KEVIN RENNERT
Resources for the Future

BRIAN C. PREST
Resources for the Future

WILLIAM A. PIZER
Resources for the Future

RICHARD G. NEWELL
Resources for the Future

DAVID ANTHOFF
University of California, Berkeley

CORA KINGDON
University of California, Berkeley

LISA RENNELS
University of California, Berkeley

ROGER COOKE
Resources for the Future

ADRIAN E. RAFTERY
University of Washington

HANA ŠEVČÍKOVÁ
University of Washington

FRANK ERRICKSON
Princeton University

The Social Cost of Carbon: Advances in Long-Term Probabilistic Projections of Population, GDP, Emissions, and Discount Rates

ABSTRACT The social cost of carbon (SCC) is a crucial metric for informing climate policy, most notably for guiding climate regulations issued by the US government. Characterization of uncertainty and transparency of assumptions are critical for supporting such an influential metric. Challenges inherent to SCC estimation push the boundaries of typical analytical techniques and require augmented approaches to assess uncertainty, raising important considerations for discounting. This paper addresses the challenges of projecting very long-term

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economic growth, population, and greenhouse gas emissions, as well as calibration of discounting parameters for consistency with those projections. Our work improves on alternative approaches, such as nonprobabilistic scenarios and constant discounting, that have been used by the government but do not fully characterize the uncertainty distribution of fully probabilistic model input data or corresponding SCC estimate outputs. Incorporating the full range of economic uncertainty in the social cost of carbon underscores the importance of adopting a stochastic discounting approach to account for uncertainty in an integrated manner.

As the primary economic measure of the benefits of mitigating climate change, the social cost of carbon (SCC) has been called "the most important number you've never heard of" (*Economist* 2017; Roston 2021). Put simply, the SCC is an estimate, in dollars, of the economic cost (i.e., damages) resulting from emitting one additional ton of carbon dioxide (CO_2) into the atmosphere. Conversely, it represents the benefit to society of reducing CO_2 emissions by one ton—a number that can then be compared with the mitigation costs of reducing emissions. There are analogous metrics for methane (CH_4) and nitrous oxide (N_2O). The SCC has deep roots in economics. Indeed, many textbooks use carbon emissions and the resulting climate change as the canonical example of an externality that must be addressed through Pigouvian taxation or other means to maximize human welfare. In particular, basic economic theory recommends that an optimal tax on CO_2 emissions (a carbon tax) be set equal to the SCC, for which marginal damages are measured along an optimal emissions trajectory (Pigou 1920; Nordhaus 1982).[1]

But the relevance and application of the SCC go well beyond its role in determining an optimal Pigouvian tax. As political leaders and stakeholders debate both the broad outlines and the fine details of policies to reduce carbon dioxide emissions, the SCC lies in the background as a remarkably important calculation, used by the US federal government for more than a decade for developing vehicle fuel economy standards and power plant emissions rules. Such analyses have been a mainstay of the regulatory rule-making process since Executive Order 12291 was issued more than forty years ago.[2]

1. This result derives from a simple model lacking many real-world complications such as leakage, tax interaction effects, and other market distortions like research and development (R&D) spillovers, but it represents a reasonable approximation.

2. Executive Order 12291 was the original Reagan-era guidance for benefit-cost analysis, later superseded by Executive Order 12866 in 1993.

The SCC has also been the basis for the value of federal tax credits for carbon capture technologies, beginning in 2018 (Rodgers and Dubov 2021), and zero-emissions credits for nuclear power in New York State.[3] The power grid operator for New York is working to include the SCC as a cost adder on top of energy supply bids submitted by power plants, thereby reflecting social costs into market prices and plant dispatch.[4] Many other states have used the SCC as the basis for climate policies and as a benchmark against which proposed carbon prices are compared.[5] Proposed applications include federal procurement decisions and royalties on oil and gas leases on federal land (Prest 2021; Prest and Stock 2021; White House 2021b, sec. 5[b][ii]).[6]

Construction of the SCC and the benefits of reducing emissions are also somewhat distinct from the distribution of benefits. That is, because the consequences of climate change will be different for different communities (country, region, income, social identity), the benefits of mitigating climate change will similarly vary. For example, rising temperatures are likely to create heavier burdens on already hot (and often poor) countries like Bangladesh than on cold (and often rich) countries like Norway. Putting greater weight on dollar-value effects in poorer communities—that is, equity weighting (Errickson and others 2021)—is not the current standard practice, however. Rather, the distribution of effects (when available) is presented alongside the aggregate, unweighted summary. Weighting becomes important as we gain understanding of the distribution of effects.

Estimation of the SCC goes back to William Nordhaus (1982) and has recently seen increasing prominence. In 2018, the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel was awarded to Nordhaus (alongside Paul Romer) for his work incorporating climate

3. State of New York Public Service Commission, Case 15-E-0302 and Case 16-E-0270, "Order Adopting a Clean Energy Standard," https://documents.dps.ny.gov/search/Home/ViewDoc/Find?id=<44C5D5B8-14C3-4F32-8399-F5487D6D8FE8>&ext=pdf, page 131.

4. New York ISO, "Carbon Pricing," https://www.nyiso.com/carbonpricing.

5. Institute for Policy Integrity, The Cost of Carbon Pollution, "States Using the SCC," https://costofcarbon.org/states; Resources for the Future, "Carbon Pricing 101," https://www.rff.org/publications/data-tools/carbon-pricing-bill-tracker/; see also Johnson (2009).

6. Many aspects of climate policy decisions are not necessarily tied to the SCC. Essentially, these include all policy design issues *beyond* measuring benefits and balancing with costs, such as optimal R&D spending amid knowledge spillovers, cost-effective policy design (e.g., uniform standards versus flexible incentive-based policies), interactions between policies (Goulder 1995; Barrage 2020a, 2020b; Borenstein and others 2019), and differences in the distribution of the costs (and in certain cases government revenues) associated with different policy approaches. These are distinct from the question of estimating the marginal benefits of reducing emissions.

change into economic analysis, including the role of the SCC in informing policy.[7]

The SCC is typically estimated using integrated assessment models, such as the Dynamic Integrated Climate Change (DICE) model developed by Nordhaus. Integrated assessment models couple climate and economic models to estimate the economic effect of an incremental pulse of CO_2 emissions (in tons) on climate and economic outcomes. The net present value of changes in economic outcomes, divided by the number of tons in the pulse, delivers the SCC. However, many integrated assessment models used in SCC estimates have not kept up with rapidly evolving climate, economic, and demographic science. Moreover, as Nordhaus (1982) noted, many of the factors underlying the SCC are deeply uncertain—notably, our understanding of Earth's climate, the effect of climate change on economic outcomes, and future socioeconomic conditions that capture the discounted consequences from changes in emissions today. The need for robust policy decisions implies we should update the SCC over time to refine central estimates and the range of uncertainty as our scientific understanding progresses.

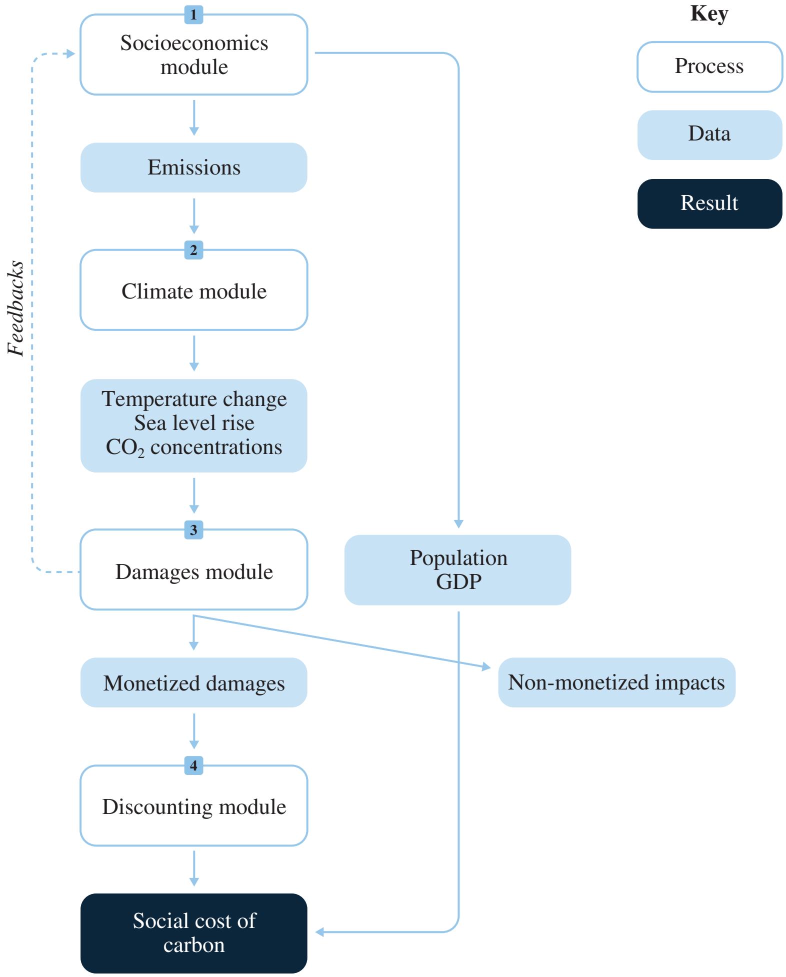
In this paper, we review efforts to update determinants of the SCC to reflect the best available science, based on the recommendations of a 2017 committee report by the National Academies of Sciences, Engineering, and Medicine (NASEM 2017). This updating is particularly relevant in light of Executive Order 13990 (January 20, 2021), which reestablished the Obama-era Interagency Working Group (IWG) on the Social Cost of Greenhouse Gases and directed it to update the SCC. We also note other research efforts on updating the SCC.

The NASEM report recommended creating an integrated framework comprising four components ("modules") underlying the SCC calculation: *socioeconomics*—probabilistic projections of population, gross domestic product (GDP), and emissions over multiple centuries; *climate*—an improved model of Earth's climate system and climate change; *damages*—the economic consequences of climate change, based on recent studies; and *discounting*—aggregated present-value marginal damages and stochastic discount factors that correctly reflect the uncertain socioeconomic drivers.

Figure 1 shows how the modules fit together, including how socioeconomics affects emissions trajectories, which are input into the climate

7. The Nobel Prize, "The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2018," https://www.nobelprize.org/prizes/economic-sciences/2018/summary/.

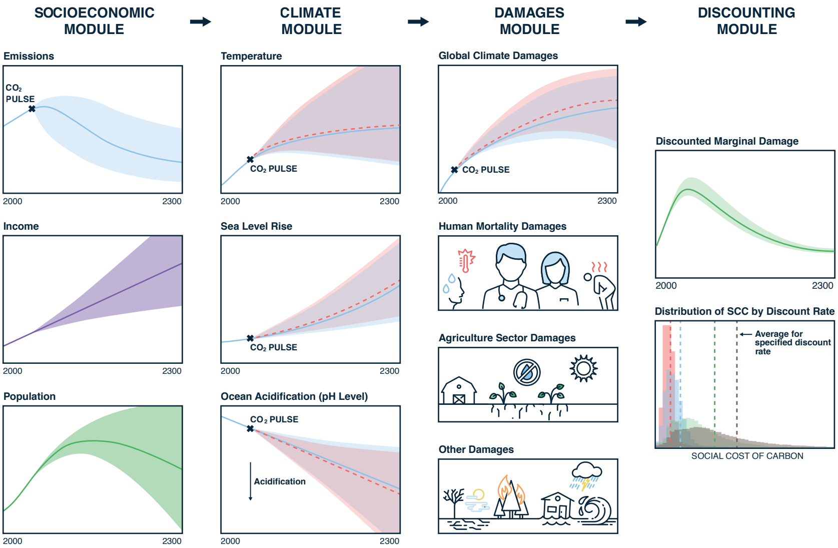
Figure 1. Modularized Approach to Estimating SCC



Source: National Academies of Sciences, Engineering, and Medicine (2017). Adapted and reproduced with permission from the National Academy of Sciences, courtesy of the National Academies Press, Washington, DC.

Note: The damages module may require regional and/or sectoral socioeconomic and climate data either as direct inputs or for calibration.

Figure 2. Estimating Social Cost of Carbon under Uncertainty



Source: Authors' calculations.

Note: Estimation involves a baseline case (solid and shaded area) versus a pulse of emissions (dashed lines and shaded area). Shading depicts probability distributions on projections.

module to project future temperatures. These temperatures are converted into a stream of future economic losses in the damages module (also influenced by socioeconomic trajectories), which are then discounted to a present value in the discounting module.

Because the SCC represents the marginal effect of an incremental ton of emissions, this entire model is run twice—once as a baseline and once with a small pulse of additional emissions (figure 2). The resulting change in the stream of economic damages per ton from this emissions pulse, in present value, is the SCC. More generally, when inputs to a module are uncertain (e.g., because of uncertainty about the climate's response to emissions or about future economic growth), modelers have incorporated that uncertainty through Monte Carlo analyses by taking draws of (potentially correlated) probability distributions of each random variable. The result is a distribution of SCCs, often summarized by its expected value. For example, the federal government's current interim value of \$51/ton CO_2 (IWG 2021) reflects the expected value of the SCC over uncertainty in the climate's warming response and scenarios of economic growth and population, at a 3 percent constant discount rate.

The NASEM report noted that the IWG's estimates of the SCC, including the current interim \$51/ton SCC value, used somewhat dated and often simplistic modules. For example, five socioeconomic scenarios were not developed with formal probabilities attached but were treated as equally likely. The scenarios did not incorporate the work done by economists, demographers, and statisticians to estimate and quantify uncertainty around long-term economic and population growth. Also, the discounting approach used a constant discount rate rather than treating the discount rate as stochastic; that choice becomes increasingly important as the decision horizon extends into the future. The IWG noted the potential for a declining term structure and correlation between the discount rate and damage outcomes but did not consider an explicit stochastic discount factor that accounts for both future discount rate uncertainty and, through uncertain socioeconomic outcomes, correlation with the damages being discounted. To address such shortcomings, the NASEM report issued recommendations for improvement, which Executive Order 13990 specifically directed the IWG to consider.

This paper documents recent work that has improved the scientific basis for the modules so that the IWG can update the SCC to reflect the best available science. Section I discusses the improved socioeconomic module, with long-term probabilistic projections of population, economic growth, and emissions. Section II illustrates how an incremental ton of emissions translates into climate and economic effects (damages). Section III discusses the crucial role of the discount rate, given recent research on declining equilibrium interest rates, plus the importance of using stochastic discount factors and the shadow price of capital for valuing effects on investment. Section IV then combines these elements into a simplified model of the SCC, with associated uncertainty bounds for the socioeconomic, climate, damages, and discounting components. Finally, section V concludes and raises issues that await future research.

I. Economic and Demographic Drivers of Climate Effects

Assessments of damages from climate change are influenced by projections of population, economic growth, and emissions. Population growth can drive emissions and increase or decrease total economic exposure to the health effects of climate change. Economic growth similarly affects both the level of expected emissions and the resulting damages, which are often estimated to scale with economic activity (Diaz and Moore 2017). For example, the monetization of mortality consequences typically depends on per capita income (Robinson, Hammitt, and O'Keeffe 2019). Economic growth projections can also influence the SCC through the discount rate if estimates are calculated using Ramsey-like discounting, where the discount rate is a function of the rate of economic growth: higher (lower) growth scenarios will yield a higher (lower) discount rate. Finally, projections of global emissions determine the background state of the climate system against which damages from an additional pulse of emissions are measured.

Estimates of the SCC are highly sensitive to socioeconomic and physical projections (Rose, Diaz, and Blanford 2017), but revised estimates have been based primarily on changes in socioeconomic projections, not on improved understanding of the climate system (Nordhaus 2017b). Explicitly considering realistic, probabilistic socioeconomic projections is thus important for improving the characterization of both the central tendency and the uncertainty in the SCC.

A robust characterization of socioeconomic contributions to SCC estimates would ideally incorporate probabilistic projections of population, economic growth, and emissions. The particular requirements of SCC estimation, however, pose significant challenges for generating such projections. One is the time horizon: given the long-lived nature of greenhouse gases in the atmosphere, the SCC needs to account for discounted damages two hundred to three hundred years into the future (NASEM 2017). Yet nearly all projections, such as the scenarios previously used by the IWG (2010) and the shared socioeconomic pathways used by the IPCC (Riahi and others 2017), end at year 2100 and are often scenario-based rather than probabilistic. New probabilistic projections that extend well into the future are required.

Another challenge is that although climate change can be projected from emissions scenarios consistent with globally aggregated projections of economic activity and population growth, the resulting climate damages are most appropriately estimated at a regional (or even local) scale. Thus, they require geographically disaggregated estimates of GDP and population.

A third challenge is that the future path of emissions likely depends on uncertain improvements in technology and on the scale and success of policy interventions outside the range of the historical record. That is, whereas historical data may be a reasonable guide to forecast population and economic activity, the same is not true for emissions. The SCC should be measured against our best estimate of future emissions, inclusive of future mitigation policies *except* the one under analysis.

The fourth issue is the interrelated nature of these variables: the projections for each variable must be consistent with one another. For example, emissions intensity might be lower with higher economic growth (and its associated wealth and technological improvements).

I.A. Past Approaches to Socioeconomic Projections

In lieu of using fully probabilistic socioeconomic projections, researchers have typically turned to socioeconomic scenarios, which can provide consistency across analyses and still incorporate specific narratives. The IWG adopted a scenario approach in its initial estimates (IWG 2016), and these same scenarios support the interim estimates put forward by the Biden administration in January 2021 (IWG 2021). The five socioeconomic scenarios were drawn from the Energy Modeling Forum 22 exercise (Clarke and Weyant 2009), selected to span roughly the range of emissions outcomes in the full set of the forum's scenarios and thus represent uncertainty across potential socioeconomic projections. Only one of the scenarios represented future climate policy. The IWG extended the five scenarios to 2300 by assuming that GDP and population growth each decreased linearly to zero in 2300. The five scenarios were assigned equal probability for computing an expected value for the SCC (no such probabilistic interpretation existed for the work by the Energy Modeling Forum 22).

The IWG scenarios were critiqued for not spanning the uncertainty in a full set of relevant socioeconomic variables (e.g., GDP, population) or reflecting the broader scenario literature overall (Rose and others 2014; Kopp and Mignone 2012). The resulting SCC estimates, then, may not reflect damage calculations based on the full range of expected variation. The NASEM panel noted that the IWG did not provide a rationale for its scenario weighting or the choice to extend the scenarios from 2100 to 2300 by assuming that GDP and population growth each decreased linearly to zero. The panel recommended using a combination of statistical methods and expert elicitation to generate a set of probabilistic long-term projections for each variable.

Subsequently, a multidisciplinary research effort developed the shared socioeconomic pathways (SSPs) (Riahi and others 2017), scenarios intended primarily to support the assessment efforts of the Intergovernmental Panel on Climate Change (IPCC). Each of the five SSPs consists of quantified measures of development and an associated narrative describing plausible future conditions that drive the quantitative elements. The SSPs end in 2100, but researchers have offered extensions to 2300 (Nicholls and others 2020; Kikstra and others 2021). The SSPs are freely available and comprehensive, have an extensive publication record, and are expected to be used in the IPCC's *Sixth Assessment Report*. For these reasons, we use the SSPs as our primary point of comparison.

Scenarios in general, and the SSPs in particular, do not come (as the IWG assumed) with associated probabilities. That limits their utility in evaluating uncertainty. Although the SSP authors have themselves cautioned against using the SSPs in a probabilistic fashion, Ho and others (2019) sought to address this limitation through an expert survey assessing the likelihood of each SSP. Others have sought to guide scenario usage by characterizing the plausibility of various scenarios (Stammer and others 2021). Even without formal probabilities, in practice, the SSPs are often interpreted in modeling exercises as representing the uncertainty between high-emissions (SSP5) and low-emissions (SSP1) futures, at times with the implication that the difference represents a "no policy" counterfactual versus a "likely policy" scenario. This has led to a recent debate over the viability of the high-emissions scenario, given the current pace of technology evolution, among other factors (Hausfather and Peters 2020).

Previous efforts to quantify the uncertainty of socioeconomic projections over a century are limited. Raftery and others (2017) used a statistical approach to generate density functions of country-level economic growth per capita, population, and carbon intensity (CO_2/GDP) to project a density of future emissions trajectories via the IPAT equation (Commoner 1972), similar to our socioeconomic approach.[8] Müller, Stock, and Watson (2020) employed a Bayesian latent factor model that projects long-run economic growth based on low-frequency variation in the historical data of country-level GDP per capita.[9] Christensen, Gillingham, and Nordhaus (2018) conducted an expert survey of economists to quantify the 10th, 50th, and 90th percentile ranges of economic growth for six groupings of countries. Comparing results with the SSP ranges, they found that the SSPs underestimated the range of uncertainty expected by the experts and that using the increased range for economic growth with the DICE model suggested that emissions were also underrepresented by the SSPs.

The NASEM (2017) report noted that statistical models based solely on historical data are unlikely to fully inform the variability of future projections over centuries, suggesting caution in using raw outputs from statistical

8. The IPAT equation is Impact = Population × Affluence × Technology, a heuristic for thinking about the impact of humans on the environment.

9. The method used by Müller, Stock, and Watson (2020) extends the approach provided in Müller and Watson (2016), which was suitable only for global estimates of economic growth, to generate internally consistent growth projections at the country level.

models over long time scales. This concern led the NASEM panel to recommend using formal expert elicitation to quantify the uncertainty around future long-run projections, which can then be used to augment projections from statistical models.

We next describe efforts undertaken by the Resources for the Future's (RFF) Social Cost of Carbon Initiative and collaborators to build on both statistical and expert-based approaches to generate distributions of projections of population and GDP per capita at the country level, plus distributions of the three primary greenhouse gases (CO_2, CH_4, and N_2O) at the global level. The resulting probabilistic distributions, collectively referred to as the RFF Socioeconomic Projections (RFF-SPs), fully incorporate the NASEM recommendations for generating an improved socioeconomic module for SCC estimation.

I.B. Probabilistic Population Projections to 2300

METHODS To develop probabilistic, country-level population projections through 2300, we start with the fully probabilistic statistical approach that has been used since 2015 by the United Nations (UN) for its official population forecasts to 2100 (United Nations 2019). We then extend the statistical model to 2300, incorporating feedback and improvements suggested by a panel of nine leading demographic experts that we convened to review preliminary results. This work is detailed in Raftery and Ševčíková (2021).

The UN uses a probabilistic method built on the standard deterministic cohort-component method of population forecasting (Preston, Heuveline, and Guillot 2001). This method projects forward the three components of population change: fertility, mortality, and migration, broken down by age and sex. The probabilistic method builds Bayesian hierarchical models for each of the three components and projects them forward probabilistically using a Markov chain Monte Carlo method, which produces a large number of trajectories (typically 1,000–2,000) of future numbers of births, deaths, and migration events in each country by age and sex. Each trajectory of fertility, mortality, and migration is then combined to give a trajectory of future population by age and sex in each country. These trajectories of population numbers in turn approximate a probability distribution for any population quantity of interest (Raftery and others 2012; Raftery, Alkema, and Gerland 2014; Gerland and others 2014).

Fertility is projected by focusing on each country's total fertility rate (TFR), which is the expected number of children a woman would have in a given period if she survived the reproductive period (typically to age 50) and at each age experienced the age-specific fertility rates of that period. The UN models the evolution of fertility in all countries using a Bayesian hierarchical model that divides it into three phases depending on where it lies in the fertility transition from high to low fertility (pre-transition, transition, post-transition). It then fits a time series model to each phase, accounting for spatial correlation between countries (Alkema and others 2011; Raftery, Alkema, and Gerland 2014; Fosdick and Raftery 2014; United Nations 2019; Liu and Raftery 2020).[10] Mortality is similarly projected by focusing on life expectancy at birth.[11] This is projected by another Bayesian hierarchical model for all countries for both sexes (Raftery and others 2013; Raftery, Lalic, and Gerland 2014). The UN has traditionally projected net international migration for each country deterministically by assuming that it would continue in the future at the same rate as currently (United Nations 2019).

We extended the UN's method, designed for projections to 2100, out to 2300 and preliminary results were reviewed by a panel of nine expert demographers that we convened.[12] While broadly supportive, the panelists were in agreement that the resulting uncertainty bounds for TFR in 2300 were too narrow and that in particular the lower bound of the 95 percent prediction interval for world TFR in 2300 (1.66) was too high. A lower bound of 1.2 children per woman for the world TFR in 2300 was suggested as a more plausible lower bound. We incorporated this recommendation by adding a worldwide random walk component to the TFR model.

Experts on the panel also suggested that international migration should be projected probabilistically, in line with the general approach, rather than deterministically as done by the UN. We implemented this by projecting net international migration using a Bayesian hierarchical model (Azose

10. The TFR has evolved in a similar way in all countries. In preindustrial times, the TFR for a typical country was high (in the range of 4–8 children per woman). Then, usually after the onset of industrialization, it started to decrease. After a bumpy decline lasting several decades to a century, the TFR flattened out at a level below the replacement rate of about 2.1 children per woman. This decline is called the fertility transition. After the end of the fertility transition, the TFR fluctuated without a clear trend, mostly staying below the replacement rate. For example, in the United States, the TFR was around 7 children per woman in 1800 and then declined, reaching 1.74 in 1976 and thereafter fluctuating up and down; it is now 1.64, close to the level it was at in 1976 (Raftery 2021).

11. The general trend since 1840 has been that life expectancy has increased steadily (Oeppen and Vaupel 2002), with slower increases for countries with the lowest and highest life expectancy and the fastest increases for countries in the middle.

12. Each panelist provided written reviews of the preliminary projections and methodology, and all except Tomáš Sobotka presented them as part of a virtual workshop convened by Resources for the Future on October 4, 2018. Panelists are listed in the acknowledgments.

and Raftery 2015; Azose, Ševčíková, and Raftery 2016). We additionally implemented the final panel recommendation to impose constraints on population density to prevent unrealistically high or low population numbers in some age groups in some countries.

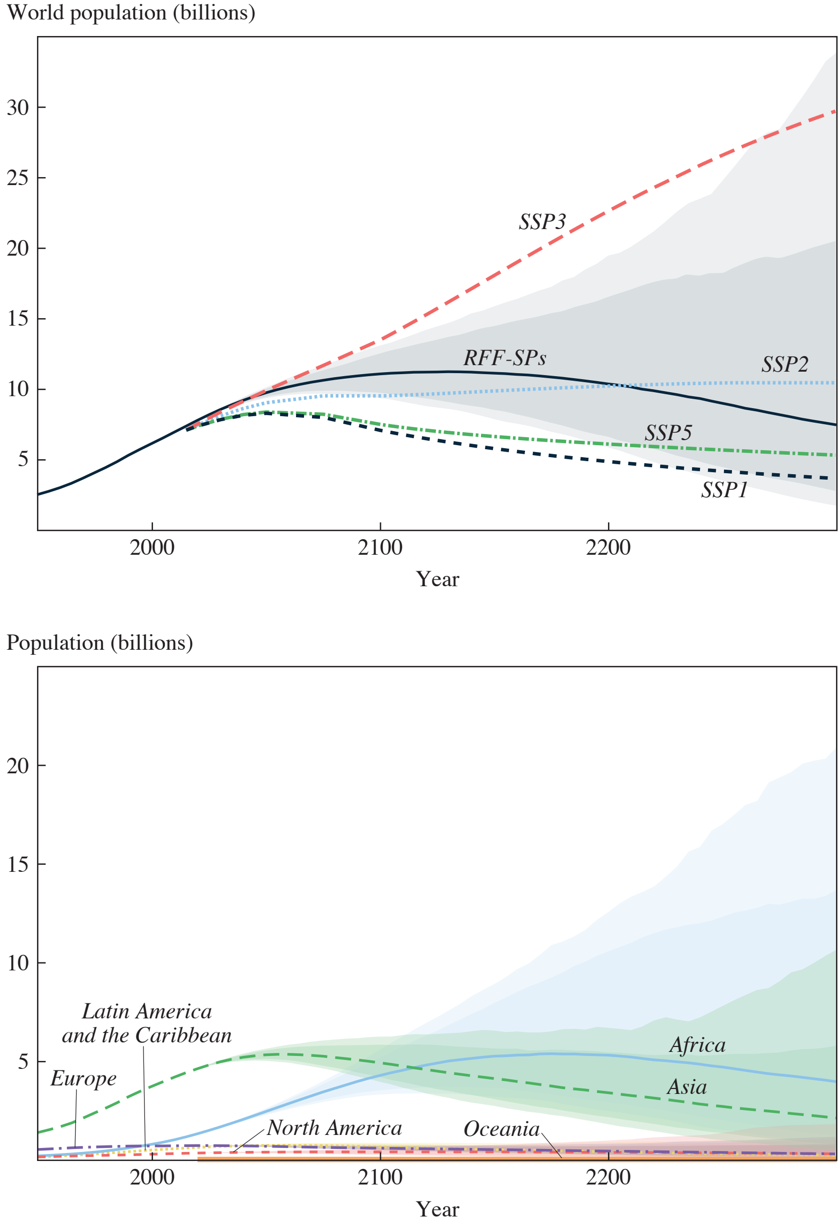
RESULTS The resulting population projections for 2300 for the world as a whole and for the continents are shown in figure 3. They show that total world population is likely to continue to increase for the rest of the twenty-first century, albeit at a decreasing rate, to level off in the twenty-second century, and to decline slightly in the twenty-third century. Uncertainty for 2300 is considerable, appropriately, reflecting the very long forecast time horizon, with a median forecast of 7.5 billion, but a 90 percent interval from 2.8 to 20.5 billion. The results agree closely with the UN forecasts for the period to 2100 (United Nations 2019).

Figure 3 also shows the results for each major continental region. The populations of Asia, Europe, and Latin America are likely to peak well before the end of this century and then decline substantially. The populations of Africa and North America are also likely to peak and then decline but much later, in the twenty-second century. In the case of Africa this is due to population momentum (with a high fraction of the population currently in reproductive ages) and current high fertility. In the case of North America it is due to a combination of modest population momentum, fertility that is closer to replacement level than in other continents, and immigration. Uncertainty for each region in 2300 is high.

In comparison to the population projections from the SSPs, our population projections are centered around a peak of slightly over 10 billion people globally reached late this century, lying closest to SSP2, although SSP2 levels off at a higher level than our median projection after 2200. Through 2300, the 90 percent confidence distribution around our median is narrower than the range indicated by the SSPs and considerably narrower through 2200. SSP1 and SSP5 lie below the 5th percentile of our distribution through almost the entire time horizon to 2300. SSP3 features a very aggressive population projection in the top tail of the distribution, at about the 99th percentile in 2300. In sum, none of the SSPs has a central tendency for population in line with our fully probabilistic projections, and the range of population given by SSP1–SSP5 is wide relative to ours.

We are aware of only three other detailed efforts to project world population to 2300, all of them deterministic, in contrast with our probabilistic method described here. One was carried out by the United Nations (2004) and was deterministic but containing several scenarios. The range of these projections for 2300 from the different scenarios went from 2.3–36.4 billion,

Figure 3. Probabilistic Population Projections for World and Major Regions, to 2300



Source: Authors' calculations based on Raftery and Ševčíková (2021).

Note: Data prior to 2020 are from the UN's *World Population Prospects 2019*. The predictive medians are shown as solid curves; the shaded areas show the 90 percent and 98 percent predictive intervals. The world population projections from the extended SSPs are shown for comparison.

compared with our 98 percent prediction interval of 1.7–33.9 billion. Although using different methodologies and carried out over fifteen years apart, the two sets of projections give results that are compatible with one another, perhaps to a surprising extent.[13]

Another such exercise was carried out by Vallin and Caselli (1997), also deterministic with three scenarios corresponding to different long-term trajectories of world TFR. Two of the scenarios led to world population stabilizing at around 9 billion, while the other resulted in 4.3 billion people in 2300. All three of these scenarios give world population in 2300 well within our 80 percent interval, though with a range that is much narrower than either ours or that of United Nations (2004). Gietel-Basten, Lutz, and Scherbov (2013) also performed a projection exercise to 2300, with a very wide range of scenarios for long-term world TFR. They obtained projections of global population yielding anything from zero to 86 billion in 2300.[14]

I.C. Probabilistic Economic Growth Projections to 2300 and Economic Growth Survey

METHODS The probabilistic projections of economic growth often used in analyses by governments and the private sector have not incorporated the time scale of centuries, as is needed to support SCC estimates and other economic analyses of climate change. Müller, Stock, and Watson (2020) took a significant step forward by providing probabilistic econometric projections over long periods. Their methodology involves a multifactor Bayesian dynamic model in which each country's GDP per capita is based on a global frontier of developed economies (countries in the OECD) and country-specific deviations from that frontier. Correlations between countries are also captured in a hierarchical structure that models countries in "covariance clubs," in which country-level deviations from the frontier vary together. The hierarchical structure also permits pooling information across countries, an approach that tightens prediction intervals. This model is then estimated on data for 113 countries over 118 years (1900 to 2017). The model yields 2,000 sets of trajectories of country-level GDP per capita from 2018 to 2300. Each can be considered an equally likely uncertain future. Each is characterized by a path for the global factor and 113 country-specific deviations from that pathway. The results are described more

13. The very high upper bound for the UN (2004) projections is likely an artifact of the perfect correlation implied by the deterministic scenarios and the aggregation of such results.

14. As in the UN (2004) projections, these very extreme outcomes are likely due in part to the perfect correlation between countries implied by the deterministic scenarios and the aggregation of such results.

fully below; for more information about the model, see Müller, Stock, and Watson (2020).

As noted earlier, however, NASEM (2017) recommended augmenting statistical models with formal expert elicitation to quantify uncertainty, especially for long-term projections. But surveying experts on long-term uncertainty of economic growth at the country level is impractical because of time constraints and the difficulty of accounting for intercountry correlations. Consequently, our study was designed to work in tandem with an econometric model that provides country-level projections and represents the intercountry dynamics. The RFF Economic Growth Survey focused on quantifying uncertainty for a representative frontier of economic growth in the OECD countries. The results informed econometric projections based on the model by Müller, Stock, and Watson (2020) of an evolving frontier (also based on the OECD), in turn providing country-level, long-run probabilistic projections.

The methodology we applied is the "classical model" (Cooke 1991, 2013) of structured expert judgment, analogous to classical hypothesis testing. In essence, the experts are treated as statistical hypotheses: they are scored on their ability to assess uncertainty based on their responses to calibration questions whose true values are known to us but unknown to the experts. This scoring allows us to weight the experts' judgments, and the scores of combinations of experts serve to gauge and validate the combination that is adopted. The ability to performance-weight experts' combined judgments has generally been shown to provide the advantages of narrower overall uncertainty distributions with greater statistical accuracy and improved performance both in and out of sample (Colson and Cooke 2017, 2018; Cooke, Marti, and Mazzuchi 2021).

Ten experts, selected for their expertise in macroeconomics and economic growth and recommended by their peers, were elicited individually by videoconference in roughly two-hour interviews in 2019–2020. They received an honorarium where appropriate. The full elicitation protocol is available in the online appendix; the general process was as follows. First, experts quantified their uncertainty for several initial questions, after which answers were provided for self-assessment; this step was intended to familiarize them with the process and alert them to potential biases. The experts then provided a median and 90 percent confidence range for eleven calibration questions for which the true values were known to us.

Experts next provided their 1st, 5th, 50th, 95th, and 99th quantiles for the variables of interest: levels of OECD GDP per capita for 2050, 2100, 2200, and 2300. For experts more comfortable working with growth rates (rather than levels), we provided a spreadsheet tool that translated average growth rates into GDP per capita levels. The experts were informed that their combined quantiles of GDP levels would be further combined with country-level econometric projections, as described below, but they were not shown the results. They were given historical data on economic growth to provide a consistent baseline of information across the panel, and they were permitted to consult outside sources if desired. The experts provided additional rationale for their quantiles verbally throughout the elicitation and concluded the survey by formally identifying the primary factors driving their low and high future growth scenarios.

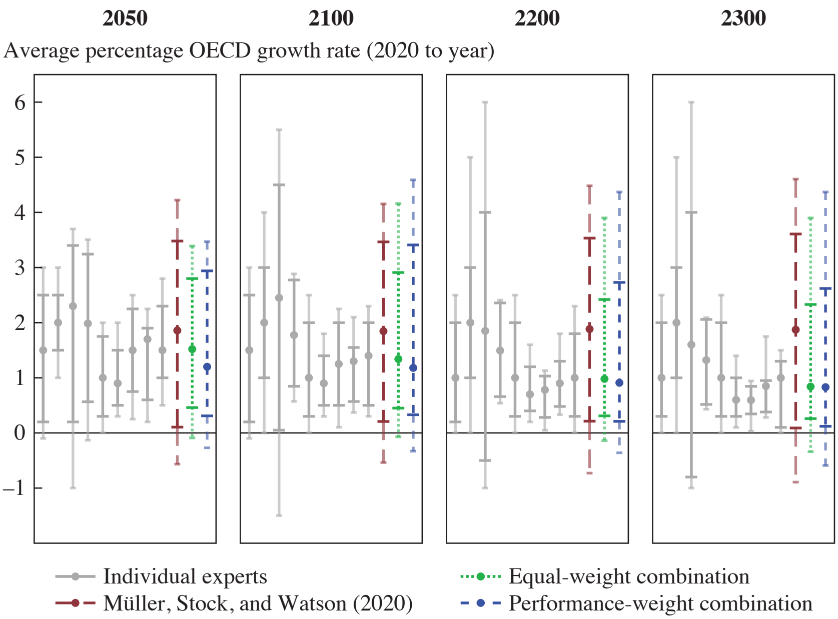
Given that the projections were being used as an input to the estimation of climate change damages, which would reduce economic activity below the projected level, the experts were specifically asked to provide quantiles of economic growth absent the effects of further climate change as well as absent further policy efforts to reduce emissions. Two of the ten experts provided a pair of modified base quantiles to reflect the absence of effects from climate damages and climate policy that are utilized here, but in general the proposed modifications to their original distributions were minor. Moreover, several experts noted that although climate change was a primary factor underlying their probability of low growth projections, the complexity of the multiple uncertain factors represented in their base quantiles precluded systematic removal, and they deemed their base quantiles appropriate for assessing uncertainty in the SCC and other analyses assessing the economic damages from climate change.

The results of the expert elicitations were combined by first fitting each expert's five quantiles for each year, in log GDP per capita, with a Johnson S_U distribution (Johnson 1949) to generate a continuous cumulative distribution function specific to each expert. We next combined the cumulative distribution functions in two ways: averaging across the set of expert functions with equal weight, and performance-weighting the experts according to their performance on the calibration questions. This process yielded a pair of final combined elicited values of OECD GDP per capita for each elicited year and quantile.[15]

RESULTS OF ECONOMIC GROWTH SURVEY On the calibration questions (see online appendix), the experts demonstrated an overall high level of statistical accuracy compared with other structured expert judgment studies and results that are robust against expert loss. As shown by their individual quantiles (figure 4) and as expressed in comments during the videoconferences, most

15. See online appendix for further detail.

Figure 4. Distributions of Future Average GDP Growth Rates for OECD



Sources: RFF Expert Growth Survey; Müller, Stock, and Watson (2020); and authors' calculations.
Note: For each bar, the circle shows the median and the lines show the 1st, 5th, 95th, and 99th percentiles of the relevant distribution.

participants' median forecast was that long-term growth would be lower than the growth rate of the past one hundred years. The responses show considerable diversity in their characterization of uncertainty around the median, however, with some of the widest ranges being driven by their explicit inclusion of events that are not present or fully realized in the historical record of economic growth on which statistical growth projections are based.[16] When asked to identify the primary drivers of the low-growth quantiles, the experts most commonly responded with climate change, followed by world conflict, natural catastrophes, and global health crises. Rapid advancement of technology was cited most often as the primary driver of high growth, followed by regional cooperation and advances in medical science. Many experts expected that technology breakthroughs in

16. The quantiles from one expert included global civilization-ending events that were outside the scope of the survey and incompatible with assumptions for US federal policy analysis; they unreasonably distorted the combined distributions toward extreme values. Quantiles from this expert were excluded in the final survey.

clean energy would dramatically lower global emissions. Implicit in this narrative is a negative correlation between economic growth and carbon dioxide emissions.

As shown in figure 4, both the performance-weighted and the equal-weighted combinations of the experts' distributions yield narrower ranges as well as lower medians than do the statistical trajectories for all four years (2050, 2100, 2200, and 2300). The median of the equal-weighted combination is consistently higher than the median based on performance weighting, but the difference shrinks throughout the period until the medians nearly converge in 2300. Overall, the experts viewed sustained long-term growth rates above 4 percent or even slightly below zero percent as highly unlikely but not impossible.

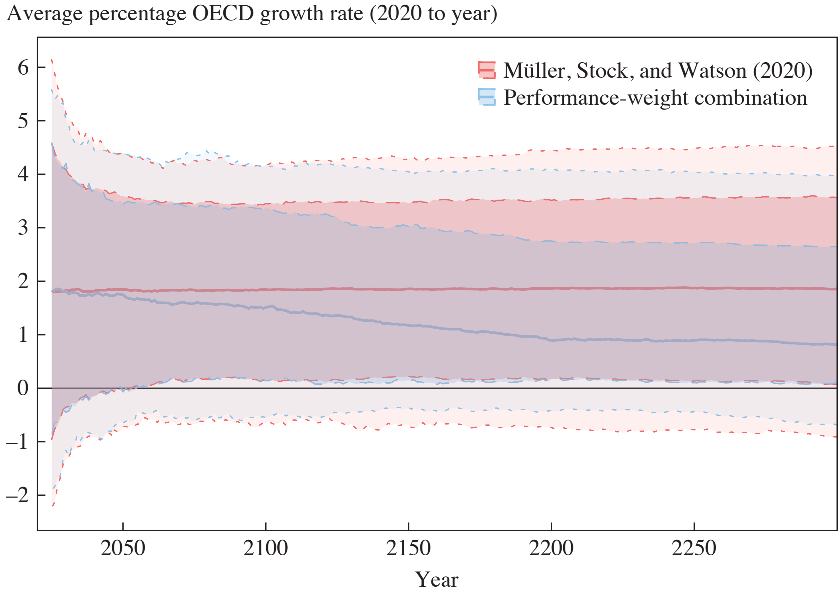
RESULTS OF ECONOMETRIC GROWTH PROJECTIONS AUGMENTED WITH EXPERT JUDGMENT We used the survey results to modify econometric projections of GDP per capita based on the methodology of Müller, Stock, and Watson (2020) and to generate density functions of internally consistent projections of economic growth at the country level. As indicated in Müller, Stock, and Watson (2020), economic growth 100–300 years into the future is highly uncertain, well beyond that captured in typical scenario projections (see figure 5).

The tails of the Müller, Stock, and Watson (2020) distribution are quite wide, leading to some implausibly small or implausibly high long-term average growth rates in the extreme tails (e.g., below the 1st percentile or above the 99th percentile). These extreme tails correspond to extremes of persistent economic growth beyond what has been observed historically over long periods (e.g., below –1 percent or above +5 percent annually on average through 2300). Specifically, according to the Maddison Project data set—one of two data sets used by Müller, Stock, and Watson (2020)—which includes country-level GDP per capita data as far back as 1500 for some countries, no country has experienced such extreme growth for such long periods.[17] In their model, those extreme tail simulated outcomes are driven by the structure of the Bayesian model with its embedded distributional assumptions rather than by the historical data used to estimate the model.

Further, the 1st and 99th percentiles of the combined distribution of long-run growth rates based on our economic growth survey are –0.6 percent

17. For example, no country in Maddison Project data has observed 100-year growth rates below –1 percent or above +3 percent. Maddison Project data are available at Clio Infra, "GDP per Capita," https://clio-infra.eu/Indicators/GDPperCapita.html.

Figure 5. Average Projected Growth Rates of GDP per Capita in OECD Countries



Sources: Authors' calculations and Müller, Stock, and Watson (2020).
Note: Shaded areas and dashed/dotted lines represent 5th to 95th (darker, dashed) and 1st to 99th (lighter, dotted) percentile ranges.

and +4.4 percent, indicating that long-run growth rates are unlikely to fall outside this range. For these reasons, and in consultation with James Stock, we omit some projections in the extreme tails of Müller, Stock, and Watson's (2020) distribution that are outside the range of historical experience and also outside the long-run range implied by our survey (see online appendix for our approach).

Our survey provides quantiles of economic growth for the OECD for four discrete years. To maintain the rich country-level information of the econometric model while incorporating the information from the experts, we reweight the probability of occurrence of each of the 2,000 draws from Müller, Stock, and Watson (2020) to satisfy the experts' combined distribution over the long run. The underlying projections from Müller, Stock, and Watson (2020) remain unchanged (aside from the omission of extreme tails described above), but the likelihood of drawing a given trajectory is modified such that the quantiles of OECD growth reflect the distribution produced by the survey.

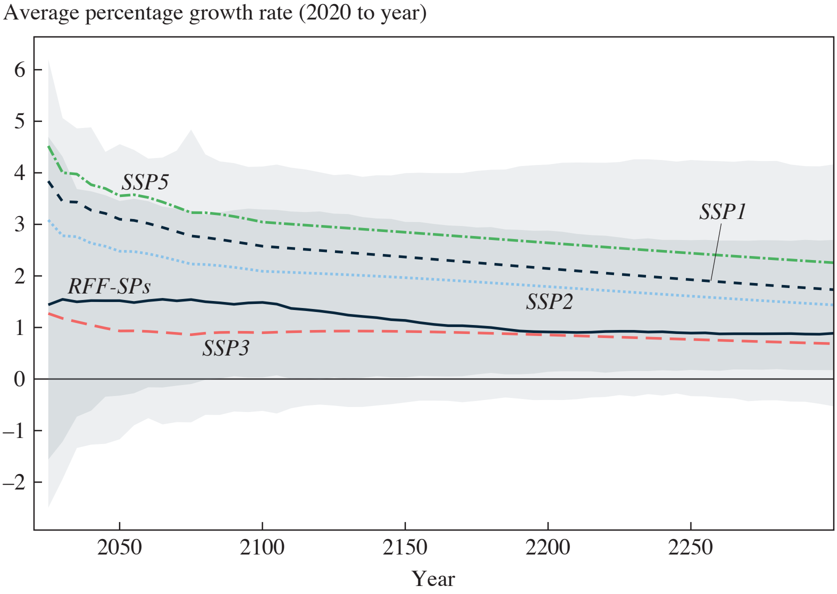
We accomplish this reweighting in two steps. First, we generate a set of target quantiles for the years 2030, 2050, 2100, 2200, and 2300 by calculating weighted averages of the combined cumulative distribution functions from the experts and the corresponding functions from the raw data in Müller, Stock, and Watson (2020). NASEM (2017) recommended giving expert judgment increasing weight for longer horizons, so the near-term weighting is governed more by historical evidence and that of the long-term future more by the experts. For this reason, we increase the weight of the survey quantiles versus Müller, Stock, and Watson's (2020) quantiles linearly over time from zero percent in 2030 to 100 percent in 2200 and thereafter.

We then use iterative proportional fitting (Csiszar 1975) to impose the target quantiles for OECD growth on the 2,000 trajectories of the frontier from Müller, Stock, and Watson (2020) for each of the four benchmark years. For each range of values between each elicited quantile, this algorithm reassigns probabilities to each trajectory whose value falls within that range by minimizing a penalty for nonequal weights, subject to matching the target quantiles. Because there are four years for which we have a combined expert distribution to satisfy, the algorithm iterates between each year until all years' distributions are satisfied. Figure 5 compares the resulting distributions from Müller, Stock, and Watson (2020) with those reweighted according to our economic growth survey.

We next generate a distribution of projected global GDP per capita rates by taking 10,000 independent samples from the population and survey projections, taking the product of population and GDP per capita at the country level, summing to yield global GDP, and dividing by the global population for that draw.[18] Figure 6 shows that the resulting median global GDP growth rates from the RFF-SPs track slightly higher than SSP3, with SSP1, SSP2, and SSP5 also falling within the 90th percentile range. The SSPs do not span the full range of potential growth paths, especially below the median for

18. The raw data set from Müller, Stock, and Watson (2020) provides growth projections for 113 countries. Here we expand on that scope of coverage to include all 184 countries represented in the SSPs by undertaking the following steps to impute each country omitted in Müller, Stock, and Watson (2020): (1) identify the country within the same continent and within 30 degrees latitude with the closest matching log(GDP/capita) for the year 2020 (or, for eleven countries missing data for 2020, we use the most recent year available, typically 2019); (2) calculate a scaling factor based on the ratio between the respective 2020 GDP/capita values; and (3) apply the scaling factor to each trajectory for the matched country to generate corresponding trajectories for the omitted country. Matches for omitted countries from Oceania were identified from within Asia. The countries imputed represent a total of 3 percent of global GDP for the year used for the match.

Figure 6. Average Projected Growth Rates of Global GDP per Capita



Source: Authors' calculations.

Note: The solid line represents the median value, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

the RFF-SP growth trajectories. As will be discussed in section IV, these relatively low-growth potential paths contribute substantially to the SCC.

I.D. Projected Emissions to 2300 Based on Economic Growth: Future Emissions Survey

METHODS To generate very long run distributions of global emissions of CO_2, CH_4, and N_2O, the RFF Future Emissions Survey elicited ten experts in socioeconomic projections and climate policy who were nominated by their peers or by members of the RFF Scientific Advisory Board. The experts surveyed were based at universities, nonprofit research institutions, and multilateral international organizations. They have expertise in and have undertaken long-term projections of the energy-economic system under a substantial range of climate change mitigation scenarios.

Like our economic growth survey, the future emissions survey employed the classical model of structured expert judgment: experts first quantified their uncertainty about variables for which true values were known, for calibration and performance weighting. Experts next provided quantiles of uncertainty (minimum, 5th, 50th, 95th, maximum, as well as additional percentiles at the expert's discretion) for four variables for a case we called Evolving Policies, which incorporates views about changes in technology, fuel use, and other conditions and is consistent with the expert's views on the evolution of future policy. The Evolving Policies case corresponds to the US federal government's approach to benefit-cost analysis, which evaluates US regulations as incremental against a more expansive backdrop of other policies and conditions and is responsive to NASEM recommendations for including future background policy in the uncertain distributions of socioeconomic projections.

Experts provided quantiles of uncertainty for (1) fossil fuel and process-related CO_2 emissions, (2) changes in natural CO_2 stocks and negative emissions technologies, (3) CH_4, and (4) N_2O for five benchmark years: 2050, 2100, 2150, 2200, and 2300. For category 1, they were also asked to indicate the sensitivity of emissions to five GDP per capita trajectories.[19]

For each expert we generate a set of cumulative distribution functions, one for each benchmark year, emissions source, and economic growth trajectory, by piecewise linear interpolation between the quantiles provided. Then, as in the economic growth survey, we generate a corresponding set of combined equal-weight cumulative distribution functions by averaging the functions in equal measure, and a set of performance-weighted cumulative distribution functions by averaging in accordance with the experts' relative performance on the calibration questions. Quantile values from the combined functions were linearly interpolated in time between each of the benchmark years to yield a distribution of piecewise linear, nonoverlapping trajectories for each emissions source and sink.

Based on the future emissions survey, we developed a distribution of emissions scenarios to pair, one to one, with our economic growth scenarios. First, we sampled from one of 10,000 economic growth trajectories, described above. Second, we sampled a value (q) on the continuous interval [0,1] to determine the percentile of the expert's emissions trajectory to evaluate. Third, at five-year intervals from 2025 to 2300 we generated an interpolated value of the qth percentile of emissions based on the realized GDP level corresponding to that GDP trajectory in that year and the qth percentile of the experts' emissions distributions for the bounding GDP values elicited. Net emissions of CO_2 were generated by sampling independent q values for direct emissions (category 1) and natural carbon stocks and negative

19. See online appendix for a more-detailed discussion of the survey methodology and the full elicitation protocol.

emissions technologies (category 2) and summing the resulting trajectories, thereby including the possibility of net negative emissions.[20]

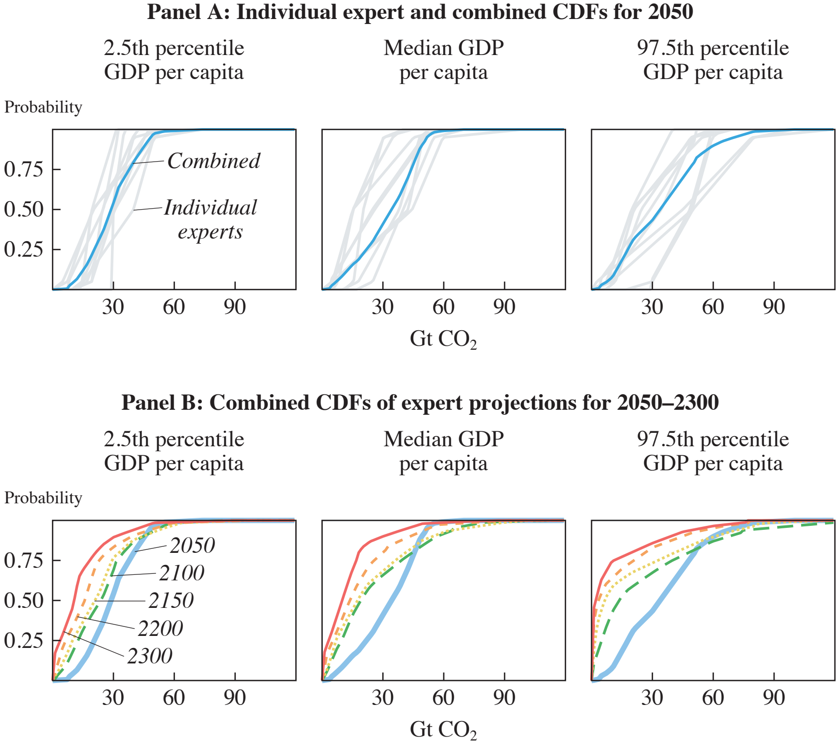
RESULTS OF THE FUTURE EMISSIONS SURVEY Experts' performance on the calibration questions was high, as measured by statistical accuracy, informativeness, and robustness of results (see online appendix). Experts described their rationale and the conditions supporting their distributions of emissions, often citing the same factors. For direct CO_2 emissions (category 1), experts viewed low economic growth as likely to reduce emissions overall but also lead to reduced global ambition in climate policy and slower progress to decarbonization. For median economic growth conditions, experts generally viewed policy and technology evolution as the primary driver of their emissions distributions, often offering a median estimate indicating reductions from current levels but with a wide range of uncertainty. Several experts said high economic growth would increase emissions through at least 2050, most likely followed by rapid and complete decarbonization, but with a small chance of substantial continued increases in emissions. In general, the distributions were inconsistent with keeping global temperature increases below 1.5 degrees Celsius, even when considering the potential for negative emissions.

Though their rationales were often similar, experts' interpretation of those narratives, as shown in their quantiles of emissions, differed substantially (figure 7). For example, for the median growth trajectory to 2050, the median emissions ranged from 15 to 45 Gt CO_2, a span encompassing a decrease of more than 50 percent to an increase of more than 30 percent from today's

20. The experts received real-time feedback about the implications of their prescribed distributions for future outcomes. After each had provided a full set of quantiles, we followed the same sampling process described above to generate distributions of emissions trajectories, except that the emissions distributions were based on input provided by only that expert rather than the full set of experts and that for expediency we presented results based on 100 to 1,000 samples at the discretion of the expert. Experts were shown their full distributions of emissions trajectories, the economic growth paths sampled, population, emissions intensity, and the resulting climate outcomes from the FaIR 2.0 climate model (described in section II) for their verification. They were permitted to modify their quantiles after seeing their distributions and resulting climate outputs, but in general they found the results to be in agreement with the intent of their quantiles and consistent with their supporting rationale.

For each emissions trajectory generated, we used a cubic spline to interpolate between 2020 emissions and 2050 (the first quantiles provided by the experts) based on the slope of the global emissions trajectories over the 2010–2020 period and the emissions trajectory post-2050. We also used a cubic spline to interpolate trajectories between the additional years for which quantiles were provided by the experts.

Figure 7. Cumulative Distribution Functions (CDFs) of Annual CO_2 Emissions

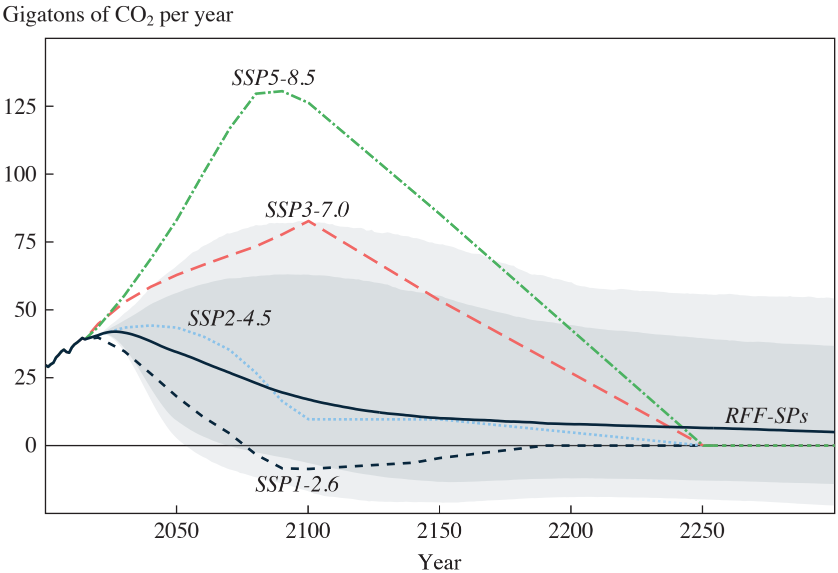


Source: Authors' calculations.

levels. Experts often provided highly skewed distributions, with significant chances that direct CO_2 emissions (category 1) would be exactly or near zero while allowing for much higher emissions in the middle and upper quantiles of their distribution.

The experts' narratives support an evolution of the combined distributions. Over time, emissions distributions for all growth trajectories exhibit a shift, particularly evident for the median and high-growth trajectories, with median emissions approaching zero in and after 2150. Emissions distributions for the lower-growth trajectory show a decreased range of emissions overall compared with the higher-growth trajectories, but the temporal trend toward lower emissions is not as strong. Higher-growth trajectories show relatively greater probabilities of increased emissions in the near term, followed by greater chances of full decarbonization in the

Figure 8. Net Annual Emissions of CO_2 from RFF-SPs and SSPs



Source: Authors' calculations.
Note: Lines represent median values, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

next century, while also allowing for the possibility of much higher emissions over the long term.[21]

RESULTING GLOBAL GREENHOUSE GAS EMISSIONS PROJECTIONS Figure 8 shows the resulting distribution of projected net CO_2 emissions based on the future emissions survey. The median emissions trajectory is a roughly 50 percent decrease from today's levels by 2100, followed by slowly decreasing levels that approach but do not reach net zero. The median of our CO_2 emissions and concentrations paths is similar to SSP2, and the 98 percent confidence interval spans a range similar to that of SSP1 through SSP3, at least through 2140.[22] The magnitude of CO_2 emissions associated with SSP5, however, is considerably higher than the upper end (99th percentile) of our distribution through the middle of the next century, consistent with the findings of

21. See online appendix for results for all emission source and sink categories and additional discussion of the experts' rationales across all categories.

22. For comparison of emissions consistent with the SSPs beyond 2100, we adopt the commonly used extensions provided by the Reduced Complexity Model Intercomparison Project (Nicholls and others 2020).

Raftery and others (2017) and Liu and Raftery (2021). Beyond the middle of the next century, all the SSP emissions trajectories increasingly lie well within our distribution because their extension beyond 2100 is constructed to achieve zero emissions by 2250. This is a weakness of the SSPs as a basis for SCC estimation, even if a subset of the SSPs spans a "reasonable range" during this century.

For CH_4 (figure OA-9 in the online appendix), the emissions distribution resulting from the future emissions survey is centered between SSP2 and SSP5 and spans a range similar to that of SSP1–SSP5, at least through 2100. After that point, as with CO_2, the emissions range spanned by the SSPs narrows, whereas the CH_4 emissions from the survey maintain a relatively wide distribution, similar to that in 2100. For N_2O (online appendix figure OA-10), the median of the emissions paths is between SSP2 and SSP5 through roughly 2200, and the full distribution from the survey spans a range wider than all the SSPs.

In sum, no single SSP is centered similarly to the median emissions paths across all three major greenhouse gases. The full range of emissions represented by the SSPs is higher than for the future emissions survey for CO_2 through 2140; by construction the range narrows to zero for CO_2 after that point and is narrower than the survey results for both CH_4 and N_2O for nearly the full period.

II. From Emissions to Monetized Climate Damages

II.A. Climate System Methods

The second step in estimating the SCC is using a climate model to calculate changes in the climate system corresponding to changes in greenhouse gas emissions. Climate models vary in their representation of the underlying physics, in their spatial and temporal resolution, and in their computational requirements. Earth system models, such as those used for IPCC analyses, require supercomputers, but SCC calculations, typically generated from tens to hundreds of thousands of samples to characterize their uncertainty, preclude use of full-scale earth system models. SCC models are designed to emulate the response of full earth system models across a subset of relevant climate outputs, such as globally averaged surface temperature.

Previous SCC calculations from the federal government used three integrated assessment models: DICE, the Climate Framework for Uncertainty, Negotiation and Distribution (FUND), and Policy Analysis of the Greenhouse Effect (PAGE), each of which employs its own reduced-form climate model. These integrated assessment models can deliver substantially different temperature increases for the same pulse of emissions (Rose and others 2014), leading to inconsistency when results are averaged to calculate the SCC. The NASEM report therefore recommended adopting a uniform climate model that met certain criteria, including that it generates a distribution of outputs across key climate metrics comparable to distributions of outputs from the full earth system models.

The Finite Amplitude Impulse Response (FaIR) model (Millar and others 2017) was highlighted in the NASEM report as a reduced-form model that met the criteria. To assess the changes in global mean surface temperatures resulting from the RFF-SPs, we ran the latest version, FaIR 2.0 (Leach and others 2021), using 10,000 draws from the emissions trajectories of CO_2, CH_4, and N_2O while also sampling across FaIR's native uncertainty in climate variables.[23]

II.B. Resulting Temperature Change from RFF-SPs

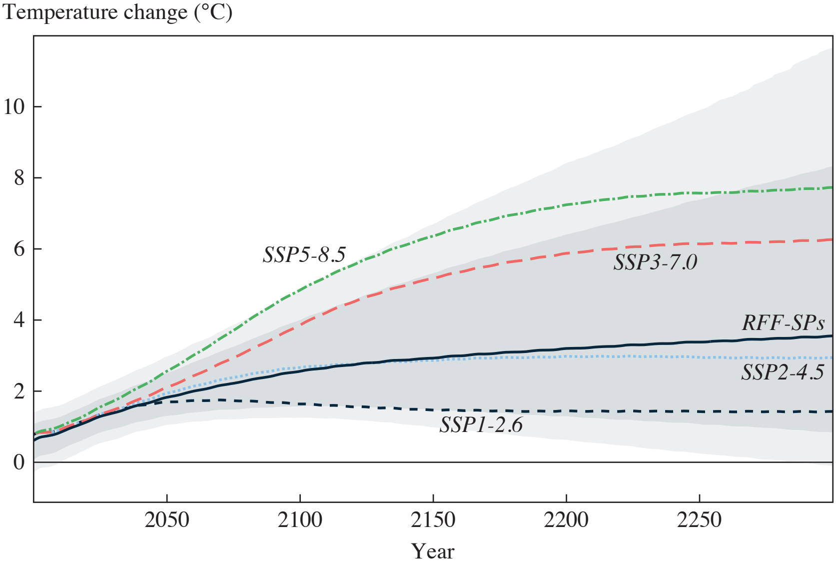
Figure 9 shows the median temperature trajectory associated with the RFF-SPs: increases reaching nearly 2.6 degrees Celsius above the average global temperature for 1850–1900 (the standard IPCC preindustrial benchmark) through 2100 and continued increases through 2300. The low end of the distribution indicates a roughly 20 percent chance that the increase will remain below 2 degrees Celsius through 2100. Our experts' expectations for negative emissions technologies lead to an increasing chance of drawing down atmospheric CO_2 to yield temperatures at current levels and below by the late 2100s.

The RFF-SP median temperature trajectory tracks closely with SSP2 through 2150, thereafter continuing to increase slightly. SSP1 is largely consistent with the 5th percentile results throughout the period. Temperatures resulting from SSP3 emissions are consistent with the 95th percentile of the RFF-SPs through the middle of the next century, at which point temperatures stop increasing, by construction. The median temperature from SSP5 is roughly consistent with the 99th percentile of temperatures from the RFF-SPs through 2100, at which point it begins to level off to meet the imposed requirement for net zero emissions by 2250.

In this comparison, uncertainty in the climate system itself, as represented by the uncertain distributions of climate parameters in the FaIR model, contributes significant uncertainty to the range of projected temperatures. The temperature distributions for the RFF-SPs include climate uncertainty

23. Trajectories for non-CO_2, CH_4, and N_2O were drawn from SSP2.

Figure 9. Global Mean Surface Temperature Change from RFF-SPs and SSPs



Source: Authors' calculations.

Note: Temperature change is relative to the standard 1850–1900 preindustrial average. Solid lines represent median values. Dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges based on the RFF-SPs. For clarity of presentation, uncertainty in the climate system is reflected in the uncertainty range only for the RFF-SPs (and not the SSPs).

from FaIR, but for clarity we omit climate system uncertainty in presenting projected temperatures from the SSPs. For a sense of scale, the 90th percentile range in temperatures from FaIR in 2300 for SSP5 is about –2.5 to +7 degrees Celsius about the median.

METHODS FOR CLIMATE DAMAGE ESTIMATION The third step in estimating the SCC is translating changes in the climate system, such as temperature, into total economic damages over time. Damages can be calculated by estimating costs for various sectors (e.g., human health and mortality, agriculture, energy usage, coastal flooding) and summing them, or by taking an aggregate approach to estimate damages across the economy as a whole.

Recent advances in methodologies for damage estimation are not reflected in the integrated assessment models used by the federal government to calculate the SCC (NASEM 2017; Diaz and Moore 2017). The NASEM report made recommendations on improving sectoral damage estimation, finding sufficient peer-reviewed research to support updates on human health and mortality, agriculture, coastal inundation, and energy demand. Since the report was issued, the literature addressing specific sectors has grown.

Nevertheless, few studies meet the full requirements (e.g., global coverage with regional detail, translation into economic damages) put forward by Diaz and Moore (2017) or Raimi (2021) to serve as the basis for an updated damage function for the SCC. For example, two independent, comprehensive reviews (Bressler 2021; Raimi 2021) found just three suitable studies (World Health Organization 2014; Gasparrini and others 2017; Carleton and others 2018). Our own further assessment of the damages literature found two candidates for agricultural damages (Moore and others 2017; Calvin and others 2020), two for energy demand (Clarke and others 2018; Ashwin and others 2021), and one for coastal damages (Diaz 2016).

Among the notable additions, the Climate Impact Lab has developed a methodology to generate empirically derived, hyper-localized damage functions accounting for adaptation. The Climate Impact Lab in its research has been applying its methodology across a comprehensive set of sectors including health, agriculture, labor, energy, conflict, coastal, and migration (Carleton and others 2018). Upon completion, this full set of sectors is intended to support fully empirically based climate damage estimates.

Much of the new sectoral damages research identified here is currently under peer review for publication, and efforts to implement the existing peer-reviewed studies will similarly be completed on a timeline that is compatible with the IWG process to update the SCC. As described below, for the purposes of this paper we have deployed the aggregate global climate damage function from the widely used DICE model (Nordhaus 2017b) to develop illustrative SCC estimates, coupled with the RFF-SPs, the FaIR climate model, and the stochastic discounting approach described in the next section.

III. Discounting Approaches for the Social Cost of Greenhouse Gases

The long residence time of CO_2 in the atmosphere implies that today's emissions will have consequences for centuries. This time horizon makes the discount rate a major factor for the SCC. For example, the IWG's 2021 interim SCC estimate is \$51/ton with a 3 percent discount rate (IWG 2021) but would be about \$121/ton at a 2 percent discount rate (RFF and NYSERDA 2021). That 1 percentage point difference alone would more than double the SCC and, by implication, greatly strengthen the economic rationale for substantial emissions reductions.

The discount rates used in federal regulatory analysis are guided by Circular A-4, issued by the Office of Management and Budget (OMB) in 2003, which endorses rates of 3 percent and 7 percent reflecting, respectively, consumption and investment rates of return (White House 2003). OMB guidance also allows for additional sensitivity analysis in cases with intergenerational consequences, such as climate change. However, this guidance runs counter to current economic thought and evidence, for three reasons: (1) a constant deterministic discount rate becomes increasingly problematic for long-horizon problems (Weitzman 1998); (2) benchmarks for the consumption rate of interest (currently 3 percent) have declined substantially over the past two decades (CEA 2017; Bauer and Rudebusch 2020, 2021); and (3) the rationale for 7 percent—to address possible policy effects on capital—is flawed in ways that are magnified for very long term decisions (Li and Pizer 2021).

The NASEM (2017) report and recent technical guidance on the SCC (IWG 2021) acknowledged those concerns. A 2021 executive order directed the OMB to reassess existing practice and consider "the interests of future generations" in revisions to Circular A-4 (White House 2021a, sec. 2). Alongside issues related to empirical discount rate uncertainty over long time horizons, the comparison of welfare across generations creates an ethical concern dating back at least as far as Ramsey (1928): Do we discount the welfare of future generations simply because they are born later?

One rationale for changing the government's discounting approach is the systemic decline in observed interest rates over at least the past two decades (Kiley 2020; Del Negro and others 2017; Johannsen and Mertens 2016; Laubach and Williams 2016; Caballero, Farhi, and Gourinchas 2017; Christensen and Rudebusch 2019; CEA 2017; Rachel and Summers 2019; Bauer and Rudebusch 2020, 2021), which along with other research on discount rates for very long-run horizons (Giglio, Maggiori, and Stroebel 2015; Giglio and others 2021; Drupp and others 2018; Carleton and Greenstone 2021) has led to calls for using a lower discount rate; 2 percent is often suggested.

The second argument for a modified discounting approach stems from uncertainty in the discount rate, which tends to lead to declining future discount rates. Weitzman (1998) showed that if one is uncertain about the future trajectory of (risk-free) discount rates, and uncertain shocks to the discount rate are persistent, the certainty-equivalent (risk-free) discount rate declines with the time horizon toward the lowest possible rate. This result stems from a straightforward application of Jensen's inequality to a stochastic discount factor, leading to declining (risk-free) discount rates

(Arrow and others 2014). At the same time, if the payoffs to investments in emissions reductions are correlated with future income, the effective *risk-adjusted* rate could be higher if the correlation is positive or lower if it is negative (Gollier 2014). This correlation is often termed the "climate beta," but it is not clear ex ante whether the beta is positive, as in Nordhaus's work and as argued by Dietz, Gollier, and Kessler (2018), or negative, as in Lemoine (2021).

The third issue is the need, in light of recent research (Li and Pizer 2021), to rethink the use of the higher discount rate (7 percent) reflecting the return to capital. Several decades ago, researchers suggested that when taxes create a wedge between consumption and investment interest rates, the alternative rates could be used to bound a benefit-cost analysis, as a shorthand version of the shadow price of capital (SPC) approach (Harberger 1972; Sandmo and Drèze 1971; Marglin 1963a, 1963b; Drèze 1974; Sjaastad and Wisecarver 1977). However, the assumptions underlying the soundness of that approach are quite restrictive: costs are assumed to occur entirely in the first period; benefits are constant and occur either in a single period or in perpetuity; and benefits displace only consumption while costs displace either investment or consumption. Li and Pizer (2021) extend Bradford (1975), showing that the traditional approach of using 7 percent as a shorthand means for representing investment impacts of regulatory costs becomes increasingly very inaccurate the farther one looks into the future.

The NASEM (2017) report foreshadowed those results and recommended using a central consumption rate estimate along with sensitivity cases. Newell, Pizer, and Prest (2021) provide some guidance, examining central values of 2 percent and 3 percent and a range of values between 1.5 percent and 5 percent (though they do not recommend those particular values). Their discussion of discount rates is based primarily on questions about the most appropriate near-term consumption rate and does not address the SPC approach. Pizer (2021) details how the SPC approach could be implemented, suggesting sensitivity cases that employ the consumption discount rate, with costs and benefits alternately multiplied by the SPC to reflect the possibility that the entirety of each of these impact streams falls on investment: an SPC of 1.2 is proposed as a conservative value. Alternatively, simply multiplying regulatory costs by the SPC provides a sensitivity case that is consistent with an (extreme) scenario where all costs fall on investment. Conceptually, this is equivalent to what is being sought with the traditional approach of discounting benefits at the higher 7 percent rate, but it has the advantage of both being analytically correct and allowing for a consistent discounting approach across different elements of benefit-cost analysis. The consumption discount rate would be employed in all cases, and the SPC approach would apply generally, not just in the context of the SCC.

Each of these discounting ideas (including stochastic growth discounting, discussed below) could be incorporated in a revision to Circular A-4, with relevance to both SCC estimation and other contexts. This would harmonize SCC discounting and broader US government guidance on benefit-cost analysis.

III.A. Stochastic Growth Discounting with Economic Uncertainty

One rationale for discounting, generally, is the concept of declining marginal utility of consumption. Intuitively, a \$100 cost in a future in which society has grown dramatically wealthier should be valued less, from today's perspective, than the same \$100 cost in a relatively poor future with stagnant economic growth. This result is often embodied by the classic equation derived in Ramsey (1928) that relates the consumption discount rate (r_t) to the rate of consumption growth (g_t) over time:

$$r_t = \rho + \eta g_t. \tag{1}$$

In equation (1), ρ represents the rate of pure time preference (how much utility is discounted over time) and η represents the curvature of an isoelastic utility function.[24] We use time subscripts to refer to the compound average value of the indicated variable from today (time 0) to year t. If average consumption growth to year t, g_t, is uncertain, as it is given the probabilistic socioeconomic scenarios discussed earlier, then the average discount rate to year t, r_t, is also uncertain. This leads to a stochastic discount factor, which is used to discount stochastic marginal damages from an incremental ton of emissions (MD_t) to a present value (PV) equivalent:

$$PV\left(MD_t\right) = E\left[e^{-r_t t} MD_t\right], \tag{2}$$

where r_t is determined by equation (1) based on the uncertain growth rate g_t. An alternative is to base the discount rate on some market proxy for the discount rate as in Bauer and Rudebusch (2021). Either way, the discount rate is considered uncertain, and the first term inside the expectation, $e^{-r_t t}$,

24. $u(c) = c^{1-\eta}/(1-\eta)$.

represents a stochastic discount factor. In our treatment, the discount factor and rate are uncertain due to the stochastic growth rate. The importance of a stochastic discount factor is well established in the finance literature, and its importance is increasingly recognized in the literature at the nexus of macro and climate economics (Cai and Lontzek 2019; Barnett, Brock, and Hansen 2020, 2021). A stochastic discount rate leads to a declining certainty-equivalent risk-free rate (Weitzman 1998). To clearly see the derivation of this result, suppose for the moment that the discount rate is normally distributed, $r_t \sim N(\mu_t, \sigma^2)$, and that it is uncorrelated with marginal damages, $corr(e^{-r_t t}, MD_t) = 0$, which corresponds to a climate beta of zero. Then it is easy to show that the certainty-equivalent rate, which is denoted r_t^{ce} and represents the rate at which to discount expected marginal damages (as in $e^{-r_t^{ce} t}E[MD_t]$), declines with the time horizon of the impacts being discounted, t:[25]

$$r_t^{ce} = \mu_t - \frac{1}{2}t\sigma^2. \tag{3}$$

Of course, equation (3) represents a special case. More generally, absent these two specific assumptions, the risk-free rate given by this equation does not account for the risk profile of the benefits of emissions reductions, namely, through the climate beta, which reflects the potential correlation of the stochastic discount rate with marginal damages. If one wants to retain the certainty-equivalent approach to discounting, Gollier (2014) shows that a risk adjustment is necessary to account for any such correlation, but the form of this adjustment depends on the potentially complex nature of the joint uncertainties. We instead take a more general approach to account for these issues by directly using the more general equations (1) and (2) to implement stochastic discounting as part of the Monte Carlo estimation of the SCC, which explicitly accounts for any such correlation. Accounting for this correlation is important in theory (Barnett, Brock, and Hansen 2021) and also,

25. A version of this result is shown in Newell and Pizer (2003), but for clarity of exposition we explain it briefly here. Starting with the definition that the certainty-equivalent rate yields the same present value of equation (2), we have $e^{-r_t^{ce}t}E[MD_t] = E[e^{-r_t t}MD_t] = E[e^{-r_t t}]\ E[MD_t]$, where the last equality follows by the assumption of zero correlation. Solving for r_t^{ce} yields $r_t^{ce} = \frac{1}{-t}\log(E[e^{-r_t t}])$. A well-known property of the exponential function, e^x, applied to a normally distributed variable, $x \sim N(\mu, \sigma^2)$, is that $E[e^{ax}] = e^{a\mu + \frac{1}{2}a^2\sigma^2}$. Applying this formula with $x = r_t$ and $a = -t$ yields the result.

as our results show, matters greatly in practice when the climate beta is not zero. Indeed, the climate beta in most integrated assessment models is implicitly taken to be close to one.

For example, in the DICE model, damages are assumed to be a percentage of GDP (where that percentage depends on global temperature), and the discount rate is a linear function of economic growth, as in a Ramsey-like framework (Nordhaus and Sztorc 2013). This implies a beta of essentially one, since higher income (and, in turn, greater discounting) is perfectly correlated with higher undiscounted damages. That is, a positive beta implies that undiscounted damages are largest when economic growth is largest, and smallest when growth is smallest. Mirroring this, with $\eta > 0$, the discount factor is smallest when growth is largest and largest when growth is smallest. Using a stochastic discount factor as in equation (2) will therefore discount damages most in states of the world where they accrue to rich future generations and correspondingly discount them least in states where the future is poor. Amid uncertainty about socioeconomic trajectories, ignoring this stochastic discount factor (and its correlation with climate impacts) could severely bias estimates of the SCC. The magnitude of this bias depends on the climate beta and on the nature of the uncertainty in socioeconomic and emissions trajectories; Newell, Pizer, and Prest (2021) and our illustrative results (below) show that this bias could change the SCC by a factor of two or more.

Despite the importance of stochastic discounting, federal government benefit-cost analysis has historically not treated the discount rate as explicitly uncertain, nor has the discount rate been connected to growth as in the Ramsey framework. Instead, the consumption discount rate used in past government estimates of the SCC has been a constant rate of 3 percent.[26] This is equivalent to implicitly choosing the discounting parameters ρ = 3 percent and $\eta = 0$, corresponding to a linear utility function. Yet this approach effectively eliminates any consideration of declining discount rates, as in Weitzman (1998), and risk premia, as in Gollier (2014). More intuitively, it also treats a \$100 cost to a member of a wildly rich future generation the same as a \$100 cost to a poor one, which is incorrect from

26. Although 3 percent was the central rate, the IWG also previously used constant rates of 2.5 and 5 percent as sensitivity cases. Because those values were estimated to roughly approximate the effects of explicitly accounting for uncertainty in risk-free and risk-adjusted rates (Newell, Pizer, and Prest 2021), those motivations are no longer appropriate when stochastic discounting can be captured explicitly in integrated assessment models, as we propose.

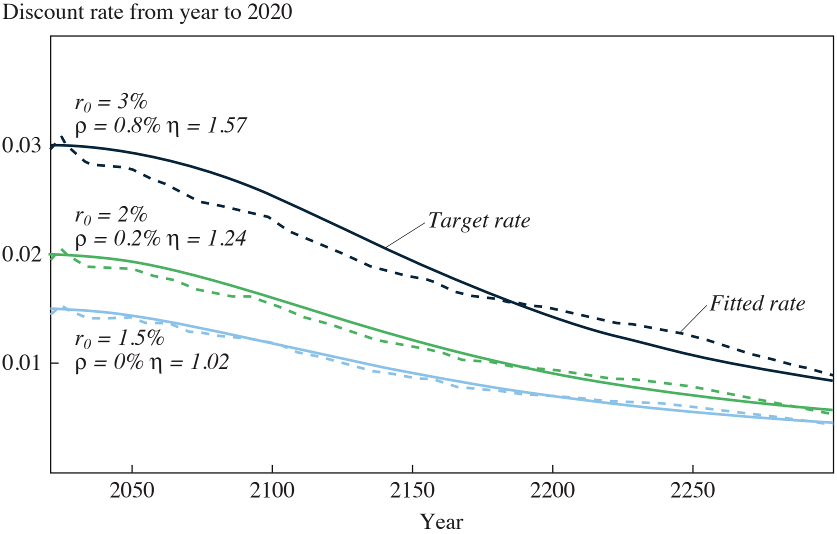
a welfare perspective. Correspondingly, such parameter values receive little support from economists working in this field (Drupp and others 2018).

Although the case for using stochastic discounting as in equation (1) is strong, the choice of the parameters in that equation is not a simple matter, and their values can lead to very different effective discount rates (Stern 2007; Nordhaus 2017a) and their connection to economic growth and climate damages. One recent paper surveyed economists about their preferred values of ρ and η (Drupp and others 2018). This is valuable, but the federal government has a long tradition of relying on descriptive, empirical approaches to informing discounting guidance, as in other aspects of benefit-cost analysis. In particular, Circular A-4 refers to observed interest rates in selecting 3 and 7 percent (White House 2003). A choice of ρ and η might therefore sensibly start with the constraint that the associated near-term rate match the consumption rate used elsewhere in benefit-cost analysis, as recommended in NASEM (2017). However, a continuum of (ρ, η) combinations can match any particular near-term rate, so another constraint is needed.

Newell, Pizer, and Prest (2021) provide such an approach. They calibrate the values of (ρ,η) such that, when applied to the Müller, Stock, and Watson (2020) growth distribution, the implied discount rate term structure starts at a specified rate in the near term (say, 3 or 2 percent) before declining with the time horizon in a manner consistent with evidence from the empirical literature on future interest rate term structures (Bauer and Rudebusch 2020, 2021).[27] Figure 10 illustrates the calibrated combinations of (ρ, η) yielding implied (fitted) term structures when applied to the RFF-SPs (dashed lines). These parameters were calibrated to be as consistent as possible with those implied by the Bauer and Rudebusch (2021) model initialized to given targeted near-term rates of 1.5, 2, or 3 percent (solid lines). For example, using the estimated model from Bauer and Rudebusch (2021) and starting with a near-term rate of 2 percent, we construct a target term structure (solid black curve). We then find the combination, (ρ, η) = (0.2 percent, 1.24), that best fits the target term structure.

27. The parameters shown here differ slightly from those in Newell, Pizer, and Prest (2021) because we calibrate them to the full RFF-SPs, corresponding to the Müller, Stock, and Watson (2020) distribution weighted based on our economic growth survey. The methodology developed in Newell, Pizer, and Prest (2021) was demonstrated on the raw distribution, before the weights were applied.

Figure 10. Calibrated Certainty-Equivalent Risk-Free Term Structures and Target Term Structure



Source: Authors' calculations based on Bauer and Rudebusch (2021) and Müller, Stock, and Watson (2020).

The calibration procedure in Newell, Pizer, and Prest (2021) can be implemented for any specified near-term rate. Here we present three cases: 1.5 percent, 2 percent, and 3 percent:[28]

$$r_t^{1.5\%} = 0\% + 1.02g_t$$

$$r_t^{2\%} = 0.2\% + 1.24g_t$$

$$r_t^{3\%} = 0.8\% + 1.57g_t$$

These ρ and η parameters lie in the middle of the range often used in the literature, particularly for target near-term rates of 3 percent and 2 percent. Implementing them simultaneously with the socioeconomic trajectories discussed in section I produces a declining term structure of

28. See Newell, Pizer, and Prest (2021, sec. 3.2) for the rationale behind each rate, and that paper's appendix for additional alternative near-term rates.

certainty-equivalent, risk-free rates consistent with the empirical literature (Bauer and Rudebusch 2020, 2021). Importantly, implementing the stochastic discount rate alongside stochastic damages via equation (2) explicitly captures risk aversion and the correlation between the discount rate and climate damages, meaning no ex post risk adjustment to the discount rate is necessary.

This calibrated stochastic discounting rule can now be used with the undiscounted damage estimates (discussed above) to estimate the SCC in an internally consistent manner.

IV. Illustrative Calculations of the Social Cost of Carbon

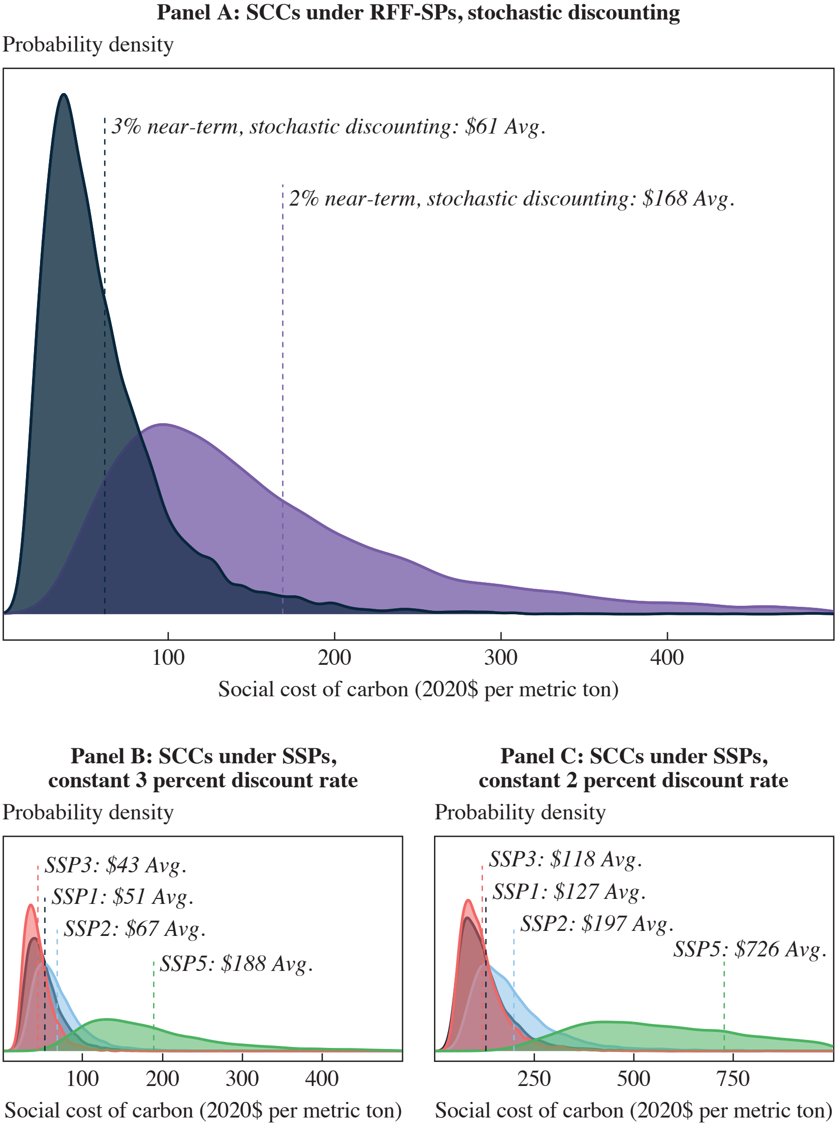
We present illustrative estimates of the SCC based on our socioeconomic projections (the RFF-SPs), the FaIR climate model, and our discounting methodology—all of which speak directly to the NASEM (2017) recommendations—and apply them using the DICE damage function (Nordhaus 2017a). This approach is directly responsive to three of the four NASEM recommendations. The fourth recommendation is to update the damage functions with the best available science on sectoral damages, rather than using an aggregate damage function such as that in DICE. We will include more recent sector-specific damage estimates, reflecting the best available science, in future work, but for the moment we use the DICE damage function to produce illustrative SCC estimates. Although the values we present here should be considered illustrative, they highlight the importance of socioeconomic uncertainty and stochastic growth discounting, and the interaction of these two important drivers of the SCC.

We also compare our SCC estimates with those from SSPs 1, 2, 3, and 5. Because of the lack of socioeconomic uncertainty in each SSP—and the lack of relative probabilities across them—we cannot meaningfully calibrate ρ and η parameters for those scenarios to deliver comparable near-term rates. We therefore apply constant discount rates of 2 percent and 3 percent to the SSPs.[29]

The results are shown in figure 11, leading to our first major conclusion: a quantitative probabilistic accounting of socioeconomic uncertainty matters

29. As an additional comparison, figure OA-13 in the online appendix presents an analogous figure to figure 11 but applying our RFF-SP-calibrated discounting parameters (ρ, η) to the SSPs. This is purely for presentational purposes, and we caution that our discounting parameters were not calibrated to the SSPs. Because the SSPs have no uncertainty within them, it is not possible to calibrate discounting parameters to them as we can do to the socioeconomic distributions (Newell, Pizer, and Prest 2021).

Figure 11. Illustrative Probability Distributions of Social Cost of Carbon (2020$/ton CO_2)



Source: Authors' calculations.

Note: The SCC estimates should be considered illustrative because they are based on alternative socioeconomic inputs, discounting approaches, the FaIR 2.0 climate model, and the DICE damage function.

Table 1. Effects of Discounting and Growth Distribution Tails on Illustrative SCC Estimates (2020$/ton CO_2)

	Stochastic growth discounting		*Constant discounting*	
	3 percent near-term $\rho = 0.8\%$ $\eta = 1.57$	*2 percent near-term* $\rho = 0.2\%$ $\eta = 1.24$	*3 percent constant*	*2 percent constant*
Mean SCC, full distribution	$61.4	$168.4	$194	$1,557
Mean SCC, drop top and bottom 1 percent global income draws	$60.6	$167.9	$96	$450

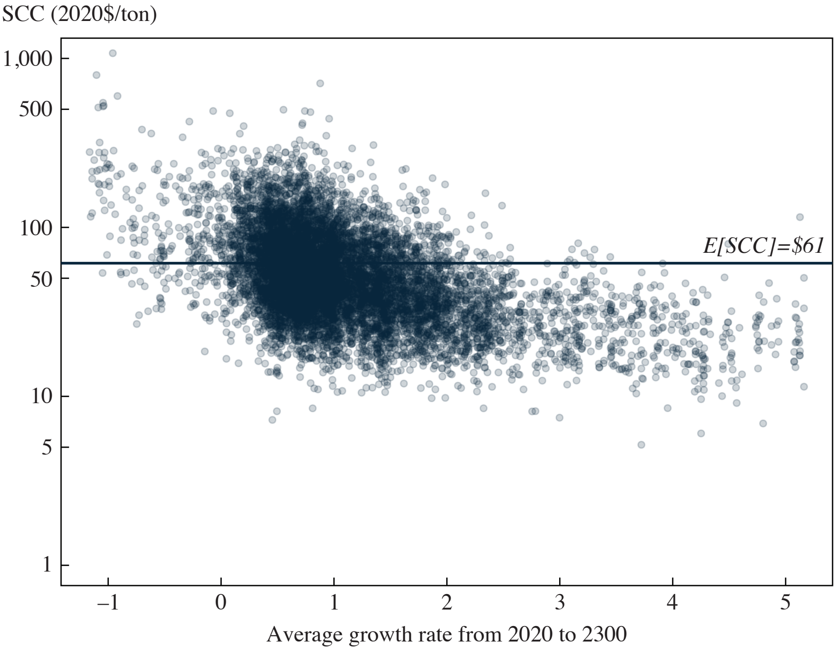
Source: Authors' calculations.

Note: The SCC estimates should be considered illustrative because they are based on alternative socioeconomic inputs, discounting approaches, the FaIR 2.0 climate model, and the DICE damage function.

greatly for the SCC. Panel A of figure 11 shows the distributions of our illustrative SCC values calibrated to 2 percent and 3 percent discount rates in the near term (means are also in the left columns of table 1). The other two panels show the SCC distributions under each SSP at 3 percent (panel B) and 2 percent (panel C) discount rates. Panel A reflects socioeconomic uncertainty implicitly, leading to central SCC estimates of $61 and $168/ton CO_2 under 3 percent and 2 percent near-term stochastic discounting, respectively. The distribution underlying those means reflects both socioeconomic and climate uncertainty. We disaggregate that distribution below, but the bottom panel shows the importance of socioeconomic uncertainty explicitly by comparing across the SSPs. SSP5 (high income growth) produces mean SCC values three to six times higher than the other SSPs. Hence, if one were to use a weighted combination of the SSPs, the resulting average SCC would reflect the relative weight given to each SSP, especially SSP5—a choice with no clear empirical basis. This result highlights the importance of incorporating a quantitative accounting of economic uncertainty, as in the RFF-SPs.

Next, figure 12 demonstrates the effect of stochastic versus constant discounting on the mean SCC, leading to our second major conclusion: stochastic growth discounting is crucially important to SCC estimation in the context of socioeconomic uncertainty. In table 1, the first two columns of the first row show mean SCCs under the RFF-SPs for stochastic growth discounting approaches consistent with 3 percent and 2 percent near-term rates (both in 2020 dollars), producing mean SCC estimates of $61.4 and $168.4/ton CO_2, respectively. These estimates, reflecting the updated socioeconomic, emission, climate, and discounting modules (three of the four

Figure 12. Illustrative SCC Estimates versus Average GDP per Capita Growth Rate (2020 to 2300)



Source: Authors' calculations.

Note: The values plotted correspond to estimates of the SCC and long-run cumulative growth rates using a 3 percent near-term stochastic growth discounting ($\rho = 0.8\%$, $\eta = 1.57$), the RFF-SPs, the FaIR 2.0 climate model, and the DICE damage function.

NAS recommendations), are 33 percent and 50 percent higher than the corresponding DICE-only SCC estimates from the 2016 IWG ($46 and $112/ton CO_2 in 2020 dollars; RFF and NYSERDA 2021).

We also present the results from the RFF-SPs with constant discounting to illustrate the importance of stochastic discounting, but as previously discussed, constant discounting is inappropriate when uncertainty in economic growth is considered, as here. When constant discounting is coupled with uncertain growth, the mean SCC is higher than is appropriate by a factor of three to nine, $194 and $1,557/ton CO_2 for 3 percent and 2 percent discount rates, respectively, because it ignores the correlation between damages and growth (the climate beta) and hence the discount rate. In other words, ignoring the risk profile of the SCC threatens to overstate the mean SCC in this example by a factor of three or more ($194 versus

$61/ton with 3 percent discounting, and $1,557 versus $168/ton with 2 percent discounting).

More specifically, the high expected values reflect a right-skewed distribution of damages. It is well known that skewed distributions and tail events can influence the expected value of the benefits of mitigating climate change (Gollier 2008; Weitzman 2011, 2014). Under constant discounting, such tail events are very rich futures with associated large amounts of consumption at risk from climate change. Yet constant discounting treats each dollar of cost to those wealthy future generations the same as a dollar of cost to a relatively poor future. Hence, with constant discounting, the effects on the future rich inappropriately dominate the expected value of the SCC, leading to a strong upward bias in the SCC estimate.

This problem is recognized in the finance literature as the result of ignoring the risk properties of an investment—namely, the correlation of an uncertain payoff with the stochastic discount rate. Stochastic growth discounting addresses this by discounting the high-growth, high-damage states at a higher rate. By discounting high-growth states more, stochastic discounting stabilizes the mean and variance of the SCC, as documented in Newell, Pizer, and Prest (2021).

The second row of table 1 highlights this greater stability under stochastic discounting by showing a sensitivity case in which we drop the top and bottom 1 percent of the global average income trajectories.[30] Under constant discounting, the mean SCC is quite sensitive to dropping these 1 percent extremes, falling from $194 to $96/ton at a 3 percent discount rate and from $1,557 to $450/ton at a 2 percent discount rate. By contrast, the mean SCC is virtually unchanged under stochastic discounting, changing by less than 1.5 percent for each of the stochastic rates that are consistent with 2 percent and 3 percent near-term rates. More generally, the SCCs with stochastic discounting change only negligibly even when much larger percentiles are dropped from the tails. For example, with stochastic discounting, the mean SCCs also change by less than 1.5 percent even when the top and bottom 10 percent of draws of global average income trajectories are dropped, whereas under constant discounting, the mean SCCs fluctuate by factors of 3 to 11. This result highlights the stabilizing effect of properly incorporating stochastic growth discounting, as anticipated in the NASEM (2017) report.

30. Specifically, we drop the draws with global average GDP per capita in 2300 in the top 1 percent and bottom 1 percent of draws, before taking the average SCC.

This stability with stochastic discounting is apparent in figure 12, which plots the individual Monte Carlo SCC draws against each draw's long-run (2020–2300) global GDP per capita growth rate, under the 3 percent near-term stochastic discounting parameters ($\rho = 0.8\%$, $\eta = 1.57$).[31] Roughly speaking, the vertical spread of SCC values in the figure largely reflects climate uncertainty for each given level of growth in GDP per capita, whereas the horizontal spread of SCC values reflects uncertainty in long-run income growth. Because the DICE damage function is proportional to GDP, undiscounted marginal damages scale roughly one-for-one with income growth, but with $\eta > 1$ they are discounted somewhat more than one-for-one with stochastic discounting, leading to a modest negative relationship between the SCC and GDP per capita growth. In other words, the SCC is higher when income growth is lower, and vice versa.

V. Conclusion

Since the SCC is a vitally important metric guiding climate policy, its calculation must be supported by the best available science, including an explicit incorporation of uncertainty. Our results demonstrate that socioeconomic uncertainty and stochastic discounting are important drivers of the SCC, and our work presents an opportunity to incorporate those uncertainties into ongoing updates.

Although the SCC estimates presented here are meant to be illustrative and use a highly simplified estimate of climate damages, they nonetheless highlight two major conclusions. First, socioeconomics matter significantly to the SCC, highlighting the importance of a quantitative accounting of socioeconomic uncertainty. Whereas scenario-based socioeconomic projections like the SSPs have no formal probabilities attached to them, our approach to quantifying uncertainties in future trajectories of population, GDP, and emissions helps account for these uncertainties in the SCC. Second, when incorporating socioeconomic uncertainty, stochastic growth discounting is crucial to account for the correlation of climate damages and the discount rate, whereas ignoring it leads to a large upward bias in the SCC estimate. Our work represents an advance in uncertain socioeconomic trajectories and discounting approaches based on empirically based explicitly probabilistic methods. Nevertheless, potentially important components

31. The shape of the curve is similar under the 2 percent near-term parameters ($\rho = 0.2\%$, $\eta = 1.24$) but shifted up to a higher level.

have not yet been fully incorporated into officially adopted SCC values. Recent work has begun to account for how the risk of tipping points influences the SCC (Dietz and others 2021). Other important factors include climate-related migration, conflict, and loss of at-risk species. Another conceptual issue is equity weighting, wherein effects on poorer regions of the world could be weighted more than equivalently sized dollar value to rich regions (Errickson and others 2021). Future research in these areas could be incorporated into official SCC values over time.

More generally, the SCC should be continually updated as the scientific frontier advances, as recommended by NASEM (2017). Our work speaks directly to those NASEM recommendations and presents an opportunity for the US government to improve on simple, deterministic approaches to socioeconomic projections and discounting methodologies to better reflect the interrelated uncertainties about future population, income, emissions, climate, and discount rates.

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