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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

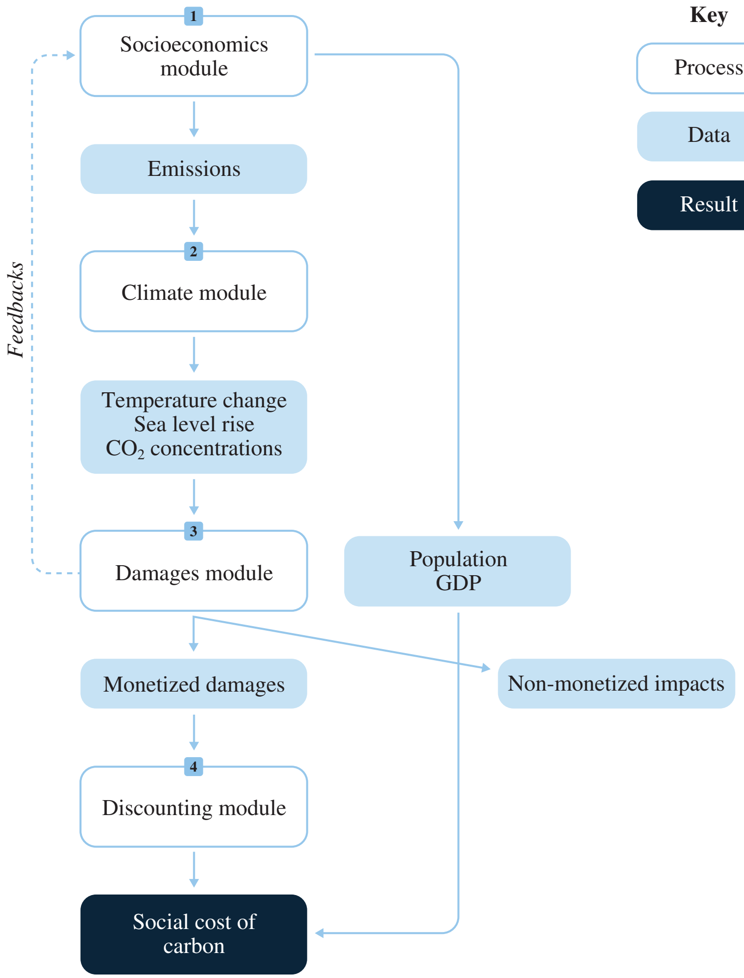
In this paper, we review efforts to update determinants of the SCC to reflect the best available science, based on the recommendations of a 2017 committee report by the National Academies of Sciences, Engineering, and Medicine (NASEM 2017). This updating is particularly relevant in light of Executive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

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

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

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

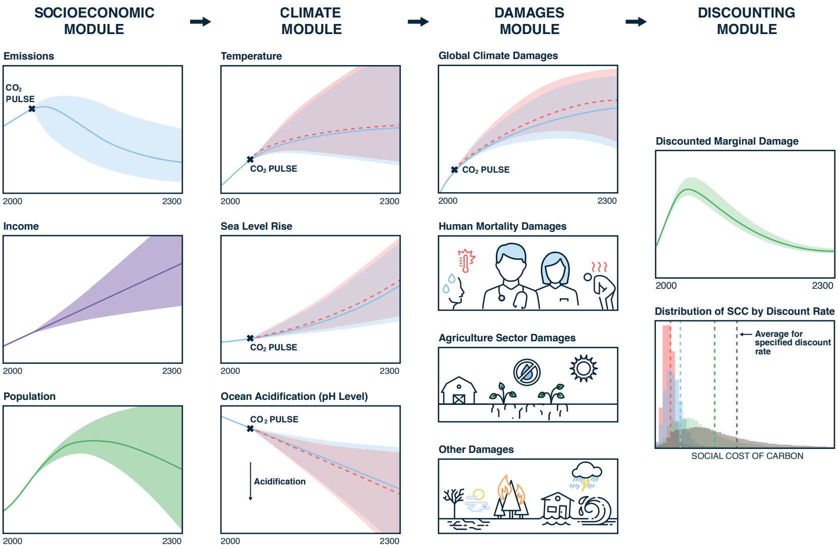
Figure 1. Modularized Approach to Estimating SCC



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

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

Figure 2. Estimating Social Cost of Carbon under Uncertainty



Source: Authors' calculations.

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

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

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

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

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

I. Economic and Demographic Drivers of Climate Effects

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

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

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

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

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

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

I.A. Past Approaches to Socioeconomic Projections

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

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

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

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

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

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

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

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

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

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

I.B. Probabilistic Population Projections to 2300

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

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

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

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

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

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

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

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

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

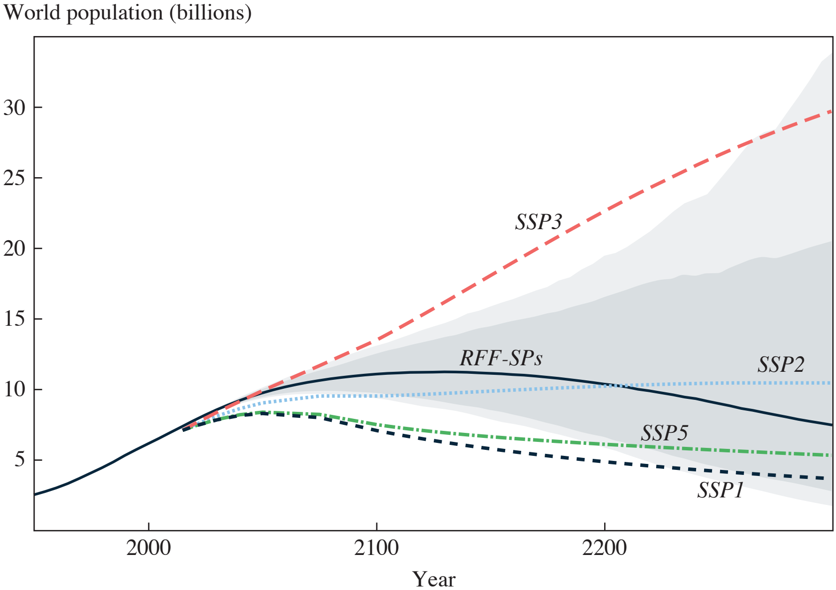
RESULTS The resulting population projections for 2300 for the world as a whole and for the continents are shown in figure 3. They show that total world population is likely to continue to increase for the rest of the twenty-first century, albeit at a decreasing rate, to level off in the twenty-second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

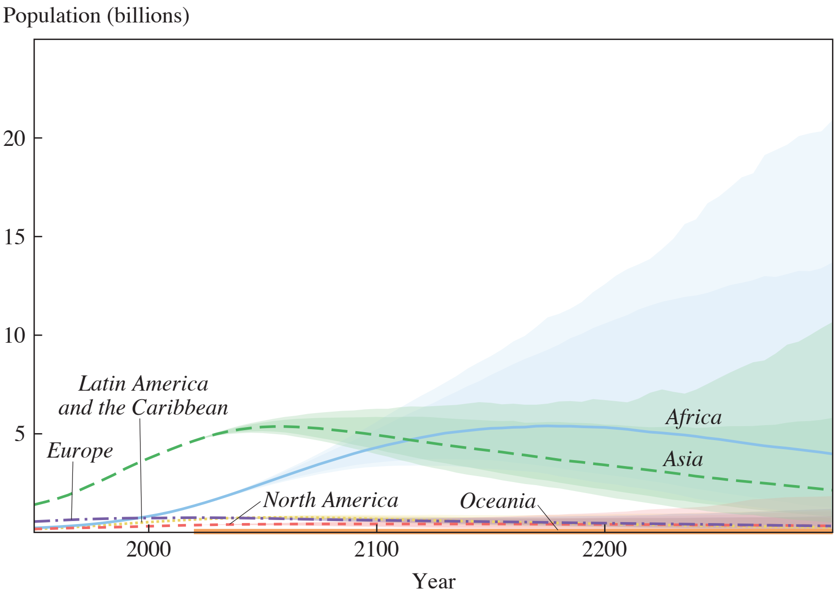
Figure 3 also shows the results for each major continental region. The populations of Asia, Europe, and Latin America are likely to peak well before the end of this century and then decline substantially. The populations of Africa and North America are also likely to peak and then decline but much later,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

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

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

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





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

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

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

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

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

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

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

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

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

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

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

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

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

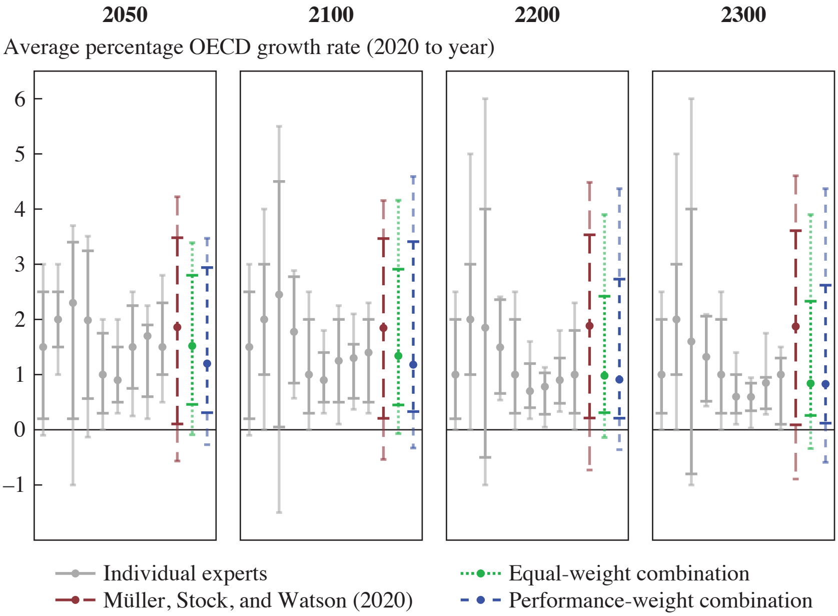
Given that the projections were being used as an input to the estimation of climate change damages, which would reduce economic activity below the projected level, the experts were specifically asked to provide quantiles of economic growth absent the effects of further climate change as well as absent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

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

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

15. See online appendix for further detail.

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



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

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

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

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

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

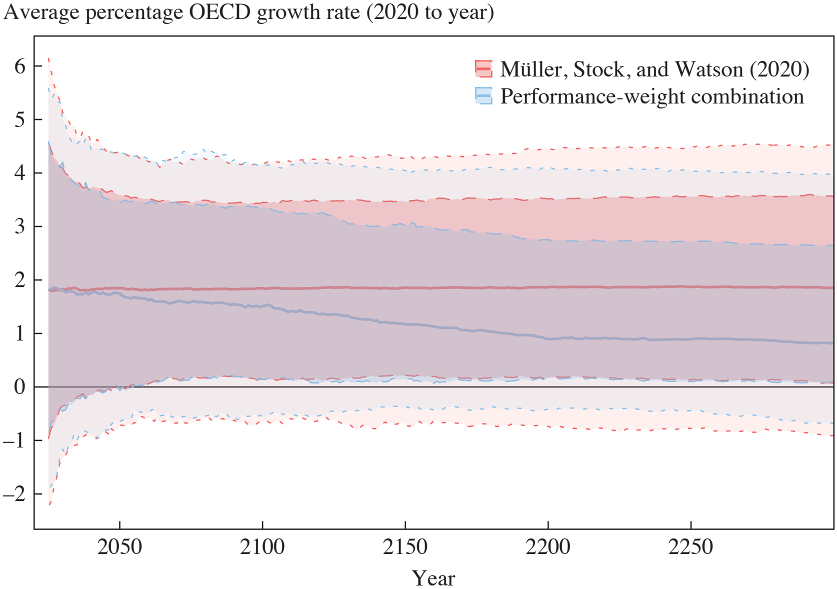
RESULTS OF ECONOMETRIC GROWTH PROJECTIONS AUGMENTED WITH EXPERT JUDGMENT We used the survey results to modify econometric projections of GDP per capita based on the methodology of Müller, Stock, and Watson (2020) and to generate density functions of internally consistent projections of economic growth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

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

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

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

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



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

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

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

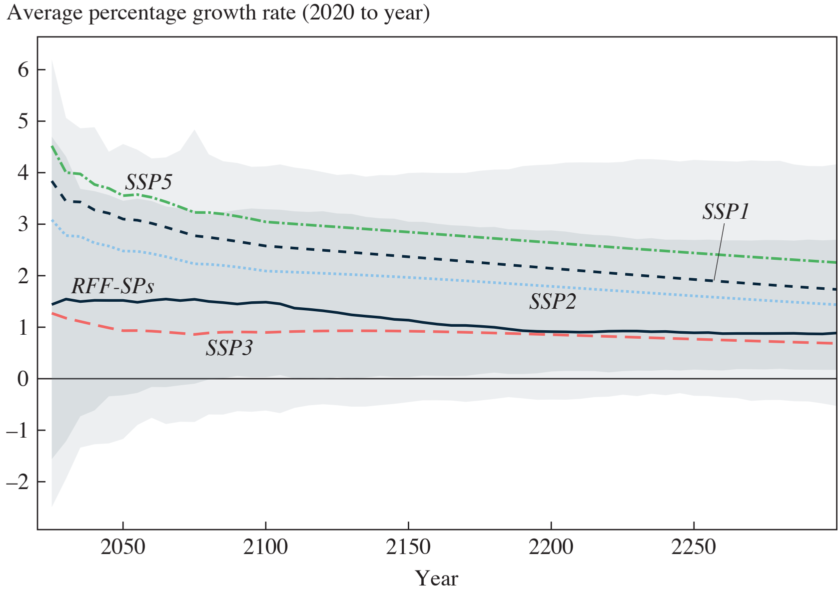
We accomplish this reweighting in two steps. First, we generate a set of target quantiles for the years 2030, 2050, 2100, 2200, and 2300 by calculating weighted averages of the combined cumulative distribution functions from the experts and the corresponding functions from the raw data in Müller, Stock,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

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

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

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

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



Source: Authors' calculations.

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

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

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

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

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

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

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

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

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

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

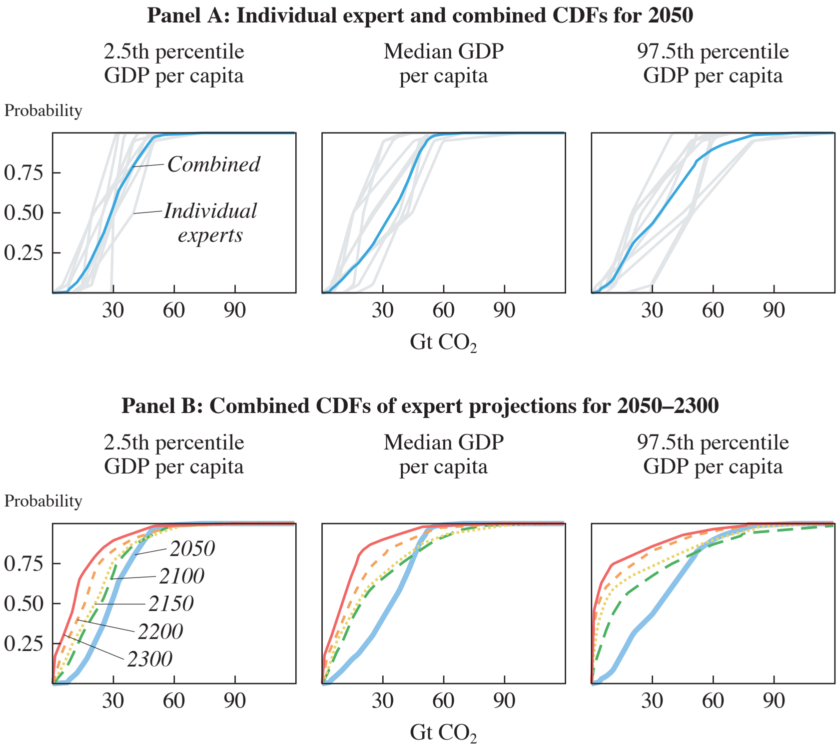
RESULTS OF THE FUTURE EMISSIONS SURVEY Experts' performance on the calibration questions was high, as measured by statistical accuracy, informativeness, and robustness of results (see online appendix). Experts described their rationale and the conditions supporting their distributions of emissions, often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

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

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

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

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

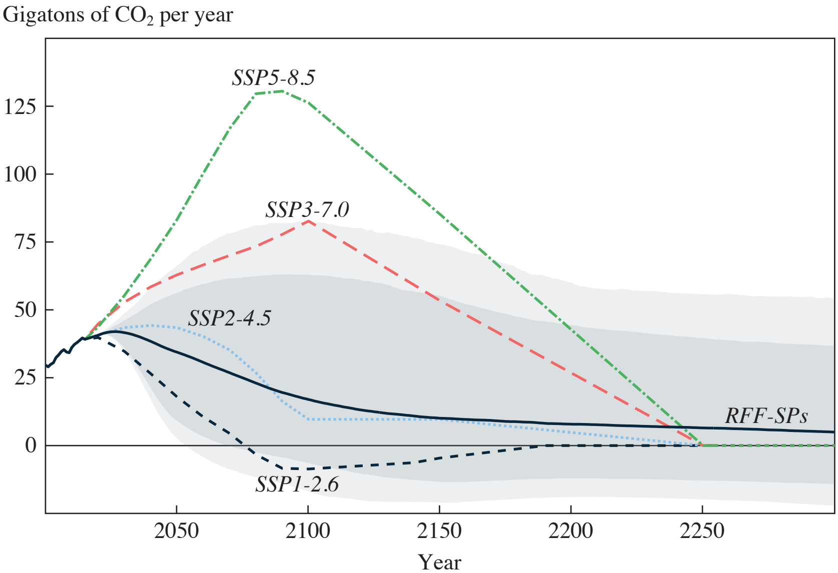


Source: Authors' calculations.

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

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

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



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

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

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

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

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

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

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

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

II. From Emissions to Monetized Climate Damages

II.A. Climate System Methods

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

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

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

II.B. Resulting Temperature Change from RFF-SPs

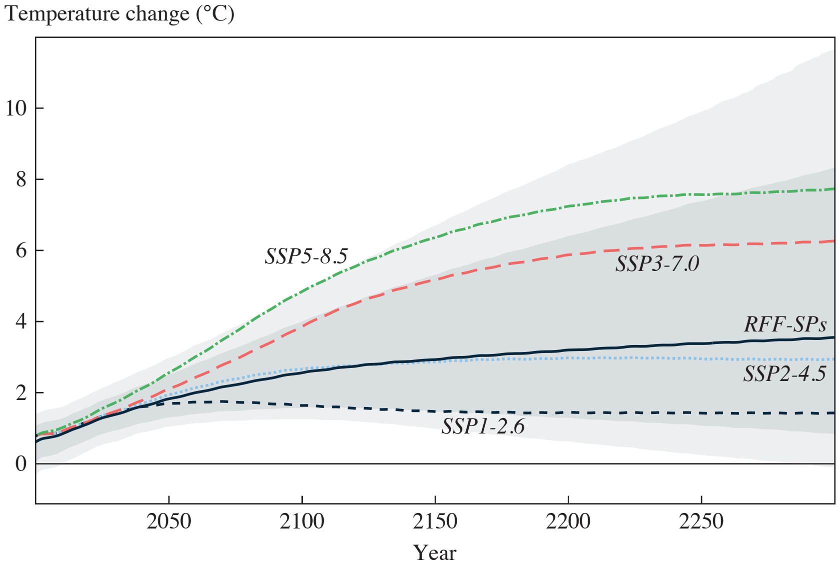
Figure 9 shows the median temperature trajectory associated with the RFF-SPs: increases reaching nearly 2.6 degrees Celsius above the average global temperature for 1850–1900 (the standard IPCC preindustrial benchmark) through 2100 and continued increases through 2300. The low end of the distribution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

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

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

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

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



Source: Authors' calculations.

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

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

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

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

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

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

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

III. Discounting Approaches for the Social Cost of Greenhouse Gases

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

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

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

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

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

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

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

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

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

III.A. Stochastic Growth Discounting with Economic Uncertainty

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

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

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

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

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

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

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

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

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

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

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

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

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

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

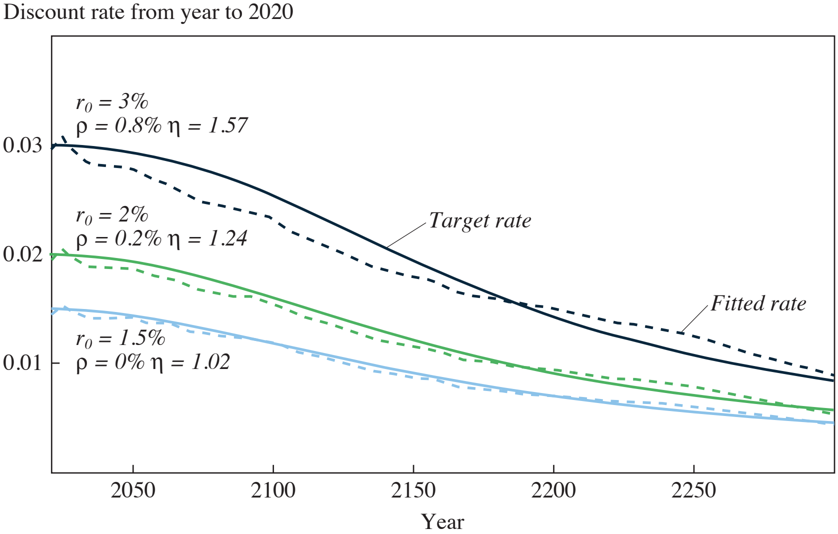
a welfare perspective. Correspondingly, such parameter values receive little support from economists working in this field (Drupp and others 2018).

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

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

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

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



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

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

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

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

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

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

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

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

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

IV. Illustrative Calculations of the Social Cost of Carbon

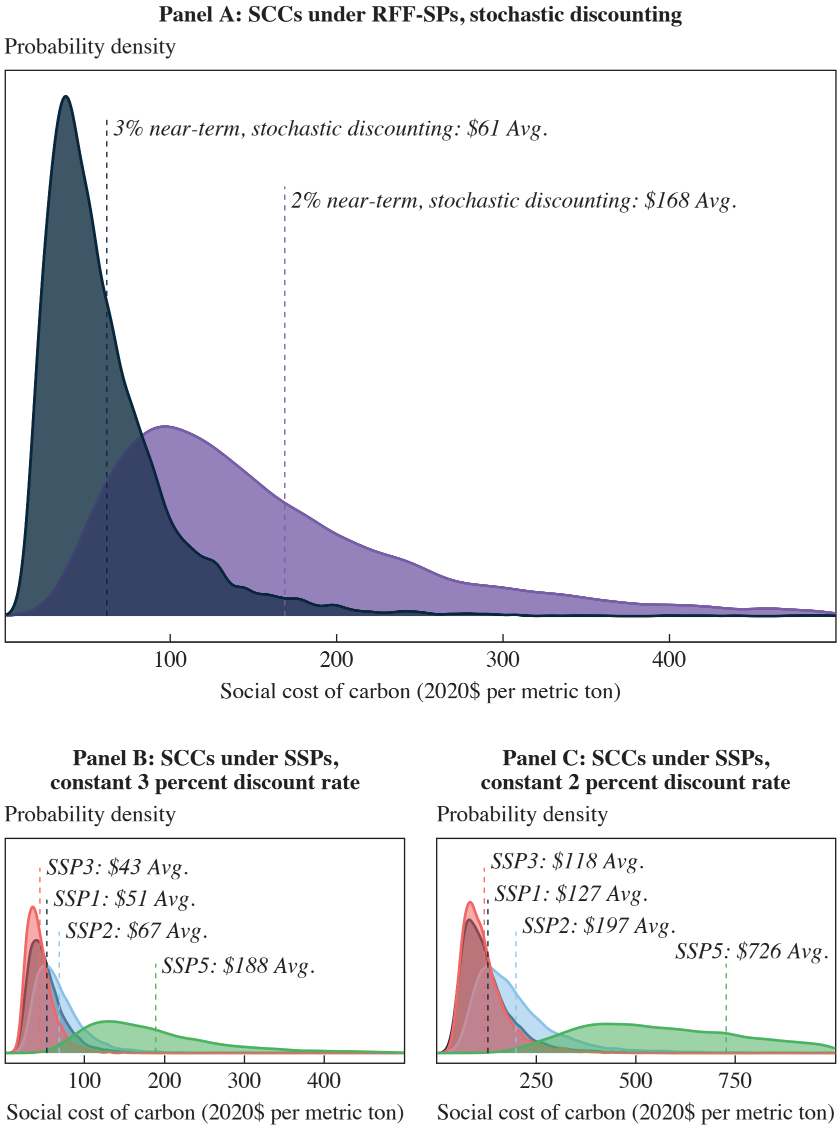
We present illustrative estimates of the SCC based on our socioeconomic projections (the RFF-SPs), the FaIR climate model, and our discounting methodology—all of which speak directly to the NASEM (2017) recommendations—and apply them using the DICE damage function (Nordhaus 2017a). This approach is directly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

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

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

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

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



Source: Authors' calculations.

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

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

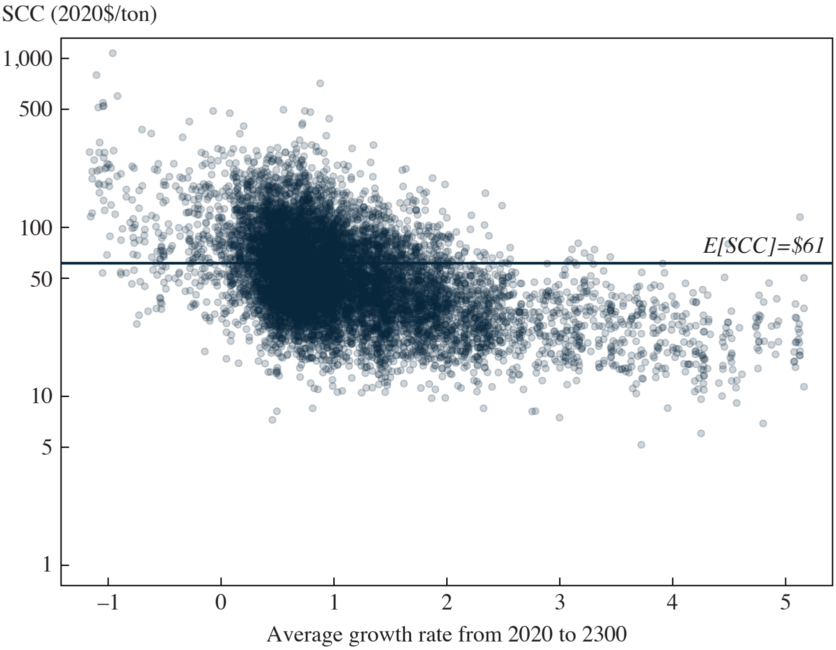
	Stochastic growth discounting		*Constant discounting*	
	3 percent near-term $\rho = 0.8\%$ $\eta = 1.57$	*2 percent near-term* $\rho = 0.2\%$ $\eta = 1.24$	*3 percent constant*	*2 percent constant*
Mean SCC, full distribution	$61.4	$168.4	$194	$1,557
Mean SCC, drop top and bottom 1 percent global income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

Source: Authors' calculations.
Note: The SCC estimates should be considered illustrative because they are based on alternative socio-economic inputs, discounting approaches, the FaIR 2.0 climate model, and the DICE damage function.

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

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

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



Source: Authors' calculations.

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

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

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

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

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

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

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

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

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

V. Conclusion

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

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

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

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

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

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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%,

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.

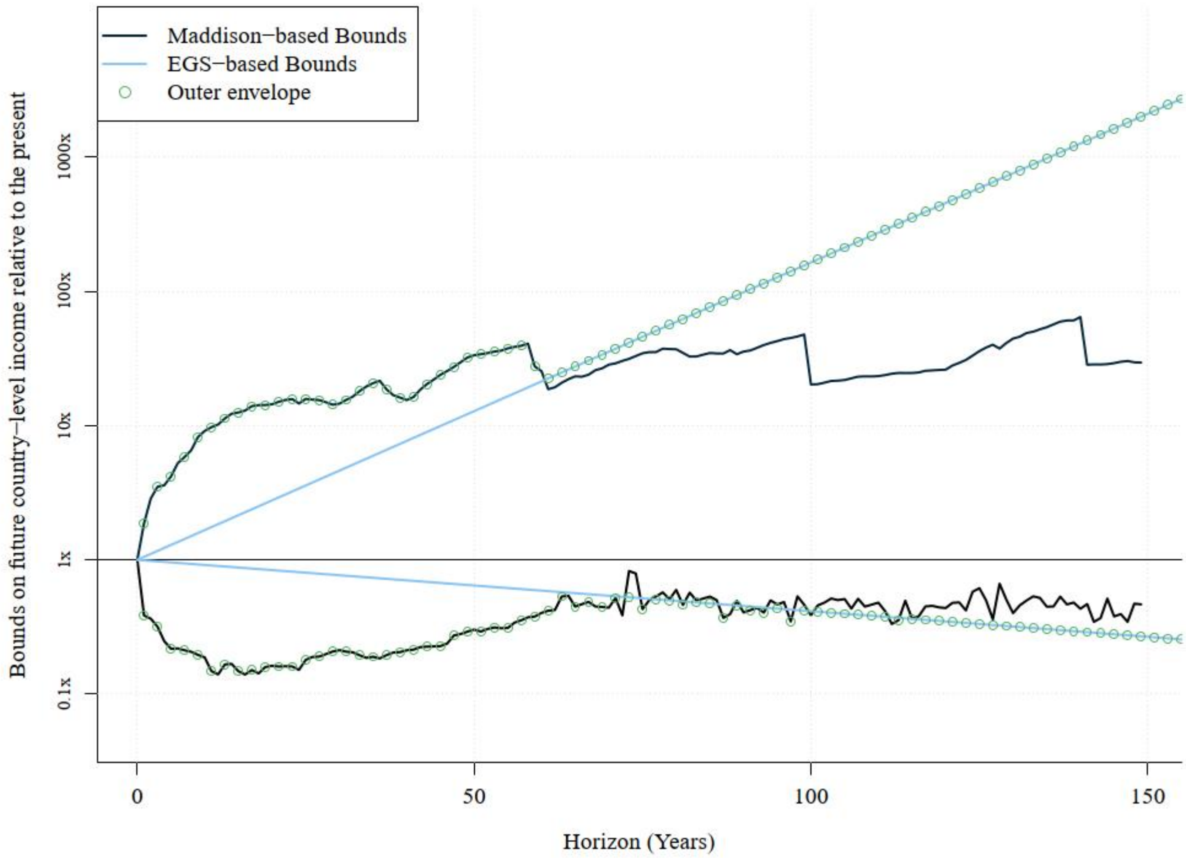

Figure OA- 1 Absorbing Bounds for Change in Country-Level GDP/capita Over Time.

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

1. Introduction

This report details 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.[3] 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 5th , 50th and 95th percentiles, or quantiles, for each calibration variable. An expert's *statistical accuracy* is the P-value (column 2 in Tables OA-3 and OA-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

[3] One expert opted out of the calibration process. Results from that expert were therefore included only in the equal weight combinations discussed below.

fall beneath the expert's 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[4].

Column 3 of Table OA-1gives the average information scores for each expert for all calibration 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 (6). 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.

[4] 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 OA-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. "# variables" 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 OA-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 the expert's highest expected score in the long run by, and only by, stating percentiles corresponding to the expert's 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 the expert tries to game the system to maximize the expert's expected weight, the expert will eventually figure out that 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 who 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 of choosing the cutoff at the traditional 5% value, termed PW05 shown in Table OA-2. All three DM's EW, PWOp and PW05 show acceptable statistical performance[5]. 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 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 OA-3.

[5] 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.

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 OA-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 OA-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 OA-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. 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 OA-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.

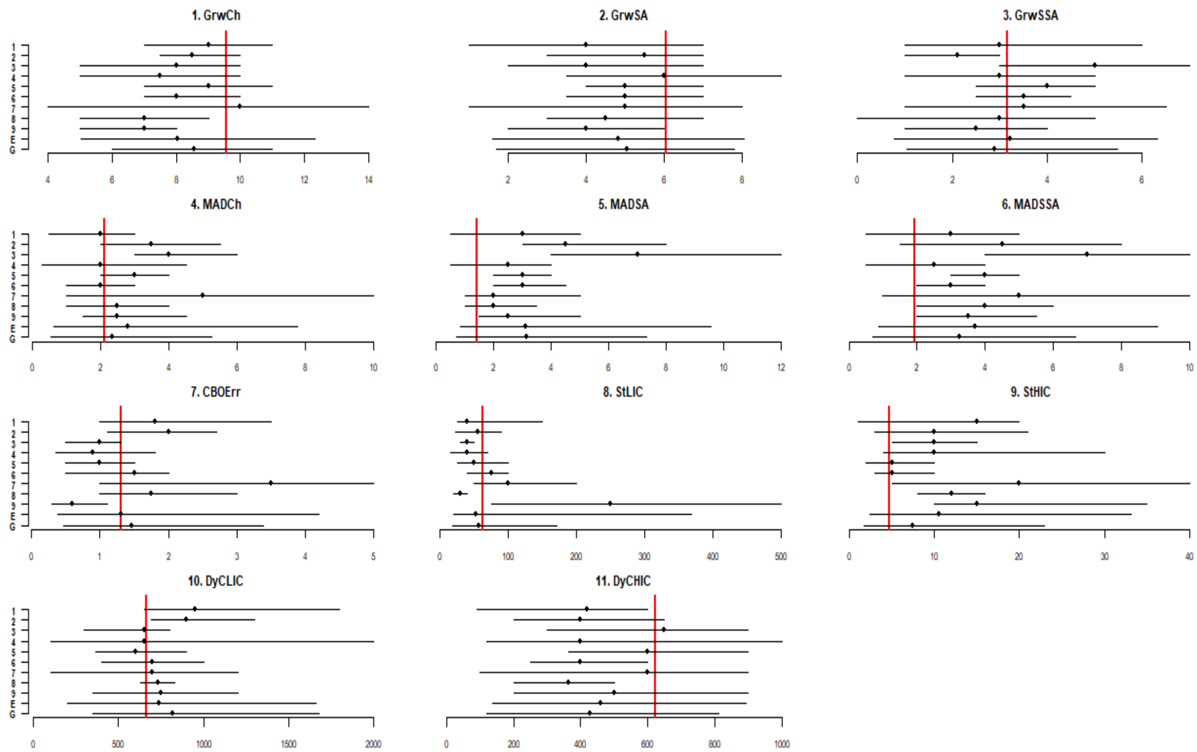

Figure OA-2 Range graphs for calibration variables for the EGS: one stacked graph for each variable. Each assessment is given by a horizontal line with 5% and 95% values as endpoints and a dot for the median. The true value is indicated by a vertical line. On each graph the order of assessments from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

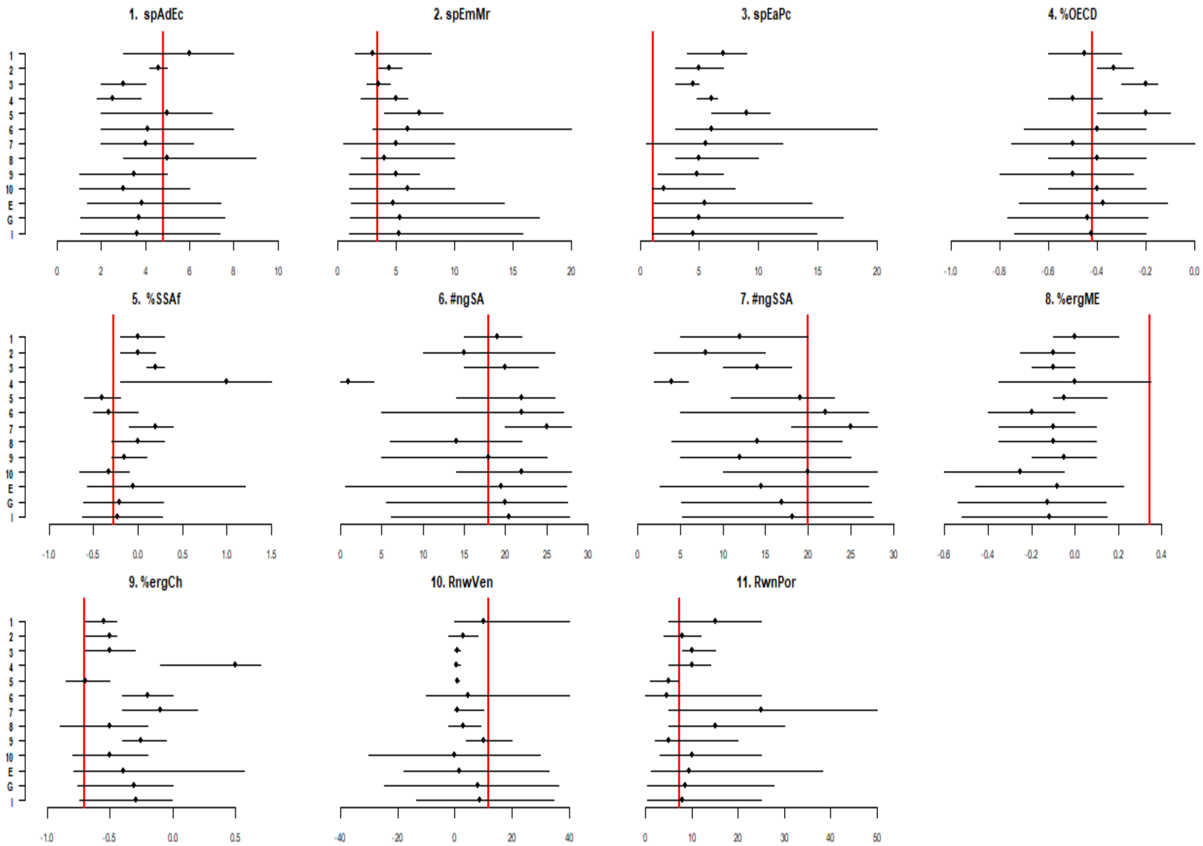

Figure OA-3 Range graphs for calibration variables for the FES: one stacked graph for each variable. Each assessment is given by a horizontal line with 5% and 95% values as endpoints and a dot for the median. The true value is indicated by a vertical line. On each graph the order of assessments from 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. 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 Figures OA-2 and OA-3 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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III. Economic Growth Survey: Additional results

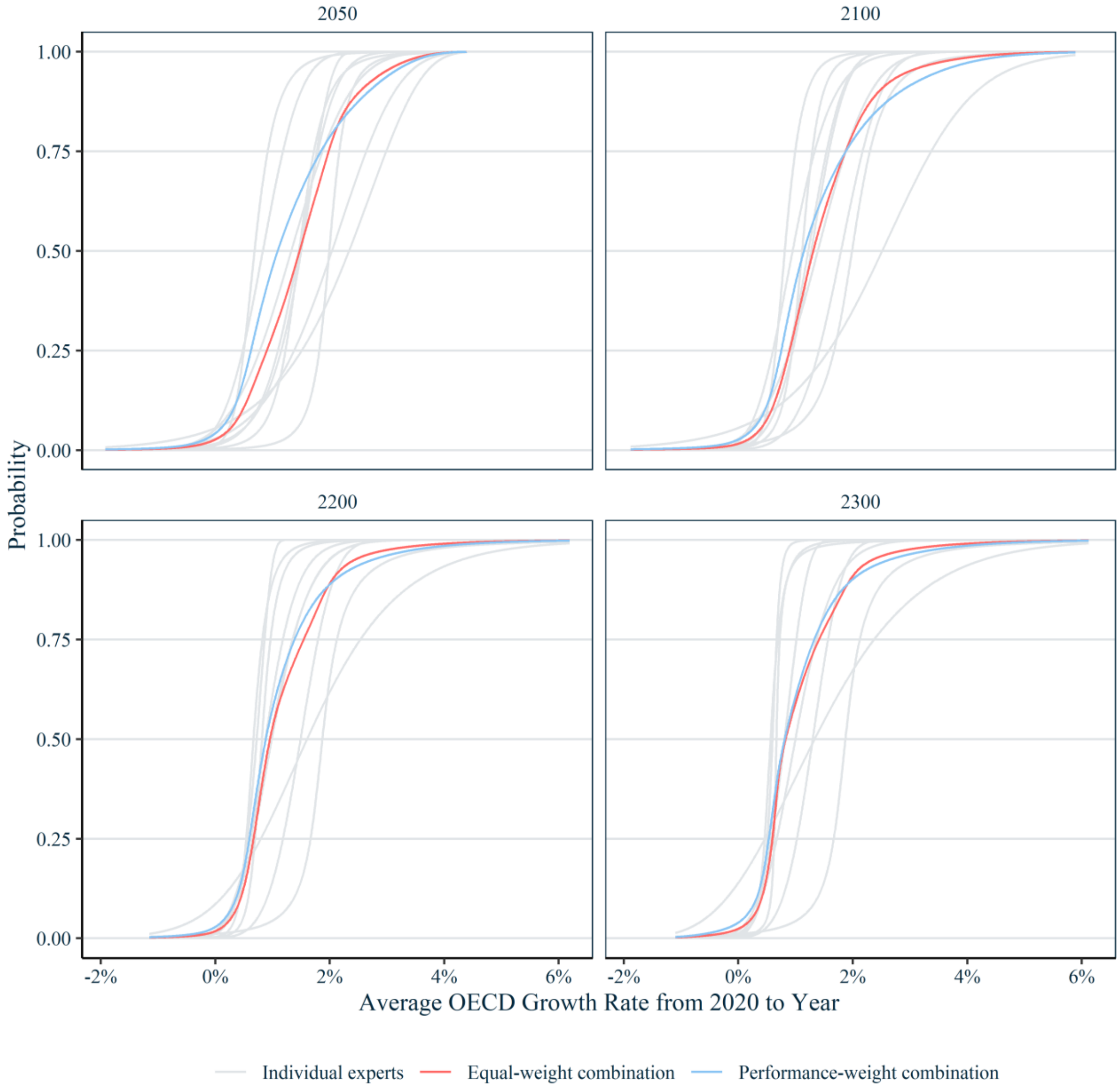


Figure OA-4. Cumulative Distribution Functions (CDFs) of Average Growth Rates of GDP per Capita for the OECD from the EGS, Individuals and Expert Combinations.

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, 2.5th percentile, 50th percentile, 97.5th 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 (5^{th} 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

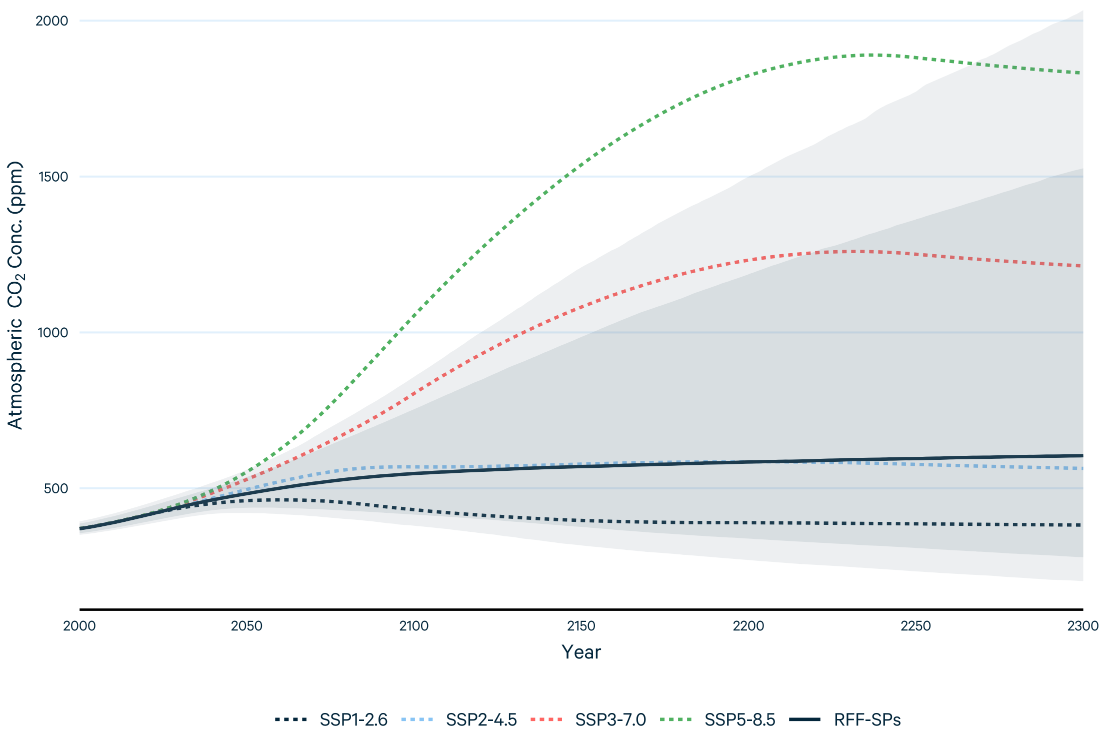


Figure OA-5: Projected total atmospheric CO_2 concentration. Solid lines represent median values, dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges based on the RFF-SPs.

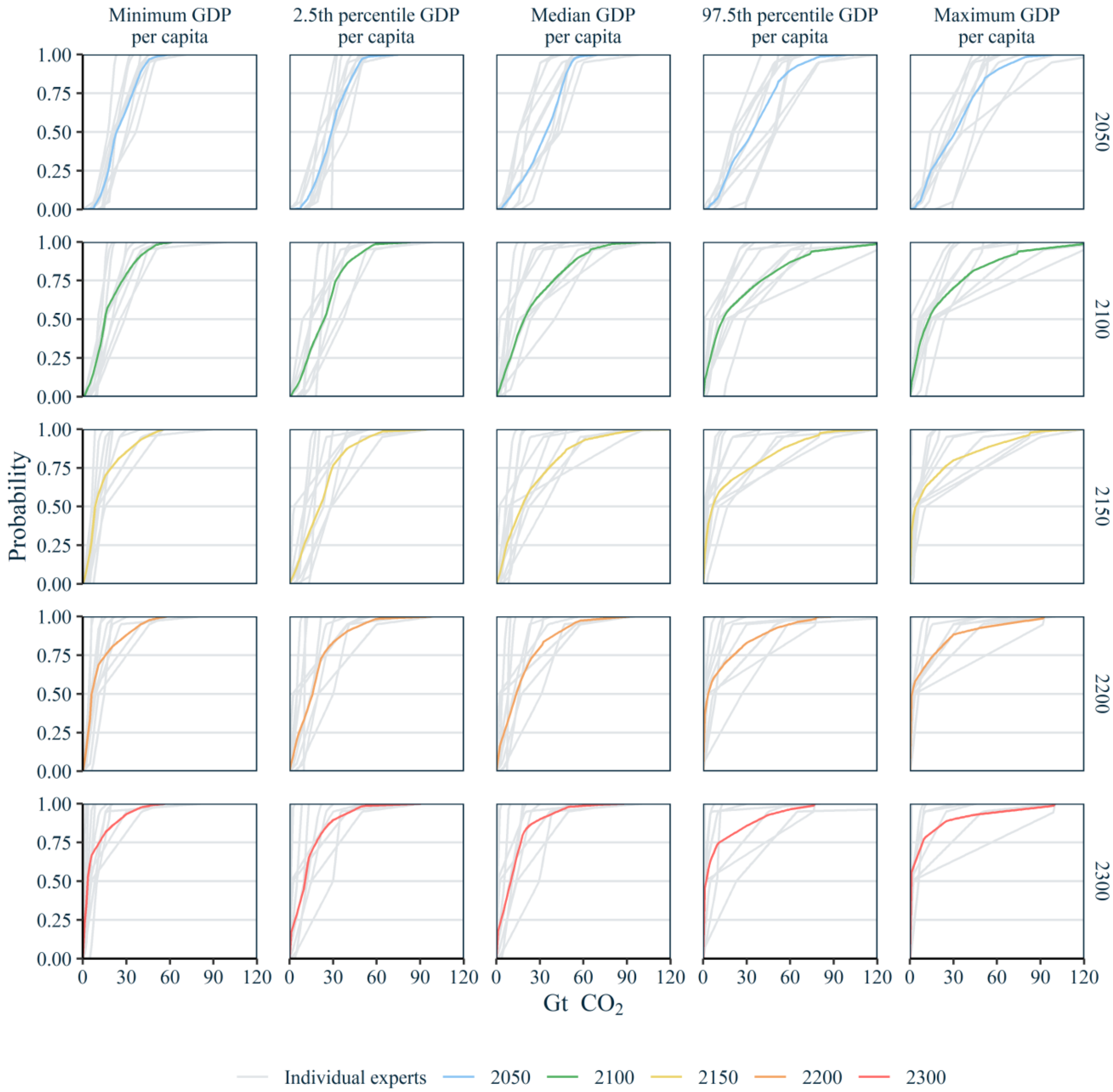


Figure OA- 6: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual CO_2 emissions across a range of timeframes and GDP per capita growth trajectories.

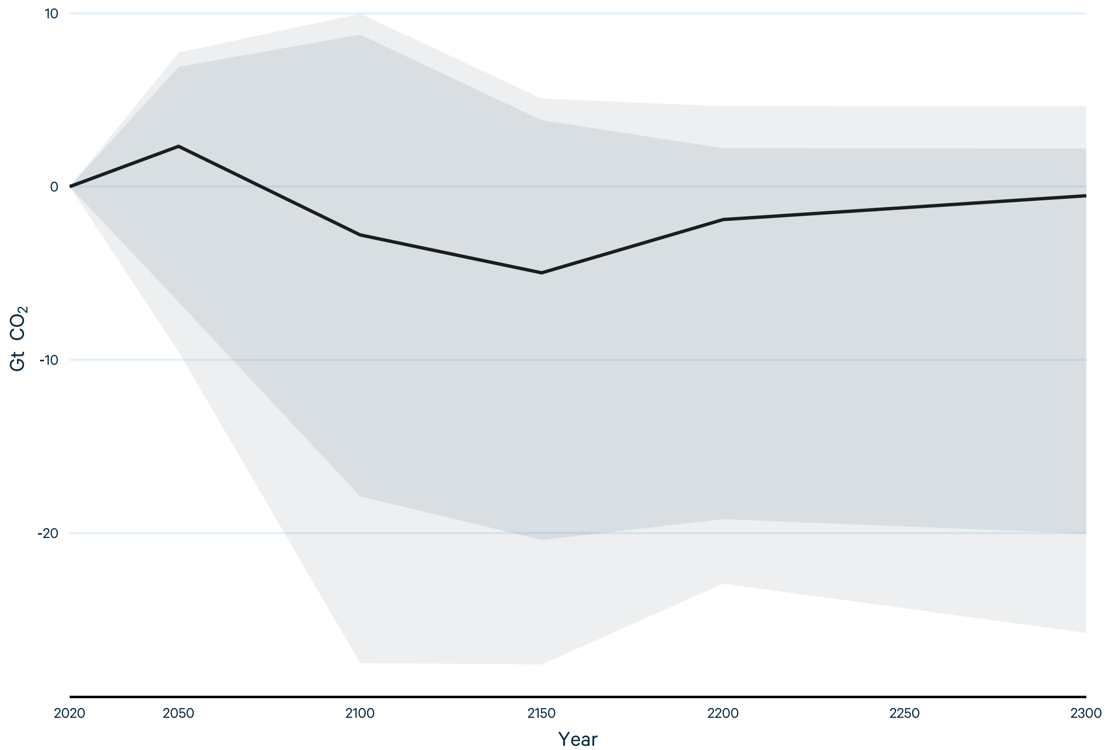


Figure OA-7: Annual net CO_2 emissions from natural carbon stocks and negative emissions technologies

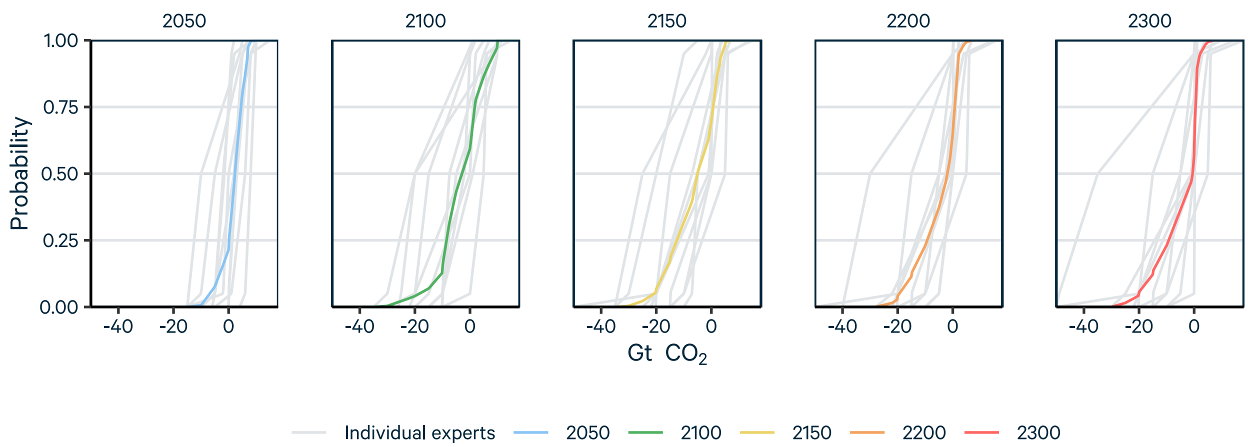


Figure OA-8: Cumulative distribution functions (CDFs) of individual and combined expert projections for net CO_2 emissions from natural carbon stocks and negative emissions technologies across a range of timeframes

CH_4 emissions

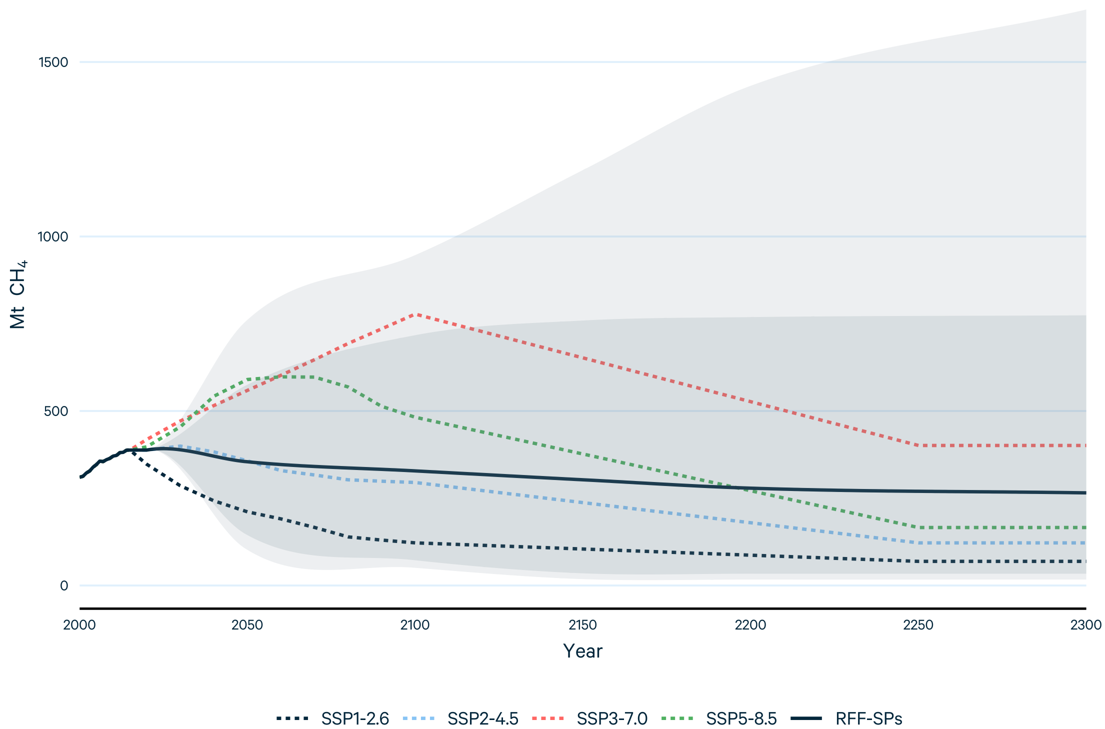


Figure OA-9: Annual emissions of CH_4 from the RFF-SPs and the SSPs. Lines represent median values, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

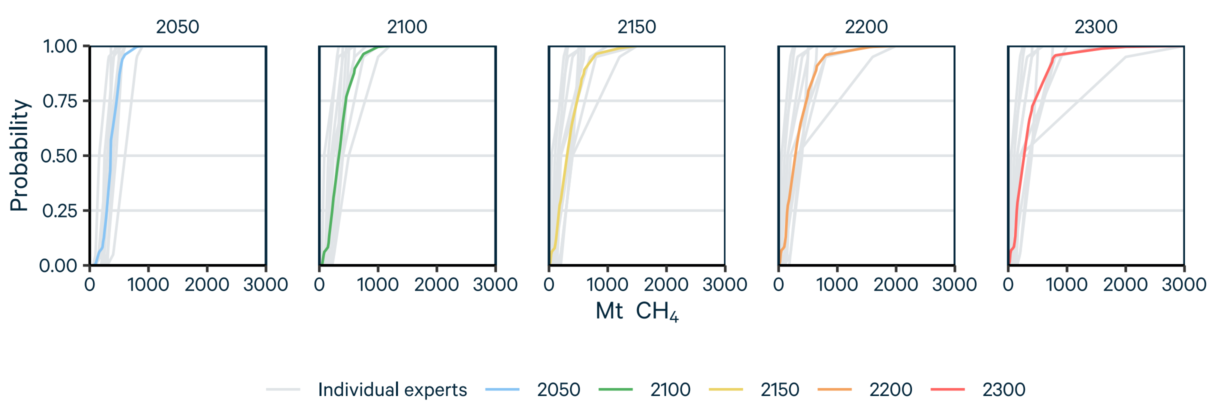


Figure OA-10: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual CH_4 emissions across a range of timeframes

N_2O emissions

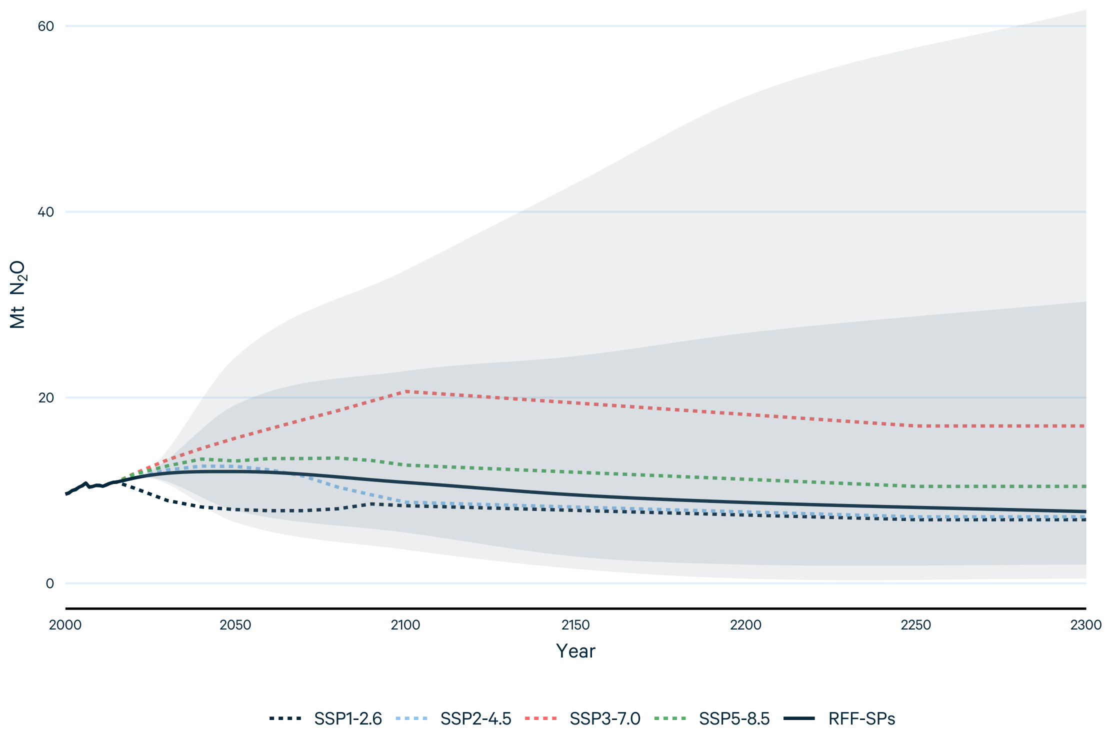


Figure OA–11 Annual emissions of N_2O from the RFF-SPs and the SSPs. Lines represent median values, and dark and light shading represent the 5th to 95th (darker) and 1st to 99th (lighter) percentile ranges of the RFF-SPs.

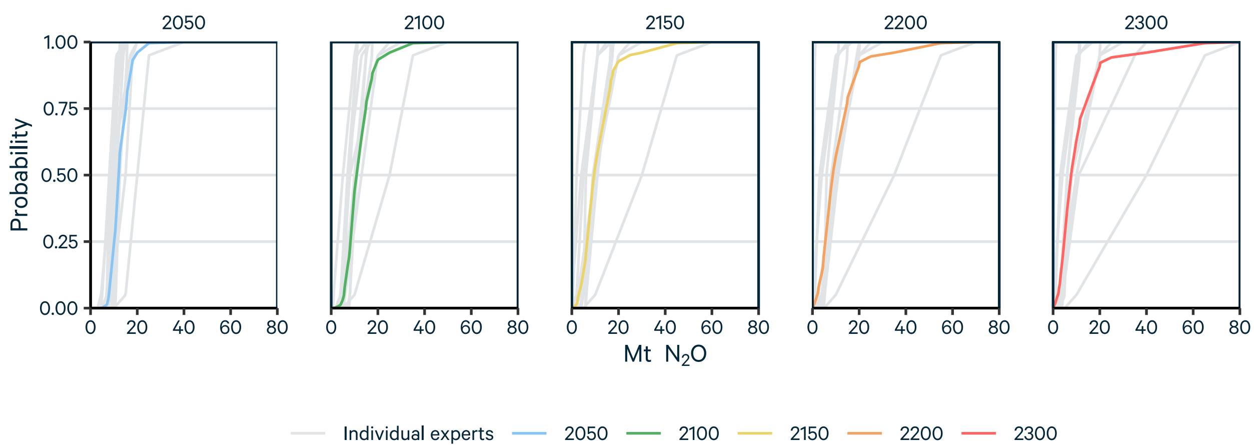


Figure OA-12: Cumulative distribution functions (CDFs) of individual and combined expert projections for annual N_2O emissions across a range of timeframes

V. Additional SCC calculations

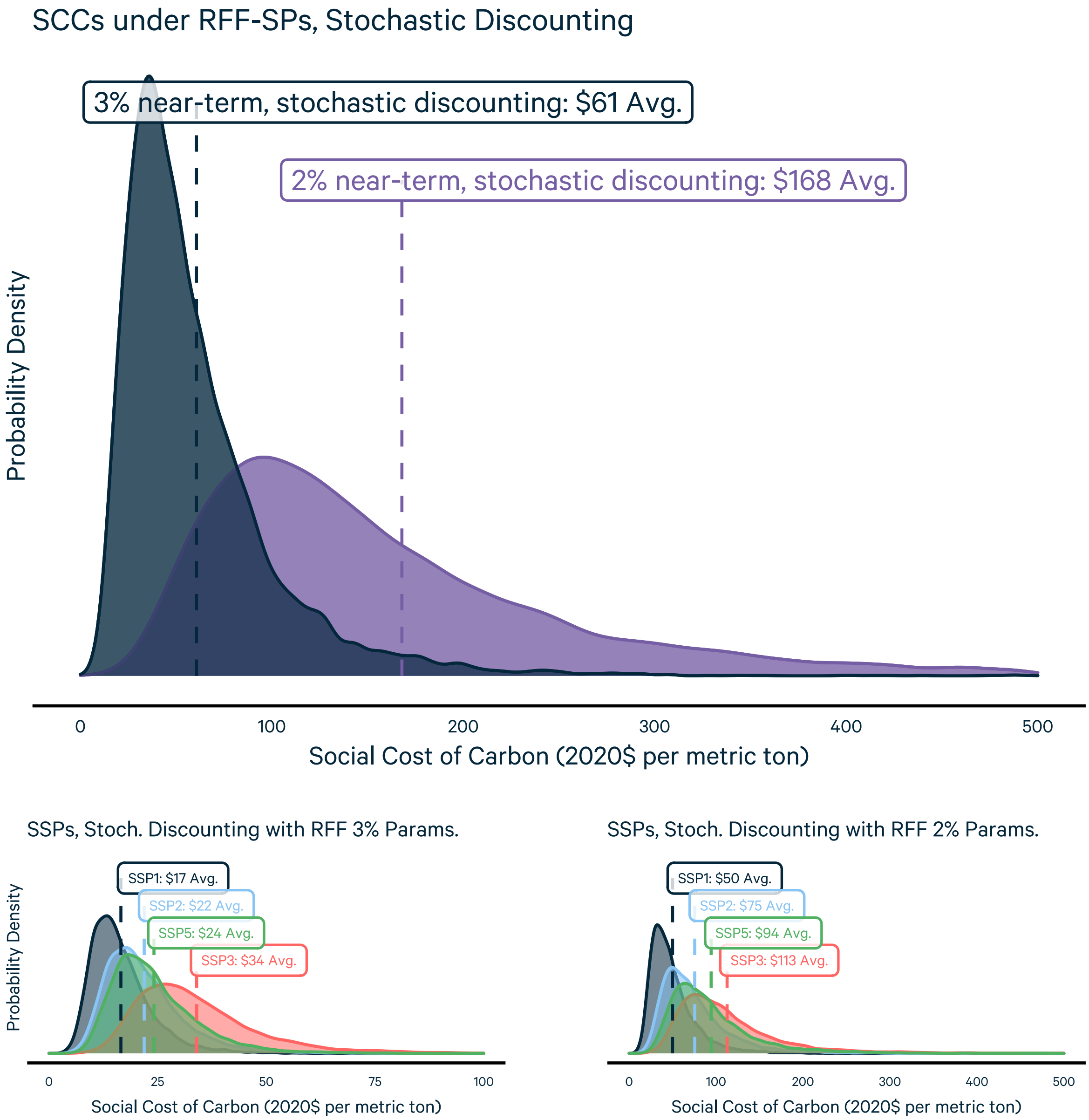


Figure OA-13. Illustrative Probability Distributions of the Social Cost of Carbon (2020$/ton CO_2) with FaIR climate and DICE damage modules, under Alternative Socioeconomic Inputs, Using Our Stochastic Discounting Parameters for All Socioeconomics ($\rho = 0.8\%$, $\eta = 1.57$ for 3% near-term, or $\rho = 0.2\%$, $\eta = 1.24$ for 2% near-term)

VI. Economic Growth Survey Elicitation Protocol

Economic Growth Survey

Overview:

Resources for the Future (RFF)is conducting its *Economic Growth Survey* to implement National Academy of Sciences (NAS) recommendations to improve the long-run economic growth projections that support estimates of the Social Cost of Carbon (SCC). The SCC is an economic metric used by the US federal government, state governments, and foreign governments to account for climate change in their actions. RFF's *Economic Growth Survey* is being carried out as a part of RFF's Social Cost of Carbon initiative.

- To implement the survey, RFF is conducting individual elicitations of ~15 leading experts in economic growth that have been nominated by their peers.
- Each expert will provide quantiles of future mean GDP per capita levels for the OECD as well as for a number of other regions, for the periods 2015-2050, 2015-2100, 2015-2200, and 2015-2300.
- Each expert will additionally quantify his or her uncertainty with regard to a set of relevant calibration variables for which true values are known.
- RFF will report combined distributions of economic growth projections based upon equal-weight combinations of the distributions provided by the experts as well as performance-weighted combinations, with performance measured via the calibration questions.
- By design, each expert achieves his or her maximal long run expected combined score on the calibration questions by, and only by, stating percentiles corresponding to his or her true beliefs.
- Expert names are preserved to enable competent peer review but are not associated with responses in any published documentation. Expert reasoning is captured during the elicitation and becomes, where indicated, part of the published record.
- Each elicitation will take approximately 2 hours and be conducted over freely available videoconferencing software. Experts receive an honorarium of $1250.

The elicitation comprises three parts:

Part 1: The expert will answer four practice questions for which, after responding, the answers will be provided to the expert. These questions are intended to orient the experts to the elicitation methodology as well as to increase their awareness to potential biases and overconfidence.

Part 2: The expert will answer 11 calibration questions that are intended to be used to performance-weight the experts when combining the full set of elicitation results on the main variables of interest.

Part 3: The expert will report values for the variables of interest for this study: quantiles of mean OECD GDP per capita levels for OECD countries, as well as for a number of other regions, for the periods 2015-2050, 2015-2100, 2015-2200, and 2015-2300.

Additional detail

Resources for the Future's Social Cost of Carbon (SCC) initiative is implementing National Academy of Sciences (NAS) recommendations to improve the socioeconomic projections (population, economic growth, global emissions) that underpin estimates of the SCC, the economic metric used by the US federal government, state governments, and foreign governments to account for climate change in their actions.

The NAS recommended that, in order to provide for the long residence time of carbon dioxide in the atmosphere, the SCC model runs (and the socioeconomic projections required) should extend far enough into the future to account for the vast majority of resulting damages (i.e. multiple centuries). The NAS further recommended that the appropriate way to address challenges inherent in quantifying the uncertainty for projections for such an extended time horizon is to use statistical methods in concert with results based upon the formal elicitation of experts, referred to as structured expert judgment. RFF's program of research, under which this structured expert judgment on economic growth falls, is intended to implement these recommendations and yield a set of very long-run (multi-century) central projections for economic growth, population, and global emissions, with associated uncertainty bounds.

Structured Expert Judgment Methodology

The goal of structured expert judgment is to generate a probability distribution for one or more variables of interest by combining a set of individual distributions for the variables that have been provided by a set of experts. There are a number of ways to generate the resulting combined distribution, the simplest being to combine the set of individual distributions in equal weights. An alternate method, which generally provides advantages of narrower overall uncertainty distributions with greater statistical accuracy and has been shown to provide greater performance both in-sample and out-of-sample, performance-weights the experts according to their ability to quantify their uncertainty for a set of calibration variables for which the true values are known. This latter approach is exemplified by the Classical Model for structured expert judgment, so called for its analogy with classical hypothesis testing. In its publication of its research on this topic, RFF will discuss distributions generated based upon both approaches.

In the Classical Model, each of the experts on a panel quantifies his or her uncertainty with regard to variables of interest as well as with regard to a set of calibration variables from the subject area for which true values are known. Experts are treated as statistical hypotheses and scored on two performance metrics -- *statistical accuracy* and *informativeness* -- on the calibration variables.

Statistical accuracy: Roughly, an expert is statistically accurate if, in a statistical sense, 5% of the true values fall below his/her 5th percentiles, 45% of the realizations fall between his/her 50th and 5th percentiles, etc. More formally, the statistical accuracy of a given expert is measured as the probability (P-Value) of falsely rejecting the hypothesis that an expert's observed inter-percentile frequencies comply with his/her probabilistic assessments.

Informativeness: The informativeness of an expert for a given question is related to the width of the uncertain distribution provided by the expert for that question. Narrower error bounds will yield a higher score for informativeness relative to wider error bounds. More formally, the informativeness of an expert is measured as Shannon relative information with respect to a background measure. Per variable, the background measures are uniform on an interval containing all assessments, with an analyst-stipulated small overshoot.

An expert's overall performance for a given question is based upon the product of his or her statistical accuracy and informativeness. Taking the product of these two metrics has the important property that it results in an *asymptotically strictly proper scoring rule*. In practice, this means that an expert achieves his or her maximal long run expected combined score by and only by stating percentiles corresponding to his or her true beliefs. Statistical accuracy is a fast function, typically varying over several orders of magnitude in a typical panel of experts. Informativeness is a slow function typically varying within a factor 3. Normalizing the combined scores of weighted experts allows statistical accuracy to dominate with informativeness modulating between experts of comparable accuracy.

Part 1: Practice questions

- *For each of the following values requested, please provide your 5th, 50th, and 95th percentiles. In other words: for the 5th percentile, provide the value for which the true value has a 1 in 20 chance of being less than; for the 50th percentile provide the value for which the true value has an equal chance of being greater or less than; and for the 95th percentile provide the value for which the true value has a 1 in 20 chance of exceeding.*
- *Please refrain from consulting outside sources, including those found on the internet, in answering these questions.*

The geometric mean of annual growth rates yields the rate at which constant growth over the full period would result in the observed changes in GDP levels from the beginning of the period to the end – e.g.: $GDP_{2017} = GDP_{1980} * ((1 + \text{geometric mean})^{38})$.

The geometric mean of the **global** annual growth rate of GDP from 1980 to 2017 was 2.86% per year.

1. **What is the geometric mean of the annual growth rate from 1980 to 2017 for Saudi Arabia?**

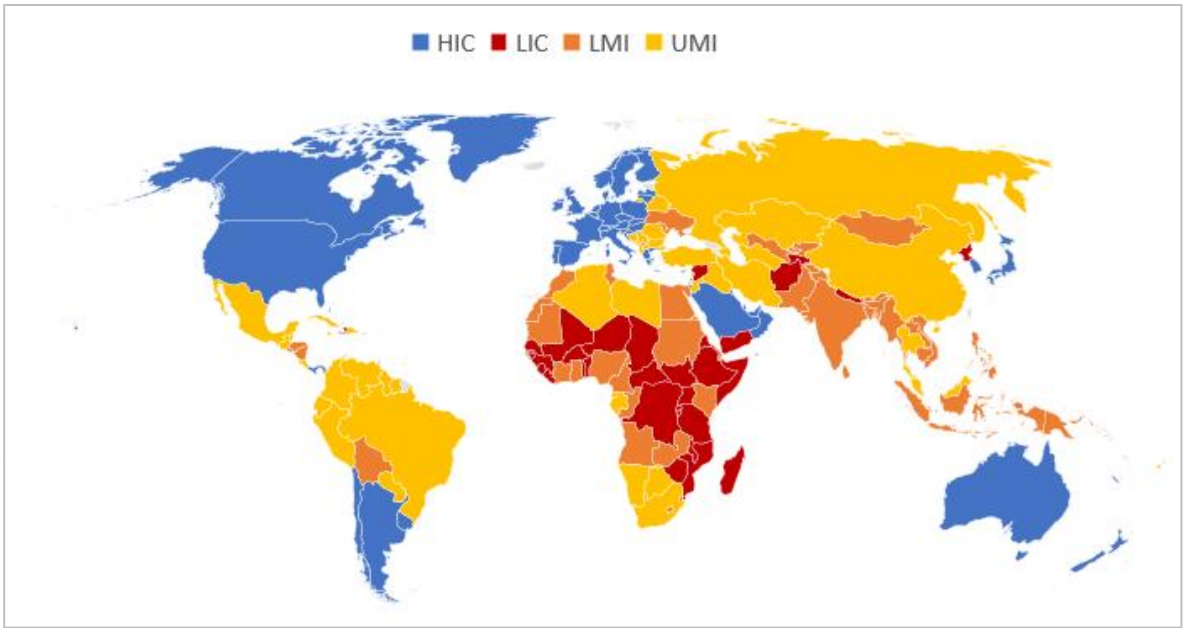
Also for Saudi Arabia, we are interested in your assessment of the **variability** of annual economic growth. One way of measuring such variability is by evaluating the Mean Absolute Deviation (MAD) with respect to the region's arithmetic mean for the full period.

$$MAD = \frac{1}{38} \sum_{y=1980}^{2017} |region\ growth\ rate\ in\ year\ y - \ mean\ region\ growth\ rate\ |$$

2. **What is the MAD of annual GDP growth for Saudi Arabia from 1980 to 2017?**

The following questions assess a metric of competitiveness and economic activity for two country groupings: Low Income Countries (LIC) and High Income Countries (HIC).

Note that LIC and HIC are two of four total income categories, along with Lower Middle Income (LMI) and Upper Middle Income (UMI). Appendix A provides a full list of countries in each category.



The *time required to start a business* -- the number of calendar days needed to complete the procedures to legally operate a business -- is a metric of competitiveness surveyed annually on a global basis.

- The survey conducted:
    - reflects the time for a small- to medium-size limited liability company to start up and formally operate in each economy's largest business city;
    - uses a standardized business that is 100% domestically owned, has a start-up capital equivalent to 10 times the income per capita, engages in general industrial or commercial activities and employs between 10 and 50 people one month after the commencement of operations, all of whom are domestic nationals;
    - considers two cases of local limited liability companies that are identical in all aspects, except that one company is owned by five married women and the other by five married men.
- If a procedure can be speeded up at additional cost, the fastest procedure, independent of cost, is chosen.

The full, detailed methodology for the survey will be provided at the request of the expert.

The unweighted country average for the world for number of days to start a business went from **51.55 days** in **2003** to **20.12 days** in **2018**.

3. What is the average number of days to start a business in 2018 for LIC?

4. What is the average number of days to start a business in 2018 for HIC?

Part 2: Performance calibration questions

- *For each of the following values requested, please provide your 5th, 50th, and 95th percentiles. In other words: for the 5th percentile, provide the value for which the true value has a 1 in 20 chance of being less than; for the 50th percentile provide the value for which the true value has an equal chance of being greater or less than; and for the 95th percentile provide the value for which the true value has a 1 in 20 chance of exceeding.*
- *Please refrain from consulting outside sources, including those found on the internet, in answering these questions.*

The geometric mean of annual growth rates yields the rate at which constant growth over the full period would result in the observed changes in GDP levels from the beginning of the period to the end. – e.g.: $GDP_{2017} = GDP_{1980} * ((1 + \text{geometric mean})^{38})$.

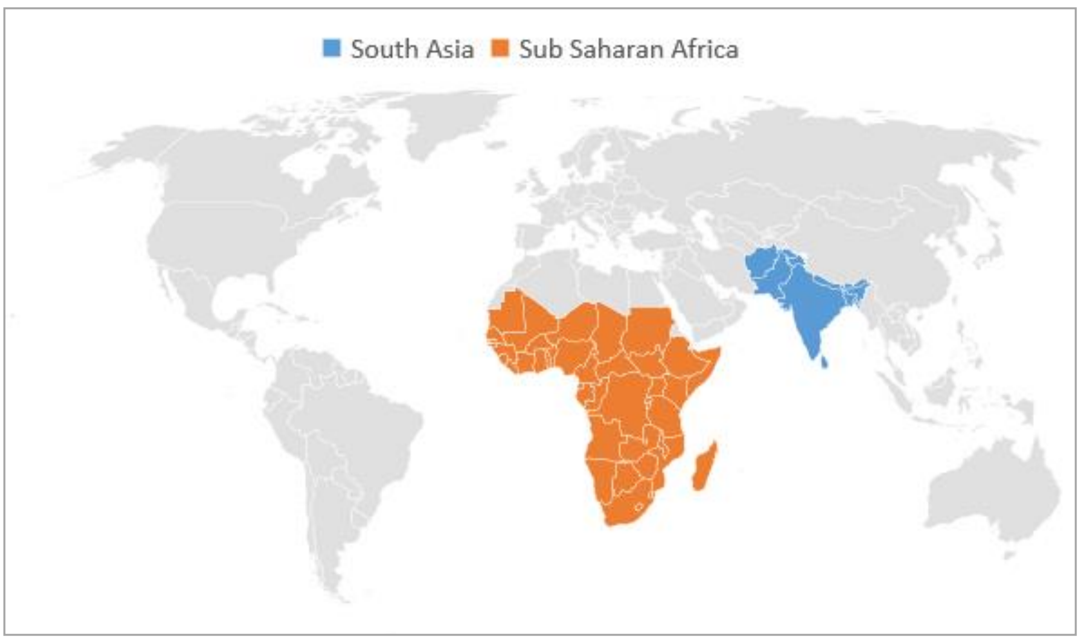
The geometric mean of the **global** annual growth rate of GDP from 1980 to 2017 was 2.86% per year.

1. **What is the geometric mean of the annual growth rate from 1980 to 2017 for China?**

2. **What is the geometric mean of the annual growth rate from 1980 to 2017 for South Asia*?**

3. **What is the geometric mean of the annual growth rate from 1980 to 2017 for Sub-Saharan Africa*?**

*Full list of countries in South Asia and Sub-Saharan Africa is included in Appendix B.



For the same set of regions, we are interested in your assessment of the *variability* of annual economic growth.

One way of measuring such variability is by evaluating the Mean Absolute Deviation (MAD) with respect to a country or region's arithmetic mean for the full period.

$$MAD = \frac{1}{38}\sum_{y=1980}^{2017} |region\ growth\ rate\ in\ year\ y - \ mean\ region\ growth\ rate\ |$$

4. What is the MAD of annual GDP growth for China from 1980 to 2017?

5. What is the MAD of annual GDP growth for South Asia from 1980 to 2017?

6. What is the MAD of annual GDP growth for Sub-Saharan Africa from 1980 to 2017?

For four decades, the US Congressional Budget Office (CBO) has prepared economic forecasts for use in making its projections for the federal budget.

- The CBO prepares *next-year* forecasts in January of a given year which forecast the geometric mean of growth from the beginning of the given year through the end of the following year.
- The CBO also reports *5-year* forecasts in January of a given year which forecast the geometric mean of growth from the beginning of the given year through the end of the following four years.

To evaluate its economic forecasts, CBO compares them with the economy's actual performance. The error of each forecast is measured as an **absolute** difference between the forecasted growth and the actual growth. The following question requests comparison of the accuracy of CBO's next-year forecasts with the accuracy of CBO's 5-year forecasts.

The average *absolute* error of **next-year** forecasts of GDP growth rate in the United States from 1992 to 2014, calculated according to the formula below, was **1.08%.**

$$\frac{1}{23}\sum_{t=1992}^{2014}\left|(avg^{*}\ growth\ forecast\ from\ t\ to\ t+1)-\ (avg^{*}\ growth\ from\ t\ to\ t+1)\right|$$

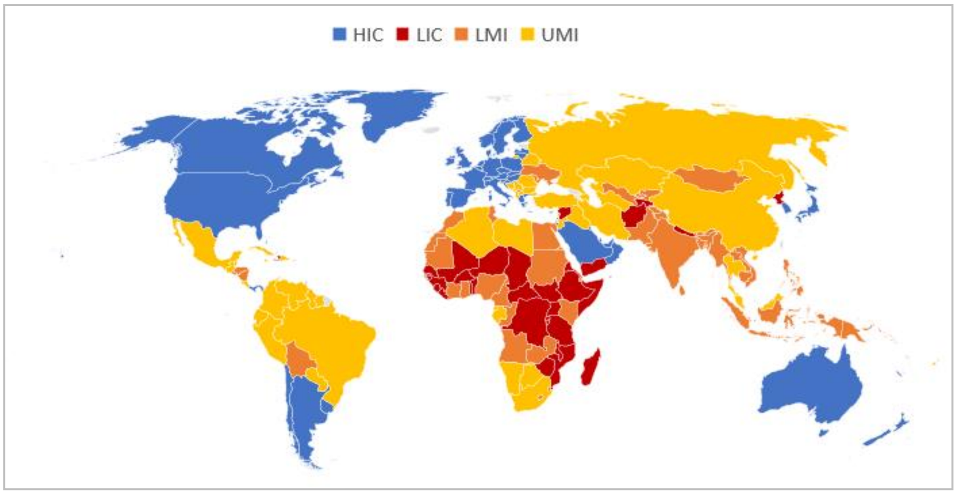
7. What is the average absolute error of CBO's 5-year forecasts of GDP growth rate in the United States from 1992 to 2011?

$$\frac{1}{20}\sum_{t=1992}^{2011}\left|(avg^{*}\ growth\ forecast\ from\ t\ to\ t+4)-\ (avg^{*}\ growth\ from\ t\ to\ t+4)\right|$$

*****averages calculated as a geometric mean of growth

As in the practice questions, the following questions request assessment of metrics of competitiveness and economic activity for two groupings of countries: Low Income Countries (LIC) and High Income Countries (HIC).

Note that LIC and HIC are two of four total income categories, along with Lower Middle Income (LMI) and Upper Middle Income (UMI). Appendix A provides full list of countries in each category.



The *average cost of starting a business*, recorded as a percentage of the economy's Gross National Income per capita (GNIpc), is surveyed annually on a global basis.

In the survey:

- The representative business is a small- to medium-size limited liability company (with details as previously described in Part I) commencing formal operations in each economy's largest business city;
- Costs includes all official fees and fees for legal or professional services if such services are required by law or commonly used in practice;
- Fees for purchasing and legalizing company books are included if these transactions are required by law;
- Although value added tax registration can be counted as a separate procedure, value added tax is not part of the incorporation cost;
- The company law, the commercial code and specific regulations and fee schedules are used as sources for calculating costs; and
- In all cases the cost excludes bribes.

The **unweighted world average** cost of starting a business as a percentage of GNIpc went from **104.68%** in **2003** to **23.88%** in **2018**.

8. **What was the average cost of starting a business as percentage of GNIpc in 2018 for LIC?**

9. **What was the average cost of starting a business as percentage of GNIpc in 2018 for HIC?**

The *time required to enforce a contract* -- the number of calendar days from the filing of a lawsuit in court until the final determination and, in appropriate cases, payment -- is surveyed annually on a global basis.

In the representative case employed by the survey:

- The case is a commercial dispute between a buyer and a seller that is resolved through a local first-instance court;
- The value of the claim is equal to 200% of the economy's income per capita or $5,000, whichever is greater.
- The dispute involves custom-tailored goods that are rejected by the buyer as being of insufficient quality.
- The seller disputes the claim in court and the judge renders a judgment that is 100% in favor of the seller.
- The buyer does not appeal the judgment. The seller decides to start enforcing the judgment as soon as the time allocated by law for appeal lapses.
- The seller takes all required steps for prompt enforcement of the judgment. The money is successfully collected through a public sale of the buyer's movable assets (for example, office equipment and vehicles).

The **unweighted world average** for time to enforce a contract went from **605.41 days** in **2003** to **647.54 days** in **2018**.

10. **What was the average number of days to enforce a contract in 2018 for LIC?**

11. **What was the average number of days to enforce a contract in 2018 for HIC?**

Part 3: Elicitation

We will now elicit your 1st, 5th, 50th, 95th, and 99th percentiles on *GDP per capita levels for OECD countries* in 2050, 2100, 2200, and 2300.

- As in the calibration questions, your 50th percentile is the value for which you believe the true value has an equal chance of being less or greater than. Your 1st and 99th percentiles are the values for which you believe the true value has a 1 in 100 chance of being less or greater than, respectively. Your 5th and 95th percentiles are the values for which you believe the true value has a 1 in 20 chance of being less or greater than, respectively.
- Many economists think primarily in terms of growth *rates* rather than levels, so we are providing a spreadsheet tool for translating between an average growth rate over a period and the resulting GDP per capita level at the end of the period.
- Given that the final variables of interest are the levels of GDP per capita, we encourage you to consciously pay attention to the levels that result from changing the growth rates in the table.
- As a part of the elicitation we will also ask you to describe your rationale for the quantiles. For example, we will ask you to describe future narratives that would plausibly yield the reported levels of GDP per capita with the likelihoods indicated.
- We will also ask you to identify the primary drivers of your low and high quantiles by selecting them from a list of relevant factors that have been suggested to us by experts as well as drawn from the growth literature. Experts are encouraged to add their own primary factors to the list if they are not included in the initial list of drivers.
- In order to capture your rationale, we will be taking notes throughout the elicitation. To facilitate such notetaking and ensure its veracity, we will also request that this section be recorded, solely for our internal use in processing the results. *Such recording is completely optional and at the discretion of the individual expert.*
- *Consulting outside sources for this part of the elicitation is permitted.*

Guide to the elicitation reporting spreadsheet:

1) The first tab in the spreadsheet, labeled 'Rationale', provides the list of potential factors that have been suggested by experts consulted and the growth literature to influence long-run economic growth.
2) The second tab, labeled 'OECD', provides the tool with which the expert can enter quantiles for growth rates to convert them into levels for final reporting. This tab additionally provides different views of the historic OECD GDP per capita levels and growth rates from 1915 to 2014.

Appendix A - Income Categories

HIC (80 countries)	**LIC (34 countries)**	**LMI (47 countries)**	**UMI (56 countries)**
Aruba	Afghanistan	Angola	Albania
Andorra	Burundi	Bangladesh	Armenia
United Arab Emirates	Benin	Bolivia	American Samoa
Argentina	Burkina Faso	Bhutan	Azerbaijan
Antigua and Barbuda	Central African Republic	Cote d'Ivoire	Bulgaria
Australia	Congo, Dem. Rep.	Cameroon	Bosnia and Herzegovina
Austria	Comoros	Congo, Rep.	Belarus
Belgium	Eritrea	Cabo Verde	Belize
Bahrain	Ethiopia	Djibouti	Brazil
Bahamas, The	Guinea	Egypt, Arab Rep.	Botswana
Bermuda	Gambia, The	Micronesia, Fed. Sts.	China
Barbados	Guinea-Bissau	Georgia	Colombia
Brunei Darussalam	Haiti	Ghana	Costa Rica
Canada	Liberia	Honduras	Cuba
Switzerland	Madagascar	Indonesia	Dominica
Channel Islands	Mali	India	Dominican Republic
Chile	Mozambique	Kenya	Algeria
Curacao	Malawi	Kyrgyz Republic	Ecuador
Cayman Islands	Niger	Cambodia	Fiji
Cyprus	Nepal	Kiribati	Gabon
Czech Republic	Korea, Dem. People's Rep.	Lao PDR	Equatorial Guinea
Germany	Rwanda	Sri Lanka	Grenada
Denmark	Senegal	Lesotho	Guatemala
Spain	Sierra Leone	Morocco	Guyana
Estonia	Somalia	Moldova	Iran, Islamic Rep.
Finland	South Sudan	Myanmar	Iraq
France	Syrian Arab Republic	Mongolia	Jamaica
Faroe Islands	Chad	Mauritania	Jordan
United Kingdom	Togo	Nigeria	Kazakhstan
Gibraltar	Tajikistan	Nicaragua	Lebanon
Greece	Tanzania	Pakistan	Libya
Greenland	Uganda	Philippines	St. Lucia
Guam	Yemen, Rep.	Papua New Guinea	Maldives
Hong Kong SAR, China	Zimbabwe	West Bank and Gaza	Mexico
Croatia		Sudan	Marshall Islands
Hungary		Solomon Islands	Macedonia, FYR
Isle of Man		El Salvador	Montenegro
Ireland		Sao Tome and Principe	Mauritius
Iceland		Swaziland	Malaysia

Israel
Italy
Japan
St. Kitts and Nevis
Korea, Rep.
Kuwait
Liechtenstein
Lithuania
Luxembourg
Latvia
Macao SAR, China
St. Martin (French part)
Monaco
Malta
Northern Mariana Islands
New Caledonia
Netherlands
Norway
New Zealand
Oman
Panama
Palau
Poland
Puerto Rico
Portugal
French Polynesia
Qatar
Saudi Arabia
Singapore
San Marino
Slovak Republic
Slovenia
Sweden
Sint Maarten (Dutch part)
Seychelles
Turks and Caicos Islands
Trinidad and Tobago
Uruguay
United States
British Virgin Islands
Virgin Islands (U.S.)

Timor-Leste
Tunisia
Ukraine
Uzbekistan
Vietnam
Vanuatu
Kosovo
Zambia

Namibia
Nauru
Peru
Paraguay
Romania
Russian Federation
Serbia
Suriname
Thailand
Turkmenistan
Tonga
Turkey
Tuvalu
St. Vincent and the Grenadines
Venezuela, RB
Samoa
South Africa

Appendix B

South Asia

- Afghanistan
- Bangladesh
- Bhutan
- India
- Sri Lanka
- Maldives
- Nepal
- Pakistan

Sub-Saharan Africa

- Angola
- Burundi
- Benin
- Burkina Faso
- Botswana
- Central African Republic
- Cote d'Ivoire
- Cameroon
- Democratic Republic of the Congo
- Congo
- Comoros
- Cabo Verde
- Eritrea
- Ethiopia
- Gabon
- Ghana
- Guinea
- Gambia
- Guinea-Bissau
- Equatorial Guinea
- Kenya
- Liberia
- Lesotho
- Madagascar
- Mali
- Mozambique
- Mauritania
- Mauritius
- Malawi
- Namibia
- Niger
- Nigeria
- Rwanda
- Sudan
- Senegal
- Sierra Leone
- Somalia
- South Sudan
- Sao Tome and Principe
- Swaziland
- Seychelles
- Chad
- Togo
- United Republic of Tanzania
- Uganda
- South Africa
- Zambia
- Zimbabwe

Request for additional information

In the projections you previously provided as a part of RFF's Economic Growth Survey, both the economic effects of **physical damages** resulting from future climate change as well as the effects of **policies to address climate change** on economic growth may have played a role in your assessment of future growth paths. Two additional expected use cases for the final, aggregate growth projections would benefit from quantifying the contribution of such effects to your projections to the extent possible.

Please respond to the following pair of questions:

1. Would specifically **excluding** the **economic effects of physical damages** resulting from future climate change significantly alter the economic growth quantiles you have already provided? If so, please use the spreadsheet provided to modify your previous quantiles to exclude such effects.

- The specific thought exercise by which to consider this question is to imagine that actions continue to be taken to address climate change throughout the period, but that in retrospect:
    - Temperature, precipitation, and other physical climate variables did not change in response to increased CO_2 levels;
    - Increased levels of atmospheric carbon dioxide did not affect the economy through other physical pathways (e.g. ocean acidification, CO_2 fertilization, etc).

2. Would specifically **excluding the economic effects of physical damages** resulting from future climate change (as in question 1) **AND** the **economic effects of future policies** to address climate change significantly alter the economic growth quantiles you have already provided? If so, could you please use the spreadsheet provided to modify your previous quantiles to exclude such effects.

- The specific thought exercise by which to consider this question is to imagine that:
    - at the start of the growth period, it is proven definitively that (as in 1) increases in greenhouse gas emissions will not result in changes in temperature, precipitation, or other physical climate variables. Nor will it lead to effects on other environmental variables (e.g. ocean acidification, plant growth, etc).
    - As a result, throughout the period, no policy actions are taken on the basis of expected climate change.

VII. Future Emissions Survey Elicitation Protocol

RFF Future Emissions Survey

Overview:

Resources for the Future (RFF) is conducting its *Future Emissions Survey* to implement National Academy of Sciences (NAS) recommendations to improve the long-run economic growth projections that support estimates of the Social Cost of Carbon (SCC). The SCC is an economic metric used by the US federal government, state governments, and foreign governments to account for climate change in their actions. RFF's *Future Emissions Survey* is being carried out as a part of RFF's Social Cost of Carbon initiative.

- To implement the survey, RFF is conducting individual elicitations of ~12 leading experts in socioeconomic projections and climate policy that have been nominated by their peers.
- Each expert will provide quantiles of future emissions for carbon dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O) and related variables for the years 2050, 2100, 2150, 2200, and 2300.
- Each expert will additionally quantify his or her uncertainty with regard to a set of relevant calibration variables for which true values are known.
- RFF will report combined distributions of emissions projections based upon equal-weight combinations of the distributions provided by the experts as well as performance-weighted combinations, with performance measured via the calibration questions.
- By design, each expert achieves his or her maximal long run expected combined score on the calibration questions by, and only by, stating percentiles corresponding to his or her true beliefs.
- Expert names and qualifications are part of the public record. The association of names and information provided is preserved to enable competent peer review but is not part of any published documentation. Expert reasoning is captured during the elicitation and becomes, where indicated, part of the published record.
- Each elicitation will take approximately 2 hours and be conducted over freely available videoconferencing software. Experts receive an honorarium of $1000.

The elicitation comprises three parts:

Part 1: The expert will answer two practice questions for which, after responding, the answers will be provided to the expert. These questions are intended to orient the experts to the elicitation methodology as well as to increase their awareness to potential biases and overconfidence.

Part 2: The expert will answer 11 calibration questions that are intended to be used to performance-weight the experts when combining the full set of elicitation results on the main variables of interest.

Part 3: The expert will report values for the variables of interest for this study as described on the next page.

Description of information provided by the experts

Experts will be asked to provide quantiles of uncertainty (minimum, 5th, 50th, 95th, maximum, as well as additional percentiles at the expert's discretion) for several variables for the following two cases:

- **Evolving Policies**: Incorporating expected changes in technology, fuel use, and other conditions, *consistent with the expert's expected evolution of future policy.*
- **Current Laws and Regulations**: Incorporating expected changes in technology, fuel use, and other conditions, *consistent with current on-the-books policies*.
    - Emissions distributions offered in under this case should represent current legislation and environmental regulations, including recent government actions for which implementing regulations were available as of August 2, 2021. The potential effects of proposed legislation, regulations, and standards—or sections of legislation that have been enacted but require funds to execute or do not have the required implementing regulations in place—should not be reflected here.

For each case, experts will be asked to provide quantiles of uncertainty for the following for the years 2050, 2100, 2150, 2200, 2300:

5) Global CO_2 emissions ($GtCO_2$) for 3 future trajectories of GDP per capita representing the 2.5th percentile, 50th percentile, and 97.5th percentile of projected economic growth (three separate responses). Experts will also specify distributions for the minimum and maximum GDP per capita for those years.
    a. Reported emissions should include net total emissions from processes involving CCS, including CCS applied to fossil energy and process-related emissions.
    b. By construction, emissions must be greater or equal to 0 in this section.
    c. To avoid double-counting, emissions accounted for in this section are not be accounted for in section 2) and vice versa.
6) Quantiles of the net emissions (CO_2 only) from the **combined sum** of:
    a. Agriculture, Forestry, and Other Land Use (AFOLU, $GtCO_2$)
    b. Sequestered emissions from Direct Air Capture (DAC, $GtCO_2$) and Bioenergy with Carbon Capture and Storage (BECCS, $GtCO_2$).
    c. By construction, total net emissions from this section may be positive (net CO_2 source) or negative (net CO_2 sink) in this section.
7) Quantiles of global CH_4 emissions ($GtCH_4$), including emissions from AFOLU.
8) Quantiles of global N_2O emissions (GtN_2O), including emissions from AFOLU

For each of the quantiles specified:

1) Quantile values will be linearly interpolated in time between each of the years elicited. Consequently, experts are specifying quantiles of piece-wise linear, non-overlapping trajectories.

   a. For example, the 5th percentile trajectory of emissions intensity represents a linear interpolation in time of the specified 5th percentiles for 2050, 2100, 2150, 2200, and 2300.

2) Quantiles for AFOLU, DAC, BECCS, CH_4, and N_2O by default will apply to all economic growth trajectories. Experts will, at their discretion, be able to provide such projections conditioned on economic growth in the same manner as for CO_2.

Additional detail

The NAS recommended that, in order to provide for the long residence time of carbon dioxide in the atmosphere, the SCC model runs (and the socioeconomic projections required) should extend far enough into the future to account for the vast majority of resulting damages, and that the year 2300 was sufficient to meet this recommendation. The NAS further recommended that the appropriate way to address challenges inherent in quantifying the uncertainty for projections for such an extended time horizon is to use statistical methods in concert with results based upon the formal elicitation of experts, referred to as structured expert judgment.

RFF's program of research, under which this structured expert judgment on future emissions falls, is implementing these recommendations to yield a set of very long-run (multi-century) central projections for economic growth, population, and global emissions, with associated uncertainty bounds. The research employs statistical methods and expert elicitation to generate probability density functions for projections of each term of the following form of the IPAT identity:

Emissions ≡ Population * (GDP/Population) * (Emissions/GDP)

Previous work under the initiative has yielded country level PDFs of population and GDP/capita. Country-level PDFs of population to 2300 are available based upon Raftery and Ševčíková (under review, 2021). Country-level PDFs for GDP/capita to 2300 are available based upon the methodology of Mueller, Stock, and Watson (2020) used in concert with results from the *RFF Economic Growth Survey*. RFF's *Future Emissions Survey* is designed to provide PDFs of global emissions and related variables, conditioned on future economic growth, based upon an expert elicitation of ~12 experts on global emissions.

Structured Expert Judgment Methodology

The goal of structured expert judgment is to generate a probability distribution for one or more variables of interest by combining a set of individual distributions for the variables that have been provided by a set of experts. There are a number of ways to generate the resulting combined distribution, the simplest being to combine the set of individual distributions in equal weights. An alternate method, which generally provides advantages of narrower overall uncertainty distributions with greater statistical accuracy and has been shown to provide greater performance both in-sample and out-of-sample, performance-weights the experts according to their ability to quantify their uncertainty for a set of calibration variables from their field for which the true values are known. This latter approach is exemplified by the Classical Model for structured expert judgment, so called for its analogy with classical hypothesis testing. In its publication of its research on this topic, RFF will provide distributions generated based upon both approaches.

In the Classical Model, each of the experts on a panel quantifies his or her uncertainty with regard to variables of interest as well as with regard to a set of calibration variables from the subject area for which true values are known. Experts are treated as statistical hypotheses and scored on two performance metrics -- *statistical accuracy* and *informativeness* -- on the calibration variables.

Statistical accuracy: Roughly, an expert is statistically accurate if, in a statistical sense, 5% of the true values fall below his/her 5th percentiles, 45% of the realizations fall between his/her 50th and 5th percentiles, etc. More formally, the statistical accuracy of a given expert is measured as the probability (P-Value) of falsely rejecting the hypothesis that an expert's observed inter-percentile frequencies comply with his/her probabilistic assessments.

Informativeness: Informativeness is measured per variable as the Shannon relative information in an expert's distribution relative to a background measure. The background measure is (log) uniform on a 10% extension of the smallest interval containing all expert quantiles for the given variable. An expert's informativeness score is the average informativeness over all variables.

• RFF Future Emissions Survey

Part 1: Practice questions

- *For each of the following values requested, please provide your 5th, 50th, and 95th percentiles. In other words: for the 5th percentile, provide the value for which the true value has a 1 in 20 chance of being less than; for the 50th percentile provide the value for which the true value has an equal chance of being greater or less than; and for the 95th percentile provide the value for which the true value has a 1 in 20 chance of exceeding.*
- *Please refrain from consulting outside sources, including those found on the internet, in answering these questions.*

The geometric mean of annual growth rates yields the rate at which constant growth over the full period would result in the observed changes in GDP levels from the beginning of the period to the end – e.g.: $GDP_{2017} = GDP_{1980} * ((1 + \text{geometric mean})^{38})$.

The geometric mean of the **global** annual growth rate of GDP from 1980 to 2017 was 2.86% per year.

3. **What is the geometric mean of the annual growth rate from 1980 to 2017 for Saudi Arabia?**

Also for Saudi Arabia, we are interested in your assessment of the **variability** of annual economic growth. One way of measuring such variability is by evaluating the Mean Absolute Deviation (MAD) with respect to the region's arithmetic mean for the full period.

$$MAD = \frac{1}{38} \sum_{y=1980}^{2017} |region\ growth\ rate\ in\ year\ y - \ mean\ region\ growth\ rate\ |$$

4. **What is the MAD of annual GDP growth for Saudi Arabia from 1980 to 2017?**

Part 2: Performance calibration questions

- *For each of the following values requested, please provide your 5th, 50th, and 95th percentiles. In other words: for the 5th percentile, provide the value for which the true value has a 1 in 20 chance of being less than; for the 50th percentile provide the value for which the true value has an equal chance of being greater or less than; and for the 95th percentile provide the value for which the true value has a 1 in 20 chance of exceeding.*
- *Please refrain from consulting outside sources, including those found on the internet, in answering these questions. For definitions see the Appendix.*

For the period **1960-2020** the **world** growth rate of GDP per capita in non-recession years was 2.1. In the five recession years (1975, 1982, 1991, 2009, 2020) the world growth average was -2.3.

The ***spread*** of world average growth between the non-recession years and recession years is 2.1 - (-2.3) = 4.4.

1. What is the spread of average growth rate between non-recession years and world recession years for Advanced Economies?

2. What is the spread of average growth rate between non-recession years and world recession years for Emerging Markets and Developing Economies?

3. What is the spread of average growth rate between non-recession years and world recession years for East Asia and Pacific Countries?

CO_2 emissions intensity is defined as CO_2 emissions (kg) per unit of GDP (2017$ PPP)

For the period 1990-2018, the **world percentage change** in CO_2 emissions intensity:

$$\frac{emissions\ intensity_{2018} - emissions\ intensity_{1990}}{emissions\ intensity_{1990}}$$

was **-0.331.**

4. For the period 1990-2018, what was the percentage change in CO_2 emissions intensity for OECD members?

5. For the period 1990-2018, what was the percentage change in CO_2 emissions intensity for Sub-Saharan Africa?

For the period 1990-2018, the year-over-year **world** percentage change in *CO_2 emissions intensity* was negative for 26 out of 28 years.

6. For the period 1990-2018, how many years (out of 28 possible) was the year-over-year change in CO_2 emissions intensity negative for South Asia?

7. For the period 1990-2018, how many years (out of 28 possible) was the year-over-year change in CO2 emissions intensity negative for Sub-Saharan Africa?

Energy intensity is defined as energy consumed (ktoe) per GDP (2015$ PPP).

For the period 1990-2018, the **world percentage change** in *energy intensity*:

$$\frac{energy\ intensity_{2018} - energy\ intensity_{1990}}{energy\ intensity_{1990}}$$

was **-0.35.**

8. For the period 1990-2018, what was the percentage change in energy intensity for the Middle East?

9. For the period 1990-2018, what was the percentage change in energy intensity for China?

For the period 1980-2018, the percentage of primary energy for the **world** coming from renewable sources -- defined here as hydropower, solar, wind, geothermal, wave, tidal, and modern biofuels, but excluding traditional biomass – increased from 6.37% to 10.96%, for an absolute change of +4.59pp.

10. For the period 1980-2018, what was the absolute change (percentage points) in primary energy coming from renewable sources for Venezuela?
11. For the period 1980-2018, what was the absolute change (percentage points) in primary energy coming from renewable sources for Portugal?

Part 3: Elicitation

We will now ask you to provide quantiles of uncertainty (minimum, 5th, 50th, 95th, maximum, as well as others at your discretion) for several variables for the following two cases:

- **Evolving Policies**: Incorporating expected changes in technology, fuel use, and other conditions, *consistent with your expected evolution of future policy.*
- **Current Laws and Regulations**: Incorporating expected changes in technology, fuel use, and other conditions, *consistent with current on-the-books policies*.
  - Emissions distributions offered in under this case should represent current legislation and environmental regulations, including recent government actions for which implementing regulations were available as of August 2, 2021. The potential effects of proposed legislation, regulations, and standards—or sections of legislation that have been enacted but require funds to execute or do not have the required implementing regulations in place—should not be reflected here.

For each case, you will be asked to provide quantiles of uncertainty for the following for the years 2050, 2100, 2150, 2200, 2300:

1) Global CO_2 emissions ($GtCO_2$) for 3 future trajectories of GDP per capita representing the 2.5th percentile, 50th percentile, and 97.5th percentile of projected economic growth (three separate responses). You will also specify distributions for the minimum and maximum GDP per capita for those years.
   a. Reported emissions should include net total emissions from processes involving CCS, including CCS applied to fossil energy and process-related emissions.
   b. By construction, emissions must be greater or equal to 0 in this section.
   c. To avoid double-counting, emissions accounted for in this section are not be accounted for in section 2) and vice versa.

2) Quantiles of the net emissions (CO_2 only) from the **combined sum** of:
   a. Agriculture, Forestry, and Other Land Use (AFOLU, $GtCO_2$)
   b. Sequestered emissions from Direct Air Capture (DAC, $GtCO_2$) and Bioenergy with Carbon Capture and Storage (BECCS, $GtCO_2$).
   c. By construction, total net emissions from this section may be positive (net CO_2 source) or negative (net CO_2 sink) in this section.

3) Quantiles of global CH_4 emissions ($GtCH_4$), including emissions from AFOLU.
4) Quantiles of global N_2O emissions (GtN_2O), including emissions from AFOLU.

For each of the quantiles specified:

- Quantile values will be linearly interpolated in time between each of the years elicited. Consequently, experts are specifying quantiles of piece-wise linear, non-overlapping trajectories.
    - For example, the 5th percentile trajectory of emissions intensity represents a linear interpolation in time of the specified 5th percentiles for 2050, 2100, 2150, 2200, and 2300.
- Quantiles for AFOLU, DAC, BECCS, CH_4, and N_2O by default will apply to all economic growth trajectories. You will, at your discretion, be able to provide such projections conditioned on economic growth in the same manner as provided for CO_2.

- Please describe your rationale for the quantiles. For example, we will ask you to describe future narratives that would plausibly yield the reported levels of emissions with the likelihoods indicated.
- In order to capture your rationale, we will be taking notes throughout the elicitation. To facilitate such notetaking and ensure its veracity, we will also request that this section be recorded, solely for our internal use in processing the results. *Such recording is completely optional and at the discretion of the individual expert.*
- *Consulting outside sources for this part of the elicitation is permitted.*

Appendix A – Country classifications

Advanced Economies

Australia	Finland	Israel	Netherlands	Sweden
Austria	France	Italy	New Zealand	Switzerland
Belgium	Germany	Japan	Norway	United Kingdom
Canada	Greece	Korea, Rep.	Portugal	United States
Cyprus	Hong Kong SAR	Latvia	Singapore	
Czech Republic	China	Lithuania	Slovak, Rep.	
Denmark	Iceland	Luxembourg	Slovenia	
Estonia	Ireland	Malta	Spain	

Emerging Markets and Developing Economies

Albania*	Lao PDR	Afghanistan	Pakistan
Algeria*	Liberia	Antigua and Barbuda	Palau
Angola*	Madagascar	Bahamas, The	Panama
Argentina	Malawi	Bangladesh	Philippines
Armenia	Malaysia*	Barbados	Poland
Azerbaijan*	Mali	Belarus	Romania
Bahrain*	Mauritania	Bhutan	Samoa
Belize	Mongolia	Bosnia and Herzegovina	Serbia
Benin	Morocco	Bulgaria	Seychelles
Bolivia*	Mozambique	Cabo Verde	Solomon Islands
Botswana	Myanmar*	Cambodia	Sri Lanka
Brazil	Namibia	China	St. Kitts and Nevis
Burkina Faso	Nicaragua	Comoros	St. Lucia
Burundi	Niger	Croatia	St. Vincent and the Grenadines
Cameroon*	Nigeria*	Djibouti	Thailand

Chad*	Oman*	Dominica	Tonga
Chile	Papua New Guinea	Dominican Republic	Tunisia
Colombia*	Paraguay	Egypt	Turkey
Congo, Dem. Rep.	Peru	El Salvador	Tuvalu
Congo, Rep.*	Qatar*	Eritrea	Vanuatu
Costa Rica	Russia*	Eswatini	Vietnam
Cote d'Ivoire	Rwanda	Fiji	
Ecuador*	Saudi Arabia*	Georgia	
Equatorial Guinea*	Senegal	Grenada	
Ethiopia	Sierra Leone	Haiti	
Gabon*	South Africa	Hungary	
Gambia,	The Sudan*	India	
Ghana*	Suriname	Jamaica	
Guatemala	Tajikistan	Jordan	
Guinea	Tanzania	Kiribati	
Guinea-Bissau	Timor-Leste*	Lebanon	
Guyana	Togo	Lesotho	
Honduras	Turkmenistan*	Maldives	
Indonesia*	Uganda	Marshall Islands	
Iran*	Ukraine	Mauritius	
Iraq*	United Arab Emirates*	Mexico	
Kazakhstan*	Uruguay	Micronesia, Fed. Sts.	
Kenya	Uzbekistan	Moldova, Rep.	
Kosovo	West Bank and Gaza	Montenegro	
Kuwait*	Zambia	Nepal	
Kyrgyz Republic	Zimbabwe	North Macedonia	

East Asia and Pacific Countries

Cambodia	Myanmar

China	Papua New Guinea
Fiji	Philippines
Indonesia	Solomon Islands
Lao PDR	Thailand
Malaysia	Timor-Leste
Mongolia	Vietnam

OECD Countries

Australia	Estonia	Italy	Norway	United Kingdom
Austria	Finland	Japan	Poland	United States
Belgium	France	Korea, Rep.	Portugal	
Canada	Germany	Latvia	Slovak Republic	
Chile	Greece	Lithuania	Slovenia	
Colombia	Hungary	Luxembourg	Spain	
Costa Rica	Iceland	Mexico	Sweden	
Czech Republic	Ireland	Netherlands	Switzerland	
Denmark	Israel	New Zealand	Turkey	

Sub Saharan Africa

Angola	Congo, Rep.	Kenya	Nigeria	Uganda
Benin	Cote D'Ivoire	Lesotho	Rwanda	Zambia
Botswana	Equatorial Guinea	Liberia	Sao Tome and Principe	Zimbabwe
Burkina Faso	Eritrea	Madagascar	Senegal	
Burundi	Eswatini	Malawi	Seychelles	

Cabo Verde	Ethiopia	Mali	Sierra Leone
Cameroon	Gabon	Mauritania	Somalia
Central African Republic	Gambia, The	Mauritius	South Africa
Chad	Ghana	Mozambique	South Sudan
Comoros	Guinea	Namibia	Tanzania
Congo, Dem. Rep	Guinea-Bissau	Niger	Togo

South Asia

Afghanistan	Sri Lanka
Bangladesh	Maldives
Bhutan	Nepal
India	Pakistan

Middle East

Islamic Republic of Iran	Iraq	Oman	Jordan
Saudi Arabia	Qatar	Bahrain	Lebanon
United Arab Emirates	Kuwait	Syria	Yemen