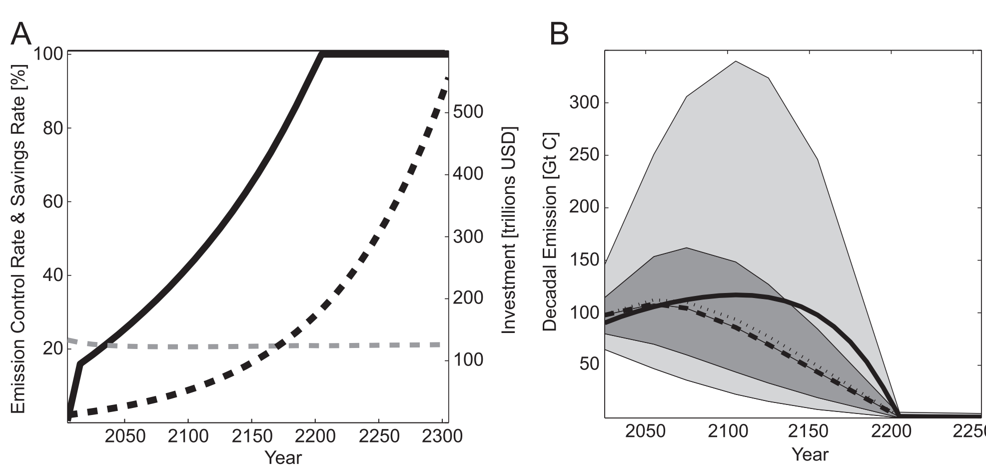

Fig. A.9. **A** The optimal policy scenario from DICE is described by the control variables: emission control rate (solid line, left axis) and investment (dashed line, right axis). The gray dashed line is the savings rate or the investment percent of global world product. **B** The distribution of emission pathways in the CDICE ensemble of SOWs for the optimal policy scenario in this study. The solid black line is the endogenous emissions pathway from the DICE optimal policy scenario described in **A**. The dashed and dotted lines are the median and mean of the emissions pathways in the CDICE ensemble in this study. Dark shaded areas represent the central 90% of the ensemble. Light shaded areas include the extremes.

Appendix B. Exogenous parameters and sampling ranges

The exogenous parameters of the DICE and CDICE models are documented in the following tables. Parameter names are as given in Nordhaus (2008) and Nordhaus (2007a) and the DICE GAMS code. See the DICE model equations in Nordhaus (2008, Appendix A). In this study, parameters are sampled uniformly within the bounds listed, but see the note below about the climate box model. Bounds were chosen based on literature references where available. Where the parameters are the results of fits to additional models (Nordhaus, 2007a), the parameters are sampled in a range of ±10–50% from the reference value, depending on the magnitude of the reference value. In some cases parameter bounds for related parameters were chosen to influence the bounds of a time series constructed from a function containing several parameters. Examples are noted below and illustrated in Fig. B.10. Care was taken to avoid parameter values which either do not make sense or cause model failures (for example, a negative value of the population limit). Parameters in bold in the tables are members of the expert set (Nordhaus, 2008, Chapter 7).

Fundamental Economic Factors No parameters in this group were sampled. The stock of fossil fuel resources (*fosslim*) is used as a constraint in the DICE GAMS optimization. This constraint is not implemented in CDICE, but violations are reported. For the BAU policy scenario, 3.4% of the SOWs violated the fossil fuel resources limit. No violations of this constraint occurred in the SOWs for the optimal or 2 °C stabilization policy scenarios in this study.

Fundamental Economic Factors

Parameter	Description [Units]	DICE value	Sampling bounds
elasmu or α	Elasticity of marginal utility of consumption [no units]	2	Not sampled
prstp or ρ	Pure rate of social time preference [per year]	0.015	Not sampled
gama or γ	Capital elasticity in production function [no units]	0.3	Not sampled
K0	2005 capital stock [trillions 2005 USD]	137	Not sampled
dk or δ_k	Capital depreciation [per year]	0.1	Not sampled
fosslim	Stock of fossil fuel resources [Gt C]	6000	Not sampled
scale1	Arbitrary scaling factor in discounted utility of consumption calculation	194	Not sampled
scale2	Arbitrary scaling factor in discounted utility of consumption calculation	31,800	Not sampled

Population or Labor These parameters are used to develop a population or labor time series. Guidance for the population estimates for *popasym* is from IIASA (2007) and UN (2011). The growth factor *gpop*0 was sampled to allow for alternative approaches to the population limit. See the illustration of the overall sampling range for the population trajectory in Panel A of Fig. B.10. Population limits over 15 billion introduce model instability.

Population or Labor

Parameter	Description [Units]	DICE value	Sampling bounds
pop0	2005 global population [millions]	6514	Not sampled
popasym	Asymptotic population limit [millions]	8600	[5000, 13,000]
gpop0	Population growth rate [per decade]	0.35	[0.20, 0.25]

Total Factor Productivity These parameters are used to develop a total factor productivity or technology efficiency time series. The function in DICE GAMS indicates efficiencies >100% in decades beyond the typical planning horizon, introducing model instability. Parameter values were chosen based on alternative functions in other Excel versions of DICE from http://nordhaus.yale.econ.edu. See the illustration of the overall sampling range for the total factor productivity trajectory in Panel B of Fig. B.10.

Total Factor Productivity

Parameter	Description [Units]	DICE value	Sampling bounds
a0	Initial total factor productivity	0.02722	Not sampled
ga0	Initial growth of technology efficiency [per decade]	0.092	[0.092, 0.200]
dela	Decline in technology efficiency [per decade]	0.001	[0.011, 0.016]

Carbon Intensity of Production In DICE the carbon intensity of production (*sigma*) is measured in purchasing power parity terms. Historical data from IEA (2010) and EIA (2012) were used to set the bounds for these parameters in the function to develop the *sigma* time series. The DICE model structure enforces a decline in the carbon intensity of production over time. See the illustration of the overall sampling range for the carbon intensity of production trajectory in Panel C of Fig. B.10.

Carbon Intensity of Production

Parameter	Description [Units]	DICE value	Sampling bounds
sig0	2005 CO_{2e} industrial emissions/ production ratio	0.13418	[0.133636, 0.152727]
gsigma	Initial growth of carbon intensity [per decade]	−0.073	[−0.016, −0.07]
dsig	Decline in decarbonization [per decade]	0.003	[0.0010, 0.0015]
dsig2	Quadratic coefficient in decarbonization	0	[0.0, 0.0002]

Land Use Change The DICE model assumes a constant decline in emissions from land use change for the current century until a constant low level is reached after 2100 with no further change. Projections for the current emissions for land use change are from IPCC (2007), WHRC (2008) and MIT (2012). The decline rate is explicit in DICE; we sampled it in this study.

Land Use Change

Parameter	Description [Units]	DICE value	Sampling bounds
eland0	2005 emissions from land use change [Gt C per decade]	11	[9, 15]
dtree	Decline rate in land use emissions [per decade]	0.1	[0.05, 0.20]

Carbon Cycle Box Model The carbon cycle box model in DICE is calibrated to the A1F1 emissions scenario in MAGICC (Meinshausen et al., 2011b) as noted in Nordhaus (2007a). There are three boxes or layers in the carbon cycle model: atmosphere, surface (land and ocean) and deep ocean. The bounds for *b*12 are 2σ from Nordhaus (2008, Table 7-1). Note that only two of the transfer coefficients are explicitly defined. The others are derived from *b*12 and *b*23.

Carbon Cycle Box Model			
Parameter	Description [Units]	DICE value	Sampling bounds
mat2000	2005 atmospheric burden [Gt C]	808.9	Not sampled
mu2000	2005 land and upper ocean burden [Gt C]	1255	Not sampled
ml2000	2005 deep ocean burden [Gt C]	18,365	Not sampled
b12	Atmosphere to surface transfer coefficient [per decade]	0.189288	[0.155288, 0.223288]
b23	Surface to deep ocean transfer coefficient [per decade]	0.05	[0.025, 0.10]
b11	Atmosphere to atmosphere transfer coefficient [per decade]	0.810712	Derived
b21	Surface to atmosphere transfer coefficient [per decade]	0.097213	Derived
b22	Surface to surface transfer coefficient [per decade]	0.852787	Derived
b32	Deep ocean to surface transfer coefficient [per decade]	0.003119	Derived
b33	Deep ocean to deep ocean transfer coefficient [per decade]	0.996881	Derived

Non-CO_2 Greenhouse Gases The DICE model assumes a steady-state for the non-CO_2 greenhouse gases after 2100. Guidance for both current and 2100 GHG forcing were taken from IPCC (2007) and MIT (2012).

Non-CO_2 Greenhouse Gases			
Parameter	Description [Units]	DICE value	Sampling bounds
fex0	2000 non-CO_2 GHG forcing [W m–^{2}]	−0.06	[−0.3, 0.0]
fex1	2100 non-CO_2 GHG forcing [W m^{-2}]	0.3	[−0.2, 0.5]

Climate Box Model The climate in DICE is represented as a two box model. It is calibrated to MAGICC (Meinshausen et al., 2011b) along with the carbon cycle box model as noted above. Note that the model fails when the climate sensitivity (*t2xco2*) is <0.5. The forcing parameter (*fco22x*) is used in the model as $\lambda = fco22x/t2xco2$. We have repeated this experiment basing the Sobol' sample of climate sensitivity (*t2xco2*) on empirical distributions (Libardoni and Forest, 2011, 2013; Olson et al., 2012) rather than the uniform distribution and find no difference in the rank ordering of sensitive parameters for the net present value metrics. The total variance, however, will be reduced by limiting the samples at the tails of the distribution. The results of this study use the updated distribution from Libardoni and Forest (2011, 2013), with total variance of climate damages intermediate between those from the uniform distribution and the sharper distribution of Olson et al. (2012).

Climate Box Model			
Parameter	Description [Units]	DICE value	Sampling bounds
tatm0	2000 atmospheric temperature change since 1900 [°C]	0.7307	Not sampled
tocean0	2000 ocean temperature change since 1900 [°C]	0.0068	Not sampled
t2xco2	Temperature sensitivity [°C per doubling of CO_2]	3	[0.5, 8]
fco22x	Radiative forcing from doubling of CO_2 [W m^{-2}]	3.8	[3.6, 3.9]
c1	Climate equation coefficient for upper level [per decade]	0.22	[0.20, 0.24]
c3	Upper to lower level transfer coefficient [per decade]	0.3	[0.27, 0.33]
c4	Lower to upper level transfer coefficient [per decade]	0.05	[0.045, 0.055]

Climate Damages The climate damages function formulation in IAMs has been the subject of criticism for the assumption of a quadratic dependence on the change in temperature. See Stanton et al. (2009) for an example of the discussion. Here we sample the exponent (See Equation (2)), but note that the model fails when the exponent is >3.5.

Climate Damages			
Parameter	Description [Units]	DICE value	Sampling bounds
a1	Linear term coefficient	0	[0.0, 0.001]
a2	Non-linear term coefficient	0.0028388	[0.002255, 0.003123]
a3	Non-linear term exponent	2	[1.5, 3.0]

Backstop Guidance for choosing the bounds for the backstop function were taken from Nordhaus (2007a) and Nordhaus (2008).

Backstop			
Parameter	Description [Units]	DICE value	Sampling bounds
pback0	Initial backstop price [USD tC^{-1}]	1.17	[0.6, 3.0]
expcost2 or θ_2	Exponent in abatement cost equation	2.8	[2.6, 3.0]
backrat	Initial to final backstop price [no units]	2	[1.5, 2.5]
gback	Initial decline in backstop price [fraction per decade]	0.05	[0.045, 0.055]

Participation in Abatement An algorithm is presented in the DICE GAMS code to develop the time series of the fraction of the global economy participating in the abatement costs. It is not used in the sample participation scenarios presented with the GAMS code. Instead, fully specified time series are used. We experiment with the algorithm as presented in this study. Early bounds are related to the Kyoto Protocol (Nordhaus, 2007a). We note that the lower bound for *part fracn* is set to prevent model failure.

Participation in Abatement			
Parameter	Description [Units]	DICE value	Sampling bounds
partfrac1	Participation in emissions abatement in 2000–2010 decade [fraction of global economy]	0.25372	[0.0, 0.25372]
partfrac2	Participation in 2010–2020 [fraction of global economy]	1	[0.25372, 1.0]
partfracn	Participation in 2180–2190 [fraction of global economy]	1	[0.5, 1.0]
dpartfrac	Rate of change of participation [fraction per decade]	0	[0.05, 0.25]

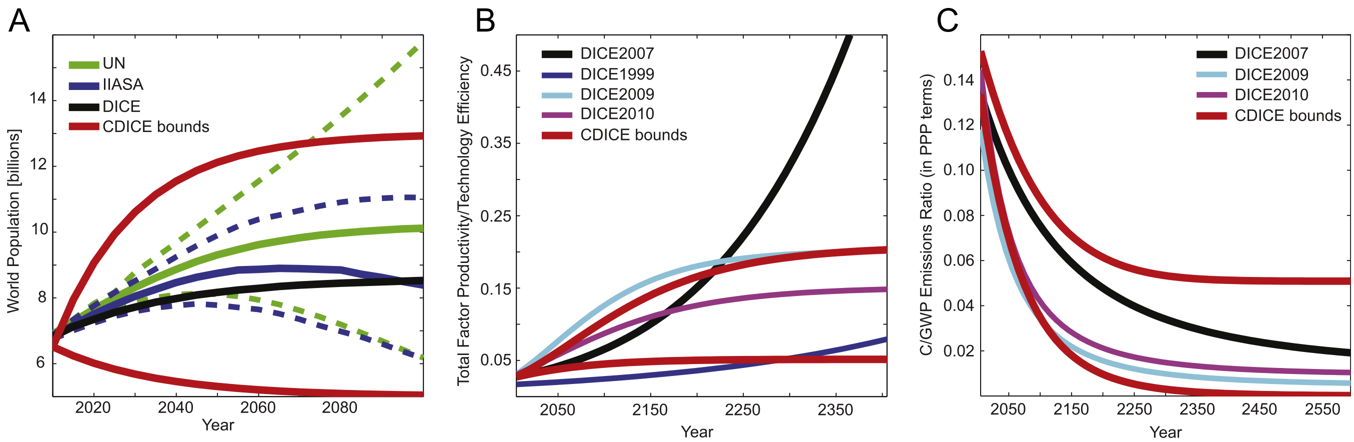

Fig. B.10. Constraining bounds for parameter choices for sub-model functions. Red lines constrain the trajectories sampled in this study. Reference time series are also shown. **A** Population, **B** Total Factor Productivity, **C** Carbon Intensity of Production (Sigma). Note that we used other versions of DICE to set the parameter ranges for total factor productivity rather than the DICE2007 trajectory. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix C. Convergence criteria

The pseudo-random sampling and Sobol' analysis require a multiple of $2(n+1)$ samples of each parameter where n is the number of parameters. The goal is to use a sample size large enough so that the bootstrapped confidence intervals for the total-order indices for the most sensitive parameters in the Sobol' analyses are ≤10% of the index values. The following table shows the total-order indices and confidence intervals for the NPV of climate damages and abatement costs metrics for increasing sample sizes for the extended set of parameters ($n = 30$) and the optimal policy scenario. Sample sizes of 2^{14}, 2^{16} and 2^{17} correspond to approximately 1 million, 4 million and 8 million model executions, respectively. Bold values in the table indicate sensitivity indices above a threshold value of 0.01 (or 1% of variance).

Model parameter	NPV climate damages			NPV abatement costs		
	2^{14} Samples	2^{16} Samples	2^{17} Samples	2^{14} Samples	2^{16} Samples	2^{17} Samples
popasym	**0.24 [0.09]**	**0.24 [0.05]**	**0.23 [0.03]**	**0.03 [0.01]**	**0.03 [0.00]**	**0.03 [0.00]**
gpop0	**0.01 [0.01]**	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
ga0	**0.19 [0.09]**	**0.20 [0.04]**	**0.20 [0.02]**	**0.02 [0.01]**	**0.02 [0.00]**	**0.02 [0.00]**
dela	0.00 [0.01]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
sig0	**0.02 [0.01]**	**0.01 [0.01]**	**0.01 [0.01]**	**0.01 [0.00]**	**0.01 [0.00]**	**0.01 [0.00]**
gsigma	**0.13 [0.05]**	**0.10 [0.03]**	**0.09 [0.02]**	**0.15 [0.02]**	**0.14 [0.01]**	**0.14 [0.01]**
dsig	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
dsig2	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	**0.01 [0.00]**	0.00 [0.00]	0.00 [0.01]
eland0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
dtree	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
b12	**0.02 [0.02]**	**0.01 [0.01]**	**0.01 [0.01]**	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
b23	**0.01 [0.01]**	0.00 [0.01]	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
fex0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
fex1	**0.02 [0.04]**	**0.03 [0.02]**	**0.03 [0.01]**	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
t2xco2	**0.56 [0.07]**	**0.52 [0.04]**	**0.53 [0.03]**	0.00 [0.01]	0.00 [0.00]	**0.01 [0.00]**
fco22x	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c1	0.00 [0.01]	**0.01 [0.01]**	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c3	**0.01 [0.01]**	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
c4	0.00 [0.01]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
a1	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
a2	**0.04 [0.03]**	**0.03 [0.01]**	**0.02 [0.01]**	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
a3	**0.47 [0.07]**	**0.48 [0.05]**	**0.47 [0.03]**	**0.01 [0.01]**	**0.01 [0.00]**	**0.01 [0.00]**
pback0	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.45 [0.02]**	**0.45 [0.01]**	**0.45 [0.01]**
theta2	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.02 [0.00]**	**0.02 [0.00]**	**0.02 [0.00]**
backrat	0.00 [0.00]	0.00 [0.01]	0.00 [0.00]	**0.01 [0.00]**	0.00 [0.00]	0.00 [0.00]
gback	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
partfrac1	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]
partfrac2	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.28 [0.02]**	**0.27 [0.01]**	**0.27 [0.01]**
partfracn	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.17 [0.02]**	**0.17 [0.02]**	**0.17 [0.01]**
dpartfrac	0.00 [0.00]	0.00 [0.00]	0.00 [0.00]	**0.03 [0.01]**	**0.03 [0.01]**	**0.03 [0.00]**

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