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Integrated assessment of climate change: state of the literature

Abstract: This paper reviews applications of benefit-cost analysis (BCA) in climate policy assessment at the US national and global scales. Two different but related major application types are addressed. First there are global-scale analyses that focus on calculating optimal global carbon emissions trajectories and carbon prices that maximize global welfare. The second application is the use of the same tools to compute the social cost of carbon (SCC) for use in US regulatory processes. The SCC is defined as the climate damages attributable to an increase of one metric ton of carbon dioxide emissions above a baseline emissions trajectory that assumes no new climate policies. The paper describes the three main quantitative models that have been used in the optimal carbon policy and SCC calculations and then summarizes the range of results that have been produced using them. The results span an extremely broad range (up to an order of magnitude) across modeling platforms as well as across the plausible ranges of input assumptions to a single model. This broad range of results sets the stage for a discussion of the five key challenges that face BCA practitioners participating in the national and global climate change policy analysis arenas: (1) including the possibility of catastrophic outcomes; (2) factoring in equity and income distribution considerations; (3) addressing intertemporal discounting and intergenerational equity; (4) projecting baseline demographics, technological change, and policies inside and outside the energy sector; and (5) characterizing the full set of uncertainties to be dealt with and designing a decision-making process that updates and adapts new scientific and economic information into that process in a timely and productive manner. The paper closes by describing how the BCA models have been useful in climate policy discussions to date despite the uncertainties that pervade the results that have been produced.

Keywords: benefit-cost analysis; climate change; integrated assessment; optimal carbon emissions; social cost of carbon.

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1 Introduction

This paper examines the use of benefit-cost analysis (BCA) in the assessment of climate policy. The paper initially discusses how these models are being used to answer questions such as "what is the optimal rate of carbon emissions?" or "what is the optimal (implicit or explicit) price to put on carbon?" This focus on optimality is a somewhat different application of BCA concepts than is often used in regulatory analysis, where the benefit-cost ratio of a particular policy intervention is the objective (that is, whether the total benefits resulting from the intervention exceed the total costs) and less direct emphasis is usually placed on assessing the appropriate scale of the intervention. From that perspective, the "optimal" carbon policies defined here are simply those *for which* marginal costs equal marginal benefits.

The paper then goes on to discuss the unique challenges that arise when BCA is used for decision making in formulating climate policy, and briefly describe some of the key debates on the topic, including the difficult issues of discount rates, equity (whose preferences matter), fat tails, climate sensitivity, tipping points, and uncertainty. The paper discusses how some of these assumptions are critical – or not – in determining the magnitude (and sometimes the direction) of the results obtained, and the various approaches that have been used or are being developed to address these conceptual and practical challenges. In addition to the numerical results produced by them, and despite the large uncertainties that accompany those numbers, these models have provided many valuable insights into climate policy development. They have been especially useful in identifying the key drivers of climate policy outcomes, and ascertaining better and more robust policies over wide ranges of input assumptions. The paper will also discuss the development and use of the concept of the social cost of carbon (SCC), as another policy context in which these BCA tools have been applied. The computation of the SCC is closer to the normal regulatory usage of BCA, where the benefits of a one-ton reduction in carbon emissions are computed and compared with the cost of that one-ton reduction in carbon emissions. The now extensive and rapidly growing literature on the use of BCA in supporting climate change adaptation decision making is covered in another paper in this issue (Li, Mullan, & Helgeson, 2014).

2 Background

As now is clear (IPCC, 2013), human-induced climate change is caused by: (1) oil, gas, coal, and bio-fuel combustion in utility and industrial boilers and land, sea, and air transportation systems that produce emissions of CO_2 and other radiatively active gases to the atmosphere; and (2) land use and land use change activities that release CO_2, methane, and/or nitrous oxide to the atmosphere. These emissions lead to net increases in the accumulations of these gases in the atmosphere above those that occur naturally. These chemical species have the property of allowing more of the heat from the sun's radiation through to the earth's surface than from the earth's surface back out to deep space. Although these gases are commonly referred to as greenhouse gases (GHGs) because of this property, their effect is much more similar to that of a blanket holding extra heat near a baby than to how a greenhouse actually works (Masters & Ela, 2007). In the aggregate, this increase in GHG concentrations in the atmosphere also leads to a concomitant increase in ocean acidity as some of this extra carbon dioxide is absorbed by the oceans. The basic physics, chemistry, and biology of these effects are not in question (IPCC, 2013), but there is uncertainty about the ultimate amount and rate of change in temperature to expect. This uncertainty stems from a lack of knowledge about the rate at which the deep ocean absorbs excess heat and the degree to which combustion products (most of which come from the same fossil fuel burning that causes the warming) impede solar radiation from reaching the surface of the earth. Lack of complete understanding about these phenomena results in uncertainty about the precise relationship between GHG concentrations in the atmosphere and observed temperature changes. These uncertainties hinder precise projections of how much temperature change to expect and the rate at which the new higher temperature equilibrium will be approached. Put differently, based on observations since the beginning of the industrial revolution, it is not yet possible to easily distinguish between a rapid adjustment to a small increase in equilibrium temperature and a very slow adjustment to a much larger ultimate equilibrium temperature level. Despite these uncertainties, however, changes in climate and impacts of those changes have already been observed over the last half century (IPCC, 2013, 2014a).

In addition to causing atmospheric changes, the extra heat in the atmosphere leads to an expansion of water in the oceans and melting of land-based ice sheets, both of which cause sea levels to rise. The warming of the earth system in the aggregate also leads to changes in the circulation of heat and air masses around the globe, which can lead to changes in regional and local temperature and precipitation patterns. These changes in local temperatures and rainfall can lead to impacts on agricultural, forest, and ecosystem productivity, as well as on human health through changes in the incidence of heat stress, infectious diseases, and illnesses caused by increased air pollution. Sea level rise coupled with more intense storms can also lead to coastal zone damage to infrastructure and property, which are often quite valuable due to their proximity to the water. Changes in other weather extremes, such as increases in droughts or floods, may also occur.

These effects on people and their property, wildlife, and ecosystems can be significant (IPCC, 2014a) and have thus led to consideration of three basic approaches for ameliorating the impacts of climate change: (1) mitigation of GHG emissions, (2) adaptation to any climate changes that might occur, and (3) geo-engineering to influence the amount of solar energy reaching the earth surface and/or the chemistry of the oceans. Since the relationships within and between the various bio-geo-chemical and socioeconomic components of the earth system can be quite complex, a number of quantitative models have been developed to study earth-system-wide climate changes and the effect of various types of public policies on projections of future climate change. These models have become known as "integrated assessment of climate change" or "integrated assessment" models (IAMs). The objective of these models is to project alternative future climates with and without various types of climate change policies in place, in order to give policy makers at all levels of government and industry an idea of the stakes involved in deciding whether or not to implement them.

Although as many as 20 or so integrated assessment models have been developed (see IAMC, 2014), they are of two basic types. Both include projections of GHG emissions and the costs of mitigating them in various ways (e.g., energy conservation, changes in production processes, fuel switching). Where they differ is in how climate change impacts are handled. The first type of IAM is more disaggregated and seeks to provide projections of climate change impacts at detailed regional and sectoral levels, some with economic valuation, but others terminating with projections of physical impacts such as reductions in crop growth, land inundated by sea level rise, and additional deaths from heat stress. The second type of IAM includes a more aggregated representation of climate change mitigation costs and an aggregation of impacts by sector and region into a single economic metric. It is this last type of integrated assessment model that is our focus here, as the main motivation for the construction of these models has been BCA for finding "optimal" climate policies. In discussing the challenges in building such models and interpreting their results, however, concepts and insights from the more complex IAMs are brought in both to critique the simple aggregate BCA models and point to where they might be improved. Obviously, there is only one earth system that both types of models seek to represent, so the two types of models should not be viewed as totally independent of each other.

Concepts and results from the integrated assessment models that are not fundamentally BCA models can be important to the BCA-oriented models for a number of important reasons. First, the cost of carbon emissions mitigation functions in the aggregate BCA-focused models are often calibrated to results from the non-BCA-focused integrated assessment models, which consider much more energy sector and land use detail (including things like agricultural and forestry activities, as well as changes in unmanaged ecosystems). In fact, these more detailed models have frequently been used to examine the "cost effectiveness" of alternative policies for meeting various climate targets, such as limits on carbon concentrations or a maximum permissible global mean temperature increase at the lowest possible societal cost.

In addition to more detailed information on the cost side of the climate BCA calculation, the non-BCA-oriented IAMs can also provide richer information on the physical and economic costs of climate change and benefits of carbon emission mitigation. This has two important implications for the BCA models in general, and this review of them in particular. First, similar to the aggregation and calibration required on the mitigation side of the BCA models, the more complex IAMs can also provide projections of the economic costs net of endogenous adaptation of climate change on key sectors by region. These estimates can be aggregated for use in the BCA models where appropriate. Since most climate impacts take place at the watershed, agricultural growing region, ecological zone, or similar level, this degree of additional geographical disaggregation is essential for improving the validity of the damage functions used in the aggregate BCA models. Second, the additional information on both the physical and economic impacts of climate change may be vitally important to decision makers in some regions and sectors, as discussed more fully elsewhere in this issue. Consideration of this additional information amounts to putting the BCA model results into a broader decision-making framework than conventional BCA, while leaving open the possibility of using the information the BCA model provides directly as a critical part of what is considered in an assessment.

The simple aggregate climate-change-focused BCA models have been used in two ways. BCA has been used for several decades to compute the optimal trajectory of global GHG emissions, and the corresponding prices to charge for those emissions. The optimal policies that are computed equate the marginal benefits (in terms of climate damages avoided) with the marginal costs (in term of mitigation effort required) of climate change policy. This is shown conceptually for the simple static one period case in Figure 1. In the single period, the marginal benefit (MB) curve for emissions reductions is flat. The figure represents alternative MB estimates in that period, with the values on the horizontal axis each representing the corresponding path of future emissions.[1] The costs of reducing carbon

1 There are many emissions trajectories that lead to the same amount of cumulative emissions over time, so these curves are not strictly speaking one-to-one functions. Since the models actually equate the marginal discounted present value of mitigation benefits (damages avoided) and costs over time, this is not a problem for them because they select a whole emissions trajectory as optimal. The purpose of this figure is simply to make the point that the optimal carbon tax is computed along the optimal benefits less costs of mitigation emissions trajectory discounted present value emissions trajectory over time, and the social cost of carbon is computed as the marginal discounted present value cost of the damages caused by an additional ton of carbon emissions at a particular point in time along a baseline scenario without assuming any future restrictions on carbon emissions.

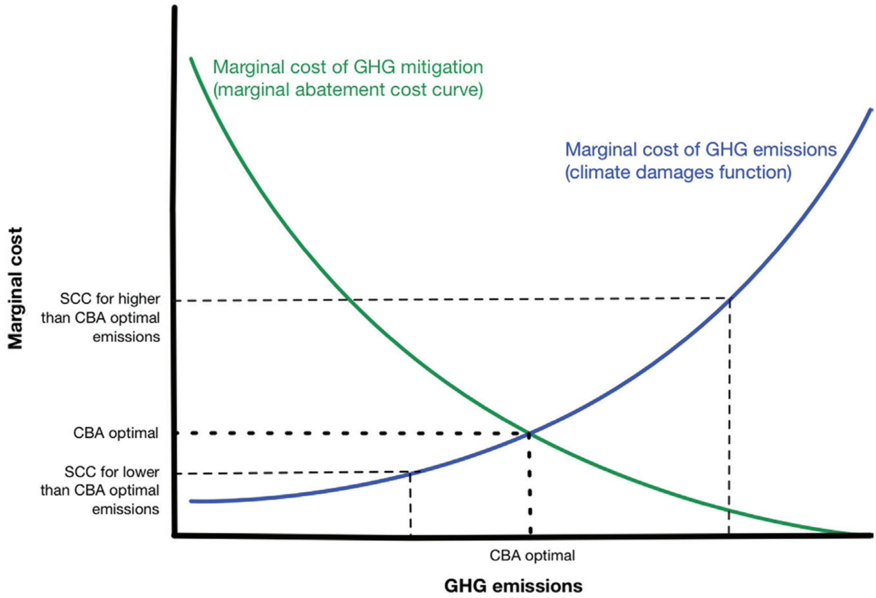

Figure 1 Conceptual overview of one period benefit-cost analysis (BCA) applied to the problem of optimal carbon emissions policy and relationship to the social cost of carbon (SCC).

emissions[2] in the single period can be similarly constructed, which allows for the optimal carbon tax and level of carbon emissions to be found at the intersection of these benefit values with the marginal abatement cost values. The point at which the marginal benefit and marginal cost curves intersect is the level of mitigation/residual climate change impacts that minimizes total societal costs.

Second, the BCA models have been used, especially in current US climate policy deliberations, to compute the SCC, which is roughly the incremental damage caused by one more ton of carbon emissions. As shown in Figure 1, the baseline emissions used in this calculation could be higher, lower, or the same as for the optimal carbon emissions case. US regulatory rules have generally required that the emissions trajectory used in computing the SCC be a "no climate policy" reference emissions path (e.g., higher than optimal emissions path).

2 From this point on this paper discusses only carbon dioxide emissions and not those of other GHGs, as the majority of the results available in the literature have focused on carbon dioxide. There are now a small number of newer analyses that add in the other GHGs on a "CO_2 equivalent" basis, and a few studies that have included these gases in a way that represents their projected impacts on radiative forcing and temperature change directly (cf., Marten & Newbold, 2012).

Thus, the SCC estimates have generally only really required use of the climate damage elements of the aggregate BCA models and not their aggregate GHG mitigation modules. Thus, for "regulatory policy requirements," BCA models are not being used in full traditional benefit-cost mode. In this case, however, it is easy to compare marginal costs and benefits for whatever emissions trajectory is used in the SCC calculations with optimal BCA results. The desirability of doing this kind of comparison will be discussed more fully later in this paper, after the three most popular aggregate BCA models and some representative results from them are described.

3 The DICE, FUND, and PAGE models

Ranges of optimal carbon taxes have been produced by several authors. Their results depend on climate change damage projections, mitigation cost projections, how costs and benefits are "discounted" over time, and how uncertainty and risk are reflected.

Projections of carbon price and quantity trajectories that satisfy BCA optimality conditions come in different varieties. The primary sources are integrated assessment BCA models. An examination of the literature (Nordhaus, 2014) finds that three aggregate climate change BCA-oriented models mentioned are the basis of virtually all estimates. One is the DICE/RICE family of models developed over a number of years by William Nordhaus of Yale University and his colleagues. A second is the PAGE model, originating with the work of Chris Hope of Cambridge University, UK, which has several vintages. The third is the FUND model, developed by Richard Tol of Sussex University, UK, with David Anthoff of the University of California at Berkeley, a co-author of the current version.

Another set of estimates come from modifications of one of these three models. Some studies take one of the models and change parameters or do sensitivity analyses with them. For example, the *Stern Review* (Nordhaus, 2007; Stern, 2007, 2008, 2013) based its quantitative modeling and estimates of optimal carbon emissions policies, including BCA results with enlightening sensitivities, on a version of the PAGE model that primarily varied the discount rate. Others are compilations or reviews of studies, which include primary models, variations of models, and reviews of models. There are a small number of independent analyses of the BCA applied to climate change and computations of the SCC. In 2013, Zhimin and Nordhaus (2013) published a systematic evaluation of estimates of SCC from 1980 to 2012. They found 27 studies that actually produced independent estimates. Of these, 19 were from different vintages of the three standard models listed above. Most of the eight other estimates were reduced-form models that took one of the three standard models and either simplified it or added specific features. The conclusion from this short summary is that most of the computations of the optimal carbon emissions policy and estimates of the SCC come from one of the three IAMs that have been developed and revised over a period of at least a decade.

In light of the central importance of the three most widely used climate change policy BCA models, they will be briefly described here to set the stage for a comparison of BCA and SCC estimates produced by the architects and critics of these models later in this paper. At the highest level, these three models are dynamic implementations of the conceptual diagram shown in Figure 1. Instead of working to equalize static costs and benefits of climate change, or equivalently minimizing the sum of climate damages and carbon mitigation costs at a single point in time, they work to equilibrate the discounted present values of carbon emissions mitigation and climate damage costs. Since the carbon emissions caused by an incremental ton emitted in any year persist in the atmosphere for many years (CO_2 molecules have a mean residence time in the atmosphere of about a hundred years, with a wide temporal distribution depending on where and how they are dispersed), the damages caused by that ton of emissions must be cumulated over a long period of time. This is generally done by discounting future climate damages (and mitigation costs), making the discount rate used for this purpose an extremely important parameter in these calculations as will be evident in the discussion that follows.

The DICE (Dynamic Intertemporal Carbon Emissions) model views climate change within the framework of economic growth theory. In a standard neoclassical optimal growth model known as the Ramsey model, society invests in capital goods, thereby reducing consumption today in order to increase consumption in the future (Koopmans, 1965; Ramsey, 1928). The DICE model modifies the Ramsey model to include climate investments, which are analogous to capital investments in the standard Ramsey growth model. The model contains simplified representations of all elements of the causal sequence from GHG emissions to GHG concentrations, through climate change to climate change damages. The geophysical equations are simplified versions derived from large models or model experiments. The first version of the global model was presented in Nordhaus (1992, 1994a; Nordhaus & Boyer, 2000). The first regional model was introduced in Nordhaus and Yang (1996), with the most recent updated version in Nordhaus (2010). A more complete description of these models is contained in Nordhaus (2008, 2010) and Nordhaus and Sztorc (2013).

FUND and PAGE share the same basic integrated structure of the DICE/RICE models in linking output, emissions, concentrations, temperature, and damages, but differ in other important respects. The FUND model (Climate Framework for Uncertainty, Negotiation and Distribution; Anthoff & Tol, 2010, 2013) was developed primarily to assess the impacts of policies in an integrated framework. It is a recursive model that takes major economic variables as exogenous. Climate change impacts are monetized and include agriculture, forestry, sea level rise, health impacts, energy, consumption, water resources, unmanaged ecosystems, and storm impacts. Each impact sector has a different functional form and is calculated separately for 16 geographic regions. The model runs from 1950 to 3000 in time steps of one year. The source code, data, and a technical description of the model are public, and the model has been used by other modeling teams (Anthoff & Tol, 2013).

The PAGE model (Policy Analysis of the Greenhouse Effect; Hope, 2006, 2011) projects future increases in global mean temperature, the economic costs of damages caused by climate change, and the economic costs of mitigation policies. It has a relatively simple economic structure, taking output and emissions as exogenous with many periods, countries, and sectors. The major innovations are detailed inventories of GHGs; reduced-form treatment of the atmospheric chemistry of gases; simplified global and regional climate models, including of aerosols; and detailed regional impacts. Moreover, the PAGE model makes uncertainty a central focus, with 31 uncertain variables (such as climate sensitivity, carbon-cycle dynamics, impacts, and discontinuous impacts). The damage structure is highly developed, with catastrophic thresholds and sharp discontinuities introduced probabilistically. The model is proprietary, but is available to others with permission and credits (Nordhaus, 2014).

In sum, the three standard aggregate BCA models used for computing optimal climate change policies and calculating SCCs are very different in their structure, assumptions, treatment of uncertainty, and economic modeling. These differences mean that there is no easy way to judge the relative reliability of the models or their results. The next section of this paper gives an overview of the optimal climate policy results, while Section 5 summarizes recent SCC projections.

4 Recent applications of BCA in informing optimal climate change policies

At the broadest level, aggregate BCA-oriented climate policy models provide guidance as to the optimal level of carbon emissions and carbon pricing at a national or international level. For example, policymakers can use estimates to determine the optimal BCA-oriented carbon taxes or the target rate of emissions reductions under a cap on carbon emissions.

Table 1 shows recent projections of the optimal cost of carbon for an incremental ton of carbon emissions in 2015 from the three aggregate cost-benefit models: DICE, FUND, and PAGE. The mean estimates range from $10 per ton for the FUND model to $18 per ton for the DICE model to $71 per ton for the PAGE model. These differences between models result primarily from differences in the climate damages functions included in the models, with FUND including the lowest cost projections and PAGE – especially with its focus on extreme events – the highest cost damage function. In addition, FUND and PAGE embed their models in a Monte Carlo simulation that draws from probability distributions over key model inputs and parameters and then uses the model to produce probability distributions over model outputs.

As shown in Table 1, for FUND a $2 value ($10 with PAGE) on the optimal carbon price is larger or equal to 10% of the simulation outputs and a $35 ($117 with PAGE) value >90% of them.

A key driver of the differences between models is their incorporation of the potential for catastrophic outcomes. FUND does not account for that possibility, while DICE and PAGE do. Moreover, the potential for a catastrophic outcome (which, in DICE, is based on a survey) accounts for roughly 70% of global damages at 2.5°C in both DICE and PAGE (Wolverton et al., 2012). Another key driver of the lower damage projections from FUND are assumptions made about the ability of those who are significantly impacted by climate change (e.g., farmers) to adapt to those changes (e.g., farmers can change crops, adjust planting schedules, incorporate irrigation, or apply fertilizer). PAGE also reports that the standard deviation of the optimal SCC is $266 per ton if all 100,000 runs in their MC simulation are included, but only $56 per ton if the highest 1% of the optimal SCC results are eliminated – highlighting the significance of the “thick tail” in their probability

Table 1 Recent social cost of carbon projection for “Optimal” BCA calculations from big three models.

Model	Optimal social cost of carbon		
	10th Percentile value	Mean value	90th Percentile value
DICE	–	$18	–
FUND	$2	$10	$35
PAGE	$10	$71	$117

Source: Nordhaus (2014).

The social cost of carbon for the marginal ton emitted in 2015 is measured in 2005 international US dollars. Therefore, for DICE $18.6 is the cost of emissions in 2015 in terms of consumption in 2015.

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distribution over damage outcomes. See further discussion of the challenges and importance of dealing with the possibility of thick tails in probability distributions over climate damages below.

Thus, model choice can easily lead to large range in the projections of the optimal carbon tax, and plausible ranges of key input assumptions (many discussed in more detail below) can lead to a similarly large spread in the range of projections from a single model. Combining model structure and model input uncertainties can lead to an order of magnitude or two in the projected optimal carbon tax. Beyond these highly uncertain numbers, however, the application of BCA models to climate change policy has provided numerous insights into many important dimensions of climate policy. BCA models have helped identify many of the most important drivers of the results produced. This has made it possible to start characterizing the level of understanding of the drivers and uncertainty about them, which has improved the ability to quantify uncertainties about model outputs of interest. The BCA models have also improved policy makers' understanding of the importance of cost effectiveness in policy development and implementation, the value of market instruments as compared with command and control regulations, the value of information about new technologies and improved science, the importance of broad participation, the potential volatility of carbon prices in policies that cap carbon emissions, and the costs of alternative approaches to reducing emissions. Perhaps the most important contribution of these models is the ability of systematic modeling to highlight the critical issues (such as discounting, risk, and damages) that arise in making the projections and to bring new scientific findings into account in a timely and orderly fashion.

The demand for optimal carbon policy emissions and price numbers on the country, regional, and international scene is strong and growing. In making decisions about climate change mitigation at this level over time, decision makers want to know how to trade off resource commitments (whether from the federal budget or the influence of their policies on the private sector) devoted to climate change against those devoted to other pressing societal priorities. On the other hand, specific numbers are hard to defend. At the very least, these calculations need to be more transparent and a full set of plausible sensitivity analyses across modeling platforms and model input and parameter assumptions needs to be considered, as is now starting to happen.

5 Recent projections of the social cost of carbon

A second application of the aggregate climate change policy-oriented BCA models is for rulemaking where countries do not have comprehensive policies covering all

GHGs. In this context, regulators might use the SCC in a calculation of the incremental social costs and benefits of policies involving energy or climate-affecting decisions. US executive orders issued since EO12291 (Reagan, 1981) have called for major regulations to be accompanied by a "regulatory impact analysis," or RIA.[3] While it is not generally necessary that regulations pass a benefit-cost test, regulators have paid close attention to the analyses. Prior to 2008, the valuations of carbon emissions were not included in monetary estimates of costs and benefits. As a result of a 2007 Supreme Court decision, the U.S. EPA was required to regulate CO_2 and other GHG emissions as "air pollutants" under the Clean Air Act.

A particularly influential and important set of estimates of the SCC was provided by the Interagency Working Group on Social Cost of Carbon, hereafter Interagency Working Group or IWG (Greenstone, Kopits, & Wolverton, 2011, 2013; Interagency Working Group, 2010). These estimates were updated in Interagency Working Group (2013). The original analysis was developed by technical experts from numerous agencies in the U.S. federal government who "met on a regular basis to consider public comments, explore the technical literature in relevant fields, and discuss key model inputs and assumptions. The main objective of this process was to develop a range of SCC values using a defensible set of input assumptions grounded in the existing scientific and economic literatures" (Interagency Working Group, 2010, p. 1). The 2013 estimates update the models but use the same methodology as the 2010 estimates. The analysis has been used for rule-making by the U.S. government. See Johnson and Hope (2012), Tol (2008, 2009), and Nordhaus (2013) for more on the projections of the social cost of carbon.

Table 2 shows the IWG estimates for the SCC. All figures in Table 2 are the global SCC for 2015 in 2005 US dollars. Panels A and B show the results of the IWG calculations (from 2010 and 2013, respectively). These use the IWG estimates and discounting methodology. The 2013 estimates are revised upward substantially for the FUND and PAGE models, reflecting the incorporation of new scientific information into those models. For the preferred 3% constant discount rate, the SCC for 2015 is revised upward from \$22.4 to \$35.8 per ton of CO_2.

As well-summarized in a recent report from the Electric Power Research Institute (Rose et al., 2014), a wide range of SCC estimates characterizes the IWG SCC reports, with results varying substantially across models and input assumptions. Figure 2, which is taken from that report, shows that – in a pattern of results similar

3 The source of regulatory analyses dates to the 1970s. The current relevant rule is Executive Order 12,866, which states that agencies must, to the extent allowed by statute, "assess both the costs and the benefits of the intended regulation and … propose or adopt a regulation only upon a reasoned determination that the benefits of the intended regulation justify its costs" (OMB, 2003).

Table 2 Estimates of the social cost of carbon for 2010 from U.S. Interagency Working Group and comparison with alternative model estimates.

Model and scenario	Constant discount rate on goods			
	5%	4%	3%	2.5%
A. Estimates of 2015 SCC from US Working Group, 2010				
DICE-2007	10.2	17.4	29.6	43.5
PAGE	7.4	15.3	31.3	50.9
FUND	−1.5	2.5	6.3	14.0
Average	5.4	11.7	22.4	36.2
B. Estimates of 2015 SCC from US Working Group, 2013				
DICE-2010	11.0	18.6	31.4	48.1
PAGE	20.2	34.4	58.6	85.3
FUND	2.7	6.9	17.3	30.4
Average	11.3	20.0	35.8	54.6

Source: Nordhaus (2014).

Panel A shows estimates of the 2010 SCC from the Interagency Working Group. The three models have harmonized outputs, emissions, populations, and temperature sensitivity coefficient (TSC) distribution and use constant discount rates.

Panel B shows the revised IWG estimates from the 2013 report.

The 2015 estimates are interpolated from the given figures in the 2010 and 2013 reports.

to the optimal carbon tax projections discussed previously – PAGE produces the highest average SCC estimates and more uncertainty than the other models, while FUND produces the lowest average SCC estimates. For all models, averages and uncertainty decline with higher discount rates due to greater discounting of the models' estimates of positive annual damages over the next three centuries. SCC results also vary by socioeconomic and emissions assumptions, with variation differing across models. As can be seen in this figure, there is roughly an order of magnitude range of SCC projections from the running of the three models with similar input assumptions, and about an order of magnitude range in SCC projections across plausible ranges of input assumptions. The critiques and challenges discussed in the next section provide additional sources of uncertainty to keep in mind when interpreting and assessing these SCC projections.

6 Critiques and major open issues for optimal climate policy and SCC projections

The benefit-cost models that have been used to help formulate optimal climate change policies and compute the SCC have been widely and constructively criti-

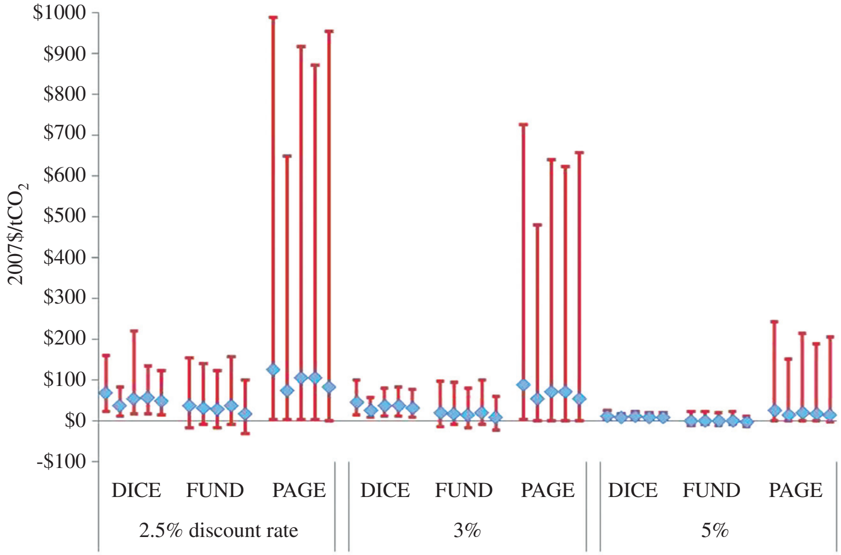

Figure 2 USG IWG 2020 SCC average and 1st–99th percentile values by discount rate, model, and reference socioeconomic/emissions assumption.
Source: Rose et al. (2014).
The figure shows SCC results from USG (2013), with averages in blue and 1st–99th percentiles in red. Each percentile range reflects USG standardized and model specific parametric uncertainties. Values adapted from USG (2013). Each point on the bottom three lines is an average SCC value for a specific year and given discount rate, averaging results across models, alternative socioeconomic scenarios, a distribution of potential climate sensitivities, and random model specific parameters; "3% (95th percentile)" is the 95th percentile from the distribution of the 150,000 SCC estimates discounted at 3%.

cized on several grounds. Most of these criticisms fall into five general categories. First are from those (perhaps appropriately referred to as extremes-oriented critics) who hold that the models exclude major dangerous or potentially catastrophic impacts of climate change. In these critiques, the optimal carbon policy solutions and SCC projections are thought to be underestimated, possibly dramatically so. Second are from those who are critical of the way in which regional costs and benefits are calculated, compared, and interpreted because they may distort or obscure fundamental equity tradeoffs across space and time (here referred to as environmental justice critics). Third are from those who believe that climate change is such a long-run phenomenon that consideration of inter-generational equity is crucially important and not well handled in the BCA models or IAMs in general (the generational justice advocates). Fourth, there are those who believe that the baseline elements of the models are very difficult to construct because of the challenge of projecting socioeconomic conditions and technological changes over long periods of time, such that even if the aggregate microeconomic cost and benefits of climate change policies can be projected reasonably well, the actual implementation of climate policies will include other fiscal and income distribution policies that will be more important than the climate account numbers on their own. This may be called the "devil is in the details" critique. A final category of concerns about the models (partly confounded with categories one through four) holds that the models and estimates are dependent on so many highly uncertain parameters and exogenous inputs that much more work needs to be done to characterize and communicate the implications of these uncertainties in order to be useful to decision makers. This could be termed the "incomplete uncertainty characterization" critique. Each of these concerns is addressed here in turn.

6.1 Tipping points, fat tails, and potential catastrophes

There have been several critiques of the calculations in the DICE model (as well as FUND and PAGE) arguing that the models omit significant earth system responses, especially when they may present themselves in a very non-linear and/or abrupt manner. For a particularly sharp assessment along these lines see Ackerman and Stanton (2010, 2012).

One of the most troubling concerns about climate change is the potential for abrupt, irreversible, or catastrophic climate change or climate change impacts to occur (see IPCC, 2012, 2013, 2014a; Lenton et al., 2008; National Research Council, 2002). Estimates for the economic costs of such scenarios are included in the PAGE model directly and captured conceptually in the damage estimates in the DICE-2013R model. However, the model does not deal explicitly with tipping elements, primarily because these have not been reliably determined. It must be emphasized that, other than expert opinion, there is virtually no basis for determining the size, timing, or probability of such events or the economic damages that would ensue.

Work on using expert elicitations to characterize the form and characterize the uncertainty of these crucially important phenomena is barely in its infancy at present. This is a vital avenue for future research, because the fundamental scientific uncertainties in this area seem unlikely to be resolved any time soon. Making this investment would bring with it an obligation to develop methods designed to use this type of information in formulating climate policy, which is also an enterprise that is just starting to take serious form in the analytical community – and which so far has dominantly used hypothesized probability distributions and utility functions applied to extreme economic outcomes with varying degrees of reasonableness. Early expert probability elicitations in the climate arena have been very useful but quite crude (Morgan & Keith, 1995; Nordhaus, 1994b), and have ignored the typical decision theory challenges of assessing whether experts are "calibrated" (roughly defined as internally consistent) and/or not "independent," which can easily occur if many of a group of experts have identical training, approaches to the analysis-modeling, and maybe even the same mentors. This latter issue can be addressed through consideration of ways of "combining expert opinions" (Browne, 1996; Clemen, 1984, 1985, 1986, 1989; Clemen & Winkler, 1985, 1986, 1987, 1992, 1993; Jouini, 1992; Jouini & Clemen, 1994; Morris, 1971, 1974, 1977, 1983, 1986), which is difficult to accomplish, but almost assuredly ultimately necessary.

Another difficulty that has not been fully addressed in the literature is the potential for highly skewed distributions of uncertain variables and potentially unbounded values of the SCC. This issue was raised in Weitzman (2009) and has been discussed extensively in the literature (cf., Weitzman, 2013). A simplified way to state Weitzman's argument is that the combination of fat tails and strong risk aversion may lead to large losses in expected welfare. As a result, the true BCA results may be unbounded or extremely large.

Table 3 (from Nordhaus, 2013) shows the SCC with and without abatement policies for different thresholds. An important feature of catastrophic damages is that the "catastrophic" SCC depends critically on whether adequate policies are taken. For the threshold of 2°C and no climate-change policies, the SCC is $1046 per ton CO_2. However, when optimal policies are taken immediately, the SCC is only $54 per ton of CO_2. This result – that fat tails or catastrophic damages generally

Table 3 Social cost of carbon with catastrophic threshold, with and without climate policy.

Threshold temperature, T*	Social cost of carbon (2015 in 2005$)	
	With optimal policy	With no policies for 100 years
1.5°C	125	1495
2°C	54	1046
3°C	24	197
4°C	19	33

Source: Nordhaus (2014).

The cases without policy assume no abatement for a century. The cases with policy assume immediate optimal abatement. The catastrophic damage function assumes that the damage-output ratio is $0.01[T(t)/T^*]^8$, where T* is the catastrophic threshold.

have extreme results on the SCC only when good policies are not taken – should be taken into account by everyone involved in climate policy development.

An important limitation of the simple climate policy benefit-cost models is that the whole climate system is represented with a very small number of equations drawn from highly reduced-form climate models (e.g., the MAGICC model) (Meinshausen, Raper, & Wigley, 2012), which were initially designed for interpolating between steady state climate regimes projected by very complex full-scale climate models. These models generally include energy balance equations only, and not the conservation of momentum and mass balance equations included in a full-scale climate or earth system model (Washington & Parkinson, 2005). In actual tests (Schaeffer et al., 2013; van Vuuren et al., 2011) these models match the behavior of full-scale climate models for scenarios in which climate conditions change gradually, but do not match very closely for scenarios in which abrupt changes occur. In other words, the two types of models produce similar results in scenarios that move gradually from one steady state to another but are not very good in cases where the dynamics of change are important. It is not clear that full-scale climate models include these dynamics very satisfactorily, but the simplified climate models do not even match what is represented in the full-scale climate models.

6.2 Treatment of geographical equity: regional, national, international

BCAs applied to climate change policy have generally been heavily efficiency focused, with equity considerations rarely addressed directly except occasionally an ex-post reporting of economic impacts across various socioeconomic strata within and between nations. This is unfortunate, because equity and fairness issues often completely dominate the political debate on what to do about climate change. Moreover, this is not something that can easily be fixed after running a model with an efficiency-based optimizing architecture because of the many equity trade-offs and approximations that are typically made in constructing those models in the first place.

For one simple example, consider the plight of the approximately two billion people who live in areas without functioning goods and financial markets. Since they have no markets, they have no (measured) income and make no (measured) expenditures. So if climate changes, they absorb no (measured) impacts and would not benefit from any reductions in those impacts resulting from any policy designed to reduce carbon emissions. If an optimal carbon policy/SCC is computed for a market or country and the desire is to include global costs and benefits in those calculations, the impacts on the poorest people on earth are not included. In fact, the global environmental justice movement includes efforts to improve "energy access" as a major objective, so these initiatives may be working to improve welfare in a way that in itself makes (measured) climate damages larger. See Adler (2012) for more on this type of critique of BCA, but also a well-developed argument for a much more nuanced use of Social Welfare Functions (SWFs) as a viable and practical alternative. As he observes in the introduction to the book cited above: "While BCA is defensible as a rough proxy for overall wellbeing, it is insensitive to the distribution of wellbeing. By contrast, the SWF approach can incorporate distributive considerations into policy analysis in a systematic way." The book also includes some simple SWFs that can be used to reflect equity considerations in a simple and transparent way (Adler, 2012, Chapter 5).

This critique may be a bit extreme and unfair to some global-scale climate policy analyses, as they do try to value "non-market" impacts in some way. In such studies, however, these calculations are quite crude and even if physically and monetarily sensible still need to be aggregated with cost and benefits for other people living under completely different circumstances. This task has historically vexed economists of all stripes (e.g., Arrow, Sen, Dasgupta, & Scrinivasan) and is sometimes disregarded by climate policy analysts as not being important because all nations transition to modern market forms of organizations. But will that actually happen everywhere, and if so, when? The answer to that question has sometimes been "by the time significant climate change impacts emerge," but to many that time has already passed (IPCC, 2014a).

Another key challenge in the BCA/SCC work on climate is aggregating across countries: whose damages should be considered and how should they be weighted in computing an aggregate metric? Some daunting analytic issues arise here, as well as some deep philosophical issues. For example, should market exchange rates or purchasing power parity weights be used to value economic damages in developing countries relative to economic damages in developed ones? This by itself can lead to a factor of two or more difference in Chinese impacts valuation vis-à-vis those in the Organisation for Economic Co-operation and Development (OECD). But the difficulty does not stop with dollar equivalent issues: weighting losses in wealthy versus poor countries is not straightforward (Adler, 2012), and it is not lost on poor countries that weighing their impacts less because they produce less marketed economic output may be patently unfair to their interest in global climate policy.

Another important, but contentious, issue is whose GHG mitigation benefits to include in the optimal carbon policy or SCC estimates. In US regulatory analysis, only costs and benefits of policies imposed on US citizens are typically included (see Gayer & Viscusi, 2014). In international negotiations, however, not including the full global impacts in these calculations is typically viewed as unfair as it leads to damages being imposed on populations around the world by US firms and citizens with no compensation. Thus, applying this practice to GHG emissions would directly violate a fundamental international negotiating principle called the "polluter pays" principle (Morin & Orsini, 2015). Although the "polluter pays" principle has no legal standing in the US, it became law in the European Union in April of 2004 (Morin & Orsini, 2015).

A final practical difficulty with global BCA is that, even if all the site-specific physical climate change impacts can be projected and valued and aggregated with impacts on other people in other sectors and other regions at a specific point in time, all the aggregations and approximations would probably need revision over time. This could arguably be done fairly well for small fluctuations, but could be problematic for the types of large systematic variations that are the biggest concern as the climate changes.

6.3 Treatment of intertemporal discounting and intergenerational equity

In one sense, the challenge of accounting for intergenerational equity in climate policy analysis brings with it all the issues just discussed regarding dealing with equity across regions and socioeconomic strata at a specific point in time. In that sense, time is just another distinction among the earth's inhabitants that needs to be dealt with. However, making tradeoffs across this dimension is particularly tricky to address, even beyond discount rate issues. First, if investment (public or private) is to be made on climate mitigation or adaptation, one needs to account for who will receive the proceeds of that investment, and whether that allocation is equitable.

Second, a large number of individuals who will be affected by future changes in climate and climate change policies are not yet born, making a direct elicitation of their preferences infeasible. As partially addressed in the papers contained in Portney and Weyant (1999), there are ways in which these challenges can be addressed (e.g., a "global referendum" on what legacy the current generation of earth's inhabitants wants to leave future generations), but these are hard to implement and almost never done.

In addition to consistency and fairness between countries it is also necessary to weigh costs and benefits over time, ultimately requiring consideration of the preferences of as-yet unborn generations. This obviously cannot be done directly, so people making decisions today on behalf of those not yet alive today need to collectively make ethical choices about what kind of opportunities they want to leave future inhabitants of planet Earth. It is a gross understatement to say that this is a very hard problem.

Central in this debate is the role of discounting. Discounting involves two related and often confused concepts (Nordhaus, 2013). One is the idea of a discount rate on goods, which is a market-based concept that measures a relative price of goods at different points of time. The discount rate is also variously referred to as the real return on capital, the real interest rate, the opportunity cost of capital, and the real return. The real return measures the yield on investments corrected by the change in the overall price level. In principle, this is observable in the marketplace, although the exact numbers differ based on the risk characteristics of the return involved. For example, the real return on 10-year U.S. Treasury securities over the period 1960–2000 averaged 3.0% per year. Similarly, the real pretax return on U.S. corporate capital (a risky investment) over the same four decades has averaged about 6.6% per year. Estimated real returns on human capital range from 6% per year to more than 20% per year depending upon country and time period (Nordhaus, 2013).

The second important discount rate concept involves the relative weights of the economic welfare of different households or generations over time. This is typically called the pure rate of social time preference or generational discount rate (Nordhaus, 2013). It is calculated in percent change in value per unit of time (as with an interest rate), but refers to the discount in future welfare, not in future goods or dollars. A zero generational discount rate means that future generations into the indefinite future are treated symmetrically with present generations; a positive generational discount rate means that the welfare of future generations is reduced or "discounted" compared with that of nearer generations (For examples, see Arrow et al., 1995, 2013; Portney & Weyant, 1999).

While the concept of discounting has very broad philosophical and ethical foundations, most analyses of the discounting issue in the economic and IAM literature use the approach of the Ramsey-Koopmans-Cass model of optimal economic growth (Cass, 1965; Koopmans, 1965; Ramsey, 1928). The economic agents in the economy are generations or cohorts. Similarly, the key parameters are α (the elasticity of utility with respect to a generation's consumption, or consumption elasticity) and r (the generational discount rate). One of the major confusions about discounting is whether the variables apply to the welfare of different generations or to individual preferences (Nordhaus, 2013). The individual rate of time preference, risk preference, and utility functions do not enter directly into the formulation. An individual may have a high rate of time preference, but this has no necessary connection with how different generations should be weighted in making social decisions. Similar cautions apply to the consumption elasticity, which relates to the social valuation of inequality across different generations and not to individual risk preferences.

Optimizing the social welfare function with a constant population, no risk or taxes, and a constant rate of growth of consumption per capita across different generations, g^*, yields the standard equation for the relationship between the equilibrium real return on capital, r^*, and the other parameters: $r^*=\rho+\alpha g^*$. This is usually called the Ramsey equation (Nordhaus, 2013). There are two ways of using the Ramsey equation as a framework for discounting in global warming or other long-run questions. One is the *prescriptive view*, in which analysts argue for particular values of the ethical parameters, r and a, and from this derive the ethically appropriate discount rate on goods. This is the approach taken in Cline (1994) and the Stern Review (2007). The latter argues that it is indefensible to make long-term decisions with a positive generational discount rate: "[Our] argument, and that of many other economists and philosophers who have examined these long-run, ethical issues, is that [a positive generational discount rate] is relevant only to account for the exogenous possibility of extinction." The generational discount rate used in the Stern Review is 0.1% per year, which is justified by estimates of the probability of extinction. The Stern Review further assumes a consumption elasticity of $\alpha=1$ and a long-run growth rate of $g^*=1.3\%$ per year, which leads to a real interest rate (discount rate on goods) of 1.4% per year. A similar approach was endorsed by Cline (1992).

A second approach is the *descriptive approach*, advocated by Lind and Ruskin (1982), Lind (1995), and Nordhaus (1994a). This approach assumes that investments to slow climate change must compete with investments in other areas. The tradeoff for this should therefore reflect the opportunity cost of investment. If the IAMs are interpreted as computing market equilibria by maximizing welfare as discussed above, then the real interest rates in the model (as with other prices and outputs) are calculated to reflect market prices. In this interpretation, there is no ethical presumption that these are the correct prices or interest rates, but they should reflect market realities. It is inefficient, in the descriptive view, to accept investments in climate mitigation with a yield of 1.4% per year if there are available investments in education or capital with yields of 6% per year. In the descriptive view, the relevant equation is still the Ramsey equation, but the primitives are the rate of return (r) and the growth rate (g), and the other two parameters must be calibrated to be consistent with observed market realities. The calibration for DICE-2010 is slightly different from these equilibrium calculations because of population growth and changing consumption growth, but the equilibrium calculations give the flavor of the results. In the baseline empirical model, a generational discount rate of 1.5% per year with a consumption elasticity of 1.5 is adopted. These yield an equilibrium real interest rate of 5% per year with the consumption growth that is projected over the next century by the model.

Most of the debate about discounting has concentrated on the ethical concerns with using a positive generational discount rate. However, the fundamental Ramsey equation includes two observable parameters (r and g) and two unobservable ethical parameters (ρ and α). A low real interest rate in the prescriptive view cannot be justified by a zero generational discount rate alone, but also depends upon the consumption elasticity, the growth rate of consumption, and population growth. Similarly, observations on the real interest and growth rates are insufficient to determine the generational discount rate in the descriptive view. In both approaches, there is one free parameter. This implies that they are observationally equivalent in a steady state (Nordhaus, 2013). The paradox of low discounting can be illustrated with a "wrinkle experiment." Suppose that scientists discover a wrinkle in the climate system that will cause damages equal to 0.1% of net consumption starting in 2200 and continuing at that rate forever after. How large a one-time investment would be justified today to remove the wrinkle that starts only after two centuries? Using a near-zero discount rate of the kind proposed by the Stern Review, the answer is that society should pay a substantial fraction of a year's consumption today to remove the wrinkle (see Nordhaus, 2008).

6.4 Projections of baseline drivers and policy implementation details

As mentioned above, calculations of the BCA-determined optimal level of carbon emissions are dependent on the carbon emissions baseline used. This dependence is even stronger for the SCC estimates, as the baseline used to calculate the incremental damages over time resulting from an additional ton of GHG emissions today is not constrained by the optimality condition (MC=MB) that characterize the BCA projections. The emissions scenario employed for this purpose could be the optimal scenario, an expected scenario, a muddling-through scenario, multiple scenarios, a scenario that maximizes utility for some stakeholders, a scenario that is robust for some stakeholders, or another scenario altogether. The SCC along the "optimal" path of emissions would be the same as the implicit or explicit price on carbon emissions produced by a traditional BCA of optimal climate policies.

Since most national- and global-scale BCAs aggregate costs and benefits over 50–100 years, a major challenge on both the mitigation and impacts/adaptation accounts is projecting the impacts of technological change on costs and benefits over such a long period of time. The challenges of including technological change into the impacts and adaptation calculations is covered in papers by Neumann and Strzepek (2014) and Li et al. (2014). That this degree of uncertainty about mitigation cost projections, especially in the technology dimension, still remains with us today is carefully and systematically documented in the IPCC's Fifth Assessment Report, *Mitigation* (2014b). In addition to the demographic and technological uncertainties, another major explanation for this large uncertainty range in mitigation cost projections is uncertainty about the specific policies that decision makers will implement to achieve their objectives: these can explain up to half of the total range of projections (c.f., Weyant, 2001).

6.5 Dealing with uncertainty and risk

The complexities of the operation of the earth system and of policies designed to cope with human-induced climate change bring with them vast uncertainties regarding key model parameters and important model outcomes. In this paper, many of these key uncertainties have already been identified as challenges to be dealt with, but there may be additional uncertain parameters and relationships that have not yet been fully observed or appreciated. There are a number of ways to deal with all this uncertainty, starting with sensitivity analysis on key parameters and inputs of the type discussed above. In addition, Monte Carlo simulations can be performed in which a large number of draws are made from probability distributions over inputs to the models and run through them, which produces probability distributions over important model outputs – such as changes in temperatures and sea levels – as well as total climate change damage and mitigation costs to be constructed. These are a good start, but two other crucial dimensions of the problem should also be included in any comprehensive attempt to inform decision making about climate policies. First, decisions made today can be revisited and modified at any point in the future as new information on climate change damages and mitigation costs becomes available. Thus, decision making about climate change is one of sequential decision making under uncertainty. One can formulate the climate change policy problem explicitly in this way using a stochastic control or stochastic dynamic programming formulation, but the data input and computational requirements of these methods can be prohibitive and the assumptions made too constraining to be practical. One technical challenge here is to distinguish between how decision makers responsible for many people should factor uncertainty into their thinking and analysis, and how the individual agents represented in the BCA models should take them into account. This difference between public and private perspectives can be very important, which calls into question the use of optimizing models that treat them (implicitly or explicitly) as being identical.

The second crucial additional dimension to be considered is the decision makers' attitudes toward risk, both individually and collectively. Much of the application of modern decision theory targets decisions where the stakes are important, but not important enough to necessitate higher derivatives of utility functions or higher moments of probability distributions. For example, since at least Raiffa's classic book on decision analysis (Raiffa, 1968), practitioners have appreciated the analytical tractability of using exponential utility functions with constant relative risk aversion to represent the preferences of individual decision makers. These assumptions tend to provide good approximations to preferences when the outcomes of decisions are not expected to have a major influence on the individual's overall level of wealth. This constant relative risk aversion assumption means that a decision on climate change, for example, can safely be analyzed without looking at the correlations between the outcomes that could emerge from that decision and all the other decisions one has made for which the payoffs are not yet known with certainty (Pratt, Raiffa, & Schlaifer, 1995). Put differently, if one were to add a constant amount to the utility measure for all alternatives the individual faces, this would not change the utility ranking of the alternatives. This property, called the "delta property" for obvious reasons by the people who first observed it (cf., Howard, 1984), does make the analysis of individual decisions by well-calibrated individual decision makers (which means that they make decisions in an internally consistent manner) much easier, as otherwise all the correlations with other investments would need to be considered simultaneously. In the case of climate change, where group decisions rather than individual ones usually need to be considered, the stakes under certain conditions can be extremely high and highly correlated with other big societal decisions, and our experts in some areas (if there are any) may not be well calibrated. The papers in this issue by Lempert (2014) and Toman (2014) provide guidance on what to do when the simplifying assumptions do not hold.

7 Conclusions and recommendations

This review summarizes the results of current optimal climate change policy BCAs and efforts to compute the social cost of carbon. Given the challenges involved in producing these numbers and the many uncertainties underlying them, it is probably appropriate to think of these numbers as providing a good rough guide to current policy development, but in need of much refinement as time goes on.

Thus, in this way they can be considered a good place to start thinking about climate policy formulation but a poor place to finish in terms of specific long-term policies involving the whole planet.

To some, however, the challenges highlighted in this paper and the complexities and uncertainties inherent in the climate problem and in its possible solutions make the models described above worse than useless. In a recent article, Pindyck (2013)[4] concludes that IAMs "are of little or no value for evaluating alternative climate change policies and estimating the SCC." Although agreeing with many of Pindyck's individual criticism, Nordhaus (2014) reaches a different conclusion regarding the usefulness of the current generation of climate policy BCA models.

Pindyck's criticism of IAMs touches both empirical and conceptual issues. Beginning with the empirical questions, he highlights (1) the social preference function, particularly the discount rate, (2) the damage function, (3) the potential for catastrophic changes, and (4) the temperature sensitivity to greenhouse gas increases.

While Pindyck's observations about the empirical weaknesses of IAMs or calculations of the SCC are worthy of careful study, the conclusion that IAMs are therefore useless fundamentally misconceives the enterprise. IAMs and the SCC are conceptual frameworks for dealing with highly complex, non-linear, dynamic, and uncertain systems. The human mind is incapable of solving all the equations simultaneously, and modeling allows making "If…, then…" analyses of the impacts of different factors. The models have provided important insights into many aspects of climate-change policy.[5]

IAMs have improved our understanding of the importance of cost-effectiveness in designing climate policies, the value of market instruments as compared with command and control regulations, the value of information about new technologies and improved science, the importance of broad participation in mitigating carbon emissions, the potential volatility in carbon prices that can result from systems that cap emissions, and the costs of alternative approaches to reducing emissions. Perhaps its most important contribution is the ability of systematic modeling to highlight the critical issues (such as discounting, risk assessment,

4 Note that Pindyck refers to only the three aggregate BCA models as "integrated assessment" models, thus missing the existence and potential contributions to understanding of the many non-BCA-focused IAMs.

5 Another concern about Pindyck's condemnation of the "integrated assessment" models is his use of results from the models discussed here from the IWG report in his alternative approach to guiding decision making on climate policy.

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and damages) and to bring new scientific findings into the assessments in a timely and orderly fashion.

The demand for the numbers the models produce at the country, regional, and international levels is strong and growing over time. In making decisions about climate change mitigation over time, decision makers want to know how to trade off resource commitments (whether from the federal budget or the influence of their policies on the private sector) devoted to climate change against those devoted to other pressing societal priorities. On the other hand, specific numbers are hard to defend at the current state of the art, and the challenges preventing more precision are so formidable that this situation will not improve any time soon. It is important to realize, though, that the complexities and uncertainties discussed here are inherent in the climate change problem and not manufactured by the models. On the contrary, the models can help us understand implications of alternative assumptions within a broader and more decision-focused whole systems context than otherwise would be possible. At the very least, the model calculations need to be made more transparent and a full set of assumptions needs to be considered – as is now starting to happen.

The emergence of the SCC concept, especially in regulatory proceedings in the US, is a useful, although at times somewhat confusing, enterprise. Motivated in large part by the successful Clean Air Act (Domike & Zacoroli, 2013), it is more narrow than what would be considered in a more traditional benefit-cost analysis, but consistent with standard regulatory impact assessments, especially those produced in the US. The idea is to compute the marginal cost of an additional ton of GHG emissions assuming no future climate policies are implemented. This calculation, which is what the U.S. EPA has used for computing the benefits of regulating much shorter lived "criteria pollutants" such as emissions of sulfur and nitrogen compounds, is thus almost assuredly higher than what would be obtained if climate policies were assumed to be in place, but many would argue that the models used leave out important impacts, which would bias the estimate in the opposite direction (i.e., lead one to conclude they are too low). This leads to a pragmatic regulatory system where the numbers can be adjusted over time as additional information about climate damages is obtained. Interestingly, Nordhaus (2014) also concludes that unless the discount rate is on the very low side of the range of current opinion, the SCC along any reasonable baseline is very close to his own optimal BCA carbon price for the first decade or two. Thus, stakeholders may scream that the numbers are too high or too low, but the system moves us in the right direction while avoiding the gridlock that can emerge if perfect numbers are deemed necessary in order to act.

Another conclusion of this review is that it is hard to apply the conventional BCA approach at the national or international level because of the large number of important stakeholders potentially involved in climate change and climate change policy development. Thus, it is challenging to work with a formulation in which it is assumed that there is a single decision maker whose framing of the problem, probability assessments, and preferences are shared by all the relevant stakeholders. There are two immediate implications of this observation. First, moving to a setting where a more unified decision frame makes sense – such as one where a major coastal zone, growing region, or urban landscape is involved – will make the problem of whose preferences to include and how to include them much easier (although not trivial given the complexity of the climate system). As Li et al. (2014) argue that circumstance has led to some very successful applications of BCA to climate change adaptation decision making at the local to regional level.

The second implication of the limitations on larger scale use of BCA in the climate change policy arena is not only the advisability of continuing to improve the information and analysis behind these more aggregated calculations, but to include a more comprehensive set of sensitivity analyses than has typically been included so far – one that includes alternative treatments of concepts such as equity, attitudes toward risk, and degrees of technological optimism. In this way, numbers and policies that are robust [see Lempert (2014) for a working definition] across all these dimensions can be identified and used to look for stochastically dominant solutions or those that minimize the expected maximum regret of major stakeholders over time.

Especially challenging areas for future work are methods for aggregating – or at least trading off – welfare across vastly different socioeconomic populations in vastly different climatological zones around the world. Another great challenge is determining how other countries will control carbon emissions, including especially whether action in one country (such as the US) will affect the extent to which other nations will control them as well. Further complications arise if it is thought that most countries will eventually decide to control carbon emissions and those that do so first will have a comparative advantage in technology and institutional innovation.

The most important results from the BCA-oriented IAMs at present are as follows: First, the cost of carbon along a BCA-determined optimal emissions trajectory from the DICE model for the current time (2015) is about \$20 per ton of CO_2 in 2005 US international prices, with a range of \$5 to \$50 over a plausible range of uncertainties. Thus, there is a lot of uncertainty in these projections across plausible inputs to one model. Second, in accordance with the intertemporal optimization formulation of DICE, this price is expected to increase at approximately the rate of interest over time, thus rising to about \$150 per ton by 2100. Third, the DICE model results are substantially lower (by about a factor of four) than one of the other two major modeling estimates (the PAGE model) but substantially higher (by about a factor of four) than the other (the FUND model). There is thus a lot of uncertainty in the results produced by the different models, even with similar input assumptions. Fourth, because of the formidable challenges required to aggregate climate damage costs and GHG mitigation costs into a single aggregated value at each point in time, all of these estimates should be viewed as rough preliminary estimates and subject to change and further interpretation (e.g., disaggregated by socioeconomic class). Fifth, work on the individual challenges discussed in this paper and complementary work with the more disaggregated IAMs should be closely monitored and used to refine the numbers currently coming from application of the models.

Finally, given all these uncertainties, decision support tools other than BCA should continue to be developed and the insights from them compared with the BCA results. Society cannot afford to wait for the BCA calculations to be refined before making climate policy decisions today, but – as suggested in several places [e.g., the papers by Lempert (2014) and Toman (2014)] – the analysis of these decisions can be put in a broader context that recognizes that the world is made up of many stakeholders with differing perceptions of the severity of the climate change problem, different stakes in climate outcomes, different preferences, different attitudes toward equity, and different attitudes toward risk. Thus, what is optimal for one group may be suboptimal for another. So unless the world quickly reorganizes into one where global welfare can be optimized and then the distribution of benefits decided upon equitably with no arguments, tradeoffs about both what is efficient and what is fair will need to be made, and these calculations continually subjected to scrutiny and revised or clarified when necessary.

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