POLICIES, PROJECTIONS, AND THE SOCIAL COST OF CARBON: RESULTS FROM THE DICE-2023 MODEL

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Policies, Projections, and the Social Cost of Carbon: Results from the DICE-2023 Model

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Summary

The present study examines the assumptions, modeling structure, and preliminary results of DICE-2023, the revised Dynamic Integrated Model of Climate and the Economy (DICE), updated to 2023. The revision contains major changes in the carbon and climate modules, the treatment of non-industrial greenhouse gases, discount rates, as well as updates on all the major components. The major changes are a significant reduction in the target for the optimal (cost-beneficial) temperature path, a lower cost of reaching the 2 °C target, an analysis of the impact of the Paris Accord, and a major increase in the estimated social cost of carbon.

Supplementary materials including the Appendices and Background Papers are available at https://bit.ly/3TwJ5nO.

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I. Background

A. Integrated Assessment Models

Many areas of the natural and social sciences involve complex systems that link together multiple physical or social networks. This is particularly true for environmental problems, which are intrinsically ones having firm roots in the natural sciences and requiring social and policy sciences to solve in an effective and efficient manner. A good example is climate change science and policy, which involve a wide variety of sciences such as atmospheric chemistry and climate dynamics, ecology, economics, political science, game theory, and international law.

As understanding progresses across the different fronts, it is increasingly necessary to link together the different areas to develop effective understanding and efficient policies. In this role, integrated assessment analysis and models play a key role. Integrated assessment models (IAMs) can be defined as approaches that integrate knowledge from two or more domains into a single framework. These are sometimes theoretical but are increasingly computerized dynamic models of varying levels of complexity.

B. DICE-2023

The DICE model views climate change in the framework of economic growth theory. In a standard neoclassical optimal growth model known as the Ramsey model, society invests in capital, thereby reducing consumption today, in order to increase consumption in the future. The DICE model augments the Ramsey model to include climate investments, which are analogous to capital investments in the standard model. The model contains all elements of the process from economic activity and emissions through climate change to damages and policy in a manner that represents simplified best practice in each area.

The DICE model (Dynamic Integrated model of Climate and the Economy) and its regional version, RICE (Regional Integrated model of Climate and the Economy), have gone through several revisions since their first development around 1990. The latest published versions are the RICE-2010 and DICE-2016 models, and this study describes the revision of DICE, whereas an updated version of RICE (joint with Zili Yang) will be available shortly. We begin with a description of the DICE-2023 model, after which we provide the detailed equations. This section draws heavily on earlier discussions (see Nordhaus 2017, 2018, 2018a, Yang 2020, Nordhaus and Sztorc 2013, and Nordhaus and Boyer 2000).

II. Objectives or goals of IAMs

IAMs can be divided into two general classes – policy optimization and policy evaluation models. Policy evaluation models generally are recursive or equilibrium models that generate paths of important variables but do not optimize an economic outcome. Policy optimization models have an objective function or welfare function that is maximized and can be used to evaluate alternative paths or policies.

The DICE model is primarily designed for policy optimization, although it can also be run as an evaluation model for given policies. In both settings, the approach is to maximize an economic objective function (the goal implicit in the problem). For the DICE model, the objective function refers to the economic well-being (or utility) associated with a path of consumption.

The use of optimization can be interpreted in two ways: First, from a positive point of view, as a means of simulating the behavior of a system of competitive markets; and second, from a normative point of view, as a possible approach to comparing the impact of alternative paths or policies on economic welfare.

In the DICE model, the world or individual regions are assumed to have well-defined preferences, represented by a social welfare function, which ranks different paths of consumption. The social welfare function is increasing in the per capita consumption of each generation, with diminishing marginal utility of consumption. The importance of a generation's per capita consumption depends on the size of the population.

The relative importance of different generations is affected by two central normative parameters: the pure rate of social time preference ("generational discounting") and the elasticity of the marginal utility of consumption (the "consumption elasticity" for short). These two parameters interact to determine the discount rate on goods, dimensionally the same as a real interest rate, which is critical for intertemporal economic choices. In the modeling, we set the normative parameters to be consistent with observed economic outcomes as reflected by market interest rates, risks, and rates of return on capital. The choice of discount rates is central to the results and is extensively discussed in the literature on discounting.

The DICE model assumes that economic and climate policies should be designed to optimize the flow of consumption over time. It is important to emphasize that consumption should be interpreted as "generalized consumption," which includes not only traditional market goods and services like food and shelter but also non-market items such as leisure, health status, and environmental services. It may also include non-human factors such as the welfare of other species or ecosystems.[4]

We add a note of interpretation of the equilibrium in the DICE model. We have specified the baseline case so that, from a conceptual point of view, it represents the outcome of market and policy factors as they currently exist. In other words, the baseline model attempts to project, from a descriptive perspective, the levels and growth of major economic and environmental variables as would occur with existing climate-change policies. The baseline is distinguished from a "no controls" policy, such as might have existed in the 1960s, with no policies anywhere targeted to slow climate change. Similarly, the baseline does not include countries' announced or aspirational policies.

Finally, we emphasize that the approach does not make a case for the social desirability of the policies or of the distribution of incomes over space or time of existing conditions, just as a marine biologist normally makes no moral judgment on the equity of the eating habits of whales or minnows.

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[4] Specifically, the DICE-2023 quantification of climate damages includes estimates of the value of the impacts of non-market goods and services where available. Income levels are initialized based on conventional output measures. The inclusion of non-market values in income levels would affect the level of total income, but because of the normalization of market output, it would not have a significant effect on the key results in our framework.

III. Equations of the DICE-2023 model

We next develop the equations of the model. We will distinguish major from minor revisions. This section is technical and may be skipped by those who would like to get the significant results.

A. Objectives

To begin with, we assume that policies are chosen to maximize a general concept of economic welfare. More precisely, we maximize a social welfare function, *W,* which is the discounted sum of the population-weighted utility of per capita consumption, where *c* is per capita consumption, *L* is population, and Ψ is the discount factor, all of which are discussed as we proceed. Equation (1) is the mathematical statement of the objective function. This representation is a standard one in modern theories of optimal economic growth.

$$(1) \quad W = \sum_{t=1}^{T\,max} U[c(t), L(t)]\Psi(t)$$

There are several further assumptions underlying this choice of an objective function. First, it involves a specific representation of the "utility" of consumption. The DICE model assumes that utility is represented by a constant elasticity utility function, as shown in Equation (2).

$$(2) \quad U[c(t), L(t)] = L(t)[c(t)^{1-\varphi} / (1-\varphi)]$$

$$= L(t)[c(t)^{1-[1.5]} / (1-[1.5])]$$

t = time periods = 2020, 2025, 2030, ….

Note that here and below, we have included the actual parameters of the equations with numerical terms in brackets, such as [1.5].

This Equation assumes a constant elasticity of the marginal utility of consumption, φ. The elasticity is a parameter that represents the extent of substitutability of the consumption of different years or generations. If φ is close to zero, then the consumptions of different generations are close substitutes; if φ is high, then the consumptions are not close substitutes. Often, φ will also be used to represent risk aversion, but these are quite distinct concepts and should not be confused. Additionally, the elasticity is distinct from *personal* behavioral characteristics. We calibrate φ in conjunction with the pure rate of time preference, as is discussed below.

Second, this specification assumes that the value of consumption in a period is proportional to the population.

Third, this approach applies a discount on the economic well-being of future generations, as is defined in Equation (3).

$$(3) \qquad \Psi(t) = (1+\rho)^{-t}$$
$$\rho = 0.01 / yr$$

In this specification, $\Psi(t)$ is the discount factor, while the pure rate of social time preference, ρ , is the discount rate which provides the welfare weights on the utilities of different generations.

Equations (2) and (3) have been slightly revised in DICE-2023 (specifically with ρ decreased from 0.015 to 0.010 and φ increased from 1.45 to 1.5). The purpose is to lower the real interest rate to reflect the decline in market interest rates over recent years. The impact is that the average real rate of return for 2020-2100 was revised from 4.2%/yr in DICE-2016 to 3.9%/yr in DICE-2023. Note as well that in the Ramsey model used to calculate economic variables in DICE-2023, real interest rates decline over time from 4.5%/year in 2020 to 3.4%/yr in 2100. See Appendix G for a more detailed discussion.

B. Population, output, and productivity

The economic sectors are standard to the economic growth literature. The main difference from standard analysis is the very long time frame that is required for climate-change modeling. While most macroeconomic models run for a few years, or in the development context a few decades, climate-change projects necessarily must run a century or more. The result is that many of the projections and assumptions are based on very thin evidence.

We begin with the standard approach to economic growth. The DICE model is simplified relative to many models because it assumes a single global commodity, which can be used for either consumption or investment. Consumption should be viewed broadly to include not only food and shelter but also non-market environmental amenities and services. Regional outputs and capital stocks are aggregated using purchasing power parity (PPP) exchange rates, as is now widely accepted in the economic-growth and IAM communities.

The next set of equations determines the evolution of world output over time. Population and the labor force are exogenous. These are simplified to be logistic-type equations. The assumed growth rate declines so that total world population approaches a limit of 10.8 billion. These numbers are from UN projections and have seen only small modifications in recent revisions.

Output is produced with a Cobb-Douglas production function in capital and labor, with adjustments for damages and abatement. Output is measured in purchasing power parity (PPP) exchange rates using World Bank and IMF estimates. Future productivity growth is based largely on estimates from Christensen et al. (2018). Technological change takes two major forms: economy-wide technological change and carbon-saving technological change. Carbon-saving technological change is represented in two ways: first, as reducing the baseline ratio of CO_2 emissions to output and, second, as reducing the cost of the backstop technology.

Production is represented by a modification of a standard neoclassical production function. Global output is shown in Equation (4):

$$(4) \quad Q(t) = [1 - \Lambda(t)][1 - \Omega(t)]A(t)K(t)^{\gamma}L(t)^{1-\gamma}$$
$$\gamma = 0.3$$
$$L(0) = 7753 \text{ million}$$
$$L(t+1) = L(t)\,[10825/L(t)]^{0.145}$$
$$A(0) = 5.84164 \text{ in 2019 US\$}$$
$$\mathrm{A}(t) = A(t-1)/(1 - 0.082 \exp[-0.0072 \cdot 5 \cdot (t-1)])$$

In this specification, *Q(t)* is measured global output net of damages and abatement, *L(t)* is population and labor inputs, A*(t)* is total factor productivity, and *K(t)* is capital stock and services. The additional variables in the production function are $\Omega(t)$ and $\Lambda(t)$, which represent climate damages and abatement costs and are discussed in the next section.

C. Damages

Equation (5) represents the economic impacts or damages of climate change, which is the thorniest issue in climate-change economics. These estimates are indispensable for making sensible decisions about the appropriate balance between costly emissions reductions and climate damages. However, providing reliable estimates of the damages from climate change over the long run has proven extremely difficult.

$$(5) \quad \Omega(t) \;= \psi_1 T_{AT}(t) + \psi_2 [T_{AT}(t)]^2$$
$$= [0.0] T_{AT}(t) + [0.003467][T_{AT}(t)]^2$$

The damage function in DICE is simplified and assumes that the increase in global mean surface temperature from pre-industrial levels (centered on 1765) is a reasonable sufficient statistic for damages. This specification omits or only indirectly captures cumulative effects (such as the effects of prolonged warming rather than instantaneous temperature on sea-level rise) and also omits effects that depend on the speed of temperature change. The damage function also implicitly assumes that damages scale proportionately with income. Based on recent reviews, we further assume that a quadratic damage function best captures the impact of climate change on output (Nordhaus and Moffat, 2017; Hsiang et al., 2017).

The 2023 model uses the same structure as earlier versions but contains several updates. The damage assessment is preliminary in "beta" status, and the current formulation is as follows.

The first component of damages is a synthesis of the current literature on damages. This compendium adds studies that were published since the review of Nordhaus and Moffat (2017) that was the basis for the earlier estimates. Our update focuses on studies surveyed in Piontek et al. (2021), which overlaps closely with global damage studies reviewed by the IPCC's AR6 (O'Neill et al., 2022). The updated results imply a 1.62% GDP-equivalent loss at 3 °C warming over pre-industrial temperatures, up from 1.22% in the previous version. It is important to note that the studies which form the basis of this estimate generally omit potentially significant climate change impact channels, such as biodiversity loss, ocean acidification, extreme events, social unrest, etc.

Second, we have added the results of a comprehensive study of tipping points (Dietz et al. 2021), which estimates an additional 1% loss of global output due to 3 °C warming.

Third, we have increased the judgmental adjustment for other excluded impacts to 0.5% of output at 3 °C warming. This adjustment reflects (i) concerns over climate change impacts not yet reliably quantified in the literature, (ii) uncertainty, and (iii) recent research that is not reflected in our synthesis of aggregate damage estimates, as described in Appendix I.

Including all these adjustments, damages are estimated to be around 3.12% of output at a 3°C global warming over pre-industrial temperatures and 12.5% of output with 6 °C warming. The resulting damage coefficient is larger by a factor of almost two compared to the 2016 model and results in a major increase in the social cost of carbon.

We put a warning label on Equation (5) when applied to large temperature increases. The damage function has been calibrated for damage estimates in the range of 1 to 4 °C. This limited range of application is appropriate because the temperatures in the different scenarios lie in this range for the first 100 years. Further, the evidence is necessarily very limited for higher warming. Note also that the quadratic functional form in (5) does not reflect potential concerns about threshold damages which might appear at 1.5 or 2.0 °C warming beyond those included in the Dietz et al. (2021) tipping points study.

D. Abatement

The next Equation is the abatement-cost function, shown in (6).

$$(6) \quad \Lambda(\mathrm{t}) = \theta_1(t)\mu(t)^{\theta_2}$$
$$\theta_1(0) = 0.109062$$
$$\theta_2 = 2.6$$

The abatement cost equation in (6) is a reduced-form type model in which the costs of emissions reductions are a function of the emissions control rate, $\mu(t)$. The abatement cost function assumes that abatement costs are proportional to output and are a polynomial function of the emissions-control rate. The cost function is estimated to be highly convex, indicating that the marginal cost of reductions rises from zero more than linearly with the reductions rate. The intercept, $\theta_1(t)$, represents the fraction of output that is required to reduce emissions to zero, beginning around 11% of output in 2020. For a discussion of trends in this parameter over time, see below in this section.

The DICE model includes a "backstop technology," which is a technology that can replace all fossil fuels, albeit at a relatively high price. The backstop technology is a benign zero-carbon technology. It might be solar or wind power, safe nuclear power, or some as-yet-undiscovered source. Conceptually, at the cost of the backstop technology, the economy achieves zero net carbon emissions.

The 2023 model uses the same functional form as earlier versions. Two minor revisions are noteworthy.

Estimates of the cost of the backstop technology are controversial, with the DICE model having a high cost relative to some estimates of the cost of renewables or carbon capture. The cost function is derived from highly detailed process models. Examining estimates of the marginal cost of scenarios with zero net emissions, we can estimate the marginal cost of the backstop technology. A statistical analysis from the results of the ENGAGE study (Riahi et al., 2021, 2021a) indicates a backstop price of \$515/tCO_2 in 2019\$ in 2050, which is the earliest year that most models can reach zero net emissions. Models assume improvements over time in the technologies needed to attain zero emissions. The decline rate of the cost of the backstop technology is assumed to be 1%/yr from 2020 to 2050, and then 0.1%/yr after that. The backstop technology is introduced into the model by setting the time path of the parameters in the abatement-cost Equation (6) so that the marginal cost of abatement at a control rate of 100 percent is equal to the backstop price.

By construction, the cost of a zero-emissions policy is determined by the cost of the backstep technology and the emissions-output ratio. A little algebra in the Appendix shows that the share of output devoted to abatement at zero net emissions (ψ), is equal to $\psi = p^B \sigma / \theta_2$, where ψ, p^B, σ, and θ_2 are the output share of abatement at zero net abatable emissions, the cost of the backstop technology, the no-controls emissions-output ratio, and the exponent of the abatement cost function. Zero-emissions abatement cost is 11% of output in 2020, declining at 1.7 percent per year from 2020 to 2100 to 2.7% of output in 2100.

The other revision is the inclusion of emissions other than energy CO_2. This addition is basically a scalar increase in the abatement cost function. For further discussion, see the section on emissions below as well as Appendix H.

E. Major accounting equations

The next three equations are standard accounting equations. Equation (7) states that output is divided between consumption and gross investment. Equation (8) defines per capita consumption. Equation (9) states that the capital stock dynamics follows a perpetual inventory method with an exponential depreciation rate. Note that the time step is five years, so the coefficient in (9) is five-year depreciation.

(7) $Q(t) = C(t) + I(t)$

(8) $c(t) = C(t) / L(t)$

(9) $K(t) = I(t) - \delta_K K(t-1)$

F. Emissions

DICE-2023 has a major revision in its treatment of GHG emissions. In earlier versions, only industrial CO_2 emissions were controllable (abatable), and other GHGs and forcings were taken to be exogenous. This was a reasonable simplification, but it is untenable in low- or zero-emissions scenarios where substantial fractions of warming potential comes from other sources, such as land emissions, methane, and CFCs. The current version therefore includes all "abatable" emissions in the endogenous category and excludes only a small fraction of forcings as "non-abatable emissions." A full discussion of the methods is contained in Appendix H.

The lion's share of GHG emissions is from CO_2. However, a large suite of processes and gases also contribute to radiative forcings. Total CO_2-equivalent abatable emissions are 140% of industrial emissions in 2020, declining to 121% of industrial CO_2 emissions in 2100. This ratio indicates the increase in abatable emissions in DICE-2023 compared to DICE-2016. The cost function is from studies of the abatement cost function for non-CO_2 emissions. Inclusion of CO_2 from land use and abatable non-CO_2 emissions will increase CO_2-equivalent abatable emissions by 35% in 2050. This extension allows a larger potential abatement and the potential for attaining more ambitious targets in an ideal world. Of course, to the extent that the non-industrial-CO_2 sources are more difficult to control (for example, methane emission from ruminants), the estimated abatement may overestimate what is realistically possible.

Projections of baseline emissions are a function of total output, a time-varying emissions-output ratio, and an emissions-control rate. The baseline emissions control rate reflects current policy, which we estimate to be a control rate of about 5% or a carbon price of about \$6/tCO_2. The emissions-control rate is determined by the climate-change policy under examination. The cost of emissions reductions in (3) is parameterized by a log-linear function, which is calibrated to recent studies of the cost of emissions reductions. There is no major change in the parameters of the abatement-cost function from earlier DICE models, but the extension to non-industrial CO_2 emissions is completely new and based on studies of the abatement cost function of those sources.

Early versions of the DICE model used the emissions control rate as the control variable in the optimization because it is most easily used in linear-program algorithms. In recent versions, we have also incorporated a carbon tax as a control variable. Using the carbon price is advantageous when considering uncertainty or using price-type administrative regimes, but the solutions are identical in deterministic cases.

The final two equations in the economic block are the emissions equation and the resource constraint on carbon fuels.

$$(10) \quad ECO2e_{base(t)} = \sigma(t)Y(t) + ECO2_{Land(t)} + \ ECO2e_{NonCO2GHGabate(t)}$$

$$(11) \quad ECO2e(t) \ = ECO2e_{base(t)[1-\mu(t)]}$$

$$\sigma(0) = [0.291 \ tCO2/(1000 \ Y(t)]$$

$$ECO2\_Land(t) = 5.9 \ GtCO2 \quad (0.9)^{t-1}$$

$$ECO2e\_NonCO2GHGabate(t) = 9.96\ GtCO2e\quad (1.0069)^{t-1}$$
t = 2020, 2025, 2030, ….

Equation (10) defines baseline abatable emissions measured on a CO_2-equivalent basis. The first term is annual industrial emissions, given by a level of carbon intensity, *σ(t),* times output. The second term is land-use emissions of CO_2, which decline by 10% per 5-year period. The third term is the abatable non-CO_2 GHG emissions. The no-controls industrial carbon intensity, *σ(t),* is taken to be exogenous and declines initially at a rate of 1.5% per year. Other emissions are taken from the SSP2 scenario (IIASA, 2022). In Equation (11), total CO_2-equivalent emissions are reduced by one minus the emissions-reduction rate, 1- $\mu(t)$, described above.

Equation (12) is a limitation on the total resources of carbon fuels, given by *CCum.* The model assumes that incremental extraction costs are zero and that carbon fuels are efficiently allocated over time by the market, producing the optimal Hotelling rents on carbon fuels when the limit is binding. In practice, current projections indicate that the constraint does not bind in the baseline case, with cumulative carbon emissions in the base path slightly more than half of total fossil-fuel carbon of 6000 GtC, so the constraint is usually omitted.

$$(12)\qquad CCum = 6000GtC \geq \sum_{t=1}^{T\,max} E_{Ind}(t)$$

G. Geophysical sectors

A key feature of IAMs is the inclusion of geophysical relationships that link the economy with the different forces affecting climate change. In the DICE model, these relationships include the carbon cycle, a radiative forcing equation and the climate-change equations. The purpose of including these is that they operate in an integrated fashion rather than taking inputs as exogenous inputs from other models or assumptions.

The next equations (13) to (21) link economic activity and greenhouse-gas emissions to the carbon cycle, radiative forcings, and climate change. These relationships have proven a major challenge because of the need to simplify what are inherently complex dynamics into a small number of equations that can be used in an integrated economic-geophysical model. As with the economics, the modeling philosophy for the geophysical relationships has been to use parsimonious specifications so that the theoretical model is transparent and so that the optimization model is empirically and computationally tractable.

As noted above, DICE-2023 includes the full suite of long-lived GHGs as abatable – that is, gases that are subject to control. So, in addition to industrial CO_2, the abatable gases include land CO_2, methane, chlorofluorocarbons, and other well-mixed gases.

For purposes of the carbon/forcings/climate modules, CO_2 emissions are linked to the carbon cycle and thence to forcings. The other GHGs are linked directly to forcings and short-circuit the atmospheric chemistry. This shortcut will introduce small errors into the correct forcings, but the size of those is likely to be small relative to total forcings.

H. Carbon Cycle

The major structural revision of the DICE-2023 model is the introduction of the DFAIR module (the DICE version of the FAIR model discussed below), which represents the dynamics of the carbon cycle. The carbon cycle and climate model are key components of any IAM. DICE-2023 has made a major change in the treatment of these modules, particularly the carbon cycle. Earlier versions in DICE and most other IAMs have used linear carbon-cycle structures. While these approaches seemed acceptable as a simplification, they did not allow for the important finding that the ability of non-atmospheric sinks to absorb CO_2 declines with higher emissions (see NAS 2017 for a discussion).

Carbon saturation was discussed as early as 1957 in Revelle and Seuss (1957). The latest and most extensive multimodel carbon-cycle comparison was in Joos et al. (2013). This study showed that the atmospheric retention at 100 years would be 70% for a pulse of 100 GtC compared to only 30% for a pulse of 5000 GtC.

While the importance of saturation has been known for many years, a simple modeling approach has become available over the last decade: the FAIR or Finite Amplitude Impulse-Response model developed by Millar et al. (2017).

The FAIR model is based on a linear four-reservoir impulse-response model of the response of CO_2 concentrations to emissions. A key innovation in the FAIR model is to introduce a structural parameter, α_t. This parameter increases the fraction of total CO_2 emissions that resides in the atmosphere as cumulative CO_2 emissions increase.

While the "reservoirs" may have geophysical names ("permanent," "long," etc.), they have no physical or structural interpretation but are variables in reduced-form dynamic equations. As a result, and important for scenarios with negative emissions, the reservoirs may take on negative values – a fact that was ignored in some earlier implementations of FAIR.

Simulations reported in the Appendix indicate that the FAIR model tracks the historical emissions-concentrations paths closely, as well as small emissions pulses. However, the FAIR atmospheric retention for very large pulses (e.g., the 5000 GtC pulse in Joos et al.) tracks the full carbon-cycle models poorly.

The equations of the DFAIR model are the following. Equation (13) is the set of equations for the four reservoirs, whose contents are R_t^i. We note that only CO_2 emissions (industrial and land-based) enter the carbon cycle, that is, CO_2-equivalent emissions from other gases are not included in the emissions term E_t. Equation (14) then sums the four reservoirs to obtain atmospheric CO_2, MAT_t. Equation (15) provides the Equation for accumulated CO_2 in non-atmospheric sinks, defined as $Cacc_t$. Equation (16) yields the predicted 100-year integrated impulse response function $IRF100_t$ and (17) implicitly defines the saturation parameter α_t. All equations are straightforward to calculate except for (17).

$$(13) \quad \Delta R_t^i = \xi_i E_t - \left(\frac{R_t^i}{\alpha_t \tau_i}\right), \text{ i = 1, 2, 3, 4}$$

$$(14) \quad MAT_t - MAT_0 = \sum_{i=1}^{4} R_t^i$$

$$(15) \quad Cacc_t = \sum_{v=1765}^{t} E_v - (MAT_t - MAT_0)$$

$$(16) \quad iIRF100_t = \varsigma_0 + \varsigma_C Cacc_t + \varsigma_T T_t$$

$$(17) \quad iIRF100_t = \sum_{i=1}^{4} \alpha_t \xi_i \tau_i \left[1 - exp\left(\frac{-100}{\alpha_t \tau_i}\right)\right]$$

The variables are:

$MAT_t - MAT_0$ = atmospheric concentrations since 1765 (GtC)

R_t^i = carbon content of carbon reservoir i in period t (GtC)

E_t = emissions of CO_2 in period t (GtC)

$iIRF100_t$ = 100-year integrated impulse-response function

$Cacc_t$ = accumulated carbon stock in the land and ocean (GtC)

α_t = scaling factor for carbon reservoirs

ξ_i = the fraction of carbon emissions entering reservoir i

τ_i = time constant for reservoir i (years)

$\varsigma_0, \varsigma_C, \varsigma_T$ = coefficients of $iIRF$ equation.

$R_t^i = E_t = Cacc_t = 0$, for t = 0 in 1765

The values of the parameters are described in the Appendix.

I. Climate equations

The other equations of the climate system contain the relationships for radiative forcing and for global mean temperature. These follow closely earlier versions of the DICE model, and changes include primarily updates of initial conditions.

On the whole, existing climate research models are much too complex to be included in economic models, particularly economic models used for optimization. Instead, we employ a small structural model that captures the basic relationship between GHG concentrations, radiative forcing, and the dynamics of climate change.

Accumulations of GHGs lead to warming at the earth's surface through increases in radiative forcing. The relationship between GHG accumulations and increased radiative forcing is derived from empirical measurements and climate models, as shown in Equation (18).

$$(18) \quad F(t) = F_{\mathrm{CO22x}}\{ log_2[M_{AT}(t)/M_{AT}(1750)]\} + F_{ABATE}(t) + F_{EX}(t)$$
$$= [3.93]\{ log_2[M_{AT}(t)/[588]]\} + F_{ABATE}(t) + F_{EX}(t)$$

F(t) is the change in total radiative forcings of greenhouse gases since 1765 from anthropogenic sources such as CO_2 and other GHGs. $F_{EX}(t)$ is exogenous forcings from non-abatable GHGs and other sources, and $F_{ABATE}(t)$ is the forcings from abatable non-CO_2 GHGs. (These sources were discussed above.) The Equation uses estimated carbon stocks and temperature in the year 1765 as the pre-industrial equilibrium. We omit the description of the treatment of non-CO_2 GHGs, which is discussed in Appendix D.

The climate module uses a two-box model of the temperature response to radiative forcing developed by IPCC AR5 and parameterized in Millar et al. (2017). The structure is similar to that used in earlier versions of the DICE model, but it has been revised to use the equation structures of AR5 and Millar et al. In this approach, higher radiative forcing warms the atmospheric layer, which then warms the upper ocean, gradually warming the deep ocean. The lags in the system are primarily due to the diffusive inertia of the different layers. The latest version of the models adjusted the equilibrium climate sensitivity (ECS) and transient climate response (TCR) climate sensitivity to the center of the IPCC range of 3.0 °C for ECS and 1.8 °C for TCR from the IPCC Sixth Assessment Report (2021). The equations of the revised model are the following:

$$(19) \quad Tbox1(t+1) = Tbox1(t)\,exp(-5/d1) + teq1\,Forc(t+1)\,[1 - exp(-5/d1)]$$

$$(20) \quad Tbox2(t+1) = Tbox2(t)\,exp(-5/d2) + teq2\,Forc(t+1)\,[1 - exp(-5/d2)]$$

$$(21) \quad TATM(t+1) = Tbox1(t+1) + Tbox2(t+1)$$

$teq1 = 0.324\ m^2KW^{-1}$

$teq2 = 0.44\ m^2KW^{-1}$

$d1$ = 236 years

$d2$ = 4.07 years

Tbox1(t) and *Tbox2(t)* represent, respectively, (i) the mean temperature of the surface and shallow ocean and (ii) the temperature of the deep oceans. Note that the equilibrium temperature sensitivity (ETS) is given by $ECS = F_{\mathrm{CO22x}}(teq1 + teq2) = 3.93 \times (0.324 + 0.44) = 3.0$. The model's transient climate response (TCR) is 1.80 °C (for the complex formula defining the value, see Millar 2017, eq. 5). This completes the description of the DICE-2023 model. A full discussion of the DFAIR module – including updates such as initial conditions relevant for 2020 – is in Appendix B.

J. Computational and algorithmic aspects

IAMs are generally computationally complex compared to physical science models, such as climate models, which use recursive time-stepped algorithms. The DICE model is a nonlinear optimization problem with nonlinear inequality and equality constraints. The model is usually solved using the CONOPT or NLP solver in the GAMS modeling system (See Brooke et al. 2005). This is based on the generalized reduced gradient (GRG) algorithm. The basic approach is to embed a linear programming algorithm inside an algorithm that linearizes the nonlinear equations. While this algorithm does not guarantee that the solution is the global optimum, our experience over the years has not suggested any solutions other than those found by the algorithm. The model can also be run using EXCEL Solver (most conveniently using the Risk Solver Platform or other premium products). Using EXCEL Solver is also much easier to understand and detect programming errors. DICE-2023 has not yet been implemented, but we expect to do so soon. For the standard run for 500 years and 11 scenarios, the execution time in GAMS is 12 seconds on a high-end 2021 PC.

One of the unfortunate byproducts of greater attention to the details of various sectors, such as the carbon cycle, is the increased complexity of the DICE model over the years. The 2023 version has about 2½ times more variables and equations that the 1992 version. However, the 1992 version, code, and computers took 180 times longer than the 2023 version, code, and computers (the 1992 experience is reported in Nordhaus 1992). Computers and software have vastly outpaced modeling, but whether that has improved accuracy will await a few more decades of experience.

The code and a description of the model are available at https://bit.ly/3TwJ5nO.

IV. Modeling Issues in DICE-2023

This sketch of the DICE model makes it clear that it is a highly simplified representation of the complex economic and geophysical realities. While small and comprehensive models have many advantages, they also have major shortcomings because of their simplifications. We discuss those related to production, taxation, and functional forms as examples.

One example of simplification is the use of a single commodity to represent all consumption, investment, and government-provided goods and services. The use of a single commodity is particularly restrictive in the context of international trade, where the essence of trade is the heterogeneity of goods across regions. This point is particularly important in the question of whether to use market exchange rates (MER) or purchasing power parity exchange (PPP) rates in measuring relative national outputs. While the issue of which approach to use in IAM modeling was for many years controversial, use of PPP measures of output is now established best-practice.

Another important set of important issues concerns taxation. The simplest models ignore the structure of the tax system. This is particularly important for energy and capital taxes and subsidies, which have large effects on energy use and on the rates of return used in making long-term decisions in the energy sector. Some of the detailed IAMs include more realistic detail on the U.S. tax and regulatory system, but they oversimplify or ignore the issues raised by international tax systems. The structure of tax systems is particularly important for the estimation of the optimal level of carbon pricing or taxation because of the need to consider the interaction of carbon pricing with the structure of pre-existing tax and regulatory distortions. (See particularly the several important studies by Lawrence Goulder and colleagues, e.g., Goulder and Hafstead, 2018.)

The issue of tax structure is just one of many inefficiencies and externalities in the real-world economy that are not reflected in the DICE model. These market failures include the co-products of fossil fuels and their impacts on public health, monopoly and regulation in the energy sector, economies of scale, and (of the greatest importance) informational inefficiencies such as endogenous technological change. Treatment of these inefficiencies is beyond the scope of the DICE model.

Many simplifications are also buried in the functional forms of models. For example, the DICE model relies on the Cobb-Douglas function to represent the production process. This is likely to overestimate substitution in some areas and underestimate it in others. Additionally, it may suggest a degree of smoothness in substitution that is not present when there are only a small number of processes, in which case an activity analysis framework would be preferable.

We must put these concerns about oversimplification in the context of the questions that are being asked. The purpose of models is not to be an exact replica of real-world processes. Aside from the impossibility of achieving that goal, greater detail would actually be less valuable for many purposes. Instead, models are used for insights into key questions. For example, if we are concerned about the long-run intertemporal tradeoffs between consumption today and consumption in the future, a relatively simple model can illustrate the issues. Similarly, to determine the uncertainties associated with future climate change, the model must be sufficiently small and manageable so that the uncertainties (including the covariation of uncertain variables) can be estimated and for which Monte Carlo or other techniques can be used to capture all the major uncertainties. However, for many other questions, such as the impact of changes in tax policies or international trade or carbon leakage or international cooperation, more detail is needed to capture the international and sectoral reactions to policy changes.

V. Scenarios to evaluate

Integrated assessment models such as the DICE model have a wide variety of applications. Among the most important ones are the following: (1) making consistent projections, i.e., ones that have consistent inputs and outputs of the different components of the system; (2) calculating the impacts of alternative assumptions on important variables such as output, emissions, temperature change, impacts, prices, and economic growth; (3) tracing through the effects of alternative policies on all variables in a consistent manner; (4) estimating the costs and benefits of alternative strategies, and (5) estimating the uncertainties associated with alternative variables and strategies. The current study presents a suite of scenarios as follows.

Baseline: In this scenario, current policies as of 2023 are extended indefinitely. This approach is standard for forecasting, say of government budgets, and is appropriate for a world of evolving climate policies. As discussed above, the baseline assumption is that the average price on CO_2 emissions is about $6/t$CO_2$, or a global emissions reduction rate of 5% of abatable GHG emissions. The "baseline" scenario foresees this carbon price as growing at 1% per year.

No controls: We sometimes will refer to a "no-controls" path. This is a run with a zero carbon price. It is for reference in calculating variables and is not used as a scenario for evaluation.

Optimal: In this scenario, climate-change policies maximize economic welfare, with full participation by all nations starting in 2025 and without climatic constraints. The "optimal" scenario assumes the most efficient climate-change policies. In this context, efficiency involves a balancing of the present value of the costs of abatement and the present value of the benefits of reduced climate damages. Although highly unrealistic, this scenario provides an efficiency benchmark against which other policies can be measured.

Temperature-limited: In this scenario, the optimal policies are undertaken subject to a further constraint that global temperature does not exceed 2 °C (or other targets) above pre-industrial levels. The "temperature-limited" scenarios are variants of the optimal scenario that build in a precautionary constraint that a specific temperature increase is not exceeded. With current assumptions, the scenario limiting temperature to 1½ °C is not feasible without an unrealistic increase in emissions reductions or a catastrophic reduction in output (see below under results for carbon prices).

Alternative discount rates. The assumptions about discounting are deeply controversial and have major implications for policies. We use alternatives by setting constant discount rates of 1%, 2%, 3%, 4%, and 5% per year. These are modeled by adjusting the parameters of the preference function to match the calibrated real interest rates.

Alternative damage function. The DICE damage function has been criticized as omitting several important damages. We therefore use an alternative damage function that has been derived by from Howard and Sterner (2017, 2022). The damage function has the same structure as the DICE version. While there are several potential results to choose from in Howard and Sterner, a reasonable middle ground of their preferred estimates is a 9% damage/output ratio at a 3 °C increase. This temperature-damage coefficient is 3 times larger than the one used in the current DICE model. While we have reservations about their sample and procedures that are discussed briefly in the background paper, the results are a reasonable and more pessimistic view of the damages literature and impacts.

Paris Accord. The Paris Accord of 2015 codified a policy that would aim to limit climate change to 2 °C above pre-industrial levels. To achieve this goal, under the Paris Agreement, countries agree to make their best efforts through "nationally determined contributions." For example, China announced that it would reduce its 2030 carbon intensity by 60 - 65% compared to 2005 levels. For the analysis, countries are assumed to meet their objectives for national contributions in 2030 according to the revised pledges as of summer 2022. We then take the implicit changes in emissions control rates from 2020 to 2030 (of about 1 percentage point per year in the aggregate) and project slightly less than ½ percentage point increase per year in the control rate from 2030 to 2100. It should be emphasized that any projections beyond 2030 do not rely upon country commitments, and projections differ greatly among modelers of the Paris Accord. This scenario assumes that all countries meet their objectives and that pledges are implemented through a system of harmonized carbon prices or of national emission caps with full emissions trading within and among countries. We note that all these assumptions are highly optimistic.

All scenarios have some important constraints built in. One constraint is that climate policies have limits on implementation. These involve emission control rates increasing at a maximum of 12% per five-year period. Additionally, the emissions control rate is limited to 100% through 2120 and to 110% after that. The control limits are drawn from runs that stress high-resolution IAMs with extremely high carbon prices. Finally, all scenarios assume 100% participation with harmonized and comprehensive carbon prices. These assumptions about policy, particularly participation and harmonization, are clearly optimistic in the extreme and will lead to lower costs and better implementation of targets than scenarios where country actions and international agreements fall short of the ideal.

VI. Results

We now report on a set of representative results. All scenarios ran smoothly with the exception of the 1.5 °C limit, which was on the borderline of feasibility, had anomalous results, and is omitted from this discussion.

A. *Emissions, Concentrations, Temperature*

For the major results, we report the baseline, optimal, 2 °C, and Paris policies. Table 1 and Figure 1 report the results for CO_2 emissions under different scenarios. The trajectory clearly needs to turn down soon to make any of the objectives.

Table 2 and Figure 2 report the results for CO_2 concentrations for different scenarios. The current policy baseline is well above the trajectories needed for achieving policy objectives. Note that the Paris Accord will reduce concentrations about one-third of the way to the 2 °C target.

Table 3 and Figure 3 report the results for global temperature. The baseline run finds 2100 temperature at 3.8 °C, while the optimal (or cost-benefit) run has 2100 temperature of 2.7 °C. The optimal is significantly above the level for the 2 °C run because damages, while substantial, do not increase sharply at that temperature level. In 2100, the Paris Accord slows the temperature increase by about one-third of the way from the base path to the 2 °C target. Note that these temperature calculations are slightly above conventional measures because they use the pre-industrial (1765) baseline rather than later benchmarks.

B. *Policies and Impacts on Income*

We next show key policy variables (a discussion of the social cost of carbon is in the next section). Table 4 and Figure 4 show the results for the emissions control rate. Recall that this applies to all of the CO_2 emissions as well as abatable non-CO_2 GHGs. The baseline emissions control rate is very low for this century because of the weak level of current policy. The emissions control rates for policies in 2050 are 25%, 40%, and 58% for the Paris, optimal, and 2 °C targets; and in 2100 are 45%, 76%, and 99% for the Paris, optimal, and 2 °C targets. These rates are low relative to earlier DICE models and to some current models because of the comprehensive nature of the controlled gases and because the runs assume complete efficiency and participation in policies, as discussed above.

Table 5 and Figure 5 show the results for the carbon price (the price of CO_2 emissions). These reflect either the trading price for universal capped emissions or the harmonized level of universal carbon taxes. The baseline price for 2022 is estimated to be \$6/tCO_2 (2019\$). Policy prices for 2040 are \$90, \$47, and \$155/tCO_2 for the optimal, Paris, and 2 °C runs. In these calculations, the average carbon prices are modest relative to other estimates primarily because the emissions control rates are lower. Note also that the prices are constrained by policy to rise at what we consider to be a feasible rate for the global price given that the current global price is around \$6/tCO_2.

We note that the 1.5 °C scenario is “infeasible” within the constraints of realism and the model. As an example, we removed constraints on the emissions control rates for a test run. In an unconstrained situation, the 1.5 °C limit was met, but it required an increase in the harmonized global carbon price from \$6/tCO_2 in 2020 to \$400 in 2040. The present value economic cost was almost \$1 quadrillion. While the likelihood of this target can be debated for a few more years, the debate will soon end as the target is likely to be passed before the end of this decade.

Table 6 shows the total “wealth” in each run. These are calculated as the present value of consumption (technically, this is the present value of utility calibrated to first-period consumption). The stakes in an efficient program are absolutely large but relatively small. The optimal program increases wealth by \$107 trillion, or somewhat less than one year’s output. There are minor differences between the optimal program and the 2 °C program because the emissions paths are similar. The Paris program makes a substantial improvement.

C. The social cost of carbon

The most important single economic concept in the economics of climate change is the social cost of carbon (SCC). This term designates the economic cost caused by an additional ton of carbon dioxide emissions or its equivalent.

More precisely, it is the change in the discounted value of economic welfare from an additional unit of CO_2-equivalent emissions. The SCC has become a central tool used in climate change policy, particularly in the determination of regulatory policies that involve greenhouse gas emissions. Estimates of the SCC are necessarily complex because they involve the full range of impacts from emissions, through the carbon cycle and climate change, and including economic damages from climate change.

The mathematics of the SCC is the following. Taking the equations of the DICE model yields the SCC at time t:

$$(22) \quad SCC_t \equiv \frac{\partial W}{\partial E_t} \bigg/ \frac{\partial W}{\partial C_t} \equiv \partial C_t / \partial E_t$$

The key definition is in the middle term. The numerator is the marginal welfare impact of emissions at time t, while the denominator is the marginal welfare impact of a unit of aggregate consumption in period t. The ratio of those two variables gives the third term of (22) in which the SCC equals the economic impact of a unit of emissions in terms of t-period consumption as a numéraire. In actual calculations, we take a discrete approximation to (22). Note that the SCC is time-indexed since the marginal damage of emissions changes over time.

Table 7 and Figure 6 show estimates of the social cost of carbon (SCC). The SCC in the baseline run is \$61/tCO_2 for the 2020 period (in 2019 international \$). This is above the SCC for the optimal run of \$53/tCO_2 because damages are smaller in the optimum. It is far below the SCC for the 2 °C run of \$85/tCO_2. The higher SCC in the temperature-limited run reflects the economic interpretation that a tight temperature limit is equivalent to a damage function with a sharp kink at the temperature limit and therefore to a sharply higher damage function above 2 °C. Note that the estimates of the SCC in the current DICE version are significantly above those in earlier vintages for reasons discussed in other sections, see particularly the next section.

One of the most instructive findings involves the importance of discounting for the SCC and other policies. Table 7 shows the powerful impact of discounting on the SCC. The social cost of carbon at a 5% discount rate is two-thirds of the DICE optimal estimate for 2020, while that of a 1% discount rate is 8 times the DICE optimal estimate for 2020.

Additionally, Figure 7 compares estimates of the SCC with several other current values. The GIVE model is a comprehensive estimate prepared by researchers at Resources for the future using probabilistic estimates of output and other components of damage estimates (Rennert et al., 2022). It uses a relatively low discount rate and has a relatively high social cost of carbon. A second set of estimates pertains to the SCC used by the federal government and prepared by an interagency working group. Figure 7 shows draft SCC estimates from EPA (2022) for both their overall assessment and specific to a damage module based on the DSCIM model (Climate Impacts Lab, 2022) for near-term discount rates from 1.5% to 2.5%. Conditional on discounting assumptions, the EPA estimates align very closely with those of DICE-2023. Figure 7 also shows a draft update (OMB, 2021) based on earlier methods and models which did not contain recommended methodological updates. This estimate is notably lower than the corresponding value in DICE-2023. The key takeaway from Figure 7 is the importance of the discount rate in determining the SCC.

D. Comparison with earlier DICE versions

We show a limited comparison of the results of the current modeling and earlier versions in Table 8. The two comparisons are with the original DICE model of 1992 and the latest version, DICE-2016. Panel A of Table 8 shows the comparison for projections to 2015, while the bottom is the comparison of projections to 2100.

Looking at Panel A, to 2015, which is history, the 1992 model had remarkably reliable projections for concentrations and temperature, but only middling projections for emissions. The 2016 version did well for all variables for 2015 (but the model was constructed before actual data were available).

For the 2100 projections (still far in the future), baseline CO_2 industrial emissions and concentrations have been revised upwards in the latest model, while temperature has varied considerably and is revised downwards in the latest model.

The history of output projections is a complete disaster. A major part of the change is due to the movement from MER to PPP exchange rates. The other part – shown in the last row of Table 8B – is a revised Zeitgeist for world output. Note that this combines slightly lower projections of population and much higher projected growth in output per person. This revision reflects highly stagnationist views about growth in the 1980s (such as seen in *The Limits to Growth)* to more robust growth assessments in the late 2010s. The latest assessments for 2100 are slightly downward, reflecting the impacts of deglobalization, the pandemic, and concerns about continued conflicts of many kinds.

A major change in the results of the DICE model over the years has been the rising estimates of the social cost of carbon. The original DICE-1992 model did not calculate a SCC, which came later to climate-change economics. However, rerunning the baseline scenario for the 1992 model gives an estimate of \$18/tCO_2 compared to \$61/tCO_2 in the 2023 model (in 2019\$). The upward revision is a notable illustration of the evolving scientific understanding of damages, discount rates, and levels of output. Further research will provide a decomposition of the sources of the change in SCC due to different components.

VII. Open Issues

This analysis is a report on the "beta3" version of DICE-2023. It is circulated for comments and criticisms from researchers and interested parties. We highlight some questions that need further discussion and analysis.

First, we note that the carbon-cycle component of the DFAIR model included here is a new implementation and has not been widely used or reviewed. In part, the concern is the model itself, which is a parametric adjustment of earlier models. In addition, the implementation here contains calibration for the five-year model and initial conditions. The model therefore needs further review.

Second, the damage module continues to be the most uncertain part of the economic analysis. This is inherent in the estimation of damages, but additionally, the estimates and techniques are highly divergent across different studies and syntheses. The damage function used here is preliminary and subject to revision.

Third, the approach here assumes "perfect implementation" of climate policy: the policies are universal and harmonized across and within all countries. This assumption is sure to be too optimistic in that some countries are unlikely to join, and the policies within and across countries are almost sure to diverge. While we know the sign of the impact of imperfect implementation, we do not know the size. Will the emissions regime cover 90% of emissions or 30% of emissions? Will policies be harmonized, or will they be a dog's breakfast of taxes, cap-and-trade, exclusions, subsidies, and regulations?

Fourth, the modeling continues to treat technological change as exogenous. The evidence is overwhelming that innovation responds to prices and regulations. Here again, the specification of the induced-innovation relationships is poorly understood, and modeling induced innovation poses algorithmic challenges for models.

Fifth, it will be useful to review the impact of changes in DICE from the 2016 version to the 2023 version. This is on the agenda for future work.

Other issues remain. However, we believe these are the most important concerns that readers and users should weigh as they consider DICE-2023.

Figure and Tables

	CO2 emissions, GtCO2/year			
Scenario	2020	2025	2050	2100
Optimal	43.2	44.0	40.5	24.5
T < 2°C	43.2	44.0	27.8	1.0
T < 1.5 °C	43.2	12.4	5.9	0.0
Alt damage	43.2	43.8	22.0	0.0
Paris extended	43.2	44.5	50.1	55.9
Base	43.2	46.2	61.7	90.0
R = 5%	43.2	43.4	45.7	42.4
R = 4%	43.2	44.9	42.8	34.2
R = 3%	43.2	46.4	37.0	21.8
R = 2%	43.2	47.8	26.0	5.6
R = 1%	43.2	48.3	21.1	0.0

Table 1. Results for CO_2 emissions in different scenarios.

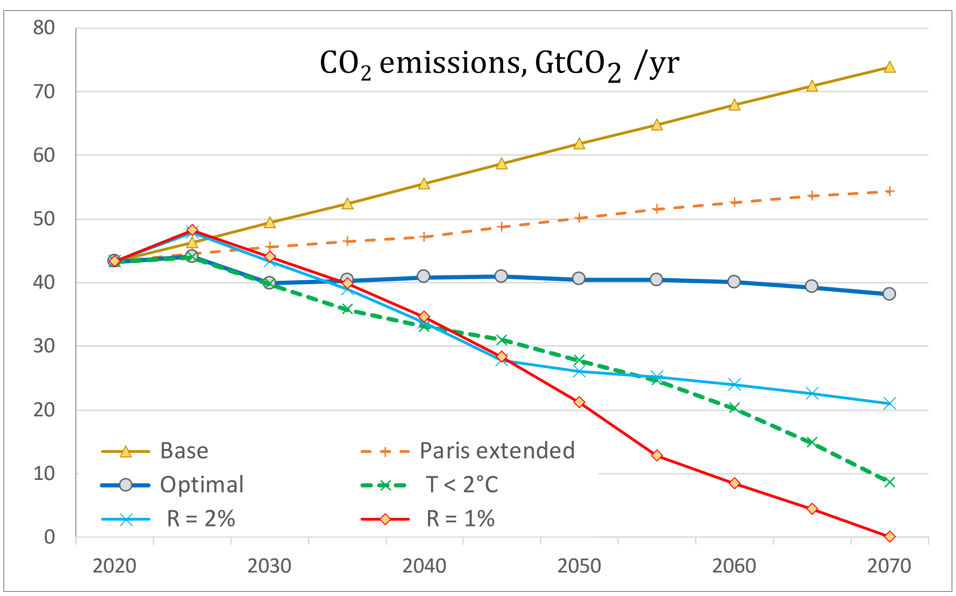

Figure 1. Results for CO_2 emissions in different scenarios
[Figures and Tables are linked to DICE22-collate-figs&tables-011923.xlsx.]

	CO2 concentrations, ppm				
Scenario	2020	2025	2050	2100	2150
Optimal	416.2	430.5	494.0	599.8	584.6
T < 2°C	416.2	430.4	477.7	475.5	463.6
T < 1.5 °C	416.2	414.6	413.1	404.7	399.0
Alt damage	416.2	430.4	470.7	465.5	413.0
Paris extended	416.2	430.7	510.2	710.1	914.2
Base	416.2	431.6	529.2	842.9	1,322.2
R = 5%	416.2	430.2	501.9	660.7	772.0
R = 4%	416.2	430.9	497.8	630.5	686.0
R = 3%	416.2	431.6	490.1	581.3	571.8
R = 2%	416.2	432.3	479.5	511.4	454.7
R = 1%	416.2	432.6	478.4	454.2	400.0

Table 2. CO_2 concentrations, parts per million (ppm)

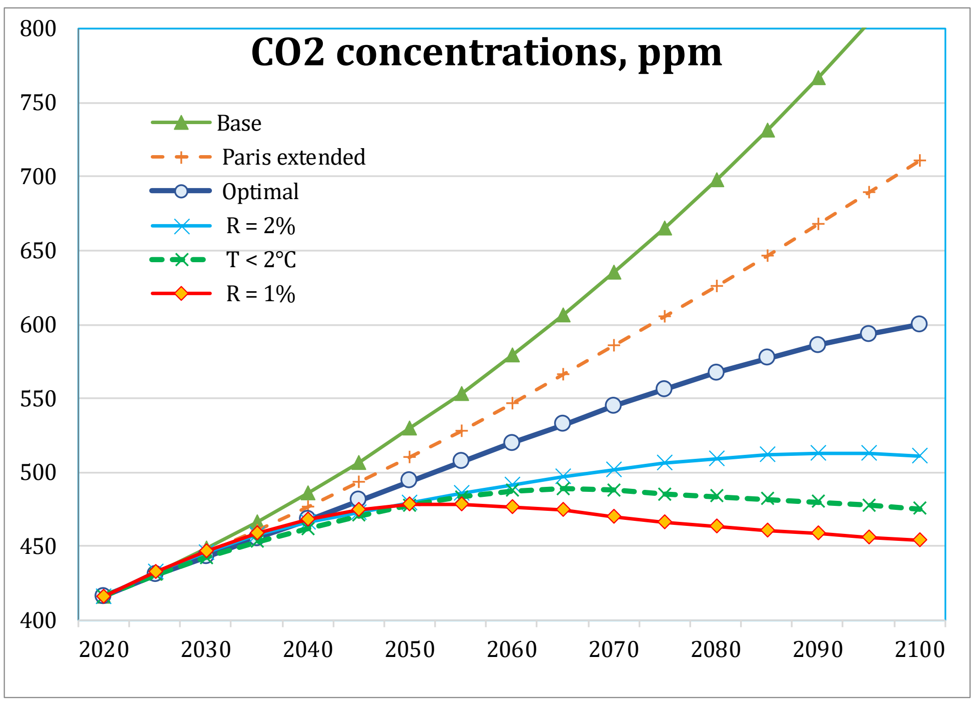

Figure 2. CO_2 concentrations, ppm

Scenario	Global temperature, °C relative to 1765				
	2020	2025	2050	2100	2150
Optimal	1.25	1.43	1.95	2.73	2.78
T < 2°C	1.25	1.43	1.86	2.00	2.00
T < 1.5 °C	1.25	1.36	1.49	1.50	1.50
Alt damage	1.25	1.43	1.83	1.93	1.66
Paris extended	1.25	1.43	2.05	3.25	4.18
Base	1.25	1.43	2.15	3.80	5.42
R = 5%	1.25	1.43	2.00	3.03	3.65
R = 4%	1.25	1.43	1.97	2.88	3.27
R = 3%	1.25	1.43	1.93	2.62	2.70
R = 2%	1.25	1.43	1.87	2.22	1.97
R = 1%	1.25	1.44	1.87	1.85	1.56

Table 3. Global temperature increases under different scenarios

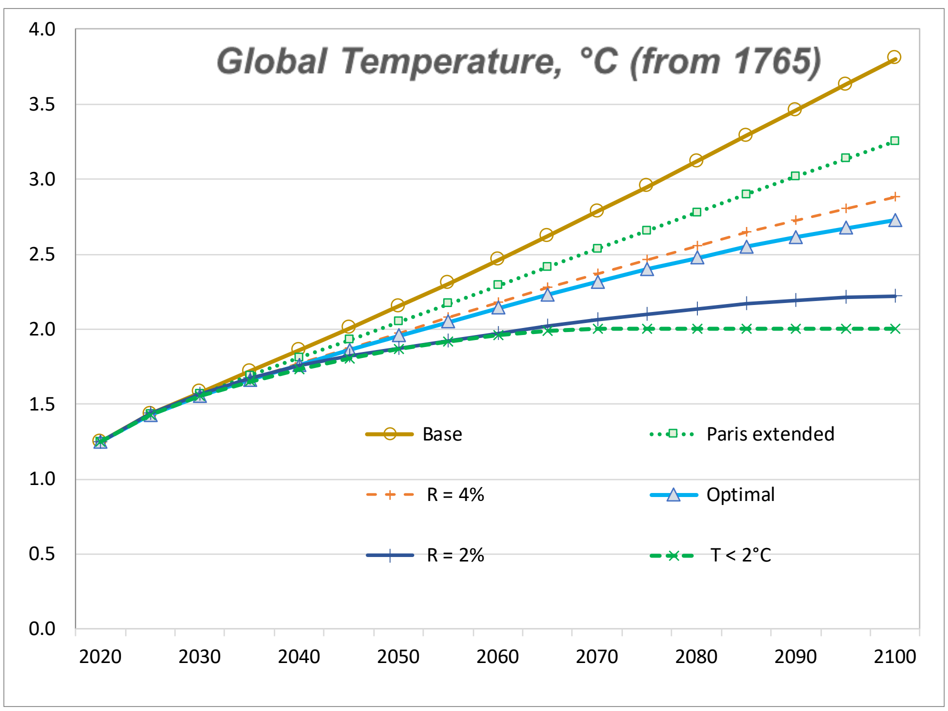

Figure 3. Global temperature increases under different scenarios

	Emissions control rate (%)					
	2020	2030	2040	2050	2060	2100
Optimal	5%	24%	32%	40%	46%	76%
T < 2°C	5%	24%	44%	58%	73%	99%
T < 1.5 °C	5%	24%	48%	72%	90%	100%
Alt damage	5%	24%	48%	67%	76%	100%
Paris extended	5%	13%	21%	25%	29%	45%
Base	5%	6%	7%	7%	8%	10%
R = 5%	5%	19%	24%	30%	34%	56%
R = 4%	5%	24%	30%	36%	42%	66%
R = 3%	5%	24%	39%	47%	53%	79%
R = 2%	5%	24%	48%	64%	70%	95%
R = 1%	5%	24%	48%	72%	90%	100%

Table 4. Emissions control rate for CO_2 and abatable GHGs (percent of no control)

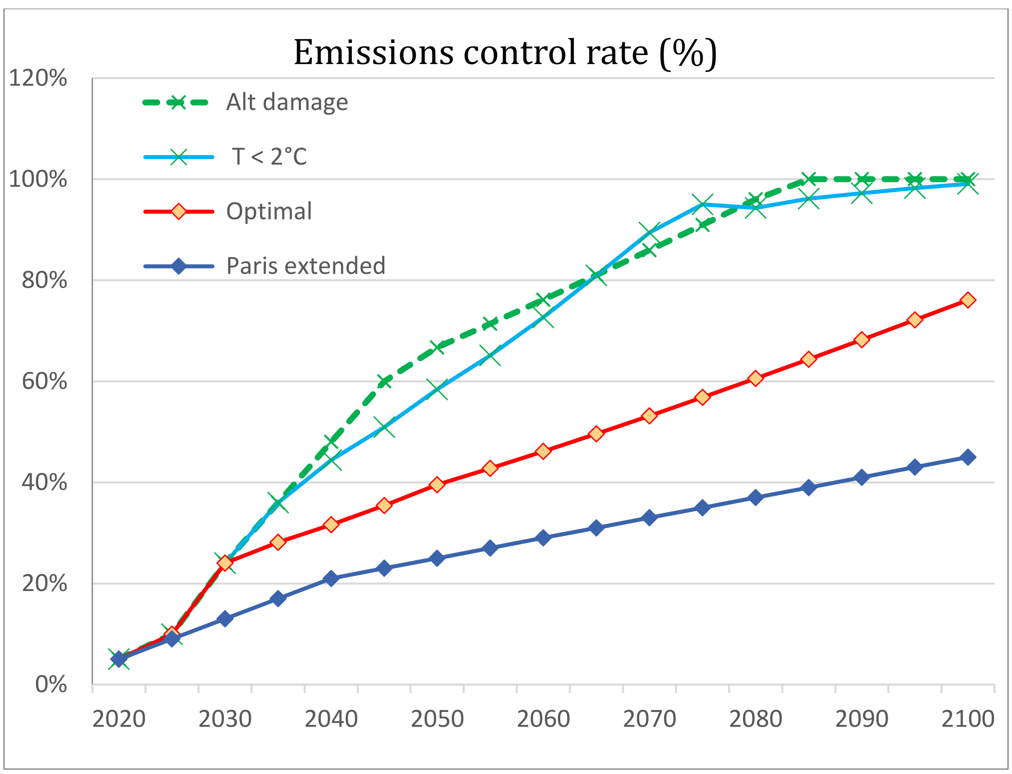

Figure 4. Emissions control rate for CO_2 and abatable GHGs (percent of no control)

Scenario	Carbon price (2019$/tCO2)		
	2020	2040	2060
Optimal	6	90	148
T < 2°C	6	155	306
T < 1.5 °C	6	176	431
Alt damage	6	176	330
Paris extended	6	47	70
Base	6	7	9
R = 5%	6	58	92
R = 4%	6	82	126
R = 3%	6	128	184
R = 2%	6	176	288
R = 1%	6	176	431

Table 5. Price of CO_2 emissions (2019 $/t$CO_2$)

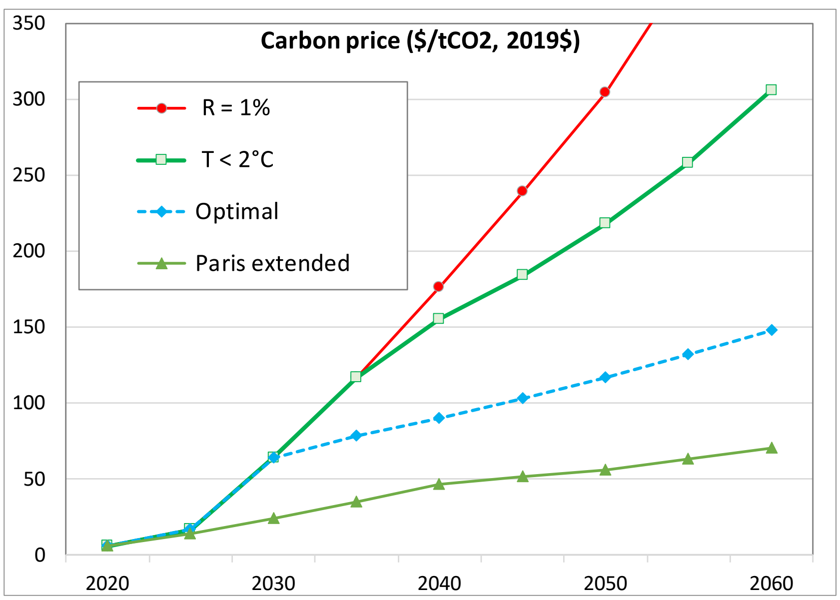

Figure 5. Price of CO_2 emissions (2019 $/t$CO_2$)

Scenario	Present value of consumption	Difference from base
	[Trillions of 2019 US international $]	
Base	6,266	0.0
Optimal	6,373	106.8
$T \leq 2°C$	6,349	82.8
Paris, updated 2022	6,342	76.4

Table 6. Total global wealth (present value of consumption), 2019 US$.

These figures use the objective function of the GAMS program to estimate the overall economic impacts of policies in units that are present value of consumption. They are benchmarked so that the value of the objective function in the baseline scenario is equal to the present value of consumption in that scenario.

Scenario	Social cost of carbon ($/tCO2, 2019$)		
	2020	2025	2050
Optimal	53	62	127
T < 2°C	85	100	236
T < 1.5 °C	3,538	4,162	16,694
Alt damage	132	156	293
Paris extended	58	68	142
Base	61	72	150
R = 5%	33	39	77
R = 4%	51	60	110
R = 3%	87	103	170
R = 2%	170	200	289
R = 1%	429	505	609

Table 7. Social cost of carbon, alternative scenarios (2019$/$tCO_2$)

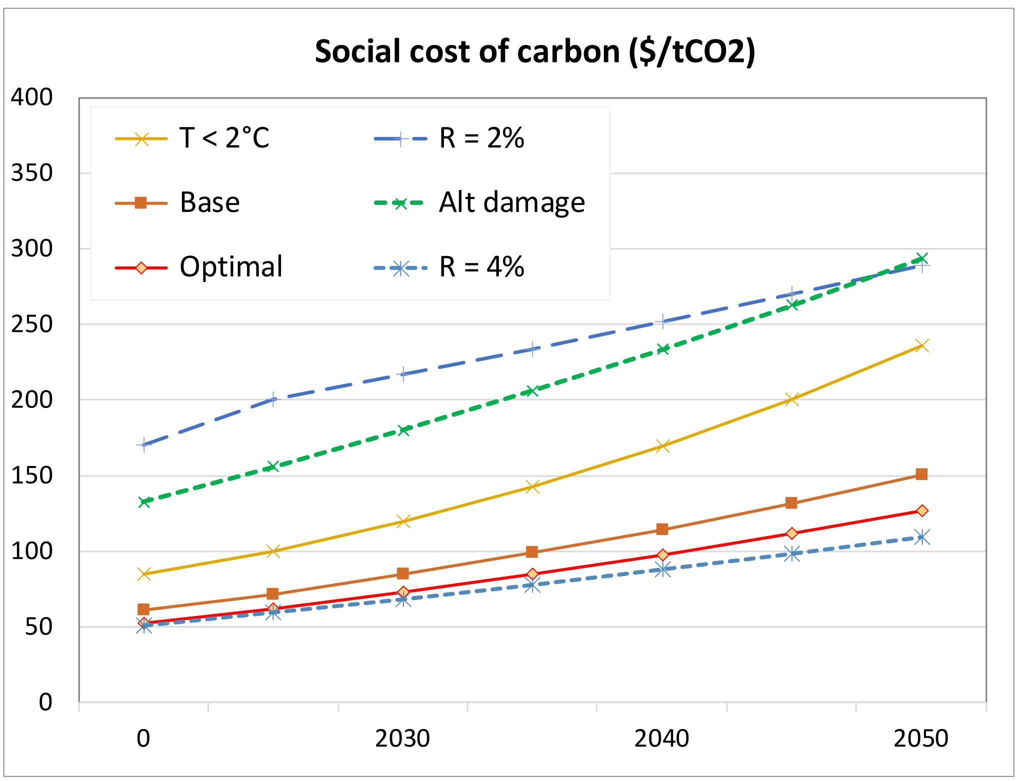

Figure 6. Social cost of carbon, alternative scenarios (2019$/$tCO_2$)

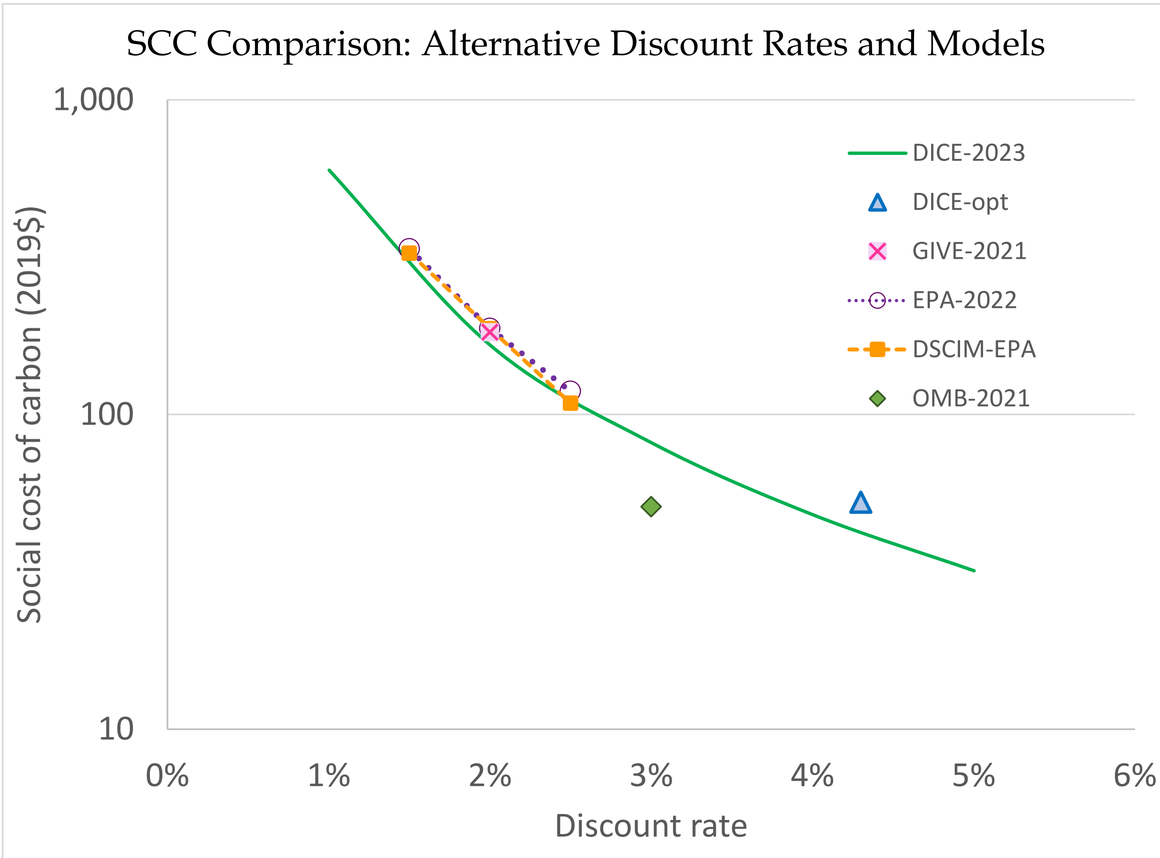

Figure 7. Social cost of carbon, 2020, alternative discount rates and models (2019$/$tCO_2$)

The figure shows the relationship between the discount rate on goods and the SCC in different scenarios of the DICE-2023 model and several other models. Results in order of the list are: "DICE 2023" is the solid green line connecting the runs for constant discount rates in DICE-2023; "DICE-opt" is the DICE-2023 estimate for the optimal scenario along with the average discount rate for the period 2020 – 2050; "GIVE-2021" is the estimate from the GIVE model (Rennert et al. 2021); "EPA-2022" are the draft EPA social costs of greenhouse gas estimates based on an overall assessment (EPA, 2022); "DSCIM-EPA" are the estimates specific to a damage module based on the DSCIM framework (CIL, 2022); "OMB-2021" is a preliminary OMB estimate (OMB 2021) which did not, according to OMB, reflect the potential changes that would likely result in a major increase of the SCC. Discount rates for EPA values correspond to near-term rates in their assessment.

A. Base projections, actual for 2015

	D1992	D2016	D2023
Industrial emissions	42.3	35.7	36.5
CO2 concen. (ppm)	399	400	402
Temperature (°C)	1.17	1.16	1.15
Global output (2019$)	41.9	113.4	118.3

B. Base projections for 2100

	D1992	D2016	D2023
Industrial emissions	78.7	70.8	91.6
CO2 concen. (ppm)	670	854	884
Temperature (°C)	3.28	4.49	3.97
Global output (2019$)	109.3	816.3	774.1

Table 8. Comparison of results for DICE-2023 with DICE-2016 and DICE-1992

The table shows the results for three vintages of models. These are the current version, the 2018 version of DICE-2016, and the original DICE model of 1992. The series are industrial emissions, CO_2 concentrations, global mean temperature, and global output. The output data in 1992 were measured in market exchange rates and thus are conceptually different. The runs are for the "base" scenario, which is current policy.

References for Main Text and Appendix

Barnett, Michael, William Brock, and Lars Peter Hansen. 2020. "Pricing uncertainty induced by climate change." *The Review of Financial Studies* 33, no. 3: 1024-1066.

van den Bremer, Ton S., and Frederick Van der Ploeg. 2021. "The risk-adjusted carbon price." *American Economic Review* 111, no. 9: 2782-2810.

Brooke, Anthony, David Kendrick, Alexander Meeraus, and Ramesh Raman (2005). *GAMS: A Users Guide,* GAMS Development Corporation, Washington, D.C.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. 2015. "Global nonlinear effect of temperature on economic production." *Nature* 527, no. 7577: 235-239.

Cai, Yongyang, and Thomas S. Lontzek. "The social cost of carbon with economic and climate risks." *Journal of Political Economy* 127, no. 6 (2019): 2684-2734.

Climate Impact Lab (CIL), 2022. *Data-driven Spatial Climate Impact Model User Manual, Version 092022-EPA*. https://impactlab.org/research/dscim-user-manual-version-092022-epa

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, et al. 2022. "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits." *The Quarterly Journal of Economics* 137, no. 4: 2037-2105.

Christensen, Peter, Kenneth Gillingham, and William Nordhaus. 2018. "Uncertainty in forecasts of long-run economic growth." *Proceedings of the National Academy of Sciences* 115, no. 21: 5409-5414.

Cline, William R. 1992. *The economics of global warming.* Institute for International Economics, Washington, DC: 399.

Dellink, R., Lanzi, E., and Chateau, J. 2019. The sectoral and regional economic consequences of climate change to 2060. *Environmental and Resource Economics* 72, 309–363.

Dietz, Simon, Christian Gollier, and Louise Kessler. 2018. "The climate beta." *Journal of Environmental Economics and Management* 87: 258-274.

Dietz, Simon, James Rising, Thomas Stoerk, and Gernot Wagner. "Economic impacts of tipping points in the climate system," *PNAS* (24 August 2021). doi: 10.1073/pnas.2103081118

Dietz, Simon, Frederick van der Ploeg, Armon Rezai, Frank Venmans. 2021a. "Are Economists Getting Climate Dynamics Right and Does It Matter?" *Journal of the Association of Environmental and Resource Economists*, 8(5). DOI: https://doi.org/10.1086/713977.

Environmental Protection Agency (EPA), 2022. "Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances" in: "Supplementary Material for the Regulatory Impact Analysis for the Supplemental Proposed Rulemaking, 'Standard of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review.'" Docket ID No. EPA-HQ-OAR-2021-0317, September 2022.

Gillingham, K. et al., 2018. Modeling uncertainty in integrated assessment of climate change: A multimodel comparison. *J. Assoc. Environ. Resour. Econ.* 5, 791–826.

Gollier, Christian. 2013. *Pricing the planet's future: the economics of discounting in an uncertain world.* Princeton University Press.

Goulder, Lawrence, and Marc Hafstead. 2018. *Confronting the Climate Challenge*. Columbia University Press.

Harmsen, J. H. M., Detlef P. van Vuuren, Dali R. Nayak, Andries F. Hof, Lena Höglund-Isaksson, Paul L. Lucas, Jens B. Nielsen, Pete Smith, and Elke Stehfest. 2019. "Long-term marginal abatement cost curves of non-CO_2 greenhouse gases." *Environmental Science and Policy* 99: 136-149.

Howard, Peter H., and Thomas Sterner. 2017. "Few and not so far between: a meta-analysis of climate damage estimates." *Environmental and Resource Economics* 68, no. 1: 197-225.

Howard, Peter H. 2022. Personal communications and unpublished manuscript.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, et al. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science* 356 (6345): 1362–69.

IPCC AR6. 2021. Masson-Delmotte, Valérie, Panmao Zhai, Anna Pirani, et al., *Climate change 2021: the physical science basis." Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*: 2.

Institute for Applied Systems Analysis (IIASA), "Shared Socioeconomic Pathways Scenario Database (SSP)". URL (accessed January 2022): https://iiasa.ac.at/models-tools-data/ssp

Joos, F., Roth, R., Fuglestvedt, J. S., Peters, et al. 2013. "Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: a multimodel analysis." *Atmospheric Chemistry and Physics,* 13, 5, 2793-2825.

Kahn, Matthew E., Kamiar Mohaddes, Ryan NC Ng, M. Hashem Pesaran, Mehdi Raissi, and Jui-Chung Yang. 2019. "Long-term macroeconomic effects of climate change: A cross-country analysis." *Energy Economics*, 104:105624.

Kalkuhl, Matthias, and Leonie Wenz. 2020. "The impact of climate conditions on economic production. Evidence from a global panel of regions." *Journal of Environmental Economics and Management* 103: 102360.

Kompas, Tom, Van Ha Pham, and Tuong Nhu Che. 2018. "The effects of climate change on GDP by country and the global economic gains from complying with the Paris climate accord." *Earth's Future* 6, no. 8: 1153-1173.

Lemoine, Derek. 2021. "The climate risk premium: how uncertainty affects the social cost of carbon." *Journal of the Association of Environmental and Resource Economists* 8, no. 1: 27-57.

Letta, Marco, and Richard SJ Tol. 2019. "Weather, climate and total factor productivity." *Environmental and Resource Economics* 73, no. 1: 283-305.

Millar, Richard J., Zebedee R. Nicholls , Pierre Friedlingstein, and Myles R. Allen. 2017. "A modified impulse-response representation of the global near-surface air temperature and atmospheric concentration response to carbon dioxide emissions," *Atmos. Chem. Phys.,* 17, 7213–7228.

NAS. 2017. National Academies of Sciences, Engineering, and Medicine. *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide*. Washington, DC: The National Academies Press. https://doi.org/10.17226/24651.

Newell, Richard G., Brian C. Prest, and Steven E. Sexton. 2021. "The GDP-temperature relationship: implications for climate change damages." *Journal of Environmental Economics and Management* 108: 102445.

Nordhaus, William D. 1992. “GAMS program for DICE Model,” Cowles Foundation Note, December 10 in “modecode.d1.”

Nordhaus, William D. 2017. “Revisiting the social cost of carbon.” *Proceedings of the National Academy of Sciences* 114, no. 7: 1518-1523.

Nordhaus, William. 2018. “Projections and uncertainties about climate change in an era of minimal climate policies.” *American Economic Journal: Economic Policy* 10, no. 3: 333-60.

Nordhaus, William. 2018a. “Evolution of modeling of the economics of global warming: changes in the DICE model, 1992–2017.” *Climatic change* 148, no. 4 (2): 623-640.

Nordhaus, William, and Joseph Boyer. 2000. *Warming the World: Economic Modeling of Global Warming*, MIT Press, Cambridge, Mass.

Nordhaus, William D., and Andrew Moffat. 2017. “A Survey of Global Impacts of Climate Change: Replication, Survey Methods, and a Statistical Analysis.” *NBER Working Papers* 23646.

Nordhaus, William, and Paul Sztorc. 2013. *DICE 2013R: Introduction and user’s manual.* Yale University and the National Bureau of Economic Research, USA.

Notes on Fair. 2022. “Notes on FAIR calibration for DICE model (DFAIR), September 4, 2022,” available from authors.

O’Neill, B., M. van Aalst, Z. Zaiton Ibrahim, L. Berrang Ford, S. Bhadwal, H. Buhaug, D. Diaz, et al. 2022. “Key Risks Across Sectors and Regions. In: *Climate Change 2022: Impacts, Adaptation, and Vulnerability.* Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.” [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)].

Piontek, Franziska, Laurent Drouet, Johannes Emmerling, Tom Kompas, Aurélie Méjean, Christian Otto, James Rising, Bjoern Soergel, Nicolas Taconet, and Massimo Tavoni. 2021. “Integrated perspective on translating biophysical to economic impacts of climate change.” *Nature Climate Change* 11, no. 7: 563-572.

Pretis, Felix, Moritz Schwarz, Kevin Tang, Karsten Haustein, and Myles R. Allen. 2018. “Uncertain impacts on economic growth when stabilizing global temperatures at 1.5 C or 2 C warming.” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376, no. 2119: 20160460.

Rennert, Kevin, Frank Errickson, Brian C. Prest, Lisa Rennels, Richard G. Newell, William Pizer, Cora Kingdon, et al. "Comprehensive evidence implies a higher social cost of CO2." *Nature* 610, no. 7933 (2022): 687-692.

Revelle, R. and Suess, H. E. 1957. "Carbon dioxide exchange between atmosphere and ocean and the question of an increase of atmospheric CO_2 during the past decades," *Tellus*, 9, 18–27.

Riahi, K. et al. 2021. Long-term economic benefits of stabilizing warming without overshoot – The ENGAGE model intercomparison. *Res. Sq.* [Preprint]. 10.21203/rs.3.rs-127847/v1.

Riahi, K. et al, 2021a. Long-term economic benefits of stabilizing warming without overshoot – The ENGAGE model intercomparison. Data provided by authors, 2021.

Rode, Ashwin, Tamma Carleton, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, et al. 2021. "Estimating a social cost of carbon for global energy consumption." *Nature* 598, no. 7880: 308-314.

Roson, Roberto, and Martina Sartori. 2016. "Estimation of climate change damage functions for 140 regions in the GTAP9 database." *Journal of Global Economic Analysis,* 1(2): 78-115.

Takakura, Jun'ya, Shinichiro Fujimori, Naota Hanasaki, Tomoko Hasegawa, Yukiko Hirabayashi, Yasushi Honda, Toshichika Iizumi et al. 2019. "Dependence of economic impacts of climate change on anthropogenically directed pathways." *Nature Climate Change* 9, no. 10: 737-741.

Yang, Zili. 2020. *The environment and externality: Theory, algorithms, and applications.* Cambridge University Press, Cambridge, UK.

Zhao, Zi-Jian, Xiao-Tong Chen, Chang-Yi Liu, Fang Yang, Xin Tan, Yang Zhao, Han Huang et al. 2020."Global climate damage in 2° C and 1.5° C scenarios based on BCC_SESM model in IAM framework." *Advances in Climate Change Research* 11, no. 3: 261-272.