

Comments and Discussion

COMMENT BY

MICHAEL GREENSTONE For a century, large temperature increases have been observed and have had a significant impact on the overall climate (IPCC 2021). Greenhouse gas emissions, including largely CO₂, play a deterministic part in rising temperatures. While reduced greenhouse gas emissions can be costly, associated mitigation in rising temperatures can lead to significant reductions in climate damages and net improvements to welfare.

The social cost of carbon (SCC) is a critical input into assessing whether potential climate policies have benefits that exceed their costs. The SCC is the monetized value of all future net damages associated with the release of an additional ton of CO₂. The SCC, therefore, provides a measure of how much society should be willing to pay for a one-ton reduction in CO₂ emissions and allows policymakers to conduct a comparison of a regulation's benefits and costs, both measured in dollars. The SCC became a key part of US climate policy in 2010 (Greenstone, Kopits, and Wolverton 2013; IWG 2013) and has been used extensively in the United States and internationally since then. The basis for the US government's estimate of the SCC is derived from William Nordhaus's seminal research estimating the costs of climate damages and the SCC, as well as the Climate Framework for Uncertainty, Negotiation and Distribution (FUND) and Policy Analysis of the Greenhouse Effect (PAGE) integrated assessment models (Nordhaus 1992; Anthoff and Tol 2014; Hope 2011). To bastardize Winston Churchill's famous quote about democracy—as of 2010, the integrated assessment models were the worst approach to estimating climate damages, except for all the others that have been tried. (Churchill's quote is

“Democracy is the worst form of Government except for all those other forms that have been tried from time to time.”¹

It is my great pleasure to discuss this paper by Rennert and others that suggests a new approach for the US government to update the SCC. The authors’ approach emphasizes socioeconomic uncertainty and its correlation with damages. My goal in this comment is to situate their contribution in the broader context of a holistic approach to updating the US government’s SCC, underline drawbacks of the previous approach, and suggest criteria for the SCC calculation that makes it consistent with advances in the literature, economic theory, and policy objectives.

Overall, my conclusion is that the authors have taken an important step in fixing what ails the SCC, but their improvements need to be digested and examined by the scientific community. Further, to this point, their solutions fail to exploit the advances in damage estimation, which many believe to be the area where the most progress has been made in the last ten to fifteen years. Overall, this is an important contribution but more is needed to return the US government’s SCC to the frontier of scientific understanding about climate damages.

BACKGROUND

The SCC in climate policy. In the United States, most major legislation requires agencies to conduct cost-benefit analyses. For policies aimed to reduce CO₂ emissions, such analysis heavily relies on the SCC. During the Obama administration, the SCC was set at \$51 by the Interagency Working Group (IWG 2013). Setting out to roll back environmental regulations, the Trump administration lowered this number to \$1–\$8 by restricting damages to domestic ones and applying higher discount rates (Plumer 2018). Currently, the Biden administration has returned the SCC to \$51 as an “interim” value and is actively working to update it.

The SCC extensively influences public policy. Through 2017, it had been used in analyzing the value of more than eighty regulations with gross benefits exceeding a trillion dollars (Nordhaus 2017). Moreover, at least eleven state governments, including Illinois and New York, use the SCC to value zero-emissions credits paid to clean energy producers (Rennert and

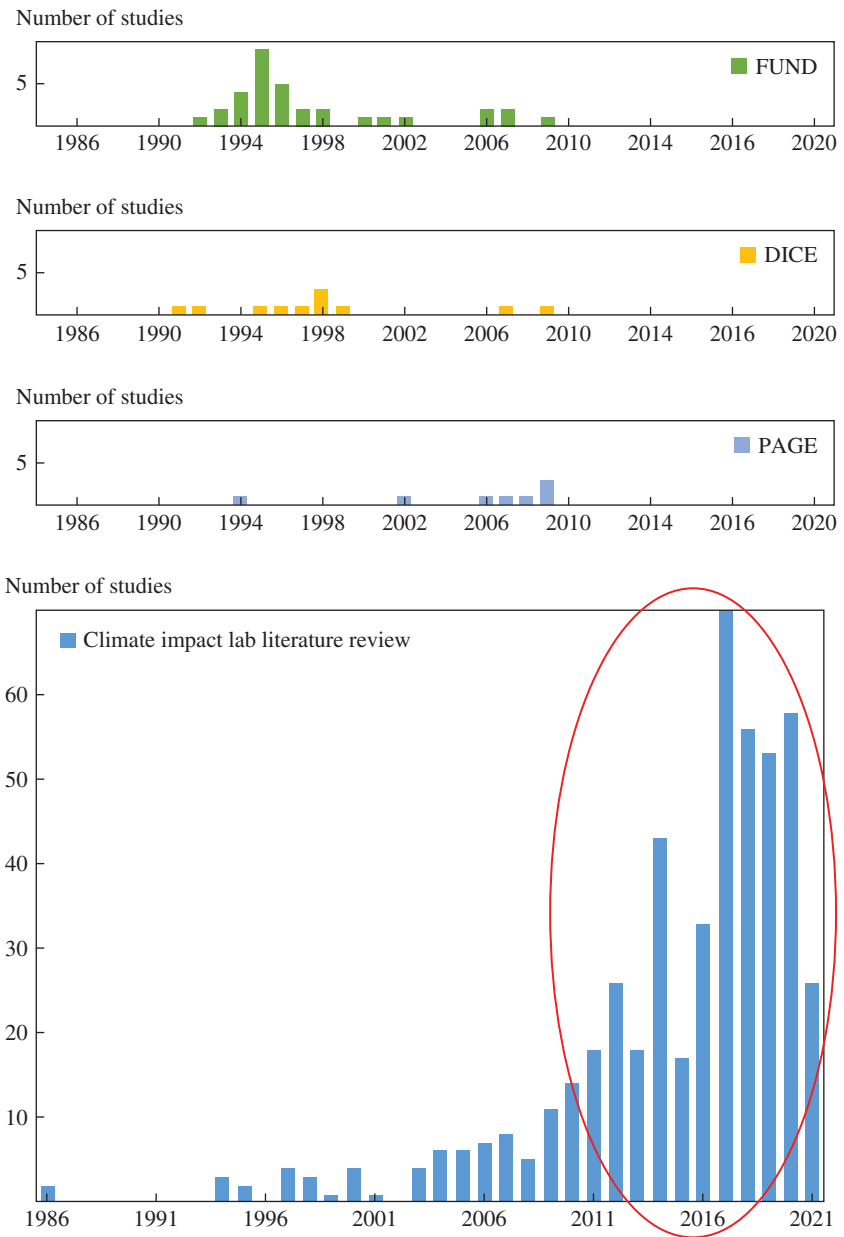
1. International Churchill Society, “Quotes,” <https://winstonchurchill.org/resources/quotes/the-worst-form-of-government/>.

Kingdon 2019). The SCC had also been implemented internationally—countries like Canada, France, Germany, Mexico, Norway, and the United Kingdom all implemented the SCC to some extent (Institute for Policy Integrity 2014). Finally, meaningful US mitigation efforts facilitate international climate negotiations and lead to significant reductions in emissions from other countries (Houser and Larsen 2021).

The US government's SCC is no longer on the frontier of understanding. I co-led the IWG in 2009–2010 along with Cass Sunstein. Nordhaus (1992) was incredibly influential in shaping the economics profession's thinking and giving us a framework to think about the SCC and climate damages. This was achieved through the Dynamic Integrated Climate Change (DICE) model, which is generically referred to as an integrated assessment model along with PAGE and FUND. These three models all date back to the 1990s and formed the basis of the SCC. Even though all three models were somewhat dated by 2010, it was reasonable to conclude that the SCC reflected the frontier of understanding because the economics profession had not done much to update them since their creation.

In the intervening dozen years, these three integrated assessment models, and the resulting SCC, have fallen behind this frontier in several key areas. First, the set of models is highly reliant on expert judgment; there is a limited set of people with knowledge of what goes on inside the models, making replication, validation, and improvements challenging. This kind of small-club approach is not the best way to make scientific progress. Second, when these three models were created, computational resources were relatively limited, which forced researchers to make several simplifying assumptions. For example, the estimated relationship between human well-being and changes in temperature in these models is based on quite limited data and a heavy reliance on functional form assumptions. In this respect, they generally have not taken advantage of the robust and rapidly growing climate damages literature (Deschênes and Greenstone 2011) that has emerged in the past two decades (see figure 1). Similarly, the underlying climate models are dated and fail to capture many climate dynamics. Third, integrated assessment models used deterministic models in most cases, and hence such models incompletely accounted for uncertainty in their estimates. Finally, these models produced highly aggregated estimates of climate impacts. Even the most disaggregated model, FUND, has only sixteen regions, assuming, for instance, that climate change will affect Miami and Minneapolis identically. Recent research has established that the impacts of climate change are highly heterogeneous, and this heterogeneity matters for the SCC calculation. For instance, Hsiang and others

Figure 1. Empirical Publications Informing the Previous Generation of Models



Source: Climate Impact Lab.

Note: Foundational research for models used for the interim SCC dates to the 1990s and hence misses out on the growing body of literature on damage function estimation, for example (Carleton and others 2020).

(2017) demonstrate that the projected end-of-century climate damages are nine times greater in the poorest 5 percent of US counties than in the richest 5 percent. Consistent with these findings, Carleton and others (2020) find significant differences in the projected change in mortality risk both across and within countries.

Given the amount of time that has passed, it is not surprising that the SCC is due for an update. Indeed, the original IWG suggested that the SCC should be updated regularly to reflect advances in the understanding of key components of the calculation (IWG 2010). The need for the update was pointed out again seven years later by the National Academies of Sciences, Engineering, and Medicine (NASEM 2017). Further, Carleton and Greenstone (2021) lay out a detailed plan for updating it. Finally, the SCC's legal durability relies on the estimation that is based on frontier science and economics.

UPDATING THE US GOVERNMENT'S APPROACH TO SCC ESTIMATION NASEM (2017) and Carleton and Greenstone (2021) explain that there are four key modules or ingredients in constructing the SCC. This section describes the authors' efforts in the paper in each of these areas, providing some context for their contributions.

Socioeconomic and emissions pathways. The current (as of March 2022) and past SCC calculations, which were developed using Energy Modeling Forum (EMF 22) scenarios (Clarke and others 2009), do not reflect the last decade of work in probabilistic scenario development. A specific concern has been that the SCC relied on five socioeconomic scenarios, which were equally weighted, and that they did not span the full uncertainty about economic growth, increases in greenhouse gas emissions, and population growth (NASEM 2017). Each of these socioeconomic variables is a key input into the SCC, meaning that it may not reflect the full range of expected variation in these variables.

For all three variables, the authors combined statistical projections of these variables with expert elicitation to generate probabilistic projections through 2300. These probabilistic projections are referred to as the RFF Socioeconomic Projections (RFF-SPs) and allow for substantially more socioeconomic uncertainty than was being captured previously.

In the case of economic growth, the authors rely on Müller, Stock, and Watson's (2019) statistical model of economic growth extended out to 2300. The model is derived from a data set that covers 113 countries from 1900 to 2017. Müller, Stock, and Watson's (2019) projections were coupled with formal expert elicitation about the "frontier of economic growth." The ten experts—Daron Acemoglu, Erik Brynjolfsson, Jean Chateau, Robert

Gordon, Lant Pritchett, Melissa Dell, Mun Ho, Chad Jones, Dominique van der Mensbrugge, and Pietro Peretto—were interviewed separately for roughly two hours each. It is worth noting that the authors “omit some projections in the extreme tails of Müller, Stock, and Watson’s (2019) distribution that are outside the range of historical experience” and outside the range specified by the experts. This choice is motivated by the fact—as the authors notice—that “such low or high sustained growth rates would lead to global GDP/capita either falling by more than 90% between 2021 and 2300 (e.g., 0.99^{279}) or rising by a factor of more than 800,000 (1.05^{279}) implying a global average income of more than \$10 billion per person” (online appendix).

With respect to population, the authors replaced EMF 22 projections with a probabilistic UN statistical model extended to 2300. Like with economic growth, due to expert disagreement concerning the projected lower bound on the total fertility rate, the model was further altered to account for population growth experts’ views. Finally, to incorporate the uncertainty of emissions, greenhouse gas emissions projections from ten experts were paired with economic growth scenarios. In the case of population, nine experts were surveyed, while ten were surveyed for emissions trends.

Climate model. The integrated assessment models used in the SCC calculation represented economists’ interpretation of climate change and did not reflect the last decade of modeling. The primary input into each model is equilibrium climate sensitivity, which represents the total warming realized from doubling CO₂ concentrations in the atmosphere. While equilibrium climate sensitivity has a tremendous impact on the interim SCC calculation, its actual value is not known with scientific precision.

Accounting for the best science available at the time, the IWG combined the equilibrium climate sensitivity estimates across all models by employing a probability distribution reflecting the likelihood of different possible climate outcomes at the end of the century adapted from the Intergovernmental Panel on Climate Change’s fourth assessment report (IPCC 2007). Even so, integrated assessment models fail to precisely measure multiple links in the causal chain from CO₂ emissions to temperature change (Dietz and others 2021; Hänsel and others 2020; Montamat and Stock 2020; NASEM 2017). Particularly, these models significantly understated the speed of warming (Montamat and Stock 2020). For instance, increased carbon concentrations lead to warmer and more acidic oceans, which in turn makes them less effective at removing CO₂ from the atmosphere. The resulting positive feedback loop is missing from both the DICE and PAGE models (Dietz and others 2021). Furthermore, delayed warming

projected in these models likely results in a downward biased estimate of the SCC as warming further into the future is discounted more heavily.

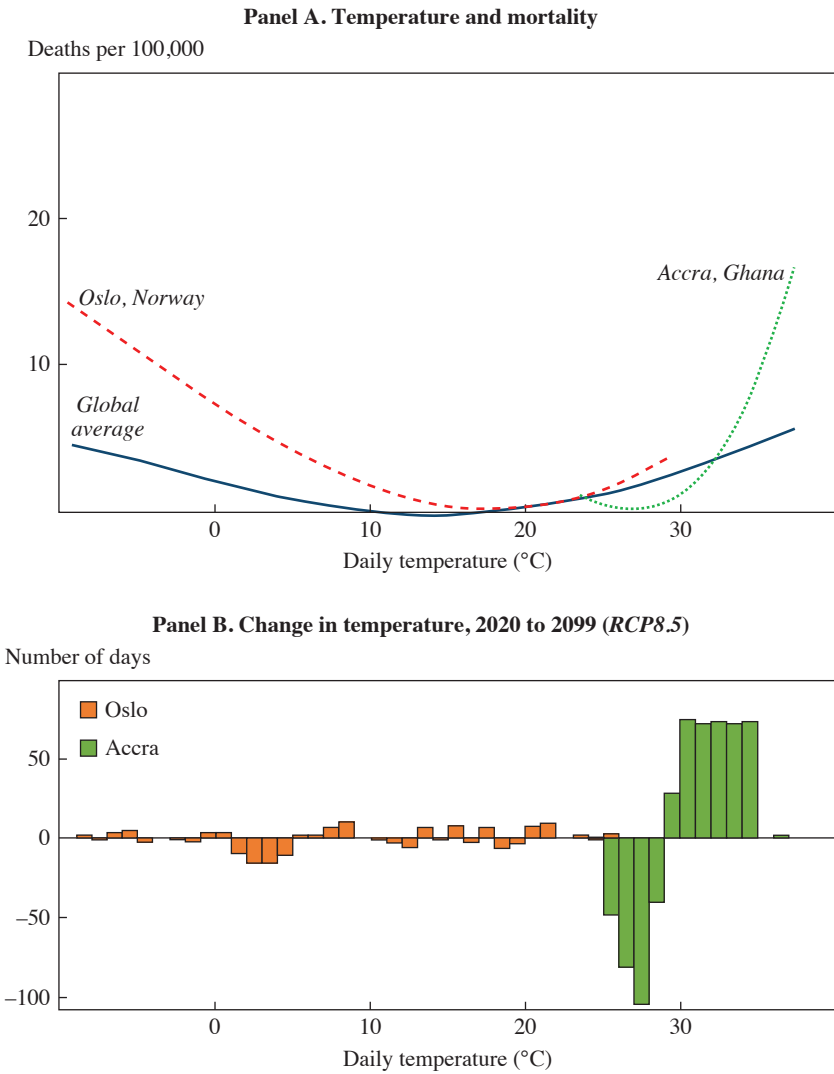
The authors address this problem by incorporating the Finite Amplitude Impulse Response (FaIR) climate model (Millar and others 2017). This choice is consistent with NASEM's key climate module criteria for the SCC calculation (NASEM 2017). The model chosen by the authors generates climate projections consistent with comprehensive, frontier science models, such as the set of models composing the CMIP6 ensemble (Eyring and others 2016), and can be used to quantify uncertainty surrounding the impact of an additional metric ton of CO₂ on global mean surface temperature. Moreover, the FaIR model is computationally feasible, transparently documented, and is commonly used in the SCC updates (Carleton and others 2020; Dietz and others 2021; Hänsel and others 2020; Rode, Baker and others 2021; Rode, Carleton and others 2021). FaIR's main limitation is that it does not capture changes in global mean sea level rise. One promising, but imperfect, way to overcome this limitation is to use semiempirical models that enable the inclusion of damages due to projected sea level changes (Kopp and others 2016).

Damage functions. The next step in calculating the SCC is to make changes in the physical climate (e.g., temperature) and determine their impact on net economic damages. The relationship between economic damages and temperature change is known as a damage function. The previous generation of damage functions, which includes the FUND, DICE, and PAGE models, was developed in the 1990s and hence omits a rapidly growing literature (see figure 1). Indeed, my judgment is that this is the area with the greatest advances in understanding in the last few decades.

There are several shortcomings in the damage function used for the SCC calculation. First, the older models rely heavily on data from wealthy countries with temperate climates. This means that these models had to rely on ad hoc assumptions to create global damage functions because there simply was no support in the available data for the hot, poor, and hot and poor places where much of the world's population lives. Given the tremendous progress in data availability over the last few decades, there is no need to rely on ad hoc assumptions any longer; instead, there are now opportunities to rely on large-scale and globally representative data.

Second, there is substantial heterogeneity around the planet—what happens in Accra when hot temperatures arrive is vastly different from the effect of these temperatures in Oslo, for example (figure 2). This heterogeneity can in part be explained by nonlinear relationships between temperature, mortality, and adaptation. The DICE model currently used by the authors

Figure 2. Climate Change Consequences Are Heterogeneous



Source: Adapted with permission from Carleton and Greenstone (2021), also available at SSRN: <https://ssrn.com/abstract=3764255>.

Note: The figure shows estimated mortality-temperature relationships for age 65 and older (panel A), as well as projected changes in temperature distribution, for Oslo, Norway, and Accra, Ghana (panel B).

as a placeholder ignores distributional impact by dividing the planet into no more than sixteen regions. To capture local nonlinearities, updated damage functions should be more granular, for example, Climate Impact Lab employs distributed computing using 24,378 regions.²

Third, even within a given region, economic and climate uncertainty is substantial in every aspect of damage function estimation: mortality, coastal, labor, agriculture, electricity, and other fuels, as can be seen in figure 3. Thus, updated damage function should account for heterogeneous effects of temperature across sectors, as well as econometric uncertainty.

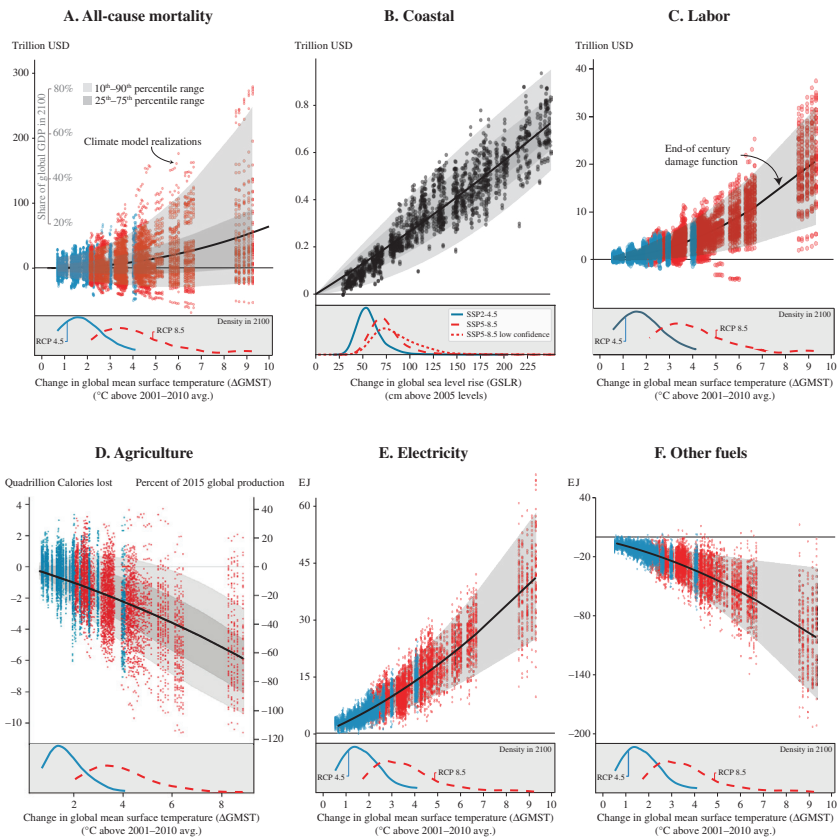
Damage functions are the engine that drives the determination of the SCC, and the authors' reliance on older DICE damage functions means that their approach is behind the frontier. This is the case in three specific ways. First, it is now possible to rely on damage functions that are empirically founded and represent plausibly causal impacts of climate change on socioeconomic outcomes. Second, recent work has demonstrated that data representative of the global population, not just rich or temperate regions, are now available and can be used to estimate damage functions. Finally, damage functions should account for both estimated benefits and costs of future adaptive investments, and this is a hallmark of the Climate Impact Lab's estimation of damage functions represented in figure 3. See Carleton and Greenstone (2021) for a fuller discussion of these issues.

Discounting. CO₂ added to the atmosphere causes a stream of damages and benefits associated with a given trajectory of warming spanned over centuries. The choice of a discount rate is therefore highly consequential for determining the SCC. To date, the SCC relied on a central constant discount rate of 3 percent, following US government's guidance on the conduct of cost-benefit analysis.

This approach fails to account for several features of current economic thinking about discounting that are especially important in the climate context where greenhouse gases can influence the climate for centuries after their release. These features include: (1) the 3 percent figure is intended to reflect the riskless rate but that rate is now likely 2 percent or lower (Bauer and Rudebusch 2020, 2021); (2) uncertainty in the riskless discount rate would lead the discount rate to decline with the time horizon (Weitzman 1998), which constant discount rates do not capture; and (3) payoffs to emissions mitigation could be correlated with future income realizations,

2. As a disclosure, I am a codirector of Climate Impact Lab, which is a team of more than thirty researchers who aim to quantify the real-world costs of climate change. For details, visit <https://impactlab.org/>.

Figure 3. Economic and Climate Uncertainty in Examined Sectors



Sources: Panel A adapted with permission from Carleton and others (2020); panel B adapted with permission from Depsky and others (forthcoming); panel C adapted with permission from Rode, Baker, and others (2021); panel D adapted with permission from Hultgren and others (forthcoming); panels E and F from Rode, Carleton, and others (2021), adapted by permission from Springer Nature.

Note: Black dots represent projected possible damages by the end of the century under the RCP 4.5 scenario (solid line represents the density of change in global mean surface temperature). Similarly, gray dots represent projected possible damages by the end of the century under the RCP 8.5 scenario (dashed line represents the density of change in global mean surface temperature). The change in temperature is in degrees Celsius above 2001–2010 average. The horizontal axis for coastal damages represents change in sea level in centimeters relative to 2005.

in which case there is effectively a “climate beta” and riskless rates are inappropriate (Gollier and Hammitt 2014).

The Ramsey (1928) equation provides a standard way to think about the intertemporal problem of discounting that can accommodate these limitations of constant discounting. It is:

$$r_t = \rho + \eta g_t,$$

where r_t represents the discount rate at time t , ρ is the pure rate of time preference, η is the coefficient of relative risk aversions, and g_t is the per capita growth in consumption at time t . When the growth rate is uncertain, as is the case with the RFF-SP probabilistic growth scenarios, then the average discount rate in year t , r_t , is also uncertain. Following Weitzman (1998), the present value of damages from an additional ton of emissions, MD_t , is then given by:

$$PV(MD_t) = E[e^{-(\rho+\eta g_t)t} MD_t].$$

This means that there is a stochastic discount factor (due to g_t) and that produces a declining certainty-equivalent risk-free rate.

An appealing feature of this approach is that it incorporates the climate beta because when $\eta > 0$, the discount factor is smallest when growth is largest and largest when growth is smallest. This captures the idea that a dollar of damages is more meaningful when we are relatively poor. To apply these insights and connect them to the current riskless rates, the authors follow Newell, Pizer, and Prest (2021) and choose values of (ρ , η) that are disciplined by the current riskless rate. In so doing, they ignore the available evidence of the values of these parameters and instead use observed interest rates to govern the choice of the parameters. This creates an inconsistency between their approach and the large body of literature that has, for example, estimated values for η that range from 1 to 4 but are generally centered around 2 (Gollier and Hammitt 2014). So this aspect of their approach has practical appeal, but it is not built on an especially solid foundation of evidence.

The authors apply this approach and demonstrate its value. An especially important finding is that when uncertainty in economic growth is incorporated (as the RFF-SPs do), then constant discounting produces values of the SCC that appear inappropriately high. This is because it places a relatively greater weight on damages that occur in good times, which does not fit the widespread evidence on the declining marginal utility of consumption. Put another way, it ignores the climate beta and leads to an upward bias in the SCC.

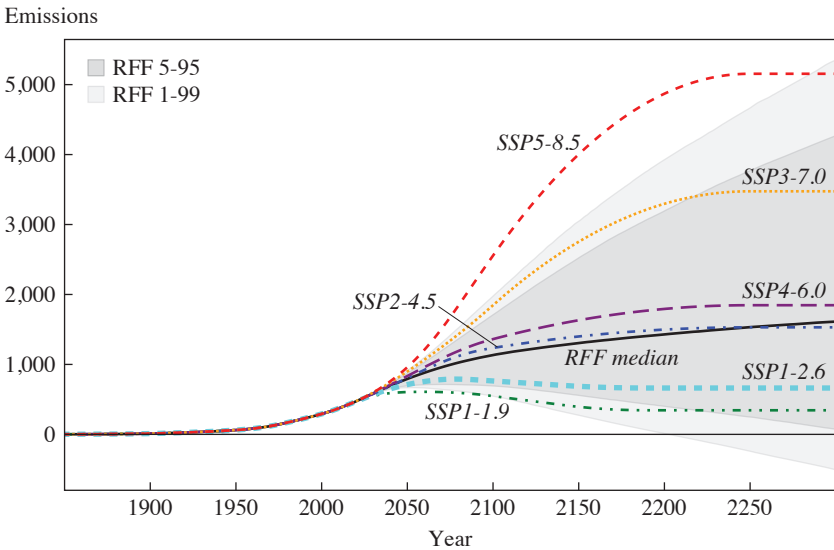
COMMENTS AND CONCLUSIONS The SCC has been overdue for a revision probably for almost a decade but certainly for at least five years since the 2017 NASEM report was issued. In many respects, this paper is a

response to the near-term items that NASEM outlined. It updates the climate model, characterizes the uncertainty in projections about economic growth, population, and emissions, and implements a Ramsey-style approach to discounting that takes advantage of the characterization of uncertainty in the socioeconomics and that climate damages may be correlated with the overall economy. These are important accomplishments.

The straw that stirs this drink and this work's primary contribution are the socioeconomic projections. As a reminder, these boil down to projections of how these variables will evolve for the next three hundred years. This is a terribly difficult task but nevertheless a critical one for getting climate economics and policy right. The choice for developing multi-century estimates of how growth, population, and emissions will evolve essentially boils down to relying on expert judgment in one form or another (e.g., the probabilistic scenarios or the deterministic shared socioeconomic pathways), using statistical models to make projections, or some combination as the authors do in this paper.

I will confess to skepticism about the value of relying on responses from prominent researchers to a two-hour survey that in many instances does not relate to the core of their scientific work. The penalty of being wrong is essentially zero and internal consistency in answers across questions is not assured. Further, I think there is little disciplining the replies besides personal opinions, prejudices, and incomplete recollections of statistical models. And yet, the academic reputation of the respondents provides credibility to the entire exercise—credibility that I think is unwarranted given the challenges I have outlined here. In contrast, good statistical projections are disciplined in transparent ways. We may argue about the statistical approach, but it is at least clear what it was.

In this vein, the following figures plot statistical features of the distribution of future global CO₂ emissions from 10,000 joint population-GDP-emissions trajectories up to 2300 simulated in the paper. These trajectories are derived by sampling from the Resources for the Future distributions of future population, GDP, and emissions, which are constructed using a combination of prior studies and expert elicitation. In particular, emissions are paired one-to-one with each of 10,000 population-GDP trajectories based on a distribution constructed through a survey of experts. I note that separate distributions were specified for direct emissions and CO₂ removal through negative emissions technologies and that the authors generated net emissions by independently sampling from these distributions and summing. These figures are designed to show the basic statistical properties of the authors' projections, and they highlight some surprising features that at least partially arise due to the use of expert elicitation to shape probability distributions.

Figure 4. Cumulative Emissions through 2300, Alternative Scenarios

Source: Author's calculations.

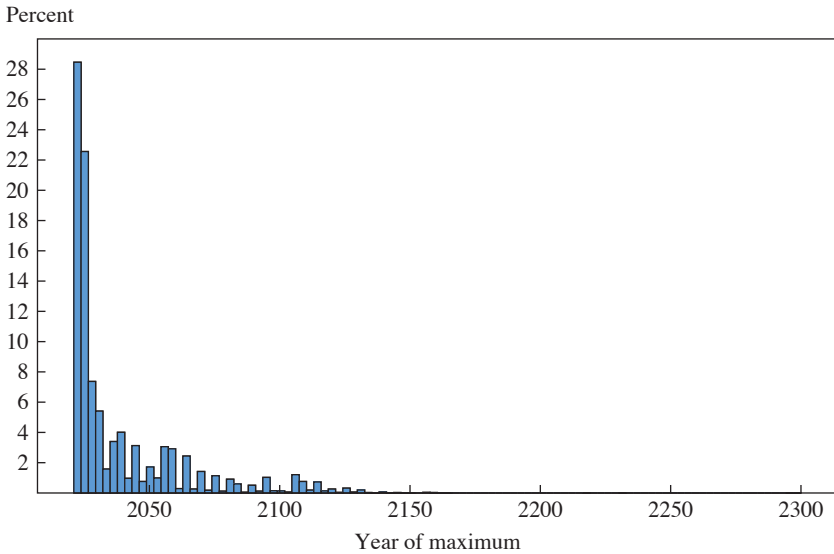
Note: For each year indicated on the horizontal axis, the solid line represents the median value of cumulative emissions across 10,000 simulations given in the paper; dark gray and light gray shaded areas respectively show the 5th–95th and 1st–99th percentile ranges across these simulations. For comparison, dashed lines represent cumulative emissions trajectories under the deterministic scenarios used in the IPCC's Sixth Assessment Report (IPCC 2021).

In figure 4, the solid line is the median across these 10,000 simulations, dark gray shading shows the 5th–95th percentile range, and light gray shading shows the 1st–99th percentile range. For comparison, the plots also show projections from the RCP/SSPs (dashed lines), which are the deterministic scenarios of socioeconomic and emissions used in the IPCC's Sixth Assessment Report (IPCC 2021).³

There are several noteworthy features of this figure. It is certainly interesting, and perhaps reassuring, that the median falls in the middle of the SSP-RCP combinations. However, I was especially struck by some of the patterns in the tail. For example, 4 percent of the projections have cumulative emissions that are negative by 2300. This can only be the case if

3. The five shared socioeconomic pathways (SSPs) (Riahi and others 2017) each contain a narrative of future conditions along with associated projections of future socioeconomic variables. In the IPCC's Sixth Assessment Report (IPCC 2021), these SSPs are paired with emissions pathways—representative concentration pathways (RCPs)—to generate combined socioeconomic and emissions scenarios.

Figure 5. Histogram of Year of Peak Annual Emissions

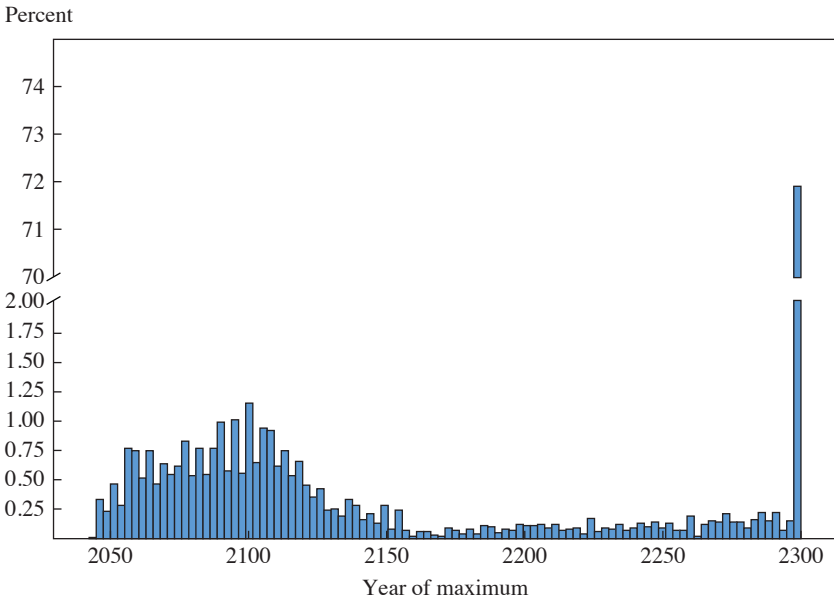


Source: Author’s calculations.

Note: The histogram represents the distribution of the year of peak annual emissions across the 10,000 simulations given in the paper. The height of bars indicates the percent of simulations that reach their peak annual emissions within a given year span.

economically and technically feasible carbon dioxide removal technologies arrive and are used so extensively that more CO₂ is removed from the atmosphere than was ever emitted since 1850. In effect, these projections assume that the optimal global temperature must be colder than preindustrial temperatures and societies continue to fund the operation of carbon dioxide removal machines until this colder optimum is reached. A not quite as astounding, but still surprising, feature of the projections is that 11.4 percent of them have cumulative emissions that are lower than current cumulative emissions. This too can only be explained by a massive use of carbon dioxide removal technologies. As a point of comparison, there are approximately zero technically and economically scalable examples of these technologies currently.

Figures 5 and 6 report histograms of the year that annual CO₂ emissions peak and the year that cumulative emissions peak (i.e., the sum of all future emissions is negative), which is also the year net-zero CO₂ emissions are achieved, respectively. In figure 5, annual global emissions peak by 2035 in 68 percent of the projections, by 2050 in 79 percent, and by 2100 in 95.7 percent. In figure 6, less than 1 percent of the projections have peak

Figure 6. Histogram: Year when Net Zero Emissions Attained, RFF CO₂

Source: Author's calculations.

Note: The histogram represents the distribution of the year of peak cumulative emissions across the 10,000 simulations given in the paper. The height of bars indicates the percent of simulations that reach their peak cumulative emissions within a given year span.

cumulative emissions occur before 2050. By 2100, 13.7 percent of the projections have reached peak cumulative emissions. Without revealing my own expert judgments, I will note that this is at great odds with the Paris Climate Accords, which set a target of achieving net-zero by the middle of the twenty-first century. It is especially striking that 71.8 percent of the projections have not reached peak cumulative emissions by 2300, which would put any of the frequently discussed temperature change targets (e.g., 1.5 or 2.0 degrees Celsius) far out of reach. Personally, I am not quite sure what to make of these findings, but it would be instructive to have them interrogated by the academic community and to be explicit about the roles of the underlying statistical models and the expert judgment in producing them.

Overall, several of the findings from these figures surprised me. Does that mean that they are wrong? No. However, I think there is a strong case for opening these projections up to the research community so that they can be analyzed carefully. It would be especially interesting to compare them to projections that are based entirely on statistical models. Regardless of what

conclusions are reached, the seriousness of the climate problem demands that such peer review be a part of the process of inserting expert elicitation-based projections into policy-relevant models of climate change.

Ultimately, my judgment is that all approaches to developing long-run socioeconomic projections are going to be unsatisfactory, but they are nevertheless necessary for devising a socially desirable policy to confront the climate change problem. The authors have made a careful effort to develop these projections. They should be carefully scrutinized with an eye toward how much weight, if any, to place on expert judgment. Regardless of what is chosen, the paper also deserves credit for demonstrating how to integrate uncertainty about these projections and recognizing that climate damages may be correlated with the overall economy into discounting through Ramsey-style discounting. Both of these contributions align with key near-term recommendations from the 2017 NASEM report.

I will close by noting that NASEM's 2017 medium- or long-run recommendations extended beyond the contributions in this paper and involved the incorporation of empirically founded damage functions into the calculation of the SCC. This NASEM recommendation came from the rapid advances in estimation techniques, data access, and computing that have made it possible to ground damage function estimation in data, rather than assumptions.

It is now possible to achieve these long-run NASEM goals. Trevor Houser, Solomon Hsiang, Robert Kopp, and I cofounded the Climate Impact Lab in 2014 to build climate damage functions empirically and use them to calculate the SCC. The guiding principles were a ruthless belief that the SCC should be based on the best available econometric evidence and that it must account for adaptation costs and benefits, be globally representative, rely on the best available climate models, and value uncertainty and unequal impacts. The result of this work is the development of the Data-driven Spatial Climate Impact Model (DSCIM), which is a modular system for computing the SCC and the global impacts of climate change at the level of 25,000 regions (e.g., a US county) around the world using data. DSCIM is built to be very flexible—for example, it can incorporate characterizations of econometric, climate, and socioeconomic uncertainty (including the authors' projections), value this uncertainty, implement essentially any approach to discounting, including the one the authors outline, and deliver estimates of climate damages where people live rather than at the global or country level.

What is ahead for SCC research? The to-do list is long but it certainly includes building out damage functions for more sectors (e.g., damages from

altered labor productivity, alterations in ecosystem services, migration, etc.), improving understanding of the costs and benefits of adaptation, understanding the interaction of impacts in sectors (e.g., agriculture and migration), and so much more. This is an exciting area of research with enormous implications for policy.

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REFERENCES FOR THE GREENSTONE COMMENT

- Anthoff, David, and Richard S. J. Tol. 2014. “The Income Elasticity of the Impact of Climate Change.” In *Is the Environment a Luxury?*, edited by Silvia Tiezzi and Chiara Martini. London: Routledge.
- Bauer, Michael D., and Glenn D. Rudebusch. 2020. “Interest Rates under Falling Stars.” *American Economic Review* 110, no. 5: 1316–54.
- Bauer, Michael D., and Glenn D. Rudebusch. 2021. “The Rising Cost of Climate Change: Evidence from the Bond Market.” *Review of Economics and Statistics*. https://direct.mit.edu/rest/article-abstract/doi/10.1162/rest_a_01109/107405/The-Rising-Cost-of-Climate-Change-Evidence-from?redirectedFrom=fulltext.
- Carleton, Tamma A., and Michael Greenstone. 2021. “Updating the United States Government’s Social Cost of Carbon.” Working Paper. Social Science Research Network, January 14. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3764255.
- Carleton, Tamma A., Amir Jina, Michael T. Delgado, Michael Greenstone, Trevor Houser, Solomon M. Hsiang, and others. 2020. “Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits.” Working Paper 27599. Cambridge, Mass.: National Bureau of Economic Research. <https://www.nber.org/papers/w27599>.
- Clarke, Leon, Jae Edmonds, Volker Krey, Richard Richels, Steven Rose, and Massimo Tavoni. 2009. “International Climate Policy Architectures: Overview of the EMF 22 International Scenarios.” *Energy Economics* 31, no. 5: S64–81.
- Depsky, Nicholas, Ian Bolliger, Daniel Allen, Jun Ho Choi, Michael Delgado, Michael Greenstone, Ali Hamidi, Trevor Houser, Robert E. Kopp, and Solomon Hsiang. Forthcoming. “An Open-Source Modeling Platform for Assessing Global Impacts of 21st Century Sea Level Rise.” Working Paper.
- Deschênes, Olivier, and Michael Greenstone. 2011. “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US.” *American Economic Journal: Applied Economics* 3, no. 4: 152–85.
- Dietz, Simon, Frederick van der Ploeg, Armon Rezai, and Frank Venmans. 2021. “Are Economists Getting Climate Dynamics Right and Does It Matter?”

- Journal of the Association of Environmental and Resource Economists* 8, no. 5: 895–921.
- Eyring, Veronika, Sandrine Bony, Gerald A. Meehl, Catherine A. Senior, Bjorn Stevens, Ronald J. Stouffer, and Karl E. Taylor. 2016. “Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) Experimental Design and Organization.” *Geoscientific Model Development* 9, no. 5: 1937–58. doi:10.5194/gmd-9-1937-2016.
- Gollier, Christian, and James K. Hammitt. 2014. “The Long-Run Discount Rate Controversy.” *Annual Review of Resource Economics* 6, no. 1: 273–95.
- Greenstone, Michael, Elizabeth Kopits, and Ann Wolverton. 2013. “Developing a Social Cost of Carbon for US Regulatory Analysis: A Methodology and Interpretation.” *Review of Environmental Economics and Policy* 7, no. 1: 23–46.
- Hänsel, Martin C., Moritz A. Drupp, Daniel J. A. Johansson, Frikk Nesje, Christian Azar, Mark C. Freeman, Ben Groom, and Thomas Sterner. 2020. “Climate Economics Support for the UN Climate Targets.” *Nature Climate Change* 10:781–89.
- Hope, Chris. 2011. “The PAGE09 Integrated Assessment Model: A Technical Description.” Working Paper. Cambridge: University of Cambridge Judge Business School. <https://www.jbs.cam.ac.uk/wp-content/uploads/2020/08/wp1104.pdf>.
- Houser, Trevor, and Kate Larsen. 2021. “Calculating the Climate Reciprocity Ratio for the US.” Rhodium Group, January 21. <https://rhg.com/research/climate-reciprocity-ratio/>.
- Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, and others. 2017. “Estimating Economic Damage from Climate Change in the United States.” *Science* 356, no. 6345: 1362–69.
- Hultgren, Andrew, Tamma A. Carleton, Michael T. Delgado, Diana R. Gergel, Michael Greenstone, Trevor Houser, and others. Forthcoming. “Estimating Global Impacts to Agriculture from Climate Change Accounting for Adaptation.” Working Paper.
- Institute for Policy Integrity. 2014. “Social Cost of Carbon Pollution Fact Sheet.” New York: New York University School of Law.
- Interagency Working Group on the Social Cost of Carbon (IWG). 2010. “Social Cost of Carbon for Regulatory Impact Analysis under Executive Order 12866.” Washington: Author. https://www.epa.gov/sites/default/files/2016-12/documents/scc_tsd_2010.pdf.
- Interagency Working Group on the Social Cost of Carbon (IWG). 2013. “Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis under Executive Order 12866.” Washington: Author.
- Intergovernmental Panel on Climate Change (IPCC). 2007. *AR4 Climate Change 2007: Synthesis Report*. <https://www.ipcc.ch/assessment-report/ar4/>.
- Intergovernmental Panel on Climate Change (IPCC). 2021. *Climate Change 2021: The Physical Science Basis*. Cambridge: Cambridge University Press, in press.
- Kopp, Robert E., Andrew C. Kemp, Klaus Bittermann, Benjamin P. Horton, Jeffrey P. Donnelly, W. Roland Gehrels, Carling C. Hay, Jerry X. Mitrovica, Eric D. Morrow, and Stefan Rahmstorf. 2016. “Temperature-Driven Global Sea-Level Variability in the Common Era.” *Proceedings of the National Academy of Sciences* 113, no. 11. <https://doi.org/10.1073/pnas.1517056113>.

- 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." *Atmospheric Chemistry and Physics* 17, no. 11: 7213–28. <https://doi.org/10.5194/acp-17-7213-2017>.
- Montamat, Giselle, and James H. Stock. 2020. "Quasi-Experimental Estimates of the Transient Climate Response using Observational Data." *Climatic Change* 160:361–71.
- Müller, Ulrich K., James H. Stock, and Mark W. Watson. 2019. "An Econometric Model of International Long-Run Growth Dynamics." Working Paper 26593. Cambridge, Mass.: National Bureau of Economic Research. <https://www.nber.org/papers/w26593>.
- National Academies of Sciences, Engineering, and Medicine (NASSEM). 2017. *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide*. Washington: National Academies Press. <https://doi.org/10.17226/24651>.
- Newell, Richard G., William A. Pizer, and Brian C. Prest. 2021. "A Discounting Rule for the Social Cost of Carbon." Working Paper. Washington: Resources for the Future. <https://www.rff.org/publications/working-papers/a-discounting-rule-for-the-social-cost-of-carbon/>.
- Nordhaus, William D. 1992. "The 'DICE' Model: Background and Structure of a Dynamic Integrated Climate-Economy Model of the Economics of Global Warming." Discussion Paper 1009. New Haven, Conn.: Yale University, Cowles Foundation for Research in Economics.
- Nordhaus, William D. 2017. "Revisiting the Social Cost of Carbon." *Proceedings of the National Academy of Sciences* 114, no. 7: 1518–23. <https://doi.org/10.1073/pnas.1609244114>.
- Plumer, Brad. 2018. "Trump Put a Low Cost on Carbon Emissions. Here's Why It Matters." *New York Times*, August 23. <https://www.nytimes.com/2018/08/23/climate/social-cost-carbon.html>.
- Ramsey, F. P. 1928. "A Mathematical Theory of Saving." *Economic Journal* 38, no. 152: 543–59. <https://doi.org/10.2307/2224098>.
- Rennert, Kevin, and Cora Kingdon. 2019. *Social Cost of Carbon 101*. Washington: Resources for the Future.
- Riahi, Keywan, Detlef P. van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C. O'Neill, Shinichiro Fujimori, and others. 2017. "The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview." *Global Environmental Change* 42 (January): 153–68.
- Rode, Ashwin, Rachel Baker, Tamma A. Carleton, Anthony D'Agostino, Michael T. Delgado, Timothy Foreman, and others. 2021. "Labor Disutility in a Warmer World: The Impact of Climate Change on the Global Workforce." Working Paper. Climate Impact Lab.
- Rode, Ashwin, Tamma A. Carleton, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, and others. 2021. "Estimating a Social Cost of Carbon for Global Energy Consumption." *Nature* 598:308–14.
- Weitzman, Martin L. 1998. "Why the Far-Distant Future Should Be Discounted at Its Lowest Possible Rate." *Journal of Environmental Economics and Management* 36, no. 3: 201–8. <https://doi.org/10.1006/jeem.1998.1052>.