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

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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 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 SCC underscores the importance of adopting a stochastic discounting approach to account for uncertainty in an integrated manner.

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I. Introduction

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."[1] 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 (e.g., Pigou 1920; Nordhaus 1982).[2]

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 rulemaking process since Executive Order 12291 was issued more than 40 years ago.[3]

The SCC also was the basis for the value of federal tax credits for carbon capture technologies, beginning in 2018,[4] and zero-emissions credits for nuclear power in New York State.[5] The power grid operator for New York is working to include the SCC as a cost "adder"

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[1] https://www.economist.com/united-states/2017/11/16/the-epa-is-rewriting-the-most-important-number-in-climate-economics;https://www.bloomberg.com/news/articles/2021-01-22/how-do-you-put-a-price-on-climate-change-michael-greenstone-knows

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

[3] Executive Order 12291 was the original Reagan-era guidance for benefit-cost analysis, later superseded by Executive Order 12866 in 1993.

[4] https://www.whitecase.com/publications/insight/carbon-capture/us-tax-credit-encourages-investment

[5]https://documents.dps.ny.gov/search/Home/ViewDoc/Find?id={44C5D5B8-14C3-4F32-8399-F5487D6D8FE8}&ext=pdf, page 131.

Conflict of Interest Disclosure:

on top of energy supply bids submitted by power plants, thereby reflecting social costs into market prices and plant dispatch.[6] Many other states have used the SCC as the basis for climate policies[7] and as a benchmark against which proposed carbon prices are compared.[8] Proposed applications include federal procurement decisions[9] and royalties on oil and gas leases on federal land (Prest 2021; Prest and Stock 2021).[10]

Construction of the SCC and the benefits of reducing emissions is 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 for 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 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 William Nordhaus (alongside Paul Romer) for his work incorporating climate change into economic analysis, including the role of the SCC in informing policy.

The SCC is typically estimated using integrated assessment models (IAMs), such as the DICE model developed by Nordhaus. IAMs couple climate and economic models to estimate the economic effect of an incremental pulse of CO_2 emissions (in tons) on climate and economic

[6] https://www.nyiso.com/carbonpricing

[7] https://costofcarbon.org/states

[8] https://www.rff.org/publications/explainers/carbon-pricing-101/, https://www.rff.org/publications/data-tools/carbon-pricing-bill-tracker/, https://www.wsj.com/articles/BL-EB-7156

[9] https://www.whitehouse.gov/briefing-room/presidential-actions/2021/05/20/executive-order-on-climate-related-financial-risk/, Sec. 5(ii).

[10] Many aspects of climate policy decisions are not necessarily tied to the SCC. Essentially, those 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 (e.g., 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.

outcomes. The net present value of changes in economic outcomes, divided by the number of tons in the pulse, delivers the SCC. However, many IAMs 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 Carbon 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 (above).

Figure 1 shows how the modules fit together, including how socioeconomics affect emissions trajectories, which are input into the climate model to project future temperatures. These temperatures are converted into a stream of future economic losses in the damages model (also influenced by socioeconomic trajectories), which are then discounted to a present value in the discounting module.

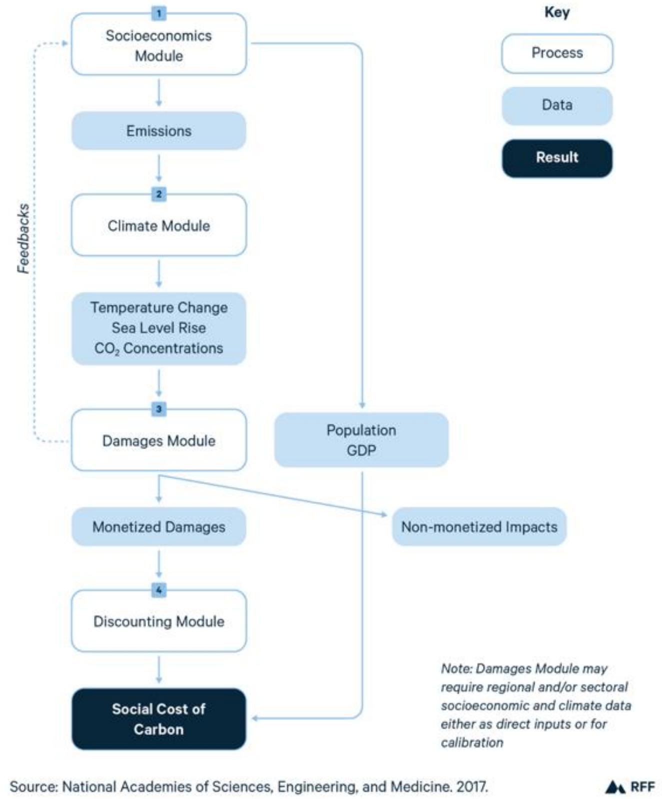

Figure 1. Modularized Approach to Estimating SCC

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 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.

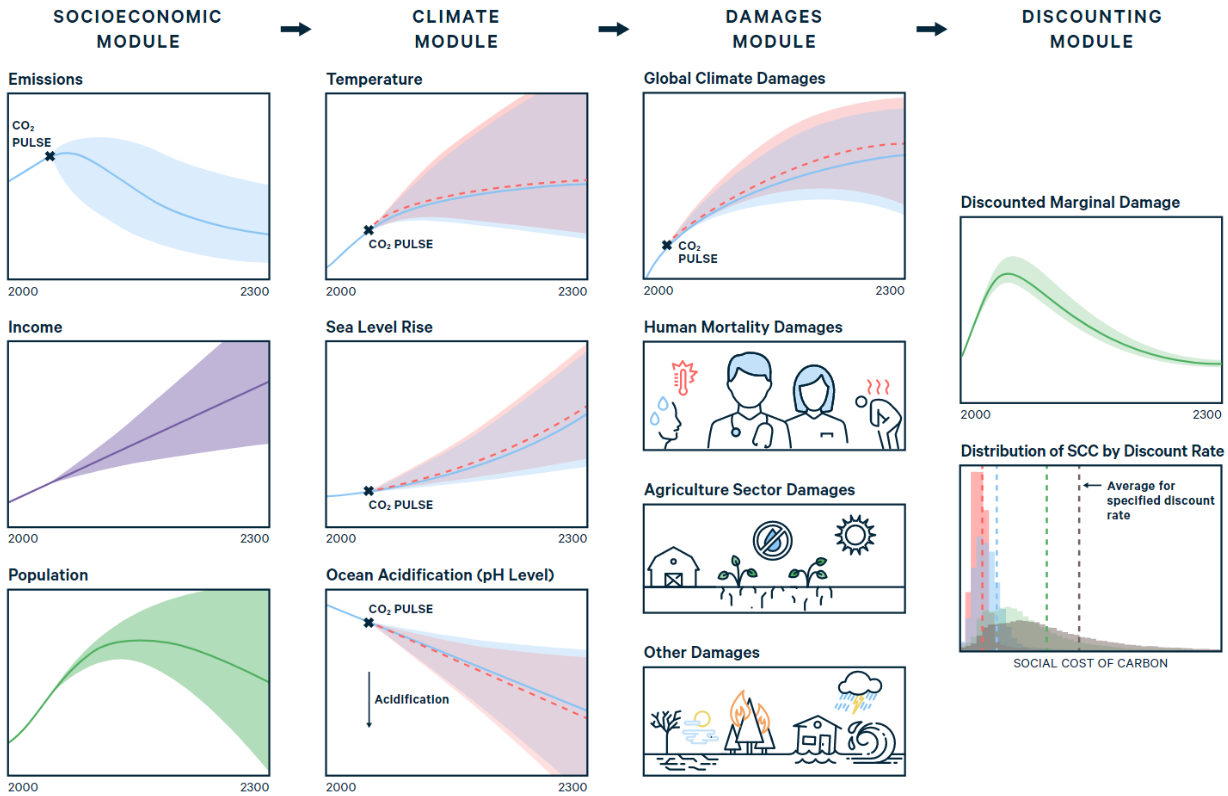

Figure 2. Estimating Social Cost of Carbon under Uncertainty

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

The NASEM report noted that IWG SCC estimates, 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. The discounting approach also 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 II discusses the improved socioeconomic module, with long-term probabilistic projections of population, economic growth, and emissions. Section III illustrates how an incremental ton of emissions translates into climate and economic effects (“damages”). Section IV 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 V 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 VI concludes and raises issues that await future research.

II. 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 2017a). For example, the monetization of mortality consequences typically depends on per capita income. 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 and others 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 200 to 300 years into the future (NASEM 2017). Yet nearly all projections 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).

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 SCC 2010), and these same scenarios support the interim estimates put forward by the Biden administration in January 2021 (IWG SCC 2021). The IWG used five socioeconomic scenarios drawn from the Energy Modeling Forum (EMF) 22 (Clarke and Weyant 2009) modeling exercise, selected to roughly span the range of emissions outcomes in the full set of EMF 22 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 EMF 22 work).

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. Müller, Stock, and Watson (2021, hereafter MSW) 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.[11] Christensen and others (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 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 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 (RFF) SCC 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.

Probabilistic Population Projections to 2300

[11] The MSW method 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.

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. 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 (2022, forthcoming).

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 (MCMC) method, which produces a large number (typically 1,000-2,000) of trajectories 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 1,000-2,000 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).[12] Mortality is similarly

[12] The TFR has evolved in a similar way in all countries. Typically, in pre-industrial times, the TFR for a typical country was high (in the range 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

projected by focusing on life expectancy at birth.[13] 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 this UN method, designed for projections to 2100, out to 2300 and preliminary results were reviewed by a panel of nine expert demographers that we convened. 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% 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 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 21st century, albeit at a decreasing rate, to level off in the 22nd century, and to decline slightly in the 23rd century. Uncertainty for 2300 is

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 has fluctuated without a clear trend, mostly staying below the replacement rate. For example, in the US, 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).

[13] 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.

considerable, appropriately, reflecting the very long forecast time horizon, with a median forecast of 7.5 billion, but a 95% interval from 2.3 to 25.8 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. They show that 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 Northern America are also likely to peak and then decline, but much later, in the 22nd 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 Northern 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% 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 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 to 36.4 billion, compared with our 98% prediction interval of 1.7 to 33.9 billion. Although using different methodologies and carried out over 15 years apart, the two sets of projections give results that are compatible with one another, perhaps to a surprising extent.[14]

Another such exercise was carried out by Vallin & 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% interval, though with a range that is much narrower than either ours or that of United Nations (2004). Gietel-Basten and others (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.[15]

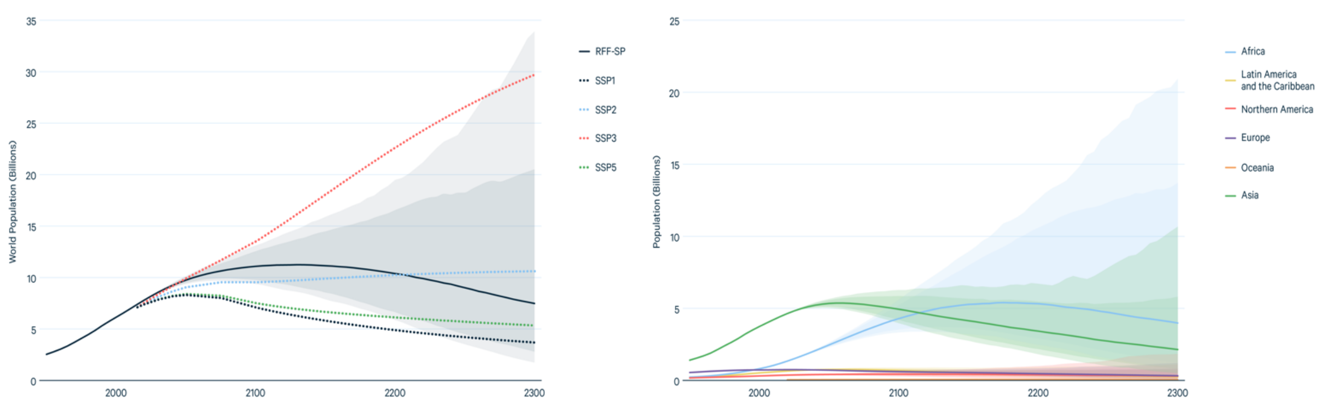

Figure 3. Probabilistic Population Projections for World and Major Regions, to 2300

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

Probabilistic Economic Growth Projections to 2300 and Economic Growth Survey

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

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

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. MSW (2019) took a significant step forward by providing probabilistic econometric projections over long periods. The MSW 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 Organisation for Economic Co-operation and Development, 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 fully below; for more information about the model, see MSW (2019).

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. Our Economic Growth Survey (EGS) focused on quantifying uncertainty for a representative frontier of economic growth in the OECD countries. The results informed econometric projections based on the MSW model 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 and others 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 11 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 in growth rates (rather than levels), we provided a spreadsheet tool that translated average growth rates into GDP per capita levels. Experts were informed that their combined quantiles of GDP levels would be combined with country-level econometric projections, as described below, but they were not shown the results. Experts 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. 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, 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 10 experts provided a pair of modified base quantiles to reflect the absence of effects from climate damages and climate policy, but in general the proposed modifications to their original distributions were minor. Moreover, several experts noted that although climate change was a primary driver of their low growth projections, the complexity of the uncertainties represented in their base quantiles precluded their systematic removal, and they deemed their base quantiles appropriate for assessing uncertainty in analyses intended to include the effects of 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 (CDF) specific to each expert. We next combined the CDFs in two ways: averaging across the set of expert CDFs 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.[16]

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 participants' median forecast was that long-term growth would be lower than the growth rate of the past 100 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.[17] When asked to identify the primary drivers of the low-growth quantiles, the experts most commonly responded 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 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

[16] See online appendix for further detail.

[17] 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.

do the statistical trajectories for all four years (2050, 2100, 2200, and 2300). The median of the equal-weighted combination is consistently higher than that 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 0 percent as highly unlikely but not impossible.

Results of econometric growth projections augmented with expert judgment. We used the EGS results to modify econometric projections of GDP per capita based on the MSW (2019) methodology and generate density functions of internally consistent projections of economic growth at the country level. As indicated in MSW (2019), economic growth 100 to 300 years into the future is highly uncertain, well beyond that captured in typical scenario projections (see Figure 5 below).

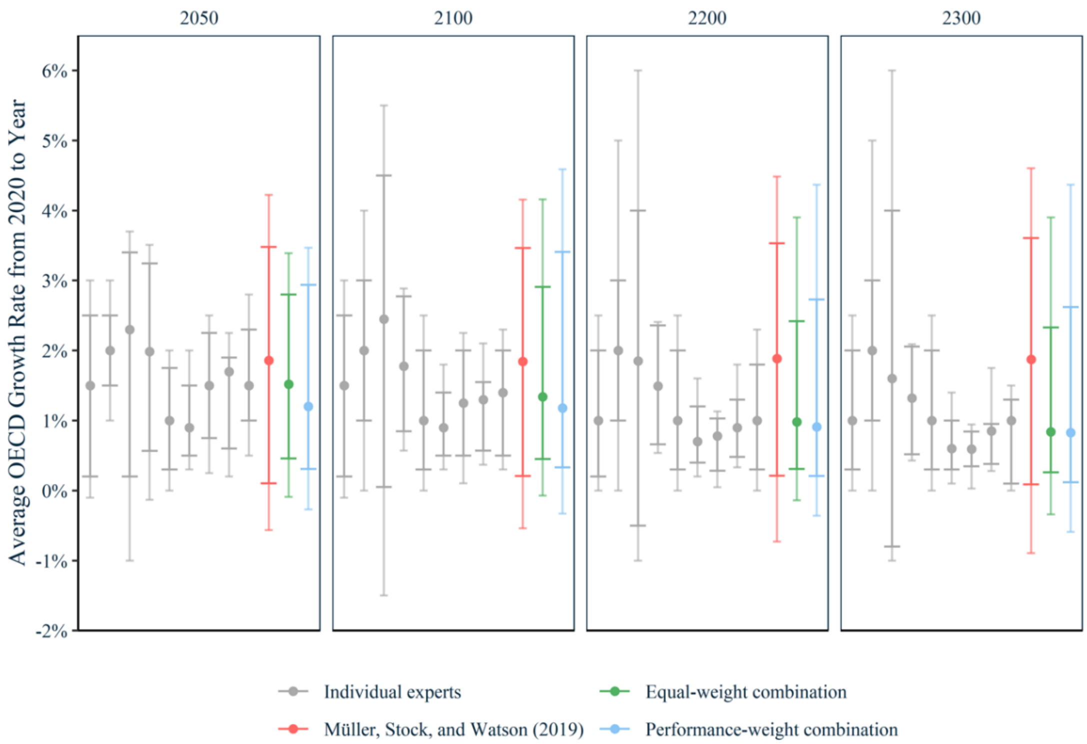

Figure 4. Distributions of Future Average GDP Growth Rates for OECD from Experts and Econometric (MSW) Sources

Note. For each bar, the circle shows the median and the lines show the 1st, 5th, 95th, and 99th percentiles of the relevant distribution.

The tails of the MSW 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 dataset (one of two datasets used by MSW),[18] 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.[19] In the MSW 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 the EGS are –0.6 percent 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 (an MSW coauthor), we omit some projections in the extreme tails of the MSW distribution that are outside the range of historical experience and also outside the long-run range implied by the EGS (see online appendix for our approach). Hereafter, we refer to this censored MSW version as the "MSW projections," while noting that it differs slightly in the extreme tails.

The EGS 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 MSW draws to satisfy the experts' combined distribution over the long run. The underlying projections from MSW remain unchanged, but the likelihood of drawing a given trajectory is modified such that the quantiles of OECD growth reflect the distribution produced by the EGS.

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 expert quantiles and the raw MSW quantiles. The NASEM report 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

[18] Available at https://clio-infra.eu/Indicators/GDPperCapita.html.

[19] For example, no country in Maddison Project data has observed 100-year growth rates below –1 percent or above +3 percent.

this reason, we increase the weight of the EGS quantiles versus the MSW quantiles linearly over time from 0 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 from MSW 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 MSW with those reweighted according to the EGS.

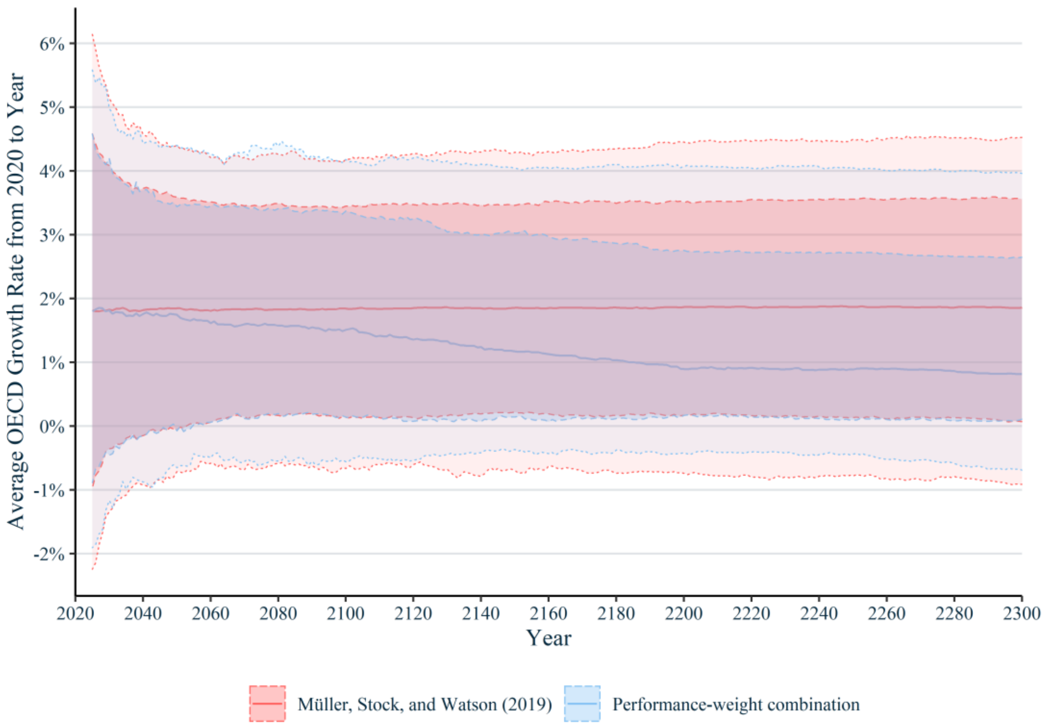

Figure 5. Average Projected Growth Rates of GDP per Capita in OECD Countries

Notes. Adapted from MSW (2019) and an EGS performance-weighted average of those data. Shaded areas and dashed/dotted lines represent 5th to 95th (darker, dashed) and 1st to 99th (lighter, dotted) percentile ranges.

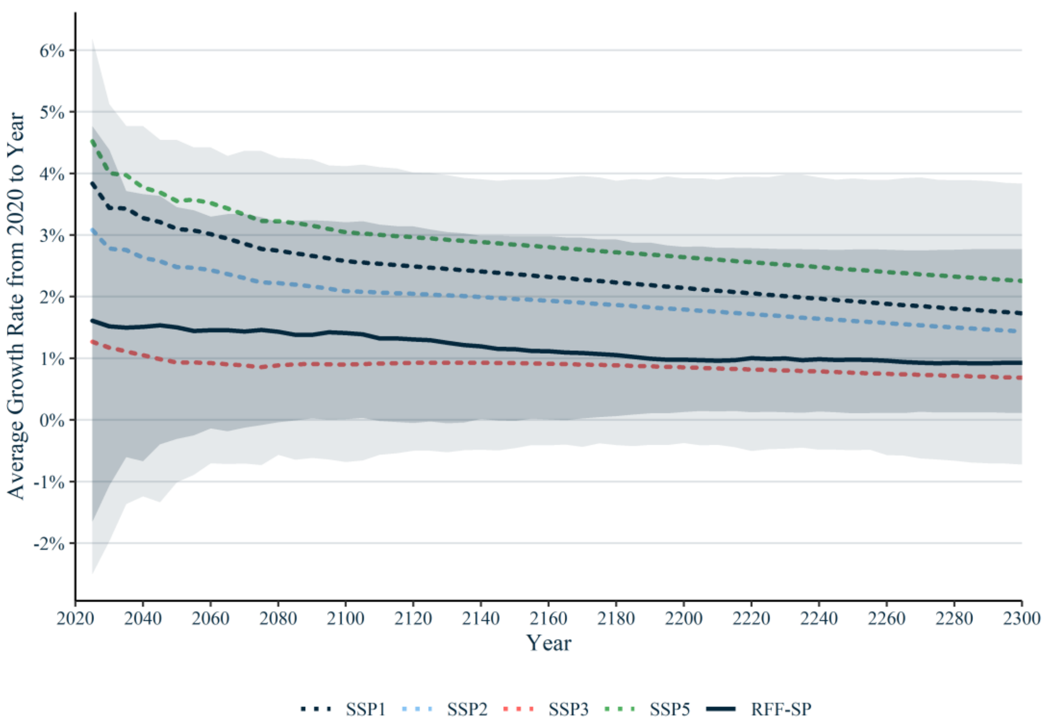

Figure 6. Average Projected Growth Rates of Global GDP per Capita

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.

We next generate a distribution of projected global GDP per capita rates by taking 10,000 independent samples from the population and EGS 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. 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 the RFF-SP growth trajectories. As will be discussed in section V, these relatively low growth potential paths contribute substantially to the SCC.

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, our Future Emissions Survey (FES) elicited 10 experts in socioeconomic projections and climate policy who were nominated by their peers and/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 FES 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 consistent with the expert's views on the evolution of future policy. The Evolving Policies case corresponds to the USG 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.[20]

For each expert we generate a set of cumulative distribution functions (CDFs), one for each benchmark year, emissions source, and economic growth trajectory, by piecewise linear interpolation between the quantiles provided. Then, as in the EGS, we generate a corresponding set of combined equal-weight CDFs by averaging the CDFs in equal measure, and a set of performance-weighted CDFs by averaging in accordance with the experts' relative performance on the calibration questions. Quantile values from the combined CDFs 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 FES, we developed a distribution of emissions scenarios to pair, 1-1, 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 emissions technologies (category 2) and summing the resulting trajectories, thereby including the possibility of net negative emissions.[21]

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[20] See online appendix for a more detailed discussion of the survey methodology and the full elicitation protocol.

[21] 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 III) 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.

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 C, even when considering the potential for negative emissions. [22]

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 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.[23]

[22] See online appendix for a more detailed summary of the rationales of the experts, including discussion of emissions from the other categories.

[23] See online appendix for results for additional years and gases.

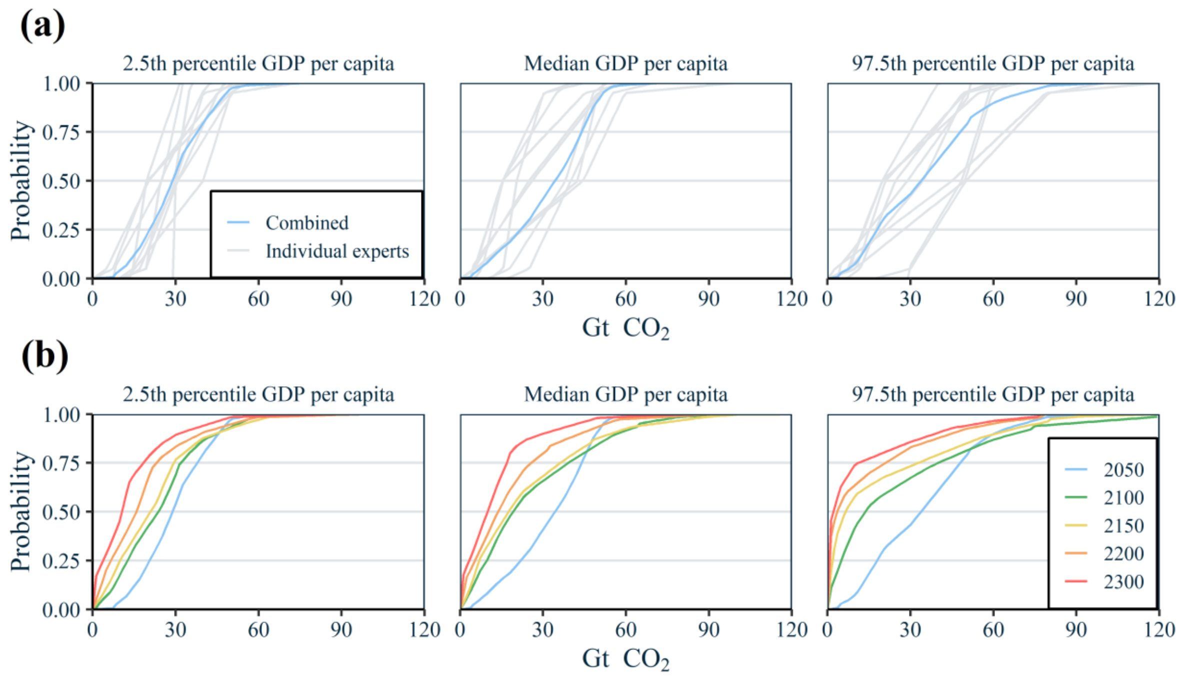

Figure 7. Cumulative Distribution Functions (CDFs) of Annual CO_2 Emissions

Panel (A): Individual Expert and Combined CDFs for 2050

Panel (B): Combined CDFs of Expert Projections for 2050 to 2300

The experts' narratives show an evolution of the combined distributions (Figure 8). 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 next century, while also allowing for the possibility of much higher emissions over the long term. (For the other categories of emissions sources and sinks, see online appendix).

Resulting global greenhouse gas emissions projections. Figure 8 shows the resulting distribution of projected net CO_2 emissions based on the FES. 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.[24] 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 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), the emissions and concentrations distribution resulting from the FES 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 FES CH_4 emissions maintain a relatively wide distribution, similar to that in 2100. For N_2O (Figure OA-10), the centers of the FES emissions and concentrations paths is similar to that of SSP5, and the full distribution from the FES spans a range wider than all the SSPs.

In sum, no single SSP is centered similarly to the FES median emissions paths across all three major greenhouse gases. The full range of emissions represented by the SSPs is higher than for the FES for CO_2 through 2140, by construction narrows to zero for CO_2 after that point, and is narrower than the FES results for CH_4 and N_2O after 2100.

[24] 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).

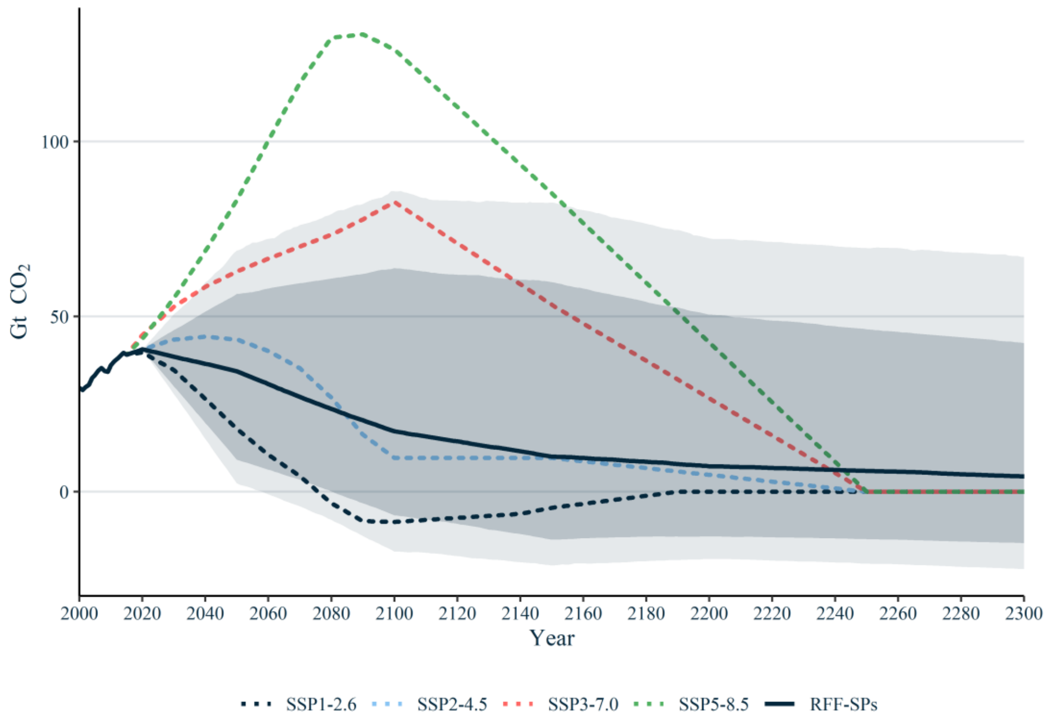

Figure 8. Net Annual Emissions of CO_2 from RFF-SPs and SSPs

Notes. 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.

III. From Emissions to Monetized Climate Damages

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 GHG 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 the integrated assessment models DICE, FUND, and PAGE, each of which employs its own reduced-form climate model. These IAMs 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 generate 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, Millar and others 2017) model 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.[25]

Resulting temperature change from RFF-SPs. Figure 9 shows the median temperature trajectory associated with the RFF-SPs: increases reaching nearly 3 degrees C 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 5 percent chance that the increase will remain below 2 degrees C 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 2200, 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.

[25] Trajectories for non-CO_2, CH_4, and N_2O were drawn from SSP2.

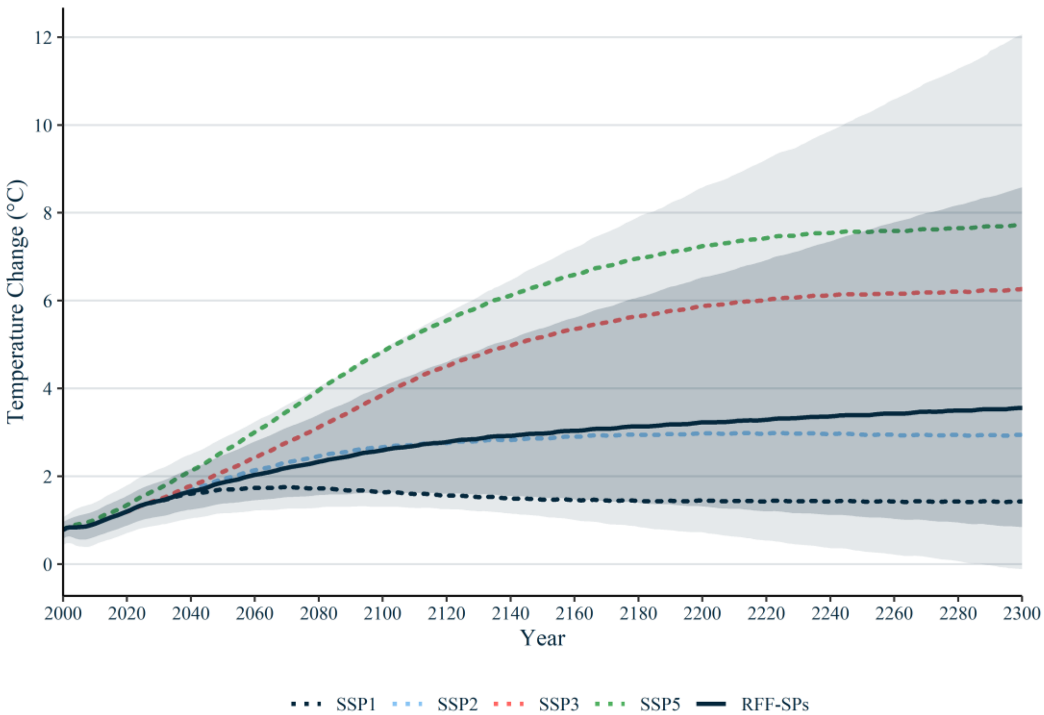

Figure 9. Global Mean Surface Temperature Change from RFF-SPs and SSPs

Notes. 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).

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 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 C 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 IAMs 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 (2017b) 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 (CIL) has developed a methodology to generate empirically derived, hyper-localized damage functions accounting for adaptation. The CIL 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.

IV. 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 SCC 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. 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 SCC 2021) acknowledged those concerns. A 2021 executive order[26] directed OMB to reassess existing practice and consider "the interests of future generations" in revisions to Circular A-4. 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 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

[26] https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/modernizing-regulatory-review/, Sec. 2.

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 and others (2018), or negative, as in Lemoine (2021).

The second argument 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 and others 2017; J. H. E. Christensen and Rudebusch 2019; CEA 2017; Rachel and Summers 2019; Bauer and Rudebusch 2020, 2021), which along with other research (Giglio and others 2015a, 2015b; Drupp and others 2018; Carleton and Greenstone 2021) has led to calls for using a lower discount rate; 2 percent is often suggested.

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) to show that the SPC approach yields a range of estimates centered on the results simply using a consumption interest rate.

The NASEM (2017) report foreshadowed those results and recommended using a central consumption rate estimate along with high and low sensitivity cases. Newell and others (2021) provide some guidance, suggesting a central value between 2 and 3 percent and high and low 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 of 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 around a central consumption discount rate, with benefits and costs alternately multiplied by a particular shadow price of capital; 1.2 percent is proposed as a conservative value. This approach to discounting sensitivity analysis would therefore include (1) a central case with a central consumption discount rate value and no use of the SPC; (2) sensitivities around this central case with low and high consumption discount rates; and (3) sensitivities around this central case with the SPC applied alternately to costs and benefits using a central discount rate. The sensitivity analysis (3) would be included only when the SCC is implemented in a particular benefit-cost analysis.

Each of those 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.

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 iso-elastic utility function.[27] 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

[27] $u(c) = c^{1-\eta}/(1-\eta)$.

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:

$$PV(MD_t) = E\left[e^{-(\rho+\eta g_t)t} MD_t\right]. \tag{2}$$

The first term inside the expectation, $e^{-(\rho+\eta g_t)t}$, represents a stochastic discount factor 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 and others 2020, 2021). A stochastic discount rate leads to a declining certainty-equivalent *risk-free* rate (Weitzman 1998). Of course, the risk-free rate does not account for the risk profile of the benefits of emissions reductions, namely through the potential correlation of the stochastic discount rate with marginal damages. This correlation (the climate beta) in most IAMs 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). 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 and others (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 central discount rate used in past government estimates of the SCC has been a constant rate of 3 percent.[28] This is equivalent to implicitly choosing the discounting parameters $\rho = 3\%$ 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 a welfare perspective. Correspondingly, such parameter values receive little support from economists working in this field (Drupp and others 2018).

Although the case 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 (e.g., Stern 2007; Nordhaus 2017a) and its 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 has referred to observed interest rates in selecting 3 and 7 percent. 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.

[28] 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 and others 2021), those motivations are no longer appropriate when stochastic discounting can be captured explicitly in the IAMs, as we propose.

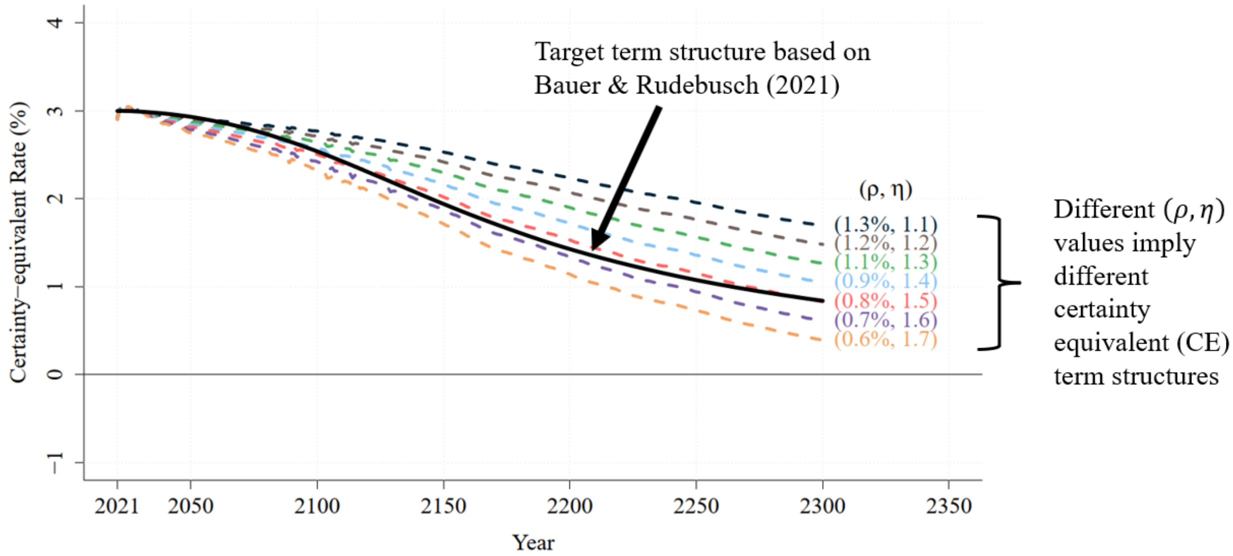

Figure 10. Certainty-Equivalent Risk-Free Term Structures under Alternative (ρ, η) Parameters, and Target Term Structure from Bauer and Rudebusch (2021)

Newell and others (2021) provide such an approach. They calibrate the values of (ρ, η) such that, when applied to the MSW 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). Figure 10 illustrates this idea, with different combinations of (ρ, η) yielding the same near-term rate but different term structures given the assumed economic growth uncertainty (dashed curves). Using the estimated model from Bauer and Rudebusch (2021) and starting with a near-term rate of 3 percent, we construct a target term structure (solid black curve). We then find the combination, (ρ, η) = (0.8%, 1.53), that best fits the target term structure.

The Newell and others (2021) calibration procedure can be implemented for any specified near-term rate. Here we present four cases: 1.5, 2, 3, and 5 percent (see section 3.2 of that paper for the rationale behind each rate, and its appendix for additional alternative near-term rates):

$$r_t^{1.5\%} = 0\% + 0.99g_t$$

$$r_t^{2\%} = 0.1\% + 1.25g_t$$

$$r_t^{3\%} = 0.8\% + 1.53g_t$$

$$r_t^{5\%} = 2.4\% + 1.86g_t$$

As discussed in Newell and others (2021), these ρ and η parameters lie in the middle of the range often used in the literature, particularly for the central rates of 3 and 2 percent. Implementing them simultaneously with the socioeconomic trajectories discussed in section II produces a declining term structure of 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.

V. 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 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 greatly for the SCC*. The top panel of Figure 11 shows the distributions of our illustrative SCC values calibrated to 2 and 3 percent discount rates in the near term (means are also in the left columns of Table 1). The bottom two panels show the SCC distributions under each SSP at 3 percent (left panel) and 2 percent (right panel) discount rates. The top panel reflects socioeconomic uncertainty implicitly, leading to central SCC estimates of \$56 and \$171/ton CO_2 under 3 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*. The first two columns of the first row show mean SCCs under the RFF-SPs for stochastic growth discounting approaches consistent with 3 and 2 percent near-term rates (both in 2020 dollars), producing mean SCC estimates of \$56 and \$171/ton CO_2, respectively. These estimates, reflecting the updated socioeconomic, emission, climate, and discounting modules (three of the four NAS recommendations), are 22% and 53% higher than the corresponding DICE-only SCC estimates from the 2016 IWG (\$46 and \$112/ton CO_2 in 2020\$, see RFF and NYSERDA 2020).

[29] As an additional comparison, Figure OA-13 of 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 and others 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 two to five, \$125 and \$785/ton CO_2 for 3 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 two or more (\$125 versus \$56/ton with 3 percent discounting, and \$785 versus \$171/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 (e.g., 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 and others (2021).

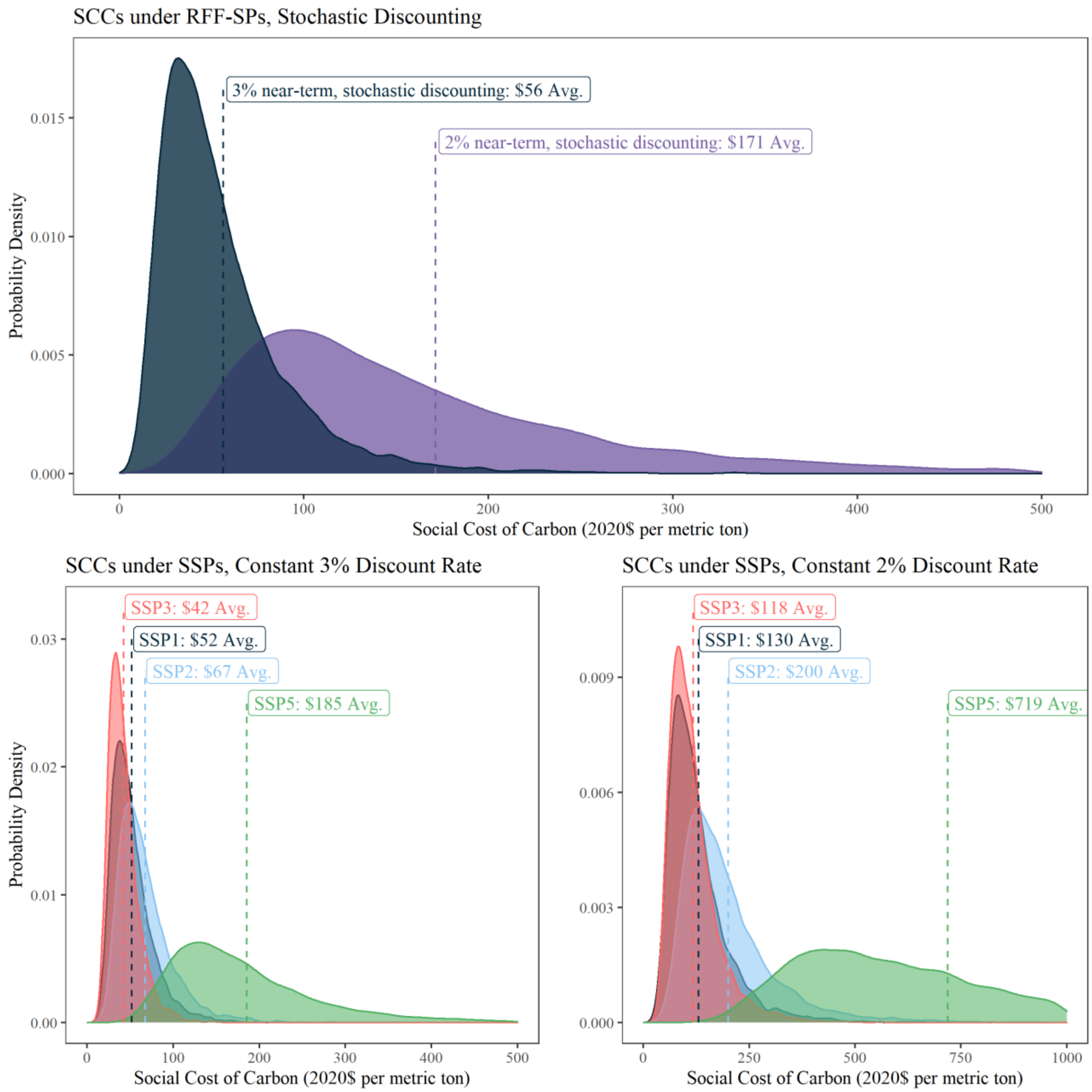

Figure 11. Illustrative Probability Distributions of Social Cost of Carbon (2020$/ton CO_2) under Alternative Socioeconomic Inputs and Discounting Approaches, with FaIR Climate and DICE Damage Modules

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 \$125 to \$85/ton at a 3 percent discount rate and from \$785 to \$371/ton at a 2 percent discount rate. By contrast, the mean SCC is virtually unchanged under stochastic discounting, changing by less than 0.5 percent for each of the stochastic rates that are consistent with 2 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 change by less than 1 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 two to four. This result highlights the stabilizing effect of properly incorporating stochastic growth discounting, as anticipated in the NASEM (2017) report.

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 ($\rho = 0.8\%$, $\eta = 1.53$).[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.

[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.

[31] The shape of the curve is similar under the 2 percent near-term parameters ($\rho = 0.1\%$, $\eta = 1.25$) but shifted up to a higher level.

Table 1. Illustrative SCC Estimates Using RFF-SPs, with FaIR Climate and DICE Damage Modules (2020$/ton CO_2)

	Stochastic growth discounting		Constant discounting	
	3% near-term $\rho = 0.8\%$ $\eta = 1.53$	2% near-term $\rho = 0.1\%$ $\eta = 1.25$	3% Constant	2% Constant
Mean SCC, full distribution	$56.2	$171.2	$125	$785
Mean SCC, drop top and bottom 1% global income draws	$55.9	$171.3	$85	$371

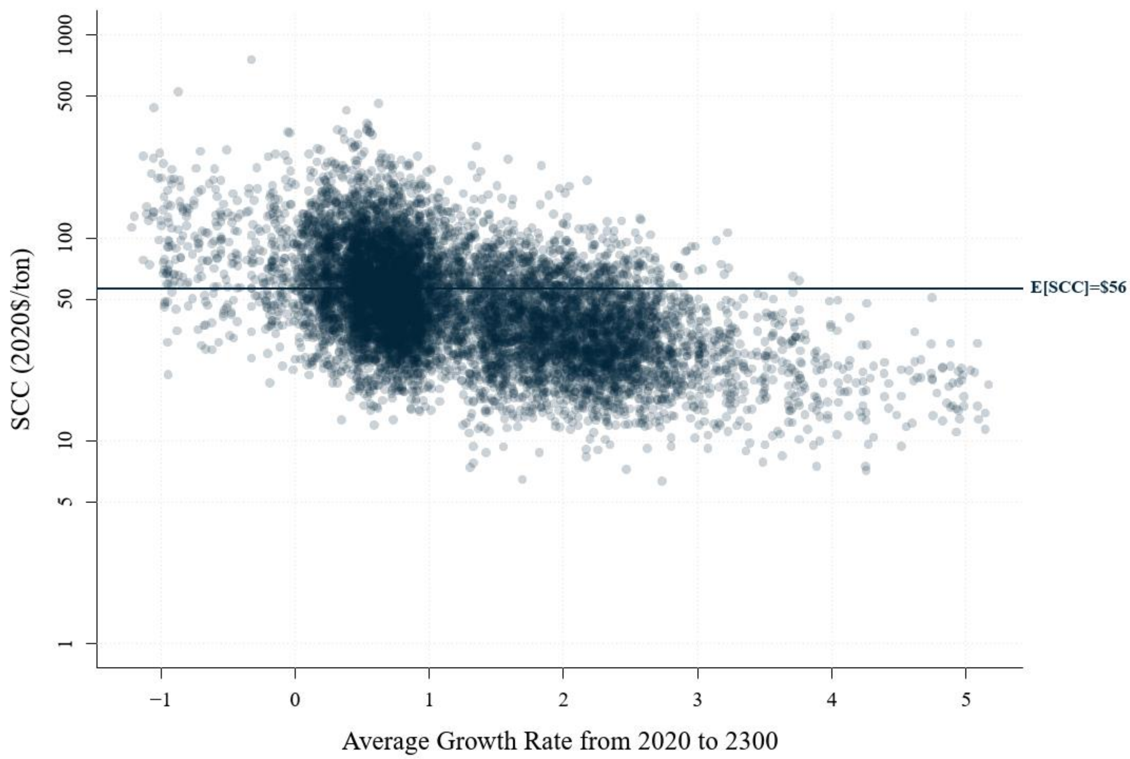

Figure 12. Illustrative SCC Estimates versus Average GDP per Capita Growth Rate (2020 to 2300), under 3% Near-Term Stochastic Growth Discounting ($\rho = 0.8\%, \eta = 1.53$), Using RFF-SPs and Stochastic Discounting, with FaIR Climate and DICE Damage Modules

VI. 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 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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The Social Cost of Carbon: Advances in Long-term Probabilistic Projections of Population, GDP, Emissions, and Discount Rates
Online Appendix

I. Description of censoring of raw MSW economic growth dataset

As indicated in MSW (2019), there is considerable uncertainty in future economic growth 100-300 years into the future. As a result, the tails of the MSW distribution are quite wide, leading to some implausibly small or implausibly large future levels of GDP per capita 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 that which has been observed for any country in the historical record over such long time periods (e.g., below -1% or above +5% annually on average through 2300), but nonetheless are possible as simulated projections given the distributional assumptions of the MSW model. Such low or high sustained growth rates would lead to global GDP/capita either falling by more than 90% between 2021 and 2300 (e.g., 0.99^{279}) or rising by a factor of more than 800,000 (1.05^{279}) implying a global average income of more than $10 billion per person. However, according to the Maddison Project dataset,[1] which includes country-level GDP/capita data as far back as 1500 for some countries, no country has ever experienced such extreme growth for such long periods of time.[2] Further, the 1st and 99th percentiles of the combined distribution of long-run growth rates based on the EGS are -0.6% and +4.4%, indicating long-run growth rates are exceptionally unlikely to fall outside this range. In the MSW model, those extreme tail outcomes are very likely driven by the structure of the Bayesian

[1] Available at https://clio-infra.eu/Indicators/GDPperCapita.html
[2] For example, no country in Maddison Project data has observed 100-year growth rates of below -1% or above +3%,

Conflict of Interest Disclosure:

model, such as its embedded distributional assumptions, rather than the historical data used to estimate the model.

For these reasons, and in consultation with James Stock (one of the authors of MSW (2019)), we lightly censor some projections in the extreme tails of the MSW distribution that are outside the range of historical experience and also outside the long-run range implied by the EGS, using a combination of two approaches. We first use the Maddison Project data to calculate, for each annual time horizon from 1 to 150 years, the minimum and maximum sustained growth rates ever observed by any country historically over that time horizon. For example, at the 50-year time horizon, these minimum and maximum rates were -2.4% (DR Congo, 1954-2004) and +7.0% (Equatorial Guinea 1958-2008). While this approach is sufficient to establish bounds for horizons up to 150 years into the future, it is less informative for the very long term (e.g., 150-300 years) because the Maddison data has relatively few countries for such long time horizons. Therefore, we augment these historical ranges using the range suggested by the extreme quantiles of the combined growth distribution from the EGS. Specifically, we use as bounding values the 0.5th and 99.5th quantiles of the combined (performance-weighted) distribution of long-run (2020-2300) growth rates from the EGS, which are -0.88% and +5.1%.

We use the outer envelope of (i.e., the less restrictive of) these two sets of bounding values for growth for each time horizon from 1 to 300 years. Specifically, these bounds are calculated as the outer envelope of the change in log(GDP/capita) implied by the horizon-specific growth rates from the Maddison data and those implied by the EGS (-0.88% and +5.1% annually). Country-by-year values in the projections that exceed these absorbing bounds are set equal to the bounds. This affects less than one percent of country-by-year draws in each tail of the distribution. The time paths of these absorbing bounds are shown in Figure OA-1.

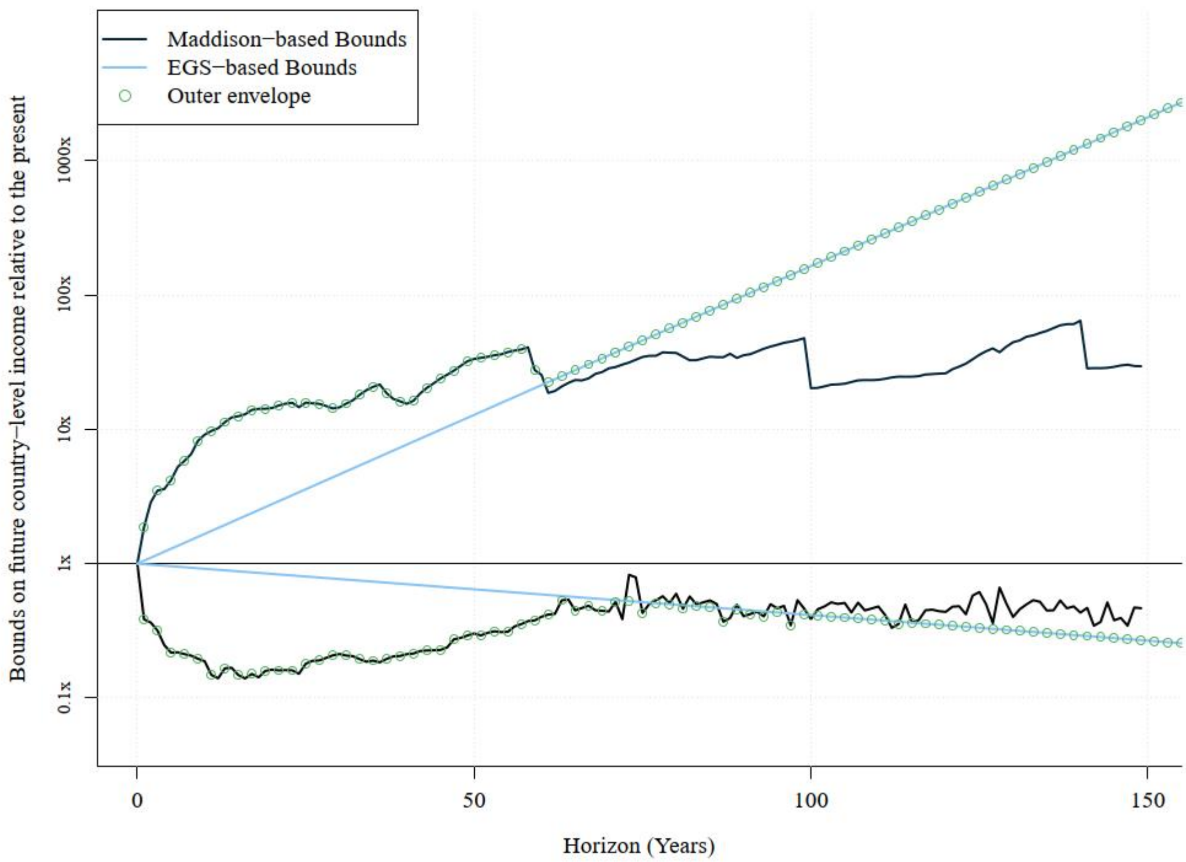

Figure OA- 1 Absorbing Bounds for Change in Country-Level GDP/capita Over Time.

II. Structured Expert Judgment: Details on experts and scoring for Economic Growth Survey (EGS) and Future Emissions Survey (FES)

1. Introduction

This report details on the structured expert judgment studies of GDP and greenhouse gas emissions conducted by RFF as part of RFF's activities to implement recommendations from the National Academies of Sciences, Engineering, and Medicine (NASEM 2017) for improving estimates of the social cost of carbon.

Ten experts participated in the Economic Growth Survey (EGS) in Washington DC in 2019-2020. Ten experts participated in the Future Emissions Survey (FES) elicitation also held at RFF in 2021. From previous experience a working minimum panel size is about six experts and more than 20 provides diminishing returns in terms of the performance of the pooled expert judgments.

The participating experts in the EGS were: Daron Acemoglu, Erik Brynjolfsson, Jean Chateau, Melissa Dell, Robert Gordon, Mun Ho, Chad Jones, Pietro Peretto, Lant Pritchett, Dominique van der Mensbrugghe. The participating experts in the FES were: Sally Benson, Geoff Blanford, Leon Clarke, Elmar Kriegler, Jennifer Faye Morris, Sergey Paltsev, Keywan Riahi, Susan Tierney, Detlef van Vuuren. Elicitations were conducted face to face remotely. Experts were provided with an introductory video and background materials to orient them to the study.

The expert judgment methodology applied here is termed the "*Classical Model*" because of its analogy to classical hypothesis testing (1). The key idea is that experts are treated as statistical hypotheses. They are scored as uncertainty assessors based on their responses to calibration variables from their field whose true values are unknown to the experts at the time of the elicitation. The purpose of scoring is twofold. First scoring enables performance weighted combinations of experts' judgments. Second, the scores of combinations of experts serve to gauge and hopefully validate the combination which is adopted.

2. Expert scoring

Each expert stated his/her 5th , 50th and 95th percentiles, or quantiles, for each calibration variable. An expert's *statistical accuracy* is the P-value (column 2 in Tables 3 and 4) at which we would falsely reject the hypothesis that an expert's probability assessments are statistically accurate. Roughly, an expert is statistically accurate if, in a statistical sense, 5% of the realizations fall beneath his/her 5th percentile, 45% of the realizations fall between the 5th and 50th percentile, etc. High values (near 1) are good, low values (near 0) reflect low statistical accuracy. An expert's *informativeness* is measured as the mean Shannon relative information in the expert's distribution with respect to a uniform background measure over an interval containing all experts' percentile assessments and the realizations, variable-wise[3].

Column 3 gives the average information scores for each expert for all variables. The number of calibration variables is shown in column 4 for each expert (in this case all experts assessed all 11 calibration variables). The product of columns 2 and 3 is the *combined score* for each expert (not shown). Note that statistical accuracy scores vary over four orders of magnitude whereas information scores vary within a factor two. Statistical accuracy is a fast function while informativeness is slow. Therefore, by design, the ratios of the products of combined scores are dominated by the statistical accuracy.

There is a loose negative correlation between experts' statistical accuracy and information. Note also that while the equal weight combination's statistical accuracy in both panels is comfortably above the 5% threshold, its information is lower than that of any expert. As mentioned, information is a slow function; halving the information score corresponds roughly to doubling the size of the 90 percent confidence bands. This information penalty of equal weighting is typical of other expert judgment panels.

Six of the nine EGS experts had a statistical accuracy score above 0.05 which is the traditional threshold below which statistical hypotheses would be rejected. For the FES panel this holds for 5 of the 10 experts. A recent review of the 49 studies conducted since 2006 found that 75% of the 530 experts would be rejected as statistical hypotheses at the 5% level. In this sense, both the EGS and the FES panels display an unusually high number of non-rejected experts. This in turn leads to lower performance differences between equal and performance weighting than is seen in many other studies.

[3] Computing the mean relative information requires fitting densities to each experts' quantile assessments. The minimal informative density relative to the background measure which complies with the expert's quantiles is chosen for this purpose. The mean relative information is proportional to the information in each expert's joint distribution if the distributions for each variable are independent. The mean is taken to prevent the importance of informativeness to depend on the number of calibration variables. The mean relative information is a global performance measure; the actual weights employ the information scores per variable and are thus variable specific.

Expert Scores EGS					
expert	**Statistical accuracy**	**mean information**	**# variables**	**weight**	**Rel.Inf to EW DM**
1	0.706	0.673	11	0.3	0.433
2	0.399	0.829	11	0.209	0.608
3	0.008	0.894	11	-	0.6
4	0.197	0.659	11	0.082	0.363
5	0.215	1.094	11	0.148	0.711
6	0.327	1.131	11	0.233	0.761
7	0.154	0.291	11	0.028	0.331
8	0.018	1.087	11	-	0.671
9	0.0003	0.727	11	-	0.511
PW05	0.492	0.457	11	-	
EW	0.37	0.266	11	-	

Table 1 Scores and weights for all 9 EGS experts when performance weights are not optimized but computed for the six weighted experts with statistical accuracy > 0.05. Statistical accuracy denotes the significance level at which the hypothesis that an expert is statistically accurate would be falsely rejected. Mean Information denotes the average Shannon relative information in an expert's assessments for all calibration variables. "# variabless" denotes the number of calibration variables answered by an expert. "Weight" for weighted experts is the normalized sum of the product of columns 2 and 3. "Rel Inf to EW DM" is an expert's relative information with respect to the EW combination of all experts.

Expert Scores FES					
expert	Statistical accuracy	mean information	# variables	weight (GWnOp)	Rel.Inf to EW DM
1	0.083	0.893	11	0.079	0.636
2	1.26E-05	1.354	11	0.000	1.003
3	1.70E-07	1.592	11	0.000	1.182
4	3.01E-04	1.357	11	0.000	1.271
5	0.003	1.295	11	0.005	0.935
6	0.399	0.548	11	0.234	0.400
7	0.018	0.748	11	0.015	0.649
8	0.169	0.676	11	0.122	0.460
9	0.327	0.846	11	0.295	0.601
10	0.385	0.611	11	0.251	0.408
GWnOp	0.615	0.308	11		0.006
GWOp	0.852	0.313	11		0.043
IWnOp	0.385	0.361	11		0.042
IWOp	0.615	0.361	11		0.210
EW	0.638	0.238	11		0

Table 2: Scores and weights for all 10 FES experts when performance weights are optimized (Op) and also not optimized (nOP, no statistical accuracy cut-off is applied). The weights in column 5 are those of GWnOP. Global weighting (GW) uses the mean informativeness over all calibration variables. Statistical accuracy denotes the significance level at which the hypothesis that an expert is statistically accurate would be falsely rejected. Mean Information denotes the average Shannon relative information in an expert's assessments for all calibration variables. "# variables" denotes the number of calibration variables answered by an expert. "Global Weight" for weighted experts is the normalized sum of the product of columns 2 and 3. Item specific weighting (IW) applies different weights for each item based on an experts' informativeness per item. "Rel Inf to EW DM" is an expert's relative information with respect to the EW combination of all experts.

3. Combining experts

A scoring system is asymptotically strictly proper if an expert obtains his/her highest expected score in the long run by, and only by, stating percentiles corresponding to his/her true beliefs. Statistical accuracy and informativeness are dimensionless. Their product termed the combined score, is an asymptotically strictly proper scoring rule if experts get zero weight when their P-value drops below some positive threshold (1). If (s)he tries to game the system to maximize his/her expected weight, (s)he will eventually figure out that (s)he must say exactly what (s)he thinks. Honesty is the only optimal strategy. The theory does not say what the cut-off value should be, so this is chosen on the basis of extra-mathematical considerations. One strategy is to choose the cut-off at the level which optimizes the combined score of the resulting decision maker. Another strategy is to choose a statistical cutoff, typically 0.05, such that weighted experts are those would not be rejected as statistical hypotheses. A third strategy is to choose a cutoff sufficiently low that all empanelled experts are weighted (termed not optimized or nOp).

For the EGS, optimal weighting resulted in expert 1 receiving weight one, other experts being unweighted. The strategy cutoff strategy choosing the cutoff at the traditional 5% value, termed PW05 shown in Table 2. All three DM's EW, PWOp and PW05 show acceptable statistical performance[4]. EW exhibits lower informativeness than any expert and lower than PWOp and PW05. Very roughly, halving the informativeness corresponds to doubling the width of the 90% confidence intervals. In this case PWOpt was rather non robust whereas PW05 was very robust (see below).

For the FES there was very little difference in performance between IWOp, IWnOp, GWOp and GWnOp. All are more informative than EW. Optimization incurs a penalty in robustness (see below) and in light of the small differences in performances, preference was given for the non-optimized versions.

The Classical Model has been applied in hundreds of expert panels and has been validated both in- and out-of-sample (2-6). In the absence of observations of the variables of interest, out-of-sample validation comes down to cross-validation whereby the calibration variables are repeatedly separated into subsets of training- and test variables. The PW model is initialized on

[4] If an expert is statistically accurate, then his/her statistical accuracy score is uniformly distributed on the interval [0, 1] and small values are significant. A difference between 0.4 and 0.5 is not important, but a difference of 0.4 and 0.008 is.

the training variables and scored on the test variables. The superiority of PW over EW in terms of statistical accuracy and informativeness has been demonstrated using this approach (2).

4. Robustness

Robustness on experts examines the effect on the preferred combination of losing individual experts. For the EGS panel, experts are removed one at a time and PW05 is recomputed as shown in Table 3.

Robustness analysis on Experts			
Excluded expert	**Information wrt background**	**Statistical accuracy**	**Information wrt original DM**
1	0.524	0.492	0.106
2	0.511	0.370	0.105
3	0.428	0.492	0.007
4	0.478	0.492	0.057
5	0.445	0.492	0.037
6	0.424	0.492	0.054
7	0.391	0.492	0.043
8	0.451	0.492	0.003
9	0.393	0.492	0.011

Table 3. Robustness on EGS experts; for explanations of columns see section 1.2, "Information wrt original DM" gives the mean relative information of the perturbed DM (with one expert removed) with respect to the original DM.

Table 4 shows that the mean relative information with respect to the original PW05 is in the order 0.05. Comparison with the values in the rightmost column of Table 2 shows that the changes wrought in PW05 by loss of a single expert are much smaller than the differences among the experts themselves. In this sense we conclude that PW05 is robust against the loss of any single expert. Had we chosen PWOpt, the difference caused by losing the expert with weight 1 would be 0.56, which is on the order of the expert differences.

Robustness against loss of a calibration variable proceeds in the same manner. Calibration variables are removed one at a time and PW05 is recomputed. These scores are extremely robust against loss of a calibration variable. A calibration variable may exert leverage on the combination of experts if all experts assess this variable poorly. That may be due to "group think" or it may be due to inappropriateness, ambiguity or error in the true value. If one variable perturbs the combination more than the others, this flags the variable in question for further scrutiny. Table 5 raises no flags in this regard. Comparing the rightmost columns of Tables 1 and 5 show that the perturbation caused by loss of a single calibration variable is small relative to the divergence among the experts themselves.

Robustness analysis on variables			
Excluded variable	Information wrt background	Statistical accuracy	Information wrt original DM
GrwCh	0.44	0.47	0.04
GrwSA	0.49	0.47	0.04
GrwSSA	0.44	0.47	0.05
MADCh	0.41	0.55	0.06
MADSA	0.51	0.55	0.05
MADSSA	0.52	0.47	0.05
CBOErr	0.45	0.55	0.04
$StLIC	0.38	0.47	0.04
$StHIC	0.45	0.55	0.02
DyCLIC	0.47	0.55	0.04
DyCHIC	0.50	0.47	0.05

Table 4: Robustness on EGS calibration questions (calib vbl); for explanations of columns see section 1.2. "Information wrt original DM" gives the mean relative information of the perturbed DM (with one expert removed) with respect to the original DM.

For the optimized combinations in the FES panel the results are non-robust against both loss of a calibration variable and loss of an expert. This information is combined in a single table below.

excluded expert	Rel Inf wrt PWnOp	rel inf wrt GWOp	Excluded item	Rel Inf wrt PWnOp	rel inf wrt GWOp
1	0.01695	0.2578	spAdEc	0.0131	0.04904
2	2.51E-06	3.39E-09	spEmMr	0.0231	0.298
3	1.79E-07	0	spEaPc	0.02474	0.2561
4	0.006481	0.2578	%OECD	0.0144	0.3188
5	0.001533	2.67E-08	%SSAf	0.07927	0.04931
6	0.08502	0.1604	#ngSA	0.07836	0.3087
7	0.009123	0.06184	#ngSSA	0.01785	0.3204
8	0.0172	0.03377	%ergME	0.06166	0.4397
9	0.04194	0.2578	%ergCh	0.02913	0.2442
10	0.07871	0.08283	RnwVen	0.05453	0.06587
			RwnPor	0.02095	0.3209

Table 5. Robustness on FES experts and items for optimized vs non optimized global weights.

5. Random Expert Hypothesis

The random expert hypothesis states that putative differences in performance between assessors is just noise and does not indicate persistent differences of the assessors (6). One way to test this hypothesis is to compare panel wide performance metrics in the original panel with the same metrics as generated by a large set (here 1000) of “scrambled panels” in which the assessments are randomly re-allocated to assessors, thus wiping out any ‘assessor effect’. Considering statistical accuracy (SA) and information *(*Inf), we are interested in the panel maxima, minima averages and standard deviations. Table 6 shows, for example, that the average SA score in the original EGS panel was 0.23. In 14.1% of the 1000 scrambled panels the average SA score was lower than 0.23. The minimum SA score in the original EGS panel was 0.0003 and in all 1000 scrambled panels the minimum SA score was greater than the original panel minimum Sa. Although the scrambling was able to exceed the panel average SA in 85.9% of the cases, it was never able to get scores as low as the minimum in the original panel. The average Inf score is always the same in the scrambled and original panels, but the scrambling was unable to reproduce the highest and lowest scores. The same pattern is observed in the second panel. The fact that significant departures from randomness (indicated by italicized values) do not occur for average or maximum values of statistical accuracy may reflect the fact that there relatively large numbers of statistically accurate experts in each panel. The random scrambling is unable to reproduce the extremes of the information scores. In any event, the conclusion that differences in expert performance arise by chance is not supported in either panel.

		Panel metrics				**In Random re-allocations**			
		average	**StDev**	**max**	**min**	**%<ave**	**%<stdev**	**%<max**	**%>min**
EGS	**SA**	0.23	0.23	0.71	3.00E-04	14.10%	30.5%	35.9%	91.2%
	inf	0.83	0.27	1.14	0.30	-	*100%*	95.7%	*100%*
FES	**SA**	0.14	0.17	0.40	1.70E-07	93.30%	76.5%	55.3%	*98.0%*
	inf	1.00	0.37	1.60	0.55	-	*100%*	*99.7%*	*98.0%*

Table 6: Results of testing the random expert hypothesis in the EGS and FES panels. Panel wide metrics for statistical accuracy (SA) and informativeness (Inf) in the original panel are compared with1000 values in each of 1000 random re-allocations of assessments. The random re-allocation wipes out any "assessor effect", thus values greater than 95% in the rightmost 4 columns indicate significant departures from randomness.

Range graphs

Range graphs give a graphic representation of all assessments of all variables together with the true values.

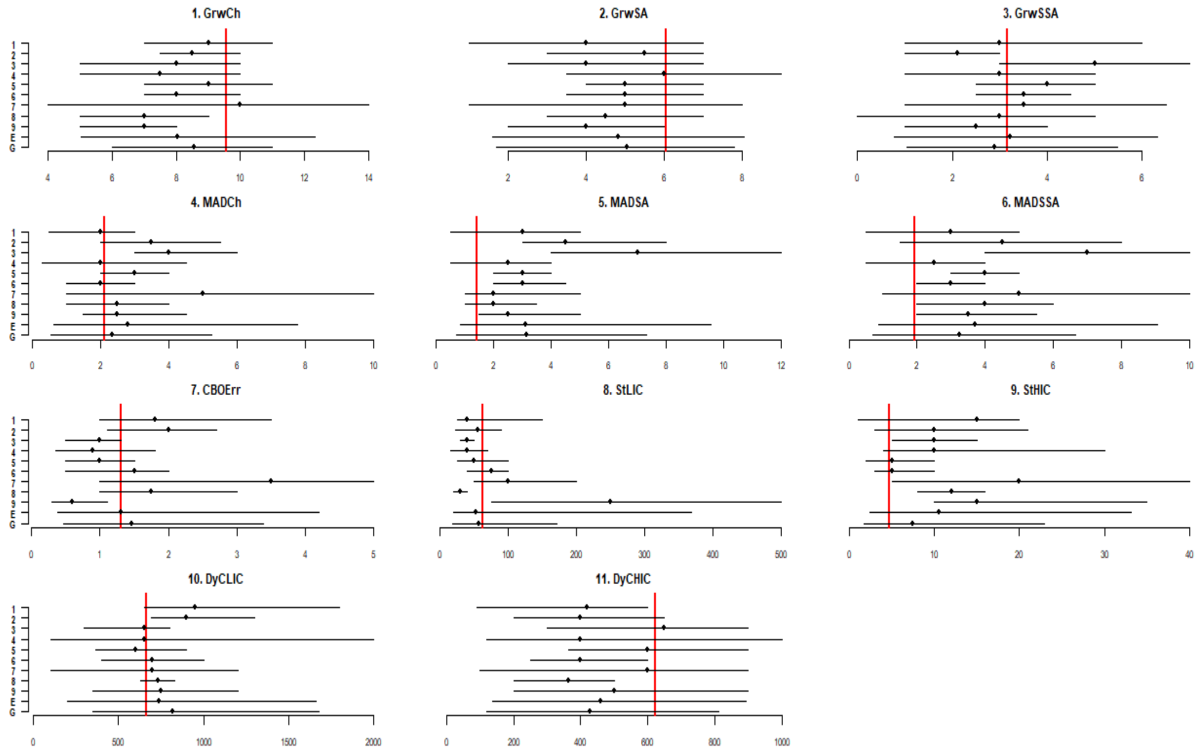

Figure OA- 2 Range graphs for calibration variables for the EGS: one stacked graph for each variable. Each assessment is given by a horizontal line with 5% and 95% values as endpoints and a dot for the median. The true value is indicated by a vertical line. On each graph the order of assessments from top to bottom is expert 1, expert 2, ...expert 9, EW, PW05.

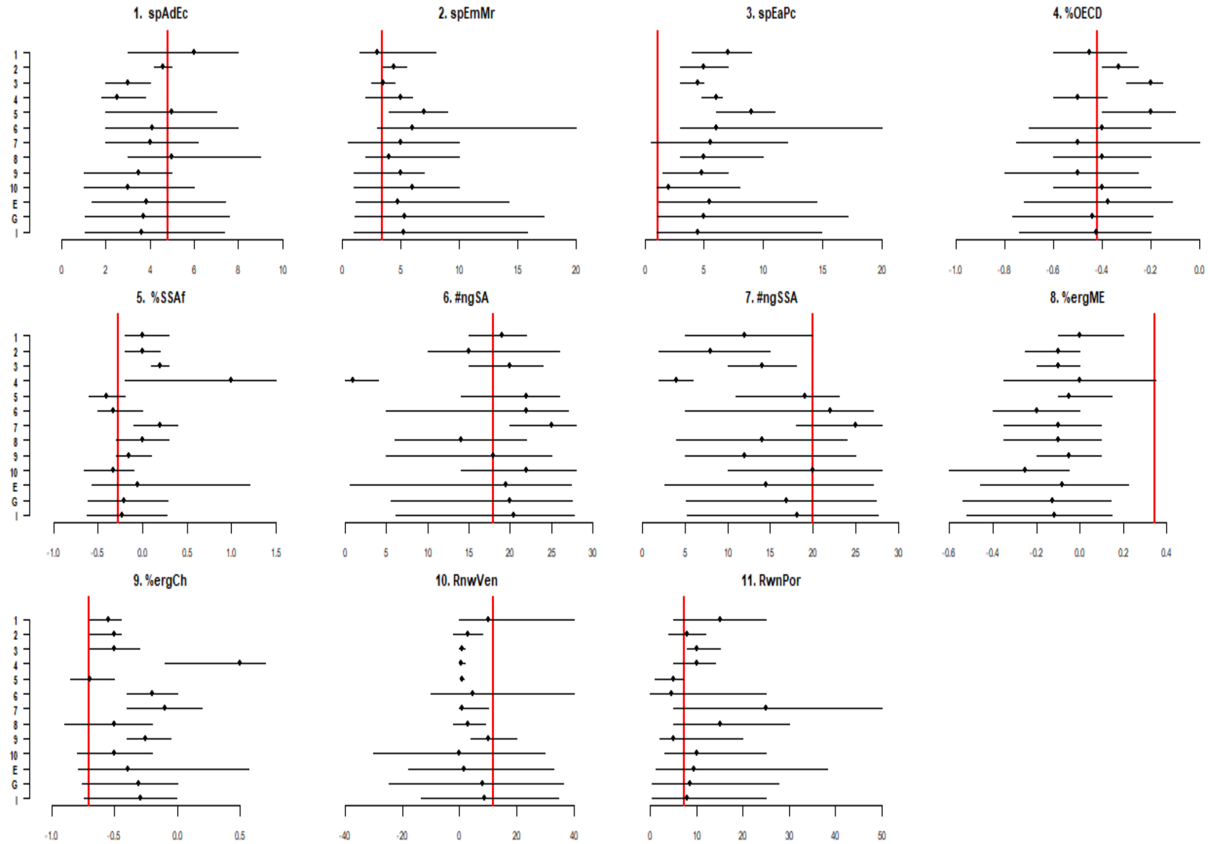

Figure OA-3 Range graphs for calibration variables for the FES: one stacked graph for each variable. Each assessment is given by a horizontal line with 5% and 95% values as endpoints and a dot for the median. The true value is indicated by a vertical line. On each graph the order of assessments from top to bottom is expert 1, expert 2, ...expert 10, EW, GWnOp, IWnOp.

Each assessment is represented as a horizontal line whose endpoints correspond to the 5th and 95th percentiles with a dot representing the median. The true value is shown as a red vertical line. For the EGS, on each graph the order of assessments from top to bottom is expert 1, expert 2, ...expert 9, EW, PW05. Range graphs are helpful in identifying any variables for which experts show structural differences: some experts may be too low while others are too high, some experts may be very confident (narrow bands) while others are very uncertain (wide bands), some experts may be isolated (non-intersecting confidence bands). Relative to other expert panels, the graphs in Figure 1 are very coherent. There are no isolated experts, and no evidence of diverging schools of thought.

6. Conclusion

The expert data presented here is unusual in the number of experts with high statistical accuracy. Both the equal weight and performance weighted decision makers show good statistical accuracy with the latter exceeding the informativeness of the former. The results are quite robust against loss of expert and loss of calibration variable. On the whole the expert group is quite coherent. When the sociology of expert judgment comes to be written, this example will be a poster child.

7. References

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3. Colson AR & Cooke RM (2018) Expert Elicitation: Using the Classical Model to Validate Experts' Judgments. *Review of Environmental Economics and Policy* 12(1):113-132.

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III. Economic Growth Survey: Additional results

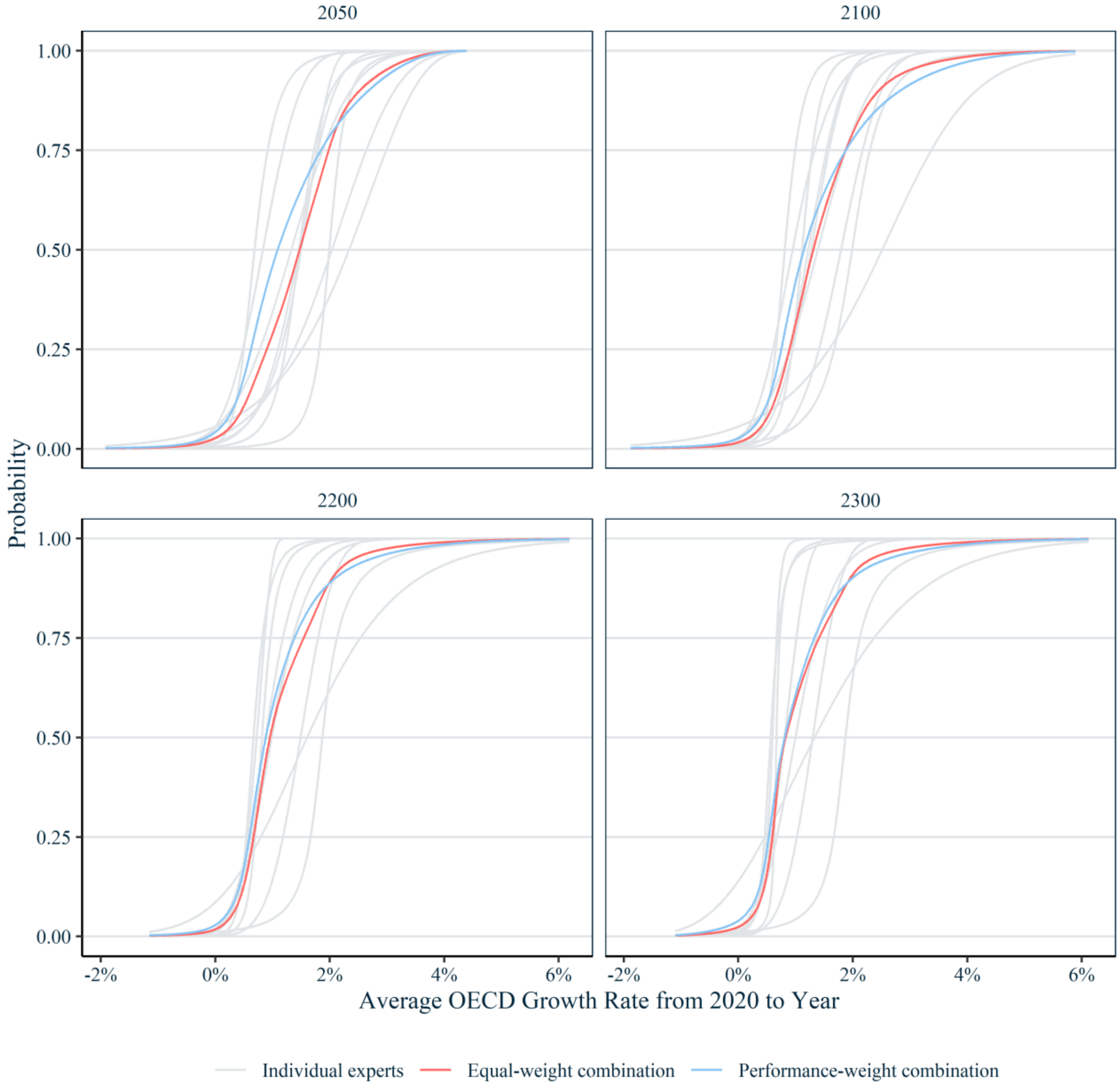

Figure OA-4. Cumulative Distribution Functions (CDFs) of Average Growth Rates of GDP per Capita for the OECD from the EGS, Individuals and Expert Combinations.

IV. Future Emissions Survey: Additional description and results

Survey methodology

To generate very long-run distributions of global emissions of CO_2, CH_4, and N_2O, our *Future Emissions Survey* (FES) elicited 10 leading experts in socioeconomic projections and climate policy that were nominated by their peers and/or by members of our Scientific Advisory

Board. The experts surveyed were based at universities, non-profit 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.

As with our *Economic Growth Survey*, the FES employed the Classical Model of structured expert judgment in which experts first quantified their uncertainty with regard to a set of relevant calibration variables for which true values are known, for the purposes of validation and performance weighting in the combining of the expert distributions. Each elicitation was conducted individually by videoconference in July and August of 2021 in sessions that lasted ~2 hours, and experts provided additional detail as needed by email and videoconference. Experts participated in the survey in their own capacity and were provided an honorarium where appropriate.

In the survey, experts provided quantiles of uncertainty (minimum, 5^{th}, 50^{th}, 95^{th}, maximum, as well as additional percentiles at the expert's discretion) for four variables for a case referred to as *Evolving Policies*, which incorporates views about changes in technology, fuel use, and other conditions, and consistent with the expert's views on the evolution of future policy. The *Evolving Policies* case corresponds to the USG 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 the following four non-overlapping categories: (1) fossil and process related CO_2 emissions; (2) changes in natural CO_2 stocks and negative emission technologies; (3) CH_4; and (4) N_2O. They did this for each benchmark year: 2050, 2100, 2150, 2200, and 2300. For the first category, they were also asked to indicate the sensitivity of emissions to five underlying GDP per capita trajectories. More precisely, they were asked to provide for each benchmark year:

1) Global CO_2 emissions for five levels of future of GDP per capita representing the minimum, 2.5^{th} percentile, 50^{th} percentile, 97.5^{th} percentile, and maximum of projected economic growth in each benchmark year (i.e., a separate set of quantiles for each of the

five GDP per capita levels drawn from the MSW dataset). Reported emissions in this category included net total emissions from processes, including CCS applied to fossil energy and process-related emissions. By construction, emissions reported for this category are greater than or equal to 0.

2) Quantiles of the net CO_2 emissions from the combined sum of Agriculture, Forestry, and Other Land Use (AFOLU) and sequestered emissions from Direct Air Capture (DAC) and Bioenergy with Carbon Capture and Storage (BECCS). By construction, total net emissions in this category could be positive (net CO_2 source) or negative (net CO_2 sink).
3) Quantiles of global CH_4 emissions including CH_4 emissions from AFOLU.
4) Quantiles of global N_2O emissions including N_2O emissions from AFOLU.

The categories were designed, and experts were specifically directed, to avoid double counting of emissions in the distributions provided. Taken together, the elicited source categories account for greater than95% of current global emissions of greenhouse gases. Experts were permitted, but not required, to provide quantiles for AFOLU, DAC, BECCS, CH_4, and N_2O conditioned on economic growth in the same manner as CO_2 emissions in category 1). Experts were permitted to consult outside sources at their discretion for this section of the survey.
During the survey, experts provided their quantiles by dictating values for their quantiles for each of the specified categories, years, and economic growth trajectories. The values were recorded in a spreadsheet visible to the expert during the elicitation via screen share.

Summary of Expert Rationale

As part of FES, experts described their rationale and the conditions supporting their provided distributions of emissions. The rationale were provided independently, but when viewed across the full set of experts, featured a number of common and primary factors, including economic growth, global climate policy ambition and success of implementation, and technology evolution. Each of these factors could work in concert with or against each other to result in the final uncertain distribution.

CO_2 distributions provided for low economic growth scenarios in general incorporated divergent potential outcomes. On one hand, low growth was viewed as providing an impediment to both policy ambition as well as further improvements in and deployment of low- or zero-emission energy technologies. On the other hand, low growth was also generally viewed to reduce global emissions generally as lower economic activity at current or decreased emissions intensity levels would lead to a decrease in emissions overall. A relatively common narrative supporting the higher end of emissions distributions was that low economic growth trajectories could lead to a revisitation of current pledges to reduce emissions and favor continued growth in energy derived from fossil fuels, leading to further lock-in of such technologies.

For median rates of per capita economic growth, experts in general viewed global policy as the primary driver, including the success or failure of countries meeting their pledges under the Paris Agreement and enhancing the ambition of those targets, as well as by the evolution of developing nations' use of fossil fuels and assistance provided. Continued evolution of technology, driven significantly by potential investments consistent with mitigation goals, also featured prominently as a driver. A common result for the 2050 and 2100 the medians of the emissions distributions was a reductions of absolute emissions from today's levels, but with an uncertain range leaving substantial probability for continued, and in some cases quite significant, increases as well. The low emission (5th percentile) quantiles generally represented significant reductions from today's levels but at a level insufficient keep global temperature increases below 1.5 degrees Celsius, even when considering reported quantiles for AFOLU.

For high rates of per capita economic growth, several experts expected that significantly enhanced economic activity would likely lead to increased emissions in the near-term (to 2050 and for some experts to 2100), as the time needed for further development and deployment of zero-emission technologies was insufficient to decrease the emissions intensity (emissions/GDP) quickly enough to offset the economic growth. High economic growth in general was viewed to support increasing attention to reducing emissions from a policy standpoint and an enhancement of global climate policy goals, leading to a more rapid medium- and longer-term transition to greatly reduced emissions overall compared with relatively lower economic growth scenarios. An alternative viewpoint expressed was that greater wealth could also allow for greater adaptation or indifference to the effects of climate change, thereby acting as a brake on policy ambition and allowing for continued increases in emissions well into the future.

Several experts also observed that, if global policy were to remain largely centered around absolute quantity targets (e.g., percent reduction from 2005 levels or net zero by a date certain), emissions would be relatively decoupled from economic growth. Their view of this decoupling manifested itself in the form of relatively low variation between their distributions across economic growth trajectories. Similarly, some of the experts felt that the high economic growth trajectories in particular represented worlds in which economic growth was decoupled from emissions.

Experts generally viewed near-term potential from DAC and BECCS as limited through 2050, but they became an increasing and more substantial part of the solution alongside natural land sinks by 2100. In general the experts allowed room for the narrative that society may wish to have net negative annual emissions for several decades even after eliminating direct emissions to draw down atmospheric CO2 concentrations to return to a level consistent with current or previous levels.

Emissions from methane are primarily driven by livestock (enteric fermentation), agriculture (including cultivation of rice), and fossil fuels (natural gas), and experts' distributions were primarily driven by their expectations on the future evolution of emissions from these sources. Experts that viewed a rapid transition to zero-emitting energy sources as relatively likely tended to have distributions that reflected the rapid zeroing out of the component of CH4 emissions from fossil fuels. Other experts allowed for the expansion of such emissions in acknowledgement that natural gas may be relied upon heavily as a transition fuel or even as a significant and substantially increasing source of uncontrolled emissions over the long-term. In nearly all cases there was a non-zero lower limit reached, even in the lower quantiles, in acknowledgment that some components of these emissions were unlikely to be fully eliminated by complete modification of diet or agricultural practices. Experts' supporting rationale for N2O, which is similarly associated with agriculture and dietary preferences, generally followed a narrative consistent with the corresponding elements from CH_4.

During the FES, some experts expressed a desire for further control over the correlations between variables. The first correlation desired was to condition emissions on population in addition to GDP per capita. Experts expressing this desire in general agreed with the design decision to condition on GDP per capita rather than GDP (the product of GDP per capita and population) as the primary variable and accommodated the study design by providing quantiles constructed to incorporate the possibility of low and high population futures. Some experts also expressed a desire to more tightly couple their quantiles of category 1 emissions with the potentially negative emissions from category 2 by providing a single distribution of net emissions from both categories. These experts generally viewed the level of negative emissions as being tailored to achieve a particular atmospheric CO2 outcome or directly to offset emissions. Accounting for this correlation would lead to narrower distributions of net emissions overall.

Additional results for CO_2 emissions

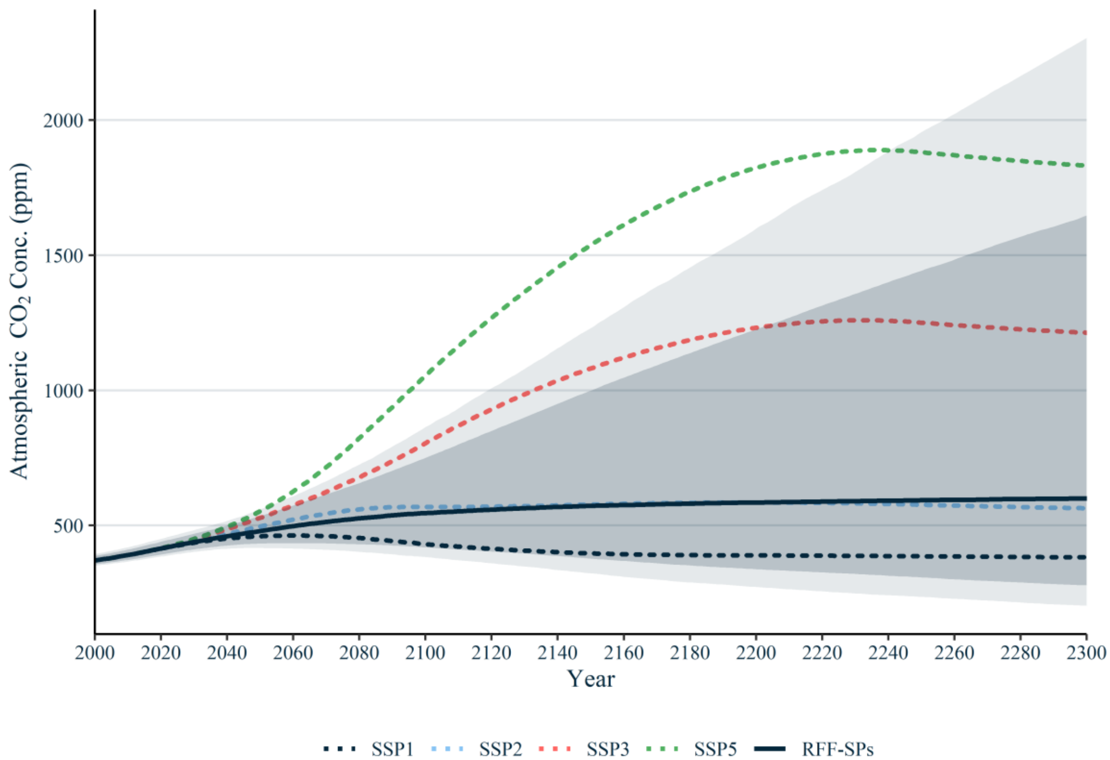

Figure OA-5: Projected total atmospheric CO_2 concentration. Solid lines represent median values, dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges based on the RFF-SPs.

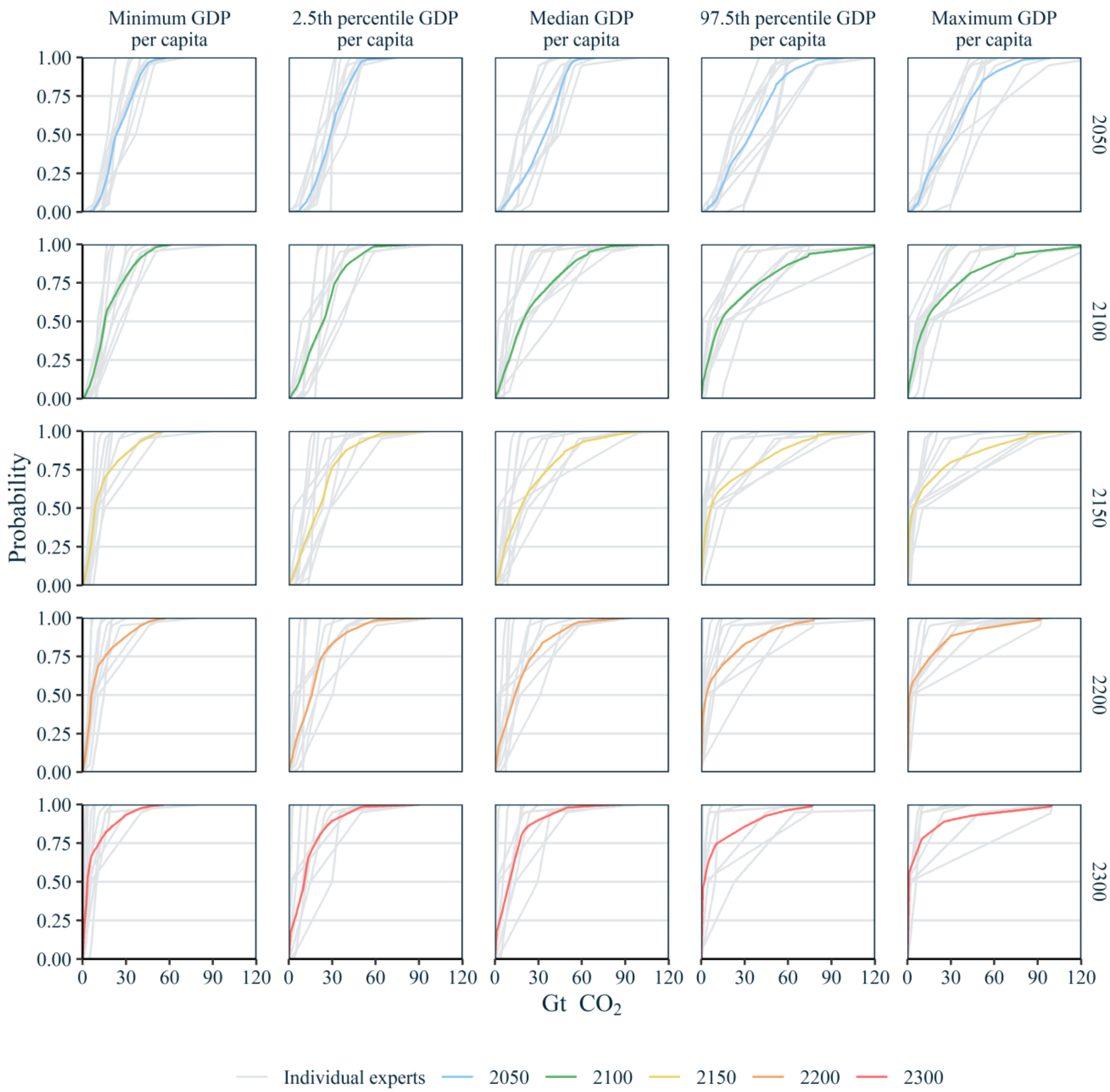

Figure OA- 6: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual CO_2 emissions across a range of timeframes and GDP per capita growth trajectories.

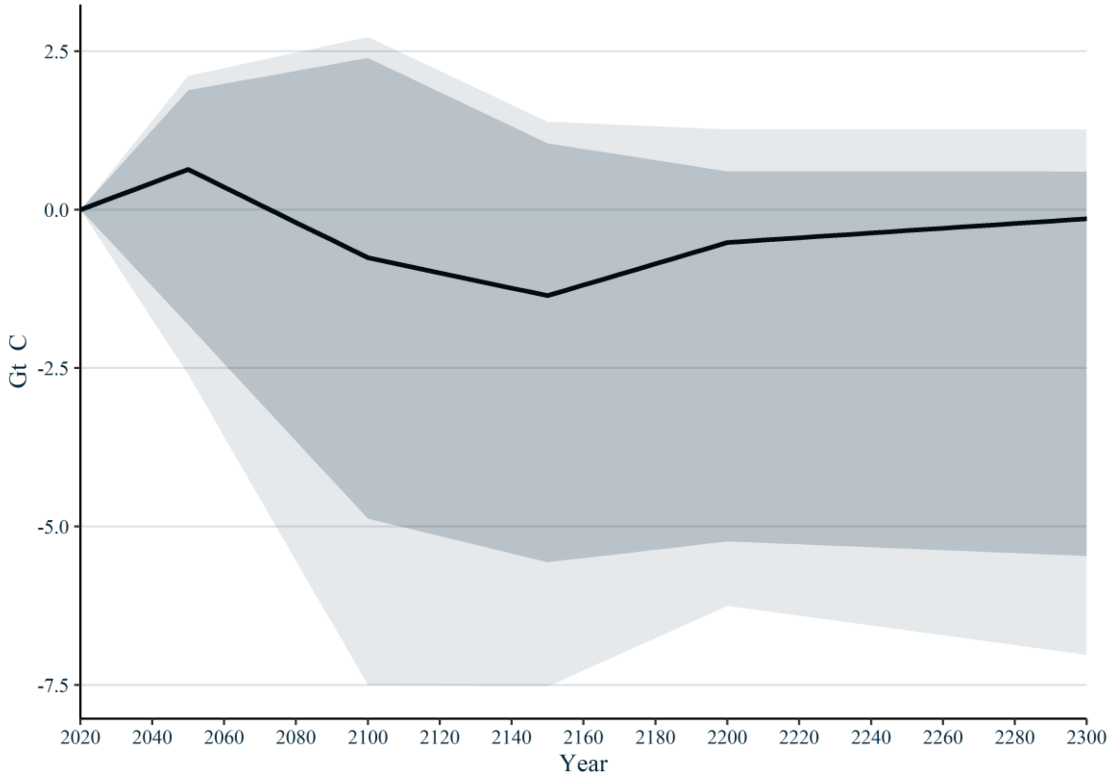

Figure OA-7: Annual net CO_2 emissions from natural carbon stocks and negative emissions technologies

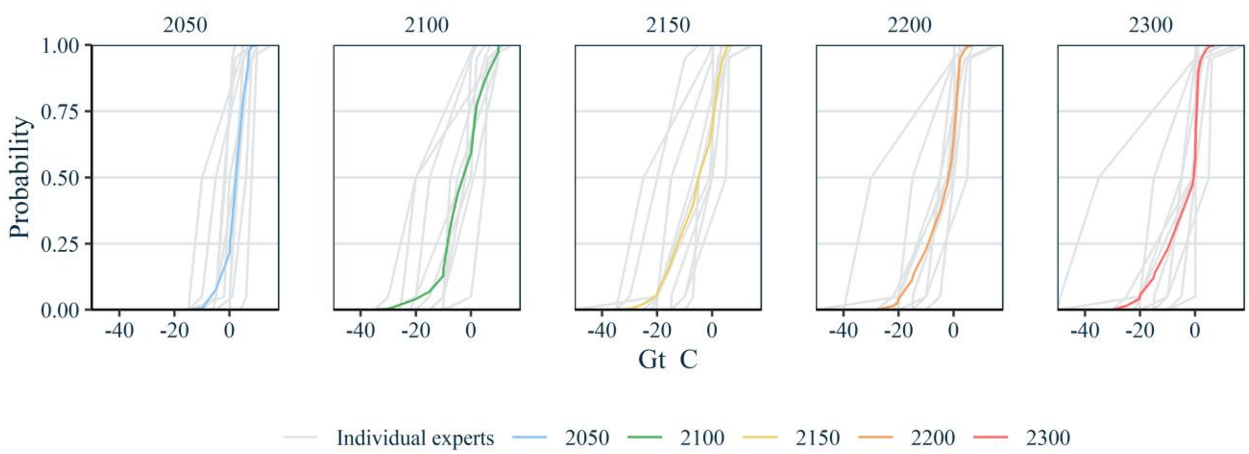

Figure OA-8: Cumulative distribution functions (CDFs) of individual and combined expert projections for net CO_2 emissions from natural carbon stocks and negative emissions technologies across a range of timeframes

CH_4 emissions

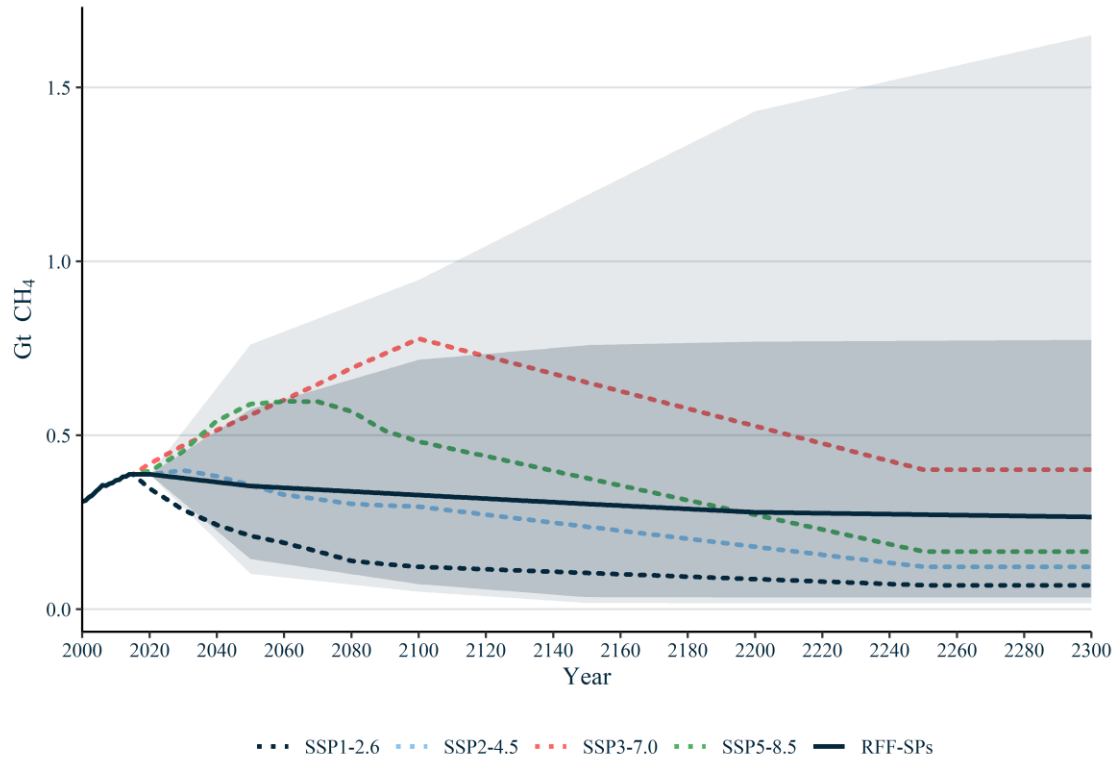

Figure OA-9: Annual emissions of CH_4 from the RFF-SPs and the SSPs. Lines represent median values, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

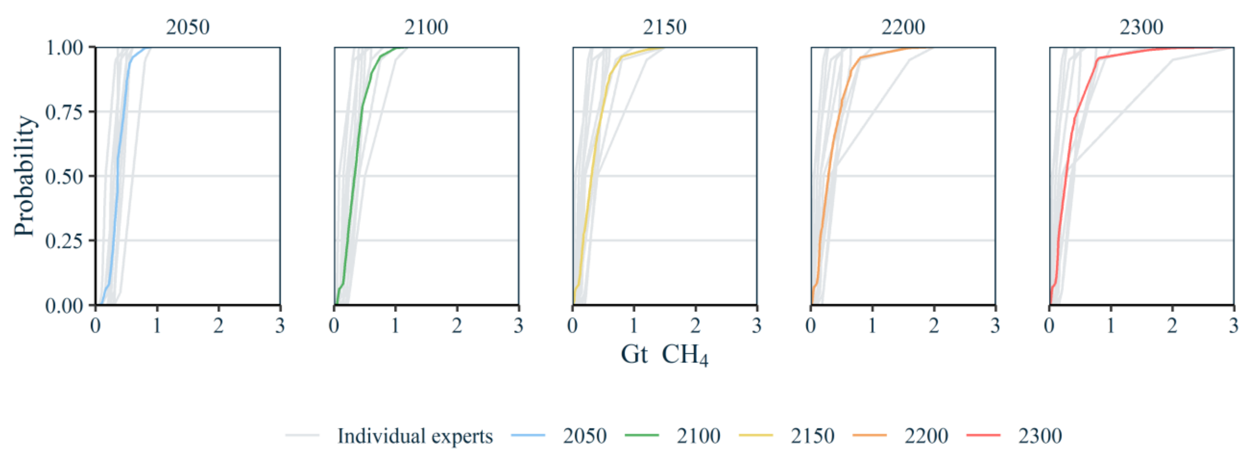

Figure OA-10: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual CH_4 emissions across a range of timeframes

N_2O emissions

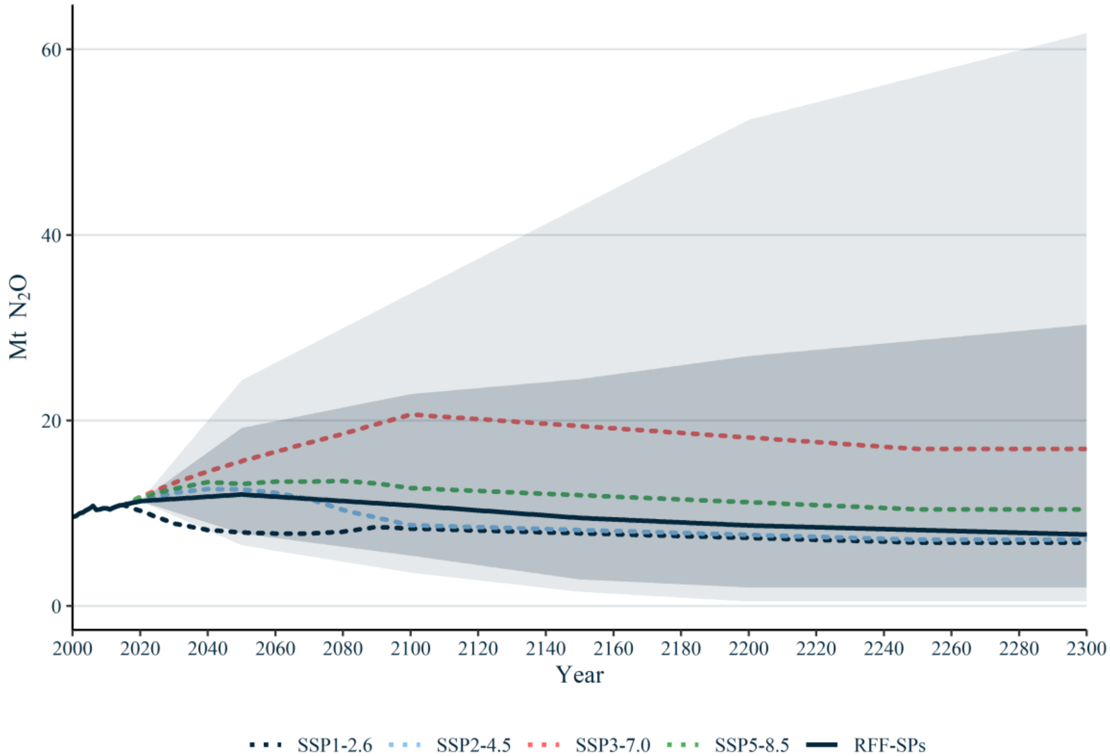

Figure OA–11 Annual emissions of N_2O from the RFF-SPs and the SSPs. Lines represent median values, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

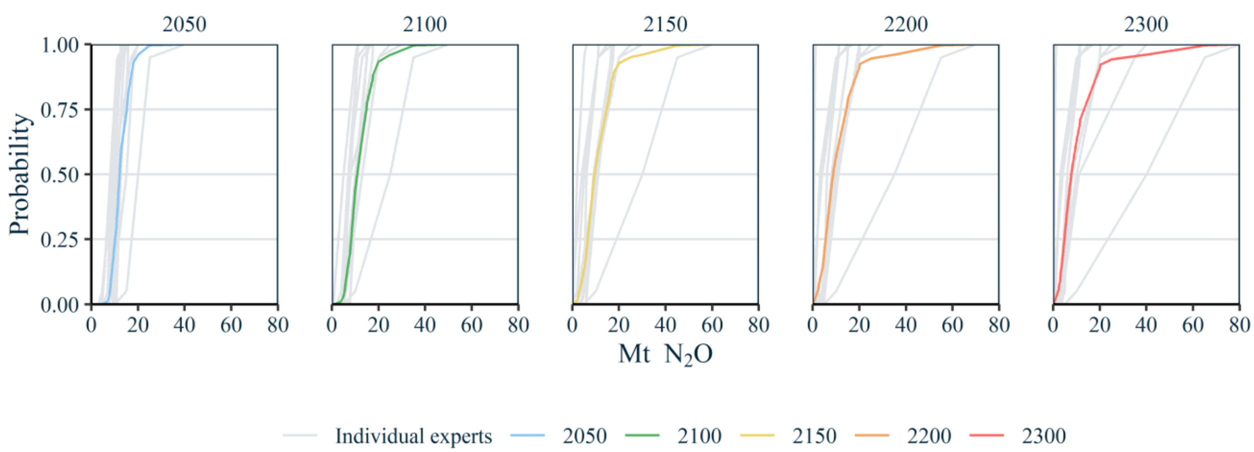

Figure OA-12: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual N_2O emissions across a range of timeframes

V. Additional SCC calculations

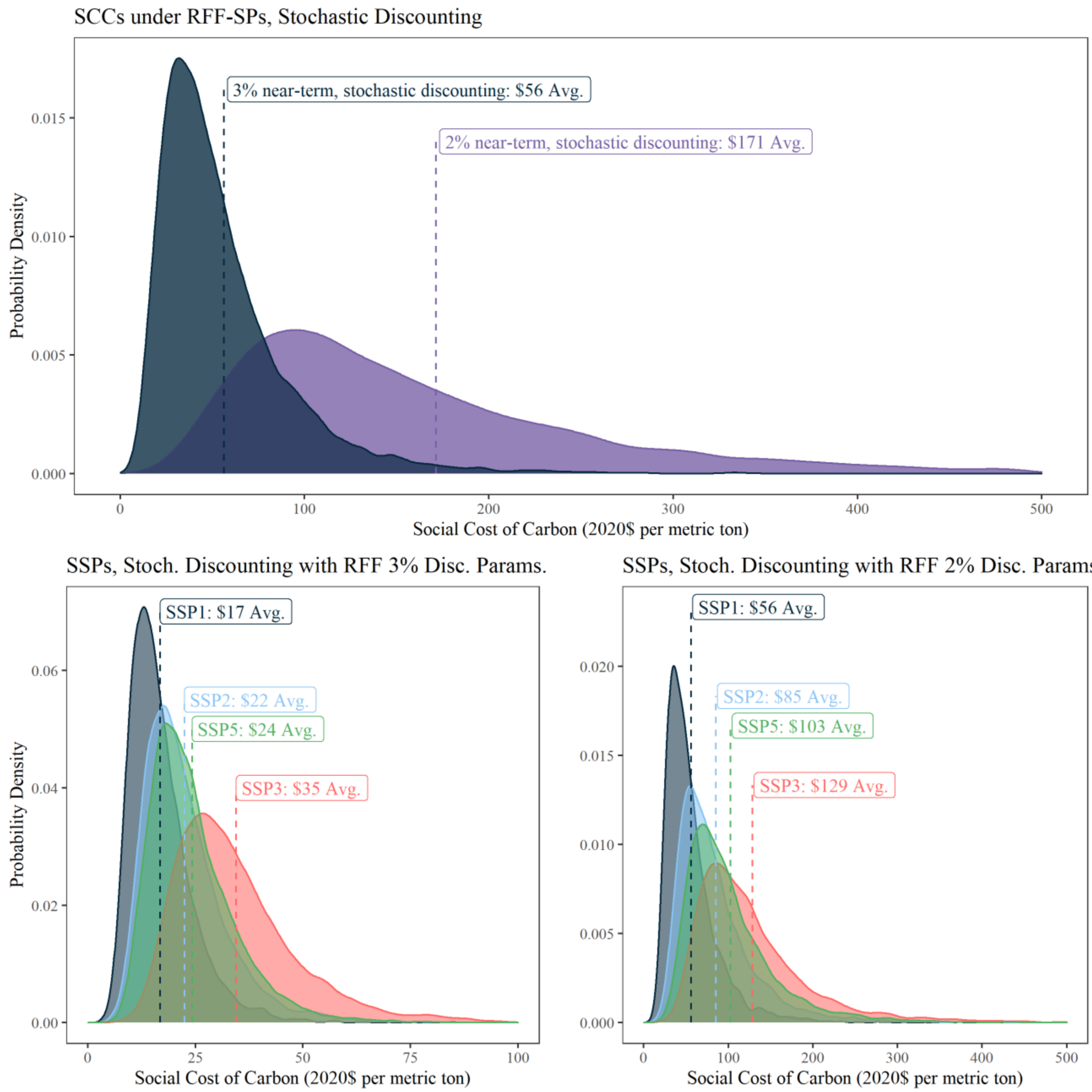

Figure OA-13. Illustrative Probability Distributions of the Social Cost of Carbon (2020\$/ton CO_2) with FaIR climate and DICE damage modules, under Alternative Socioeconomic Inputs, Using Our Stochastic Discounting Parameters for All Socioeconomics ($\rho = 0.8\%$, $\eta = 1.53$ for 3% near-term, or $\rho = 0.1\%$, $\eta = 1.25$ for 2% near-term)

VI. Economic Growth Survey Elicitation Protocol

The full EGS survey protocol will be included with the final published version of this manuscript.

VII. Future Emissions Survey Elicitation Protocol

The full FES survey protocol will be included with the final published version of this manuscript.