Expert Elicitation and the Social Cost of Greenhouse Gases

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Executive Summary

Researchers often formally elicit the views of subject-matter experts to help clarify consensus on complex or uncertain topics. This technique, known as expert elicitation, can be used to improve forecasts and inform the assumptions behind predictive models, among other applications. Several expert elicitations published in recent years offer useful insights on the dynamics and impacts of climate change.

The Interagency Working Group on the Social Cost of Greenhouse Gases ("Working Group") can use the findings from expert elicitations to improve the U.S. federal government's social cost of greenhouse gas estimates, which are used in regulatory cost-benefit analysis and other policy contexts. In its recommendations for updating the modeling behind the social cost of greenhouse gases, the National Academies of Sciences, Engineering, and Medicine included a call to use expert elicitation in the development of some components of the reduced-form Integrated Assessment Models ("IAMs") that underlie the social cost of greenhouse gas estimates.

The results from expert elicitations can be used to help calibrate several IAM parameters. Calibrating key parameters to match the consensus views of experts will lead to a more comprehensive account of likely climate impacts. Based on related recalibration efforts, the result would likely be a significant increase in the social cost of greenhouse gas values.

As part of its current update of the social cost of greenhouse gas estimates, the Working Group should consider several component updates that incorporate data from expert elicitations, including:

Socioeconomic and Emission Scenario Updates – The Working Group should no longer use the outdated socioeconomic and emission scenarios from the EMF-22 modeling exercise, and instead consider using the Shared Socioeconomic Pathways. It should also stop weighting scenarios equally. Ideally the Working Group should calibrate a joint probability distribution function for all socioeconomic and emissions scenario components including GDP, population, and emissions. If that is not feasible in the current timeframe, it should consider assigning probabilities based on existing expert elicitation findings.

Climate Science Assumption Updates – The Working Group should replace or update its modeling of climate science by adopting the FAIR climate model, after updating FAIR to match new data from the sixth IPCC assessment report once it is released in July 2021. It should also use expert elicitation to inform longer-term updates to climate-science assumptions.

Climate Damage Estimate Updates – It is critically important that the Working Group update the damage functions in reduced-form IAMs to reflect the best available, *current* information. The Working Group

should strongly consider using existing expert elicitations to improve the climate damage functions, especially given the short timeframe for the current update. Another option would be to conduct meta-regressions of climate damages, including damage estimates from expert elicitation and other methodologies beyond the traditional enumerative strategy.

Discount Rate Updates – The Working Group should supplement its calibration of the discount rate by considering evidence besides just market data and consider moving toward discount rate schedules based on the extended Ramsey discount rate equation, which can be informed by expert elicitation and the latest economic literature as well as any updated and reliable market data. There is a strong consensus forming around consumption discount rates between 1% and 3%. Within this range, the Working Group will need to select an appropriate discount rate or schedule for its central estimates, as well as additional rates or schedules for sensitivity analysis. Expert elicitation can help inform those decisions.

Expert elicitation can also play an important role in longer-term efforts to improve the social cost of greenhouse gas metrics, after the current update is completed. To help improve the quality of the modeling assumptions, the Working Group or its member agencies can solicit or conduct expert elicitations on such topics as climate science parameters, regional and sector-based damage estimates, and the dynamics and costs of adaptation.

The Working Group should view expert elicitation as a valuable tool for improving the quality of the social cost of greenhouse gas estimates.

Expert Elicitation in the Context of Climate Change

Researchers often formally elicit the views of experts in a field in order to improve the understanding of complex topics and highlight areas of consensus. This process, known as expert elicitation, captures the prevailing views of subject-matter experts and the level of uncertainty underlying those views. The technique can be used to improve forecasts and inform the assumptions behind predictive models, among other applications.

Researchers and policymakers regularly use expert elicitation to better understand climate change-related topics. To determine consensus on climate issues, the United Nations established the Intergovernmental Panel on Climate Change (IPCC) and tasked it with providing a consensus-based, scientific view on the current understanding of climate change and related consequences. Through the IPCC's deliberative review process, thousands of climate experts from across the globe assess the most recent scientific, technical, and socioeconomic information, and then synthesize their findings. The IPCC reviews the research of economists and solicits their participation in the working group on "Impacts, Adaptation, and Vulnerability," which has explored the consensus view on the social cost of carbon and other topics.

However, there are drawbacks to the deliberative process used by the IPCC (and others) to identify consensus. Group deliberations can lead to "groupthink," sometimes causing deliberation processes to suffer from censorship and uniformity (Sunstein, 2005). Indeed, the IPCC has been criticized for moving too slowly and adopting only the "lowest-common denominator" conclusions, leading to overly conservative results that ignore more up-to-date viewpoints (McKibben, 2007). In fact, actual measures of sea-level rise have tracked the high end of the IPCC's projections, and the IPCC's past temperature predictions were shown to be low (Rahmstorf et al., 2007; Rahmstorf et al., 2012). In other words, the IPCC has tended to underestimate the rate of climate change (Oreskes et al., 2019).

Besides deliberation, an alternate method for identifying the consensus opinion of experts is to use surveys and find a group's median or mean answer. Well-developed theories on "the wisdom of crowds" explain why the average answer from a group is likely to be more accurate than the answers of most individuals in that group, and why large groups perform better than small groups.[1] For example, groups of experts have been shown to significantly outperform individual experts on predicting such uncertain (and climate change-related) quantities as the annual peak rainfall runoff of various countries or changes in the U.S. economy (Armstrong, 2001). By comparison, deliberating groups tend only to do about as well as their

[1] In particular, the Condorcet Jury Theorem states that the probability of a correct answer by a majority of the group increases toward certainty as the size of the group increases, if each individual person is more likely than not to be correct (Surowiecki, 2004).

average members on making accurate predictions, and not as well as their best members (Gigone & Hastie, 1997).

Compared to deliberation, surveys and statistics can often produce a more nuanced understanding of expert consensus, and help reveal the full range of opinions in a group. Deliberation tends to reduce variance, since deliberations can amplify cognitive errors and overemphasize common knowledge, causing a group to converge on a common—though not necessarily accurate—answer. By showing the diversity of opinion, surveys can indicate where debate still exists on an issue and where a consensus might emerge in the future. Surveys can also measure the level of uncertainty on a topic, which can be especially important for policymakers who are risk averse or who seek to maximize future policy flexibility.

Targeted surveys and other forms of expert elicitation can be especially useful in helping inform estimates of climate change damages, given that such estimates rely on numerous projections and assumptions across a wide range of disciplines. Expert elicitation research has been cited in several important policy decisions related to climate impact estimation.[2]

Expert elicitations can be helpful to modelers who calibrate the reduced-form Integrated Assessment Models ("IAMs") that underlie estimates of the social cost of greenhouse gases. Some level of expert judgment is inevitable when designing structural models under vast uncertainty, as some structural assumptions remain untested and some reduced-form parameters are highly uncertain or unmeasurable. By tying model calibration decisions to a formalized elicitation process, modelers can help ensure that key assumptions align with the consensus views of experts (Oppenheimer et al. 2016). Using expert elicitation to clarify the level of agreement (and disagreement) within the climate economics community over key inputs into IAMs can align these models with the predominant views in the field (Cooke 2013). This methodology is currently underutilized in the climate-economic literature (Oppenheimer et al. 2016), though it has become more prominent in recent years (Drupp et al. 2018; Pindyck 2019).

As the Interagency Working Group on the Social Cost of Greenhouse Gases ("Working Group") develops updated estimates for the social cost of greenhouse gas metrics, it can use the findings from expert elicitations to inform many calibration decisions.

[2] For example, New York State's Department of Environmental Conservation cited Drupp et al. (2018) as primary evidence to justify its use of a 2% discount rate in the calculation of its central value of carbon. Similarly, the U.S. government's Interagency Working Group on the Social Cost of Carbon (2021) cited Drupp et al. (2018) and Howard and Sylvan (2020) as evidence supporting their interim recommendation to allow agencies to apply discount rates below 2.5% when valuing climate impacts. Outside of the climate context, expert elicitation has been used by several agencies: the U.S. Environmental Protection Agency developed concentration-response functions for mortality from particulate matter exposure using expert elicitation (Howard, 2019); and the Department of Interior relied on the expert opinion of Dr. Stephen Brown of UNLV to develop a multitude of parameters for its MarketSim model when estimates were unavailable in the literature (BOEM, 2015).

In its recommendations for improving the modeling behind the social cost of greenhouse gases, the National Academies of Sciences, Engineering, and Medicine ("NAS") included a call to use expert elicitation in the development of some IAM components (NAS, 2017). The full NAS recommendations will likely provide a framework for many of the Working Group's decisions, so this report generally uses those recommendations (on expert elicitation as well as other topics) as a starting point. Given the compressed timeframe for the Working Group's current update of the social cost of greenhouse gas metrics, we specifically recommend some ways that expert elicitation findings can be used to improve modeling in cases where there will not be sufficient time to fully incorporate certain NAS recommendations.

The results from expert elicitations can be used to help calibrate IAM parameters including socioeconomic and emissions scenarios; climate science; climate damage functions (including assumptions related to adaptation, technology availability, and abatement costs); and discount rates. Calibrating these parameters to match the consensus views of experts will lead to a more comprehensive account of likely climate impacts. Based on related recalibration efforts, the result would likely be a significant increase in the social cost of greenhouse gas values (Howard & Sylvan, 2020).

Expert Elicitations that Can Inform Climate Impact Quantification

Several expert elicitations conducted in recent years can help inform the calibration of different aspects of reduced-form IAMs. The most prominent elicitations in each subject area are highlighted in this section. These studies are discussed in more detail later in the report, with additional detail about how they can be used to inform model calibration.

Socioeconomic and Emission Scenarios

Ho, E., Budescu, D. V., Bosetti, V., van Vuuren, D. P., & Keller, K. (2019). Not all carbon dioxide emission scenarios are equally likely: a subjective expert assessment. *Climatic Change*, *155*(4), 545-561.

Ho et al. (2019) present probabilistic judgments from experts who were asked to assess the distribution of emissions in 2100 under a Business-as-Usual scenario and a policy scenario aligned with the Paris Climate Agreement. The elicitation method relies on pairwise comparisons of various ranges of emissions, and despite wide variability among individual experts, clear patterns emerge. Using these elicitations, the paper derives a probability distribution function for carbon dioxide emissions. The paper also contrasts these judgments with the emission projection ranges derived from the shared socioeconomic pathways (SSPs) and a recent multi-model comparison producing probability-weighted socioeconomic and emissions scenarios.

Howard, P. H., & Sylvan, D. (2021). Gauging economic consensus on climate change. Institute for Policy Integrity.

This large-sample survey of economists who have published on climate change included questions on a variety of topics that can help inform climate impact quantification and the design of models' socioeconomic/emissions scenarios. Based on respondents' estimates of renewable energy expansion and the availability of negative emission technologies, experts appear to believe that future policies will likely be consistent with the Paris Climate Agreement.

Climate Science

Zickfeld, K., Morgan, M. G., Frame, D. J., & Keith, D. W. (2010). Expert judgments about transient climate response to alternative future trajectories of radiative forcing. *Proceedings of the National Academy of Sciences, 107*(28), 12451-12456.

Zickfeld et al. (2010) conducted a formal expert elicitation of 14 scientists on a variety of climate science issues including the equilibrium climate sensitivity and transient climate response parameters. Consistent with the IPCC, Zickfeld et al. (2010) found considerable tail risk, with 10 of the 14 experts estimating probabilities greater than 17% for the equilibrium climate sensitivity parameter exceeding 4.5°C, though some experts have narrower distributions than the climate models. This study was also able to confirm that the equilibrium climate sensitivity parameter and transient climate response are independent from one another; this indicates that establishing correlations between the key climate parameters is possible within the elicitation framework. Consistent with past expert elicitations, the study also suggested that learning about climate science, including these parameter values, will continue at a slow pace.

Cai, Y., & Lontzek, T. S. (2019). The social cost of carbon with economic and climate risks. Journal of Political Economy, 127(6), 2684-2734.

This study calibrates the probability of triggering climate tipping points using an expert elicitation by Kriegler et al. (2009). This survey included a variety of tipping points: the reorganization of the Atlantic Meridional Overturning Circulation, the melting of the Greenland ice sheet, the disintegration of the West Antarctic ice sheet, the dieback of the Amazon rainforest, and the shift to a more persistent El Nino regime. In addition to identifying the probability of triggering these tipping points, the paper was able to identify the existence of a domino effect: the triggering of one tipping point increased the probability of triggering others.

Bamber, J. L., Oppenheimer, M., Kopp, R. E., Aspinall, W. P., & Cooke, R. M. (2019). Ice sheet contributions to future sea-level rise from structured expert judgment. Proceedings of the National Academy of Sciences, 116(23), 11195-11200.

Bamber, J. L., & Aspinall, W. P. (2013). An expert judgement assessment of future sea level rise from the ice sheets. Nature Climate Change, 3(4), 424-427.

These papers use expert elicitation to analyze the melting and collapse of icesheets and the impact on sea-level rise, finding that the median expert value is higher than past IPCC predictions, with substantial tail

risks. This indicates the possibility of much more rapid ice loss than previously predicted. Bramber et al. (2019) also produces probability distribution functions for sea-level rise that can be used in reduced-form IAMs.

Javeline, D., Hellmann, J. J., Cornejo, R. C., & Shufeldt, G. (2013). Expert opinion on climate change and threats to biodiversity. *Bioscience*, *63*(8), 666-673.

This study surveys 2,329 environmental biologists about future levels of warming and non-microbial species loss. Based on mean average response, the study finds that biologists predict that 9.5% of species will go extinct this century due to climate change with 21% on their way to extinction and 51.8% relocating to alternative geographic ranges. These estimates are only slightly more conservative than those provided by experts with 10 or more publications on "biotic responses to climate change."

Climate Damage Estimates

Nordhaus, W. D. (1994). Expert opinion on climatic change. American Scientist, 45-51.

Nordhaus interviewed 19 experts on climate change (10 economists, four other social scientists, and five natural scientists), each of whom had a working knowledge of economic statistics. The survey included estimates of climate damages to GDP (market impacts only) under three scenarios. For each of these scenarios, he also asked respondents to determine the share of these impacts borne by the market and to estimate the probability of catastrophic damages equivalent to a 25% decline in GDP. These findings formed the basis of the early DICE damage function.

Schauer, M. J. (1995). Estimation of the greenhouse gas externality with uncertainty. Environmental and Resource Economics, 5(1), 71-82.

Using a survey of 14 experts (of which 10 report climate impacts), Schauer (1995) estimated mean and median declines in global GDP of 5.2% and 2.6%, respectively, with a variance of 71.3% for a doubling of CO2; this is equivalent to the impact of a 2.5°C increase relative to pre-industrial temperature.

Howard, P. H., & Sylvan, D. (2015). Expert consensus on the economics of climate change. Institute for Policy Integrity.

Howard, P. H., & Sylvan, D. (2020). Wisdom of the experts: Using survey responses to address positive and normative uncertainties in climate-economic models. Climatic Change, 162(2), 213-232.

This survey of economists focusing on climate economics and policy was conducted in 2015. Based on the responses to a series of questions soliciting forecasts under different climate scenarios, Howard and Sylvan (2015; 2020) calibrated a damage function for the DICE reduced-form IAM. The survey found substantially higher estimated climate damages than the standard calibration, with mean and median estimates of -9.2% and -5% global GDP losses, respectively, for a 3°C increase.

Pindyck, R. S. (2019). The social cost of carbon revisited. Journal of Environmental Economics and Management, 94, 140-160.

Pindyck (2019) conducted a survey on climate damages, emissions, and discount rates. His respondents also provided relatively high climate damage estimates (slightly higher than Howard and Sylvan (2020)), and a low discount rate. Using these results, Pindyck calibrated an average social cost of carbon based on a formula developed in this study, though these responses could be used to calibrate a damage function and distribution.

Howard, P. H., & Sylvan, D. (2021). Gauging economic consensus on climate change. Institute for Policy Integrity.

This survey solicited damage forecasts for several climate scenarios. Respondents predicted damages significantly higher than the standard DICE calibration for all scenarios. The survey findings can also inform assumptions for adaptation costs, as respondents projected relatively lower climate damages under scenarios with higher income levels and slower rates of warming—these findings can be used to calibrate the impact of the rate of temperature change and per-capita income on net damages, using alternative damage scenarios. As the paper elicits climate damages and implicit adaptation levels and costs at multiple temperature levels covering the relevant warming space (1°C to 7°C), this survey allows for the calibration of a more sophisticated damage function than past studies.

Discount Rates

Weitzman, M. L. (2001). Gamma discounting. American Economic Review, 260-271.

Weitzman (2001) conducted an e-mail survey of more than 2,000 Ph.D. economists on the social discount rate. Using "unscreened sampling" of economists of varying backgrounds and fields to ensure balance, Weitzman asked respondents to provide the appropriate discount rate to use in climate change cost-benefit analyses. His mean and median responses were approximately 4% and 3%, respectively; he had a standard deviation of approximately 3%. Similarly, in a sub-sample of 50 "blue ribbon" economists, Weitzman again found a mean response of approximately 4% and a standard deviation of 3%.

Drupp, M. A., Freeman, M. C., Groom, B., & Nesje, F. (2018). Discounting disentangled. American Economic Journal: Economic Policy, 10(4), 109-34.

Hänsel, M. C., Drupp, M. A., Johansson, D. J., Nesje, F., Azar, C., Freeman, M. C., ... & Sterner, T. (2020). Climate economics support for the UN climate targets. Nature Climate Change, 10(8), 781-789.

From May 2014 to April 2015, Drupp et al. (2018) conducted an expert elicitation on social discount rates and related parameters. Critically, the authors found strong support for a median discount rate of 2%, with a strong consensus for a range of 1% to 3%. Using data from Drupp et al (2018), Hansel et al. (2020) recalibrates the simple Ramsey equation underlying DICE-2016R2 to the median response to questions on the pure rate of time preference and elasticity of marginal utility of consumption finding values of 0.5% and 1, respectively, and to the preferences parameters underlying the median social cost of carbon path finding values of 0% and 2.

Howard, P. H., & Sylvan, D. (2020). Wisdom of the experts: Using survey responses to address positive and normative uncertainties in climate-economic models. Climatic Change, 162(2), 213-232.

In this expert elicitation of economists, Howard and Sylvan (2015; 2020) found strong support for using a median discount rate of 2% in climate-related contexts, consistent with Drupp et al. (2018).

Pindyck, R. S. (2019). The social cost of carbon revisited. Journal of Environmental Economics and Management, 94, 140-160.

In this expert elicitation of a combined group of economists and natural scientists, Pindyck (2019) also finds strong support for a median discount rate of 2% in climate-related contexts. Pindyck reports higher mean discount rates than Drupp et al. (2018) and Howard and Sylvan (2020), indicating more skewness in his underlying elicited data.

How to Recalibrate Models Using Data from Expert Elicitations

As part of its update of the social cost of greenhouse gas metrics, the Working Group can make several recalibration decisions to improve the quality of key model components. Expert elicitation data can play an important role in these calibrations. This section provides recommendations on how to approach the updates for each major model component, along with more detailed context and technical descriptions.

Updating Socioeconomic and Emission Scenarios

Socioeconomic scenarios are the starting point for the Working Group's application of reduced-form IAMs. These scenarios play a key role in IAMs by laying out internally consistent pathways for GDP, population, and emissions (of carbon dioxide and other greenhouse gases) (IWG, 2020). The socioeconomic scenarios that underlie IAMs (including DICE, FUND, and PAGE) are characterized by deep uncertainty, as they involve structural and parametric assumptions about future technology, policies, demographic changes, and economic trends. Despite the dependence of socio-economic scenarios on a multitude of assumptions made by the developer of detailed-structural IAMs, socioeconomic scenarios are often conditional on policy assumptions. For example, Business-As-Usual scenarios within detailed-structural IAMs represent the modelers' judgement of emissions levels without climate policies (IWG, 2010, p. 10). Given that modelers make different assumptions – ranging from optimistic to pessimistic – one model's estimate of emissions under Business As Usual may overlap with another model's estimate of emissions under a very different scenario (such as current policies, global climate pledges, or even net-zero emissions) (IWG, 2010; Climate Action Tracker, 2021; IPCC WG3 AR5, Figure 6.23). In this context, climate policies shift the probability distribution of greenhouse gas emissions to the left (Ho et al., 2019).

Key Recommendations

Recommendations for the Current Update

- The Working Group should no longer use the socioeconomic and emission scenarios from the EMF-22 modeling exercise, as these scenarios are out of date. The recently developed Shared Socioeconomic Pathways (SSPs) represent a good alternative, as they incorporate more current data. The Working Group should also review the upcoming sixth IPCC report before making a final decision on which scenarios to use.
- Consistent with recommendations from NAS (2017), the Working Group should no longer weight scenarios equally. Instead, it should ideally calibrate a joint probability distribution

function for all socioeconomic and emissions scenario components including GDP, population, and emissions. Given the time constraints for the Working Group's current update, it may be unable to develop a full socioeconomic and emissions module (as suggested by NAS (2017)) before 2022. If this is the case it should rely on the expert elicitation work in Ho et al. (2019), which calculates probability distributions for emissions scenarios and probability weights for the SSPs. As Ho et al. (2019) does not develop weights for population and output, we recommend weighting the SSPs (or other scenarios within a chosen scenario library) as the best way forward for the 2022 update.

- NAS (2017) calls for calculating scenario probability distributions based on the likelihood of policies.[3] Given that the social cost of greenhouse gas metrics are primarily used in cost-benefit analyses (rather than in efforts to understand the first-best policy outcome) we believe it is more defensible from a policy and legal perspective to calibrate the models to match existing policies, and make updates each time the models are reevaluated. As Ho et al. (2019) calculates probabilities for emissions scenarios conditional on both Business-as-Usual and the Paris Climate Agreement, the Working Group could consider using a using an estimate close to the average of the probabilities across these policy scenarios.
- Using Ho et al. (2019), we can assign a probability to the five EMF-22 scenarios employed by the Working Group and to the five SSP scenarios employed in Ho et al. (2019). Using equal and probabilistic weighting, we construct an estimate of average emissions path; see Figures 1 and 2. For the IWG (2010) scenarios, probabilistic weighting shifts down average CO_2 emissions in 2100 from 62.8 Mt CO_2/yr under equal weighting to 54.3 under Business-As-Usual probabilistic weighting and 48.1 under Paris probabilistic weighting. Similarly, using the SSP scenarios, emissions decline from 59.2 62.8 Mt CO_2/yr to 55.2 and 45.5, respectively. Comparing these estimates across scenario libraries, we can see that the Working Group emissions scenarios are initially lower than the SSPs and then rise rapidly to slightly above them.
- Using these weights, we can also construct the most likely GDP and population scenarios; see Figures 1 and 2. The probabilistic weights have little impact on GDP and population relative to equal weighting. However, across libraries, global GDP increases by approximately 83% from the Working Group scenarios to the SSPs over this century following a shift in the IAMs from calculating GDP using market exchange rates to purchasing power parity (Nordhaus, 2017). Given the use of proportional damage functions, this will increase the social costs of greenhouse gases by a similar amount. The weighted SSPs imply an average temperature increase between 3.5°C to 3.7°C by 2100, while the average Working Group scenarios imply less warming as their cumulative emissions are lower over the first century.
- When calculating the social cost of carbon using scenario libraries, analysts weight the scenario-specific social cost of carbon estimates by these probabilities before aggregating, not the inputs

[3] If the Working Group does follow this recommendation (which we think could be problematic, as stated above) it could consider findings from Howard and Sylvan (2021), in which experts appear to believe that future policies will likely be consistent with the Paris Climate Agreement.

(GDP, population, and emissions). Applying the Ho et al. (2019)'s weights, the social cost of carbon slightly increases; see Table 1. As these weights reduce the importance of lower and higher emission scenarios, which correspond to the lowest social of carbon estimates, weighting towards the center increases the social cost of carbon.

Longer-Term Recommendations

- Future work should integrate additional information on technology into the process recommended NAS (2017), as it is unclear whether these elicited probabilities accurately account for "future emissions mitigation policies and technological developments" (as requested by the NAS (2017)). Consistent with the NAS (2017) methodological framework, future research should add an additional step where the analyst conducts an expert elicitation of technology experts from various fields to develop distributions for the likelihood and efficiencies of various technologies (van Sluisveld et al., 2018; Howard and Sylvan, 2021).[4] These distributions could then be provided to emission experts along with the GDP-population distributions when developing their projects for reference, just as Ho et al. (2019) provided figures of the SSP emission paths to the experts, and the resulting emission paths could be checked for consistency (van Sluisveld et al., 2018).

Likely Effects of These Recommendations

The net impact of our suggestions for the current update will be to increase the social costs of greenhouse gases. This is primarily driven by the shift from market exchange rates to purchasing power parity. The impact of probabilistic weighting is less clear, though the change is likely minimal since equal weighting appears to roughly approximate the results from Ho et al. (2019). Weighting will only significantly lower the social cost of greenhouse gas metrics if experts start to believe that the most likely emissions path is near 550 ppm by 2100, though even in that case the decline would be relatively small compared to other empirical issues.

Context and Technical Details

Given the significant uncertainties over socioeconomic and emissions parameters and the fact that model outputs tend to be conditional on the assumed future policy state, it can be beneficial to assign probability weights to different socioeconomic and emission possibilities. Historically, uncertainty over socioeconomic scenarios has been addressed in three underlying ways: (1) treat all scenarios as "plausible alternatives" without assigned probabilities; (2) assign equal probability to each scenario; and (3) explicitly assign probabilities to each scenario (Ho et al., 2019). When there is truly insufficient data to assign probabilities, research has shown that assigning equal weights is "good starting point" (Ho et al.,

[4] For two time periods (2030 and 2050) and policy states (Business-As-Usual and 2°C target), van Sluisveld et al. (2018) elicits from technology-specific experts about the total installed capacity and share in total energy electricity production (%) in their expertise of wind, solar, nuclear, or biomass or the CO_2 capture rate and the share in total electricity production from CCS if their expertise is in CCS technologies.

2019). However, despite the difficulty of assigning probabilities to scenarios, there is considerable value to doing so, in part because this allows probabilities to be transparent instead of implicit (Ho et al., 2019).

Past Working Group Actions

The Working Group (2010) took the equal-weighting approach due to the absence of reliable probability estimates and a lack of information to assign probabilities itself (IWG, 2010, p. 16). Specifically, the Working Group (2010, pp. 16-17) equally weighted five socioeconomic and emission scenarios from the EMF-22 modeling exercise: four "Business-As Usual Scenarios" (IMAGE, MERGE Optimistic, MESSAGE, and MiniCAM) and one scenario consistent with "moderately strict mitigation measures" that achieves stability of greenhouse gas emissions at 550 ppm. In this context, "Business-As-Usual" does *not* refer to the more colloquial definition of SRES A2 or RCP 8.5, as is commonly believed, as only MERGE Optimistic (117.9 gigatons of annual carbon dioxide emissions in 2100) is roughly consistent with this definition. Instead, using more colloquial terms (as represented by Climate Action Tracker Data in 2020 and 2021), the Working Group (2010) emission scenarios include emissions levels commonly thought of by other models and modelers as: Optimistic Zero-Emissions Scenarios (12.8 gigatons of annual CO2 emissions in 2100) to a Low Business-As-Usual Scenario (117.9 gigatons of annual CO2 emissions in 2100) with a High Pledge Scenario (42.7), a Low Current Policy Scenario (60.1), and High Current Policy Scenario (80.5) in between (Climate Action Tracker Data, 2020; Climate Action Tracker Data, 2021). Thus, despite these scenarios representing no or moderate policy assumptions for their corresponding model, most of these emission scenarios are consistent with other models' climate policy and pledge runs (IWG, 2010, p. 17; Climate Action Tracker Data, 2020). Despite this wide emission range, the IWG (2010, p. 17) decided against lower emission paths consistent with 1.5°C and 2°C targets (see Climate Action Tracker) as some detailed-structural IAMs are unable to reach these lower emission paths.

National Academy of Sciences Input

The National Academy of Sciences (2017) recommended against the continued reliance on scenario libraries and the equal-weighting assumption employed by the Working Group (2010), and instead supported the development of a socioeconomic module informed by expert elicitation and other tools. According to the 2017 National Academy of Sciences report (NAS, 2017), the Working Group should build a socioeconomic and emission scenario module with a joint probability distribution for scenario components to fully capture uncertainties.

Specifically, the NAS (2017) proposes a methodological framework that the Working Group can use to develop near-term (two to three years) and long-term (four to six years) probabilistic socioeconomic scenarios, relying heavily on expert elicitation. In the near term, the NAS (2017) proposes a multi-step strategy: (1) derive three GDP projections using new statistical techniques, which will be weighted and

adjusted by experts; (2) use expert elicitation to derive three population projections for each GDP projection, by extending and weighting existing demographic studies beyond 2100; and (3) derive three emission projections, including mean and percentile projections for each relevant greenhouse gas under likely policies, using expert elicitation. This implies a total of 27 probability-weighted scenarios conditional on likely policy and technology developments.

In the long-term, the NAS (2017) proposes that the Working Group strive for the ideal of a joint continuous probability distribution function in which expert elicitation continues to play a prominent role for long-run projections of GDP, population, and emissions at the aggregate global and disaggregate regional-sector scales (in an internally consistent manner). Both techniques require significant advances in the field, such that peer-reviewed research on these topics may not be published by the Fall of 2021 despite continued work by Resources for the Future.[5]

Technical Details of Our Recommendations

For the 2022 update, the Working Group should use findings from the Ho et al. (2019) expert elicitation to develop a probabilistic weighted emissions scenario conditional on the assumed policy state. Given the likely requirement of using peer-reviewed publications to calibrate or construct its reduced-form IAM, the Working Group will simply not have time to develop or apply the NAS (2017) methodology. Instead, the working group should either apply: (1) Ho et al. (2019)'s continuous distributions for emissions under Business-As-Usual or the Paris Climate Agreement, or (2) assign weights to its chosen scenario library using Ho et al. (2019)'s weights for SSP scenarios. While the former methodology corresponds more closely to the NAS (2017) recommendation, this procedure is unable to produce internally consistent GDP and population distributions.[6] Therefore, we recommend the latter approach. The Working Group should continue to improve the socioeconomic and emissions scenarios after the 2022 update, in preparation for the following update.

For calculating the social costs of greenhouse gases, the Working Group should carefully consider whether it should use scenario weights conditional on the existing policy instead of the most likely path (Howard, 2019). Historically the social costs of greenhouse gases are calculated on the Business-As-Usual emissions path (Nordhaus, 2014), though there is precedent within the federal government to use the existing policy path (see the Energy Information Administration's choice of baseline for the NEMS model). However, to our knowledge, there is not a precedent for assuming the most likely emissions path, particularly in the context of cost-benefit analysis. Additionally, it is critical to remember that the calculation of the social costs of greenhouse gases and cost-benefit analysis more generally are not economic exercises in finding

[5] See https://www.rff.org/topics/scc/social-cost-carbon-initiative/

[6] The second methodology uses Ho et al. (2019)'s weights to assign probabilistic weights library emission scenarios. However, as these weights are not conditional on GDP or population, such that analysts must assume that respondents in Ho et al. (2019) are implicitly weighting the full socioeconomic paths, like the SSPs, and *not* just emission paths.

the socially optimal policy. Instead, the aim of cost-benefit analysis in the context of federal rulemaking is to determine whether the benefits of a policy currently exceed the costs, with some alternatives analysis included to ensure that other, more desirable policy approaches are not available. As regulations can always be repealed or rewritten in the future, it is not in the purview of the economists to determine if a better policy to reduce emissions will be forthcoming. But these distinctions are minor in this context, given the relatively narrow difference between emissions for Business-As-Usual and the Paris Agreement in Ho et al. (2019). Additionally, Howard and Sylvan (2021) found that a large sample of climate economists believed that the current Paris pledges represent the most likely future policy state.[7]

Future work should integrate additional information on technology into the process recommended by NAS (2017), as it is unclear whether these elicited probabilities accurately account for "future emissions mitigation policies and technological developments" (as requested by the NAS (2017)). Consistent with the NAS (2017) methodological framework, future efforts should add an additional step where the analyst conducts an expert elicitation of technology experts from various fields to develop distributions for the likelihood and efficiencies of various technologies (van Sluisveld et al., 2018; Howard and Sylvan, 2021).[8] These distributions could then be provided to emission experts along with the GDP-population distributions when developing their projects for reference, just as Ho et al. (2019) provided figures of the SSP emission paths to the experts, and the resulting emission paths could be checked for consistency (van Sluisveld et al., 2018). As this extension of the NAS (2017) and Ho et al. (2019) methodologies is currently inconsistent with the IWG's 2022 timetable, we suggest that any probabilistic emissions paths should be checked against expert elicitations on technological availability, for purposes of consistency before deployment.[9]

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[7] In a large sample survey of economists publishing on climate change, the average respondent believed that slightly more than 50% of global energy will come from zero-emission technologies. As Howard and Sylvan (2021) did not specify a scenario and the vast majority (79%) of respondents believe that negative emission technologies will NOT become viable until 2060 or after, these results can be interpreted as the majority of respondents believing that existing climate pledges and targets under Paris, which achieve between a 37% to 66% reduction in 2050 relative to Business-As-Usual according to Climate Action Tracker, is the most likely future policy state. These results support the National Academy of Sciences (2017) assessment that Business-As-Usual is not the most likely outcome.

[8] For two time periods (2030 and 2050) and policy states (Business-As-Usual and 2°C target), van Sluisveld et al. (2018) elicits from technology-specific experts about the total installed capacity and share in total energy electricity production (%) in their expertise of wind, solar, nuclear, or biomass or the CO_2 capture rate and the share in total electricity production from CCS if their expertise is in CCS technologies.

[9] van Sluisveld et al. (2018) compares technology predictions from expert elicitations and detailed-structural IAMs under a Business-As-Usual and 2°C scenario. Specifically, the authors find that the two methodologies make similar projections under Business-As-Usual, despite experts predicting greater adoption of solar and other renewable technologies and less nuclear than IAMs, while the two methods differ to a greater extent for the 2°C scenario as experts favor renewables, particularly solar and biomass, over CCS and nuclear However, van Sluisveld et al. (2018) make apples-to-apples comparisons across methodologies, while we are instead proposing an apples-to-oranges comparison within a methodology. Specifically, we are calling for the comparison of likely emission paths and likely technology inputs into these paths within expert elicitation. Thus, this comparison may require detailed-structural IAMs to be calibrated to these elicited responses on technologies to compare emission paths results. Beyond the methodological challenge, analysts will also have to overcome making comparisons subject

Updating Climate Science Assumptions

The scientific information underlying the IAMs is represented in the simple climate model and the impact functions. The climate model translates greenhouse gas emissions into future temperatures. As their name implies, simple climate models simplify the climate science underlying Earth's climate system and global warming, and they can replicate primary results of complex climate models to varying levels of success.

Expert elicitations of natural scientists can help improve the calibration of climate impact functions (i.e., dose-response functions) that translate warming into physical impacts (not economic damages). This is most relevant for FUND-style models that model climate-impact endpoints and their dynamics over time. Expert elicitations can also inform the scientific assumptions underlying the inclusion of tipping points into IAMs.

Key Recommendations

Recommendations for the Current Update

- For the 2022 update, the Working Group should follow the NAS (2017) recommendation to either build a new reduced-form IAM that adopts the FAIR climate model, or use FAIR as a replacement for the climate model in existing reduced-form IAMs. This is critical in the case of DICE-2016R2, as the climate model is miscalibrated (Howard and Sylvan, 2020; Hansel et al., 2020). The Working Group should review the sixth IPCC report once it is released in July 2021 and update FAIR accordingly.

Longer-Term Recommendations

- Moving forward, the Working Group should recognize that the IPCC's estimates of the rate of climate change and its impacts tend to be overly conservative (possibly due to groupthink and the existing system for selecting IPCC panels). To avoid these overly conservative estimates, the Working Group or one of its member agencies should solicit or conduct an expert elicitation on key climate parameters, including the three short-run climate parameters identified in NAS (2016) as well as the equilibrium climate sensitivity parameter. This elicitation should include a broad sample of relevant scientists, including some who are not directly involved in the IPCC process. Such an elicitation can build on well-stablished examples of this methodology that focus on the equilibrium climate sensitivity and transient climate response parameters, such as Morgan (1995) and Zickfeld et al. (2010).
- The Working Group can also use expert elicitation to calibrate the science on hard-to-measure impacts, including tipping points (building on Kriegler et al., 2009; Bamber and Aspinall, 2013; and Bamber et al. (2019)) and biodiversity loss (building on Javeline et al., 2013). The Working

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to significant uncertainties, though analysts can rely on comparing median elicitation and modeling outcome as in van Sluisveld et al. (2018).

Group or one of its member agencies should conduct a literature review to determine other impacts that can benefit from expert elicitation. For instance, the modeling of sectors that face multiple climate pressures—like forestry, which faces threats from disease, fire, temperatures, precipitation, and other climate drivers—may also benefit from expert elicitations focusing on the synthesis of total impacts (Morgan, 2001). This approach is consistent with the NAS (2017) recommendations.

Likely Impacts of These Recommendations

The net impact of using FAIR is not clear, particularly if it is updated to reflect the forthcoming publication by IPCC Working Group I, though it will certainly increase the social cost of carbon if DICE-2016R2 is recalibrated due to its climate model miscalibration (Hansel et al., 2020; Howard and Sylvan, 2020). The net impact of our future suggestions will be to increase the social costs of greenhouse gases. This is primarily driven by more accurately capturing the rapid rate of climate change and the inclusion of omitted impacts, including multiple climate tipping points, biodiversity, and forest loss.

Context and Technical Details

As climate models and simple climate models continue to improve, it is essential that the Working Group capture these improvements and reflect up-to-date science. This is consistent with the Working Group's past decisions. Specifically, in 2010, the only critical change that the Working Group (2010) made to the reduced-form IAMs with respect to climate science was to recalibrate the equilibrium climate sensitivity parameter to reflect the most recent IPCC report. Specifically, the Working Group inserted a Roe and Baker distribution recalibrated to the science data from the IPCC (2007). For the current update, the Working Group can pursue some similarly straightforward scientific updates.

National Academy of Sciences Input

After the publication of the IPCC's 2014 report, the NAS concluded that the Working Group should not recalibrate the distribution, as called for by some conservative groups, as it would make little difference to the social cost of greenhouse gas results (NAS 2016; 2017, p. 34). Instead, the NAS (2016) suggested a focus on three other key climate parameters: transient climate response, transient climate response to emissions, and the initial pulse-adjustment timescale. The NAS concluded that these parameters are more important than the equilibrium climate sensitivity parameter for determining global average surface temperature on the shorter time scale relevant for calculating the social costs of greenhouse gases. Unlike these parameters, the equilibrium climate sensitivity parameter is a long-run equilibrium climate parameter.

In 2017, the NAS (2017) published a second report suggesting the development of a more rigorous climate model that is transparent, replicable, and calibrated to match up-to-date science (verifiable using

a series of tests). Specifically, the NAS suggests that the simple climate model should be calibrated to IPCC reports when available, due to their use of multiple lines of evidence. For parameters that are not reviewed by the IPCC, the NAS suggests consulting experts (preferably authors of the relevant IPCC chapters) and available studies. To reflect the best available science, the NAS suggests using FAIR – a simple climate model that does meet meets these requirements (NAS, 2017, p. 88). Additionally, the NAS requests that the Working Group specify a (joint) probability distribution function for all the relevant climate parameters, including short-term warming and carbon pulse parameters in addition to the equilibrium climate sensitivity parameter. Finally, the NAS concludes that all the relevant reduced-form IAMs should model sea-level rise and ocean acidification. Temperature, sea-level rise, and ocean acidification should be downscaled to the appropriate temporal and spatial scales of IAMs using pattern scaling.

Technical Details of Our Recommendations

For the 2022 update, the Working Group should follow the NAS (2017) recommendations as closely as possible. Specifically, the Working Group should construct its own reduced-form IAM using the FAIR model, or replace the selected reduced-form IAMs' climate models with the FAIR model. This should be relatively simple, as the open-source MIMI platform[10] has FAIR and several other climate models available, along with several existing reduced-form IAMs. Given that an updated IPCC report[11] will be released in July 2021, the Working Group should review this publication upon its release and replace any parameters or parameter distributions with the updated values. Any other baseline assumptions should be updated as needed to match the new IPCC data. [12]

For future updates, we believe that the Working Group should conduct a comprehensive expert elicitation over key climate parameters, including those reviewed in the IPCC report. A review of all parameters is necessary, as natural scientists, particularly through the IPCC process, have systematically underestimated the pace and severity of climate change (Oppenheimer et al., 2019). Specifically, the IPCC consistently underestimates projections of climate change. In the words of Oreskes et al. (2019), "the combination of these three factors—the push for univocality, the belief that conservatism is socially and politically protective, and the reluctance to make estimates at all when the available data are contradictory—can lead to "least common denominator" results—minimalist conclusions that are weak

[10] *See* https://www.mimiframework.org/menu2/

[11] *See* https://www.ipcc.ch/report/sixth-assessment-report-working-group-i/

[12] If the Working Group chooses to adopt the most up-to-date versions of the reduced-form IAMs and replace and update their simple climate models, they should be aware of two complications: DICE no longer explicitly models sea-level rise (Nordhaus, 2019) as requested by NAS (2017); and PAGE-ICE makes explicit several arctic feedbacks that may or may not be included in the IPCC's updated equilibrium climate sensitivity parameter distribution forthcoming in the 2021 IPCC report. If the Working Group decides to use the PAGE-ICE model, it should be careful to ensure that these arctic feedback effects are accounted for after replacing PAGE-ICE's climate model with FAIR and updating the climate models to reflect the 2021 IPCC report.

or incomplete." To achieve goals of "inclusivity, accuracy and comprehension", Oppenheimer et al. (2019) and Oreskes et al. (2019) recommend that the IPCC and others try alternative methods for assessing group consensus that support independent and complete expert views, including formal expert elicitation. If the Working Group should conduct such an expert elicitation, it should expand the group of relevant experts beyond the relevant IPCC panel to consider a comprehensive set of opinions. This is necessary in part because the process for choosing the IPCC's authors promotes conservative assessments, particularly as relevant academics with heterodox opinions are often excluded (Oppenheimer et al., 2019).

This expert elicitation should include all relevant climate parameters, including the four highlighted by the NAS (2017) report, using methodologies that are well established in the literature. The Working Group can look to Zickfeld et al. (2010) as an example. Updating Morgan (1995)'s expert elicitation over the equilibrium climate sensitivity parameter, Zickfeld et al. (2010) conducted a formal expert elicitation of 14 scientists on a variety of climate science issues including the equilibrium climate sensitivity and transient climate response parameters (two of the four climate parameters discussed above). Consistent with the literature, this elicitation found tail risk in the equilibrium climate sensitivity, captured correlation between climate parameters, and suggested learning about climate science will continue at a slow pace.

Outside of the climate parameters, expert elicitation can be applied to other critical scientific issues underlying reduced-form IAMs, including tipping points and sector-specific impact calibration. In stochastic dynamic IAMs, expert elicitation has been used to calibrate multiple, realistic climate tipping points. Specifically, Cai and Lontek (2019) calibrate the probability of triggering tipping points using an expert elicitation by Kriegler et al. (2009). This survey included a variety of tipping points: the reorganization of the Atlantic Meridional Overturning Circulation, the melting of the Greenland ice sheet, the disintegration of the West Antarctic ice sheet, the dieback of the Amazon rainforest, and the shift to a more persistent El Nino regime. In addition to identifying the probability of triggering these tipping points, the paper was able to identify the existence of a domino effect: the triggering of one tipping point increased the probability of triggering others. Likewise, Bamber and Aspinall (2013) and Bamber et al. (2019) analyze the melting and collapse of icesheets and the impact on sea-level rise, finding that the median expert value is higher than past IPCC predictions, with substantial tail risks. This indicates the possibility of much more rapid ice loss than previously predicted (Oppenheimer et al., 2016). Critically for the Working Group, Bramber et al. (2019) produces probability distribution functions for sea-level rise that the Working Group can employ.

Expert elicitation can also help inform model assumptions regarding difficult-to-measure climate impacts that relate to the natural sciences. Biodiversity is a difficult concept to address in reduced form-IAMs. To make improvements, the Working Group should look to papers like Javeline et al. (2013) or conduct its own expert elicitation to determine the estimated number of climate-induced species extinctions and their

potential economic value. Similarly, the modeling of sectors that face multiple climate pressures—like forestry, which faces threats from disease, fire, temperatures, precipitation, and other climate drivers—may also benefit from expert elicitations focusing on the synthesis of total impacts (Morgan, 2001).

Updating Climate Damage Estimates

Damage functions translate temperature changes into economic impacts as measured by a percentage change in GDP. Traditionally, these damage functions are proportional to GDP, affecting the level of income rather than the growth rate. Different IAMs' damage functions vary in terms of sectoral and regional scale. For instance, DICE uses a global aggregate damage function while FUND uses regional damage functions for each type of climate impact (Howard, 2014). To estimate climate damages, FUND, PAGE, and early versions of DICE (e.g., DICE-1999 and DICE-2007) used the enumerative method (i.e., a bottom-up strategy) whereby the IAM developers use their discretion to calibrate aggregate, regional, or regional-sector-specific damage functions to the existing literature. Other damage estimation methods exist in the literature, such as statistical (including cross-sectional, spatial and time panel), computable general equilibrium (similar to the enumerative method in its calibration concept), science-based, and expert elicitation (Howard and Sterner, 2017). Analysts can use meta-regression to combine these estimates in a single damage function. In fact, Nordhaus moved to the meta-regression approach in DICE-2013R and DICE-2016R2, though he specifies an alternative meta-regression damage function in Nordhaus (2019) based on Howard and Sterner (2017).

Key Recommendations

Recommendations for the Current Update

- It is critically important that the Working Group update the damage functions in reduced-form IAMs to reflect the best available, *current* information. It should not rely on past and current damage functions from reduced-form and other IAMs (such as computer-general equilibrium and hybrid IAMs) as they are outdated and seriously underestimate damages by failing to incorporate data from hundreds of new, relevant publications.
- The Working Group should strongly consider using expert elicitation to improve the climate damage functions in reduced-form IAMs, especially given the short timeframe for the current update. While input from NAS (2017) favors other approaches, these may not be feasible before 2022 and they suffer from other drawbacks. Even a complete review of the literature will fail to capture many hard-to-measure impacts, so expert elicitation likely represents the most comprehensive *and* efficient approach for improving damage functions in the near term.
- A compromise between our position and the NAS (2017) input would be to conduct meta-regressions of climate damages, including damage estimates from expert elicitation and other methodologies beyond the traditional enumerative strategy (Howard and Sterner, 2017; Nordhaus and Moffat, 2017).

- Regardless of whether the Working Group chooses a meta-regression or expert-elicitation approach, we believe that prudent choice moving forward would be to choose either the mean or median damage value, depending on which they believe to be better supported by the evidence (see below), and then conduct sensitivity analysis using the other approach.

Longer-Term Recommendations

- Beyond top-down estimates, future expert elicitations and meta-regression studies should also focus on regional and sector-based damages to determine impact pathways. The Working Group or one of its member agencies should solicit or conduct such studies. Researchers that conduct future elicitations should broaden the group of appropriate experts and develop seed questions to improve overall accuracy (Howard and Sylvan, 2020).
- The Working Group or one of its member agencies should solicit or conduct expert elicitations that address adaptation and its costs. IAMs can implicitly represent adaptation (e.g., DICE and FUND) by accounting for the rate of temperature change and different income levels, as both factors affect the ability of society to adapt. New elicitation findings could improve the modeling of adaptation. IAMs that model adaptation explicitly (e.g., PAGE) will require additional analysis.

Likely Impacts of These Recommendations

The net impact of updating the damage function using expert elicitation or meta-regression will be an increase in the value of the social cost of greenhouse gases; see Table 2. Recent expert elicitations by Howard and Sylvan (2020; 2021), found damage estimates of approximately 0% to 1% of global GDP for approximately a 1°C temperature increase and 5% to 10% of global GDP for a 3° increase (based on the median or mean). Beyond a 3° rise, damages would continue to increase, though at a decreasing rate (partially driven by the anticipated slowing of the rate of temperature increase). The expert-elicitation methodology also produces a 95th percent confidence interval pointing to standard errors increasing with temperature and the potential for much higher damages, particularly if climate change is faster or income grows more slowly than expected.

In the case of meta-regression, the results depend on whether analysts apply Nordhaus and Moffat (2017) or Howard and Sterner (2017). Howard and Sterner (2017) account for omitted variable bias and heteroskedasticity and include a wider range of impact methodologies and expert elicitation studies,[13] finding expected impacts of 7% to 8% of GDP for a 3°C for non-catastrophic damages.

[13] Nordhaus and Moffat (2017)'s elicitation weights place a vast majority of their weight on enumerative/CGE models and studies dating to 2006 or earlier.

Context and Technical Details

Past Working Group Actions and Underlying Model Details

The reduced-form IAMs' damage functions upon which the Working Group relies are outdated, and they understate the economic costs of climate change. Modelers used enumerative methods (i.e., bottom-up strategies) to build the reduced-form IAM damage functions used in the 2021 interim estimates (IWG, 2021). This process involved the IAM developers using author discretion to calibrate aggregate, regional, or regional-sector-specific damage functions to the existing literature. These results are outdated due to several factors:

- the impact studies they include predominately date to the 1990s (Howard, 2014; Howard, 2019; Revesz et al., 2014; Auffhammer, 2018; NAS, 2017; IWG, 2020);
- they omit many impacts and climate drivers (e.g., ocean acidification, weather variability, precipitation, wildfires) (Howard, 2014; Howard, 2019; NAS, 2017); and
- they rely on ad hoc damage calculations (e.g., DICE-1999's health impacts[14] and PAGE's benefit transfer).[15]

As such, it is critically important that the Working Group update its damage estimates in 2022 and again in any future updates.

The reduced-form IAMs have not been meaningfully improved in this area since the last significant update to the Working Group (2013) estimates, so the Working Group should not just look to the updated versions of the models.

[14] For example, Nordhaus and Boyer (2000) notes that "In the absence of systematic estimates of health impacts, we have relied on estimates based on the current prevalence of climate-related diseases" to calibrate health impacts in DICE-1999. Nordhaus and Boyer (2000) starts by dividing data on regional disease incidence (Murray and Lopez, 1996) into climate-related (dengue-fever, malaria, schistosomiasis, other tropical diseases, and air pollution health impacts) and climate-unrelated impacts. It is important to note that DICE-1999 omits diarrheal diseases, cardiovascular and respiratory disorders, and hurricane and storms included in FUND, along with labor productivity and demand shocks from health impacts included in ICES and ENVISAGE (Cromar et al., forthcoming). To calibrate the DICE-1999 health impacts, Nordhaus and Boyer take the average of impacts across three methods: (1) they assign half of the decrease in years of lives lost from climate-related diseases from 1990 to 2020 to impacts of a 2.5°C; (2) they adjust the years of lives lost in 1 for differences in regional climate exposure; and (3) the regress warming on years of lives lost.

[15] In PAGE09, market, non-market, and catastrophic damages from Europe into other regions using regional coastline length relative to the European Union (Rose et al., 2014, 6-4; Hope, 2011, p. 5).

FUND's damage estimates remain unchanged since Working Group (2013), leading it to continue to predict net economic benefits from climate change up to approximately 3°C (Howard and Sterner, 2017).[16]

DICE-2016R2 shifted away from prior DICE approaches, as it uses damage functions calibrated using a meta-regression rather than the enumerative strategy. However, the damage estimates actually shrink by -17% relative to DICE-2008. This is because the underlying data and estimation methodology are flawed in several ways. The data still dates predominately to the 1990s and early 2000s,[17] and the methodology suffers from omitted-variable bias as well as other econometric problems (Howard and Sterner, 2017; Howard and Sterner, 2020);[18] and omits catastrophic impacts despite a 25% upward adjustment to the damage estimates (Howard, 2014; Howard and Sterner, 2017; Howard and Sterner, 2020). Using the same meta-regression methodology, Howard and Sterner (2017) find a damage function that is 3.5 times higher due to differing selection criteria; the inclusion of additional types of damage studies; the use of (subjective) weighting; and control variables (Howard and Stener, 2020).[19]

PAGE-ICE (Yumashev et al. (2021) incorporates a recalibrated market damage function to (the often debated) Burke et al. (2015).[20] Though non-market damages remain unchanged, Yumashev et al. (2021)

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[16] According to the FUND website, the only substantial updates between FUND 3.8 is to the simple climate model: updating the exogenous forcing of SO_2, updating the initial CO_2 concentration, updates the climate calibration. Just as before, the document for version 3.10 explicitly refers to its reliance on Tol (1995; 2002a; 2002b) and Link and Tol (2004) for the calibration of various sectors, including agriculture, ecosystems, human health categories, and sea-level rise.

[17] Using weighted-least squares, Nordhaus and Moffat (2017) places approximately 76% of their weight on enumerative studies – which tend to be older and/or be based on older data – approximately 50% weight on studies that are 15 years or older. Jointly, this implies that 98% of the weights in Nordhaus and Moffat are on enumerative based studies (including CGE studies) or studies from 2006 or earlier due to the interdependence and duplication of damage estimates between studies. In fact, Nordhaus and Moffat (2017) also place considerable weight on specific authors: 40% of weights on their own publications; 90% on authors associated with University College of London or Yale, as defined in Tol (2009); and 75% of weights on Nordhaus, Tol, and Bosello and 60% on the trio's enumerative estimates.

[18] Critically, Nordhaus and Moffat and Tol (2018) due to control for whether impacts are market only, non-market only, or include catastrophic impacts leading to an estimate that is biased downwards (Howard and Sterner, 2017; Howard and Sylvan, 2020). Inconsistent with standard meta-regression practices, Nordhaus and Moffat (2018) also fails to control for heterogeneity and address dependence.

[19] Nordhaus (2019) uses the Howard and Sterner (2017) estimates as an alternate damage function.

[20] Despite being cited extensively in IPCC (2018), the findings of Burke et al. (2015) have been a topic of debate as its findings contradict previous research by Dell et. (2012) and recent research by Letta and Tol (2019) and Newell et al. (2021). Newell et al. (2021) shows that three primary assumptions underlying this, and related work are untestable and argues that their results are outliers relative to all possible assumption combinations. Even so, two large sample surveys of climate economists conducted by Howard and Sylvan (2015; 2020; 2021) in 2015 (at the time of publication of Burke) and 2021 (after the publication of these critiques) found nearly identical mass support for the hypothesis that climate change will impact economic growth: approximately 80% think that it is likely compared to 5% who think it is unlikely. As the above statistical studies study historical data, while Howard and Sylvan (2020; 2021) focus on the future, economists likely believe that statistical methods are unable to pick up the inevitable impact on growth as laid out recently by Stern and Stiglitz (2021). However, Howard and Sylvan (2020) and Howard and Sylvan (2021) find evidence of lowering climate impacts than Burke et al. (2015) despite experts accounting for non-market and catastrophic impacts in addition market impacts.

improves the representation of climate tipping points by explicitly modeling arctic greenhouse gas feedbacks[21] and implicitly capturing the collapse of Greenland and West Antarctic ice sheets through a fat-tailed distribution for sea-level rise. Adaptation is also less effective in PAGE-ICE than PAGE09 (Yumashev et al., 2021).

Despite the stasis in the reduced-form IAM literature over the last eight years, other damage estimates advanced considerably over this timeframe with respect to data and methodologies. Hundreds of new, relevant publications, many of which suggest that damages are being seriously underestimated, are now unaccounted for in the current reduced-form IAMs (Howard, 2019).[22]

While some arguments in the literature may appear to indicate that using past or current reduced-form IAM damage functions is defensible, these arguments are flawed, and the position is indefensible. Tol (2021) finds that the social cost of carbon has not changed over time after controlling for discount rates, emission year, and inflation. However, based on a simple equation for the social cost of carbon (known as a closed-form solution) derived using an analytic IAM, the only remaining parameters of importance are climate damages and structural modeling assumptions (Golosov et al., 2014). Thus, the Tol (2021) results merely reflect the static nature of these reduced-IAMs' damage functions and structural assumptions. As most papers on the social cost of greenhouse gases simply rerun DICE, FUND, or PAGE with one parametric or structural alteration, we should expect that the social cost of greenhouse gas estimates will be evenly distributed around the existing estimates.

Similarly, using the new panel-data methods developed in Dell et al. (2012) and Burke et al. (2015) to explore whether and how much climate change affects global economic growth, Newell et al. (2021) finds that their preferred "models of GDP *levels* effects yield a … distribution of GDP impacts centered around 1–3% losses, consistent with damage functions of major integrated assessment models." Regardless of whether these controversial econometric results are true, this statement is a misinterpretation of their findings, as this technique only captures potential market impacts correlated with temperature and

[21] In comparison to PAGE09, PAGE-ICE explicitly models the impact of several artic feedback effects that impact the equilibrium climate sensitivity parameter: permafrost carbon and non-linear (instead of constant) surface albedo feedbacks using reduced form techniques (i.e., emulators). The remaining environmental tipping points are still captured in an abstract discontinuity impact following PAGE09, though this damage estimates are rescaled as it only accounts for a smaller subset of environmental tipping points not captured by the equilibrium climate sensitivity parameter as well as these adjustments and the socio-economic tipping points. As many of the slower moving feedback effects / tipping points are not explicitly modeled in the baseline versions, the speed of the abstract tipping point is increased to reflect the more rapid nature of the implicit tipping points.

[22] For example, the current agricultural damage function still shows global benefits out to 5°C (Auffhammer, 2018) leading to significant climate benefits in FUND (Cromar et al., forthcoming). However, if damages are updated to reflect the latest research in in economics and agronomics, agriculture shifts from a source of climate benefits to damages leading to a more than doubling of the SCC (Moore et al., 2017). These latter results are consistent with two recent large-sample elicitation of experts finding that climate damages will likely turn or have turn negative by a 1°C compared to FUND's 3°C estimate (Howard and Sylvan, 2020; Howard and Sylvan, 2021).

precipitation over the historical records studied (1960 to 2010). Thus, Newell et al. (2021) excludes the bulk of climate impacts in reduced-form IAMs' damage functions: sea-level rise, health impacts (outside labor productivity), biodiversity and ecosystems, cultural and climate amenities, storms, and catastrophic impacts and tipping points (Dell et al., 2012, p. 92; Burke et al., 2015).[23] An apples-to-apples comparison of the Newell et al. (2021) results to agricultural and other market impacts reveals that this historical range of impacts in reduced-form IAMs falls between -0.46% in DICE-1999 to -1% in FUND, with PAGE09 likely in-between.[24] If we assume that the total difference between all sectors matched the difference between the DICE-99 and Newell et al. (2021) for overlapping market damages, then Newell et al. (2021)'s total estimates would range between -8% and -25% of GDP assuming a 4°C increase in temperature by the end of the century, consistent with DICE-2016R2. These estimates may seem high, but are also relatively consistent with Carleton et al. (2020)'s finding that the climate-driven costs to health are much higher than past reduced-form IAM estimates. Specifically, their estimates of -3.2% of GDP by 2100 implies a difference of a factor of 12.5 compared to DICE-1999's estimate of -0.26% of GDP at a 4°C increase by 2100.

Finally, some may argue that parametric and structural differences can be partially addressed through running multiple models and averaging across them as in Working Group (2010). As we have shown above that the three reduced-form IAMs' damage are systematically biased downwards, this approach is not sufficient to address the problem.

Likewise, the Working Group should also not attempt to address the shortcomings of the reduced-form IAM damage functions by adopting other types of IAMs or their damage functions. Specifically, the Working Group may be tempted to include a larger set of IAMs beyond reduced-form IAMs, such as the commonly cited CGE-IAMs or hybrid IAMs. While most CGE-IAMs, like ICES and ENVISAGE, are calibrated to newer data relative to reduced-form IAMs, they are still out of date as they do not reflect the current state of the literature. Moreover, the CGE-IAMs omit non-market impacts and catastrophic damages, making them unusable for the purposes of calculating the social cost of greenhouse gases. In the case of WITCH, the damages are based on ICES (Bosello et al. 2012) and DICE-2007 (Nordhaus, 2007). Thus, the WITCH damage function is still significantly outdated and likely reflects many of the damage studies from the 1990s already captured by reduced-form IAMs. Thus, it is not a solution to switch damage functions.

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[23] They also exclude general equilibrium impacts of trade, adaptation at a more global scale and over longer timeframe, and inter-regional impacts (Dell et al., 2012).

[24] In DICE-1999, agricultural and other market impact estimates are -0.18% for a 2.5°C increase implying a -0.46% increase by the end of the century assuming a quadratic damage function. Alternatively, FUND clearly predicts -1% of damages by the end of the century for just electricity demand, agriculture, and water. PAGE09 estimates market impacts in Europe equal to -1.1% of GDP for a 4°C increase before adaptation. As regional weights are lower for all other regional and adaptation is possible, the corresponding estimate in PAGE is certainly below FUND and the Newell range.

National Academy of Sciences Input

The NAS (2017) directly recommends that the Working Group should update the climate damage functions. Specifically, the NAS (2017) recommends that the Working Group conduct a short-run update to reflect the current state of the empirical literature. In doing so, the NAS (2017) endorses the enumerative approach of building damage functions sector-by-sector and region-by-region, while recognizing that adopting existing enumerative-based damage functions from IAMs is not a suitable way forward. A challenge of this approach is that since 2017, another four years' worth of publications have accrued, and there are likely several hundred relevant studies for the Working Group to consider.[25] Luckily, Resources for the Future (RFF)'s Social Cost of Carbon initiative has taken this approach by reviewing the "best available literature." However, as of now, no summary publication is available.

Alternatively, Climate Impact Lab is applying statistical methods to big data to develop its own empirically based damage functions. Climate Impact Lab is not synthesizing past research but is instead developing new publications. If these publications are made available in time, the Working Group should use all data deemed of sufficient quality and then determine if there are sufficient gaps such that the use of expert elicitation should be considered.

Recent efforts to use big data and advanced empirical methods to improve climate damage estimates are not a panacea, as they still focus on many of the same sectors as reduced-form IAMs.[26] The more difficult a climate driver or impact is to measure, the more likely it is to be excluded or poorly measured (Yohe, 2008). For now, data-driven approaches are more likely to capture deterministic climate trends, like average temperature rise and sea-level rise, excluding impacts with a range of outcomes and strong non-linearities (for example, fires, extreme weather events, and weather variability). Similarly, physical impacts that are harder to measure and/or value as well as non-linear/abrupt changes are more likely to be excluded (Yohe, 2008). Thus, the big-data approach will still tend to omit non-market damages—particularly ecological damages and biodiversity loss. While there is promise that big data will help improve global estimates of socially contingent impacts (Carleton et al., 2016, Koubi, 2019) and even put dollar numbers on these impacts in some limited cases (Houser et al., 2015), global climate damage functions are currently unavailable and are unlikely to be available in time for modeling by the Fall of 2021. And as always, big data will be limited in its ability to measure impacts that have not yet occurred, like tipping points, and will shed little light on climate-impact relationships for high temperature increases due

[25] As one point of reference, Figure 5 in IWG (2020) stops in 2016, and researchers appear to be publishing impact studies at an increasing rate.

[26] For example, the Climate Impact Lab is predominately focused on updating impacts to sectors already included in existing reduced-form IAMs or CGE-IAMs (such as human health, energy demand, agriculture, manufacturing, and labor productivity) with the critical exception of including socially contingent damages (such as migration, social and political conflict, violence and crime).

to potential non-linearities and abrupt changes (including in human behavior).[27] As such, many of the impacts missing from existing IAMs are likely still to be missing after summarizing the new empirical literature. In fact, Pindyck (2013, 2017a, 2017b) and some other economists question whether climate damages are truly knowable, particularly at high temperatures, and whether more attention should be spent on damage uncertainty and ambiguity, including tipping points and tail risk.

Over the long run, the NAS (2017) advocates for taking a comprehensive approach to damage modeling to ensure that difficult-to-measure impacts are included, though it needlessly restricts itself from some powerful tools to help understand these impacts. Specifically, for estimating climate damage functions, NAS (2017) argues for using only the enumerative and meta-regression approaches. This limited set of approaches could be problematic, particularly if meta-regressions are narrowly focused on enumerative estimates (as in Nordhaus and Moffat (2017)), as the magnitudes of damage estimates are often highly dependent on the methodology employed (Howard and Sterner, 2017). Beyond this issue, a narrow approach does not address the issues of unknowability and ambiguity raised by Pindyck (2013, 2017a; 2017b).

Technical Details of Our Recommendations

Given the uncertainty, ambiguity, and incompleteness underlying climate damage estimates, it would be prudent to consider a wider array of estimation methodologies including science-based approaches and expert elicitation, in addition to enumerative and statistical approaches. This could be done either through: (1) sensitivity analysis with respect to the estimation strategy underlying the climate damage function, or (2) an integration of these various methods via meta-regression. The former approach would be consistent with past EPA practices,[28] while the latter is consistent with the NAS (2017) approach with a slight expansion of the qualifying estimation methodologies (as reflected in the Howard and Sterner (2017) and Nordhaus and Moffat (2017) estimates). In either case, expert elicitation is a valuable methodology and should not be excluded from the Working Group portfolio based on a misguided recommendation by NAS (2017).

The Working Group should strongly consider using existing expert elicitations to improve the climate damage functions in reduced-form IAMs, including Pindyck (2019) and Howard and Sylvan (2020; 2021). In making its recommendations, the NAS (2017) favored enumerative and meta-regression strategies, singling out top-down elicitation methods for climate damages as flawed. The NAS (2017)

[27] According to Howard and Sterner (2017), a high temperature increase is 4°C, which would be reach by 2100 under some Business-as-Usual scenarios. At these temperatures, Pindyck (2013) argues that economists do not even have a strong grasp of the damage functional form or whether climate change impacts levels or growth.

[28] Howard (2019) states "The use of multiple methodologies to estimate benefits of a regulation is also consistent with previous cost-benefit practices by federal agencies. For example, EPA developed a concentration response function to estimate mortality caused by particulate matter exposure by using published epidemiological studies and EPA's own expert elicitation (Walton, 2009). Each of the employed methodologies should be transparent and systematic to make them easily updatable."

opposes elicitation in this context "because it lacks traceability to damage pathways, may not have a strong scientific rationale, or may not address nonmarket damages." This argument is problematic for several reasons. Enumerative and statistical-based strategies have historically omitted hard-to-estimate impacts, whereas expert elicitation is more capable of providing a complete set of damages (Pindyck, 2019; Howard and Sylvan, 2020).[29] While it is true that expert elicitation has trouble attributing impacts to sectors and regions, meta-regression at the global scale also struggles with this issue due to a lack of data. In the near future, expert elicitation can overcome this challenge at least in part, by using sector-specific and region-specific questions. Expert elicitation also has a strong scientific rationale, as noted by the NAS (2017) report for inputs unrelated to damages; has shown to produce consistent results (Pindyck, 2019; Howard and Sylvan, 2020; and Howard and Sylvan, 2021); and has methods at its disposal to further improve reliability—consistency checks (Howard and Sylvan, 2020) or seed questions (Howard and Sylvan, 2021). Furthermore, the use of expert elicitation is consistent with past EPA practices, such as the development of concentration-response functions for particulate matter exposure (Walton, 2009), and the EPA has already developed guidelines for using expert elicitation. Finally, as data and all estimation methodologies improve, the research community is still decades away for a comprehensive and accurate impact estimate.[30] In the meantime, important scientific tools should not be ignored, particularly one like expert elicitation that can capture difficult to measure and currently omitted climate impacts.

The Working Group should continue to view expert elicitation as a valuable tool for estimating climate damages. As the methodology improves, it should be evaluated alongside meta-regression and enumerative-based estimates, according to the NAS (2017) critiques of elicitation discussed in the previous paragraph. If some elicitation studies focus on regional and sector-based damages rather than global damages, these could help determine impact pathways, while the identification of relevant experts and the development of seed questions could improve overall accuracy (Howard and Sylvan, 2020).[31] With methodology improvements, expert elicitation may also be better equipped to identify impact pathways relative to other methodologies, by asking experts to explain their reasoning.

New expert elicitations should also focus on issues related to adaptation, such as the impacts of regional income and the rate of temperature increase. The ability to adapt increases with income (Tol, 2009), while

[29] As noted by the NAS (2017), expert elicitation can be effective at addressing difficult-to-measure impacts that are ignored by statistical methods, though there appears to be no reason that expert elicitation should not be used to value market impacts, including agricultural and health impacts. Given the difficulty of cleanly identifying specific impacts, the multitude of climate drivers, and the inability of statistical methods to capture high-temperature impacts, expert elicitation may be particularly useful in this regard.

[30] As noted by Anthoff and Hope at the NAS's third committee meeting in Washington, D.C. on November 13, 2015, the improvement of damage estimates will take decades. This is true for expert elicitation as well as it is true for statistical methods, benefit-transfer analysis, and scientific understanding of limits of humans to climate change.

[31] Just as the NAS (2017) envisaged a series of expert elicitations to build socioeconomic scenarios, one possible way forward is a series of consecutive expert elicitations on climate drivers, impacts, and valuation. These could be done at a global-aggregate scale and/or sectoral and regional scales.

it declines (and adaptation becomes more costly) as temperatures rise, particularly in faster-warming scenarios where there is less time for society to adapt and to develop adaptation technologies (Kopp et al. 2012; Howard and Sylvan, 2021). Specifically, researchers can ask experts to estimate net damages under scenarios that vary with respect to time, temperature, and income, to tease out the impacts of adaptation and its costs (Howard and Sylvan, 2021). Efforts to address adaptation through expert elicitation have already begun (Nordhaus, 1994a; Howard and Sylvan, 2021).

A compromise between our position and the NAS (2017) input would be to conduct meta-regression consistent with Nordhaus and Moffat (2017) and Howard and Sterner (2017). Specifically, this methodology is one of three methodologies recommended for assembling damages by NAS (2017). Additionally, both meta-regressions include expert elicitation studies at the global scale: Nordhaus (1994a) is accounted for in both studies, while and Howard and Sterner (2017) also accounts for Howard and Sylvan (2015). Meta-regression of global climate damages allows for the combination of damage estimates in a transparent manner that allows for reproduction and robustness checks. With respect to the attribution of impacts to sectors, meta-regression at the global scale currently suffers from the same sector-regional shortcomings as noted above. Howard and Sterner (2017) control for damage types at a sector scale similar to PAGE controlling for market, non-market, and catastrophic damages. Nordhaus and Moffat (2017) and Tol (2009; 2014; 2018) do not control for any sectoral differences between the studies, leading to biased estimates (Howard and Sterner, 2017). A potential solution is to include regional damage estimates and sectoral estimates to allow for a disaggregation of control variables, as in Howard and Sterner (2017), to a regional and sectoral scale.

Regardless of whether the Working Group employs expert elicitation directly or indirectly (through meta-regression), the Working Group should consider using mean and/or median damages. On the one hand, as climate damages are "*ex post* verifiable", a true damage function exists and current elicited values only "differ due to asymmetric information and judgement" (Howard and Sylvan, 2020). In this case, the mean expert response is the best approximation of true climate damages, according to the Central Limit Theory, such that calibrating a damage function to the mean response minimizes forecast error (Freeman and Groom, 2015). As such, calibrating damage functions to the mean response has been the standard practice in the damage literature (Nordhaus 1994b; Roughgarden and Schneider 1999; Gerst et al. 2010; Pindyck 2019). On the other hand, the median response is more appropriate when responses are highly skewed, as is common in damage estimates including expert elicitation (Nordhaus, 1994a; Schauer, 1995; Roughgarden and Schneider 1999; Howard and Sylvan, 2020; Howard and Sylvan, 2021), or if damages are truly unknowable as raised by Pindyck (2013, 2017a; 2017b). Specifically, if either assumption holds, then the median may be preferred based on voting theory, and its ability to minimize forecast error when outliers are present (Lorenz et al., 2011). If the Working Group chooses a meta-regression or expert elicitation approach, we believe that the prudent choice moving forward would be to choose either the

mean or median, depending on which they believe to be better supported by the evidence, and conduct sensitivity analysis using the other approach.[32]

Updating Discount Rates

The discount rate captures the rate at which society is willing to tradeoff current and future consumption. As cost-benefit analysis is interested in societal tradeoffs over time, the Working Group should focus on social discount rates instead of private rates. For reasons of observability and their link to revealed preferences, private market rates are often used to approximate these social rates, following the descriptive approach. If the world had no distortions (such as taxes, market power, externalities, and differences between social and private risk premiums), the Working Group could focus on discount rates faced by consumers or producers, as they would be equal. This is clearly not the case, as the consumption discount rate is lower than the capital rate (due primarily to taxation, according to the literature). However, the consumption discount rate can also be calculated using the simple Ramsey equation. This latter methodology, known as the prescriptive methodology, is often calibrated based on normative arguments from the economics literature. While both the descriptive and normative approaches produce a range of discount rates, there is strong consensus that the central discount rate and maximum discount rate appropriate for analysis in the climate context are lower than previously calculated.[33] The Working Group can use expert elicitation to further calibrate and refine the appropriate choice for both its central discount rate and a reasonable range of rates to use for sensitivity analysis.

Key Recommendations

Recommendations for the Current Update

- The Working Group should supplement its calibration of the discount rate by considering evidence besides just market data and consider moving toward discount rate schedules based on the extended Ramsey discount rate equation, which can be informed by expert elicitation and the latest economic literature as well as any updated and reliable market data.
- There is a strong consensus forming around consumption discount rates between 1% and 3% (Drupp et al., 2018). Within this range, the Working Group will need to select an appropriate discount rate or schedule for its central estimates, as well as additional rates or schedules for sensitivity analysis. To estimate the central rate or schedule, the Working Group should consider

[32] In meta-regression, the mean is consistent with the choice of ordinary least squares in Howard and Sterner (2017), as the mean minimizes the sum of squared errors when elicited damage values follow a normal or other symmetric distribution. This median is consistent with the choice of median regression in Nordhaus and Moffat (2017)'s meta-regression of global climate damage estimates to address outliers.

[33] See Howard and Schwartz (2021) for a discussion of structural shortcomings of the simple Ramsey rate, particularly as they relate to intergenerational cost-benefit analysis. Table 3 below shows our regression results.

using expert elicitations and selecting the median parameter value following standard voting procedure, as that approach will yield time-consistent and more efficient values than other expert elicitation rules (which result in time-inconsistency).

- The Working Group should consider four different methods for applying voting procedures to calibrate the simple Ramsey rate using elicited data: (1) select the median discount rate; (2) select the median discount schedule; (3) select the median parameters underlying the Simple Ramsey equation; or (4) select the median pure rate of time preference and calibrate the elasticity of marginal utility of consumption to replicate the median social discount rate (Howard and Sylvan, 2020; Hansel et al., 2020). These methods generally derive an average rate between 1.7% and 2.4% over the 300-year time frame applied by the Working Group, though there are several practical advantages to the fourth approach (i.e., selecting the median pure rate of time preference and calibrating the elasticity of marginal utility) from a policy perspective. Similar techniques could be used to calibrate an extended Ramsey equation.
- To derive a range for sensitivity analysis, these calibration approaches could be combined with the minimum and maximum social discount rates values of 1% and 3% found in Drupp et al. (2018).
- Given the intergenerational context of climate change, the Working Group can use regression analysis to address concerns about declining discount rates and relative prices. Specifically, analysts can use data from in-depth expert elicitations and jointly regress the social discount rate and the pure rate of time preference on indicator variables for whether respondents discussed declining rates or whether they discussed relative prices using median regression. Using this methodology to account for these intergenerational discount rate features, we found the preferred social discount rate declines to 1% with a range of -0.5% to 2%, which closely matches recent evidence on market rates and economic theory.[34]

Longer-Term Recommendations

- In the long run, the Working Group should consider adopting a more realistic, though complicated, discount rate formula than the simple Ramsey equation. Beyond the standard extended Ramsey rate, the Working Group should consider relative prices, project risk, and Epstein-Zin-Weil preferences; see Howard and Schwartz, 2021).

Context and Technical Details

Past Working Group Actions

Since 2010, the Working (2010, p. 19) has relied predominately on the descriptive approach for calibrating discount rates, despite informing their opinion with various economic arguments in the

[34] See Howard and Schwartz (2021) for additional discussion.

literature. Focusing on the consumption discount rate, as theory supports (Howard and Schwartz, 2021), the Working Group (2010) selected three constant discount rates: a central rate of 3%, consistent with Circular A-4 and the after-tax riskless interest rate; a lower-end rate of 2.5% to account for discount-rate uncertainty; and an upper rate 5% rate to account for the positive correlation between economic growth and climate damages. As discussed in Howard and Schwartz (2021), the economic theory and data underlying these discount rates is out-of-date such that accounting for updated information implies a much lower range of discount rates in both the intra-generational and inter-generational cases.[35]

National Academy of Sciences Input

The NAS (2017) recommended that the Working Group move to the simple Ramsey discount rate equation $r = \rho + \eta \times g$ where ρ is the pure rate of time preference, η is the elasticity of the marginal utility of consumption, and g is the growth rate in per capita consumption. Following standard practice in IAMs, the intergenerational context of climate change is a strong reason to emphasize the simple Ramsey equation and the results of expert elicitation when calculating the social costs of greenhouse gases. As there are few inter-generational market rates from which to derive the appropriate intergenerational rate, discount rates in the climate change context are sounder when derived from "ethical considerations reflecting society's views concerning consumption tradeoffs across generations (NAS, 2017)."

There are many pieces of evidence that economists can consider when calibrating the parameters for the Ramsey equation. In 2010, the Working Group reviewed the literature available at the time and found that the pure rate of time preference ranged from 0% to 3% and the elasticity of marginal utility of consumption ranged from 1 to 4. Those values imply a wider range than the more recent consensus on the discount rate between 1% to 3% found in Drupp et al. (2018). Many researchers have invested considerable effort and made serious progress toward explaining this disparity and how to select the appropriate discount rate under heterogeneous views.[36]

Technical Details of Our Recommendations

A literature has developed on how to select a socially efficient rate under heterogeneous views. In the cost-benefit context, Weitzman (2001) famously demonstrated that the aggregation of a (persistently) heterogeneous constant social discount rate is a declining instantaneous certainty-equivalent discount rate from its mean at time-period 0 to its lowest possible value in the distant future.[37] Using large-sample

[35] For impacts in the next 30 to 40 years, a central discount rate of 2% with a range of 1% to 3% is sensible based on both the descriptive approaches. In intergenerational settings, a central rate of 1% with a range of 0.1% to 2.5% is reasonable.
[36] In this context, we choose heterogeneity over uncertainty as uncertainty implies something resolvable with more information and time. Instead, heterogeneity implies the existence of a diverse set of opinions for which differences may be unresolvable.
[37] The result follows directly from the fact that the expectation is over the discount factor and not the discount rate (Arrow et al., 2014; Cropper et al., 2014).

survey data, Weitzman (2001) estimated a gamma discounting with an immediate discount rate of 4% that declines to 1% by approximately 2100 and 0% by 2300,[38] though Freeman and Groom (2015) develop a less-steep gamma schedule interpreting the elicited social discount rates as spot rates instead of forward rates. As the Weitzman (2001) analysis lacks the theoretical underpinning of the Ramsey discount rate recommended for adoption by the NAS (2017), a series of papers solved for the efficiency discount rate under heterogeneity within the Ramsey framework (Gollier and Zeckhauser, 2005; Jouini et al., 2010; Jouini and Napp 2014; Heal and Millner, 2014). Specifically, this literature solves for "a discount rate that achieves a Pareto efficient consumption over time" when a diverse group of individuals with competing preferences must jointly manage a consumption asset over time (Howard and Sylvan, 2020). The resulting schedules and gamma rates may be time inconsistent, and so as an alternative, Millner and Heal (2018) demonstrate that defaulting to a voting procedure whereby the median voter determines the collective pure rate of time preference (the sole source of heterogeneity within the model) is both time consistent and welfare enhancing relative to the non-commitment, time-inconsistent approaches (for realistic parameter values).

There are four ways to apply the voting procedure, together pointing to an average discount rate between 1.7% and 2.4% over the 300-year timeframe applied by the Working Group (2010). Specifically, Howard and Sterner (2020) and Hansel et al. (2020) develop four ways to calibrate the simple Ramsey rate in reduced-form IAMs to elicited data (Hansel et al., 2020; Howard and Sylvan, 2020): (1) select the median constant discount rate; (2) select the median discount rate schedule; (3) select the median parameters underlying the simple Ramsey equation; and (4) select the median pure rate of time preference θ and then calibrate the elasticity of marginal utility of consumption η to replicate the median discount rate r assuming the simply Ramsey equation.

Using this first method, Howard and Sylvan (2020) select the median discount rate from their survey of experts on climate economics, finding a median discount rate of 2% as the appropriate intergenerational discount rate in the climate change context. Drupp et al. (2018) asks experts to provide their minimum and maximum social discount rate values, and finds a large majority of economists believe the acceptable range covers 1% to 3% with a central rate of 2%. However, the use of constant discount rates is not consistent with NAS (2017) recommendations. Using the second methodology, Hansel et al. (2018) solves for the median expert social cost of carbon in a recalibrated DICE model, assuming individuals vote on the social cost of carbon subject to their preferred parameter values. They find a pure rate of time preference of approximately 0% and an elasticity of marginal utility of consumption of 2, implying a discount rate of 2.4% within DICE-2016R2. Applying the third methodology to the Drupp et al. (2018)

[38] Weitzman (2001) assumed equal weighting and that the sample responses are approximately gamma distributed.

dataset, Hansel et al. (2020) find a pure rate of time preference of 0.5% and an elasticity of marginal utility of consumption of one, implying an average discount rate of 1.7% in DICE-2016R2.

Alternatively, Howard and Sylvan (2020) argue that economists should simply approximate the true discount rate using a simple Ramsey equation, as economists hold complicated and diverse views about the discount rate structure beyond just its parameterization. Specifically, Drupp et al. (2018) finds significant disparities between the elicited social discount rate r and simple and extended Ramsey rate constructed from the same experts' elicited parameters $\hat{r} = \theta + \eta \times g$. This (along with comments submitted as part of the study) indicates that respondents assumed much more sophisticated preference structures under uncertainty, increasing environmental scarcity, project risk, and the equity premium puzzle than the simple and extended Ramsey rates (Drupp et al., 2018).[39] As alternative assumptions result in a far more complex Ramsey equation (see Howard and Schwartz, 2021), we cannot be certain what structural assumptions the respondents had in mind except in the cases of those who provided comments. These issues also further complicate how to interpret the elasticity of marginal utility of consumption being elicited under a simple Ramsey rate when respondents disagree with the structural assumptions underlying isoelastic preferences and when the parameter has many interpretations in the simplistic isoelastic structure (i.e., relative risk aversion, aversion to inter-generational inequality, aversion to intra-generational inequality, the inverse of the elasticity of intertemporal substitution, and prudence in the extended Ramsey context) that may differ in the real world.

A potential solution is to use the discount rate approximation method in Howard and Sylvan (2020) whereby the analyst re-interprets the simple Ramsey rate as an approximation of the true rate and calibrates the elasticity of marginal utility of consumption η to replicate the median discount rate r subject to the median pure rate of time preference θ. Thus, $r_{median} = \delta_{median} + \hat{\eta} * g$. As the elicited (constant) social discount rate implicitly contains the respondent's true version of the Ramsey equation and the appropriate social welfare parameters (Cooke, 2013), the constant rate roughly approximates the true rate and we can roughly approximate the constant rate using a simple Ramsey rate (Marten et al., 2015).[40] While this approximation of the median discount rate formula relies on several assumptions,[41]

[39] Of the 173 members, 37 respondents (21%) provided social discount rate consistent with (i.e., within 1% of) the simple Ramsey rate calibrated to their elicited parameter values; this increases to 26% if we allow for 5% error.

[40] Note that this is simply the reasoning of Marten et al. (2015) in reverse when he argues for approximating a simple Ramsey rate with a constant discount rate.

[41] Howard and Sylvan (2020) state: "To calibrate δ and η using the Millner-Heal voting procedure, we require several additional assumptions: (1) experts responded to Question 12 by providing the average SDR across the time frame of IAMs (approximately 300 years in DICE), (2) the source of heterogeneity in r is via heterogeneity in δ (Drupp et al., 2018) and damages, (3) respondents have a homogenous η (a standard assumption when aggregating preferences assuming heterogeneous δ (Heal and Millner, 2014)), and (4) the median δ equals the median value found in Drupp et al. (2018), i.e., δ=0.5. Thus, we set δ equal to the median pure rate of time preference (i.e., δ=0.5 by assumption 4) and select η given the assumed level of climate damages (e.g., the mean elicited response to Question 13) such that the average discount rate in DICE-2013R matches the median elicited SDR."

most prominently that η is homogenous, the resulting bias should be minimal as the coefficient of variation for the pure rate of time preference is double that of the elasticity of marginal utility of consumption in the Drupp et al. (2018) data, such that heterogeneity of the former far exceeds heterogeneity in the latter. Additionally, IAMs (e.g., DICE) commonly assume that economic growth will decline over the multi-century timeline they model, even without climate impacts, resulting in the declining relative importance of the heterogeneity of η over time in determining the social discount rate. To calibrate the model, Howard and Sylvan (2020) set δ_{median} to the Drupp et al. (2018) median response of 0.5 and calibrated η within the DICE frameworks (and its growth dynamic g) such that the discount rate averaged to $r_{median} = 2\%$ in Drupp et al. (2018) over the model's 300-year timeframe. The resulting elasticity of marginality utility of consumption is between 1.24 and 1.60 when calibrated within the existing DICE-2013R and DICE-2016R2 frameworks where additional variation also comes from the selected damage function.

The Working Group should consider using this methodology, as it has several promising attributes. First, this method ensures that the social discount rate equals the median elicited rate.[42] Second, this method is consistent with the NAS (2017) discount rate recommendations. Finally, it avoids imposing structural assumptions and relying on the elicited elasticity of marginal utility of consumption, which has a multitude of meanings in the literature and is overworked. Even considering these potential advantages, all four methods have their theoretical, empirical, and policy justifications and drawbacks; see Figure 3.

Given the intergenerational context of climate change, the Working Group could also use regression analysis to address concerns about declining discount rates and relative prices. Specifically, some experts accounted for declining discount rates and relative prices according to their comments in the Drupp et al. (2018) survey. Thus, we can use regression analysis to make informed opinions of the elicited rates under the preferred structural assumptions for an intergenerational discount rate. Just as Drupp et al. (2017) found that experts who support a declining discount rate and relative prices independently decreased the social discount rate by 0.7% and 1%, respectively, we can run a more sophisticated multi-variate analysis by controlling for these attributes simultaneously using social discount rate (minimum, best, and maximum) and the pure rate of time preference; see Table 3 using OLS and a median regression. Focusing on the median regression, as it is roughly equivalent of a voting procedure, we find a range of -0.5% to 2.0% with a central value of 0.5% to 1.0% and a central pure rate of time preference of 0%.[43] Using these

[42] Technically, this methodology can be applied with any social discount rate, though ideally its value should be consistent with the pure rate of time preference. Therefore, the Working group could also apply this approach with the low and high social discount rate values of 1% and 3% in Drupp et al. (2018).

[43] As the declining coefficient is not significant in the median regression and there is some evidence from Howard and Sylvan (2020) that support of a declining rate does not lead to a lower social discount rate, we can redo this analysis solely accounting for the impact of relative prices finding a social discount range of 0% to 2% with a central social discount rate of 1% and a central pure rate of time preference of 0%.

alternative values for the social discount rate and time preferences, we can then recalibrate the discount rate using one of the four preferred methodologies above, imposing desirable structural assumptions.[44]

In the long-run, the Working Group should consider adopting a more realistic, though complicated, discount rate formula as opposed to the simple Ramsey equation. Beyond the standard extended Ramsey rate, the Working Group should consider relative prices, project risk, and Epstein-Zin-Weil preferences; see Howard and Schwartz (2021). How to identify the appropriate structural discount rate model and calibrate it is beyond the scope of this report, though expert elicitation can clearly play a valuable role.

Conclusion

The results from expert elicitations can be used to help calibrate reduced-form IAM parameters including socioeconomic and emissions scenarios; natural science assumptions; climate damage functions; and discount rates. Calibrating these parameters to match the consensus views of experts will lead to a more thorough account of anticipated climate impacts and will likely increase the values of the social cost of greenhouse gas metrics.

The Working Group should treat expert elicitations as valuable tools as it works to update these metrics. In many cases, doing so will align with suggestions from the NAS. Incorporating findings from relevant elicitations can make the Working Group's current update both more efficient and more comprehensive.

[44] Additional controls can be included, like the % weighting of normative issues and their interactions with these critical variables; see Table 4. Interestingly, the work finds that researchers supporting the descriptive approach clearly support a consumption discount rate, not a capital rate, and they also support a rate equal or less than the corresponding normative rates when we account for desirable structural assumptions.

References

Armstrong, J. S. (Ed.). (2001). Principles of forecasting: a handbook for researchers and practitioners (Vol. 30). Springer Science & Business Media.

Arrow, K. J., Cropper, M. L., Gollier, C., Groom, B., Heal, G. M., Newell, R. G., ... & Weitzman, M. L. (2014). Should governments use a declining discount rate in project analysis?. Review of Environmental Economics and Policy, 8(2), 145-163.

Auffhammer, M. (2018). Quantifying economic damages from climate change. Journal of Economic Perspectives, 32(4), 33-52.

Bahn, O., de Bruin, K., & Fertel, C. (2019). Will adaptation delay the transition to clean energy systems? An analysis with AD-MERGE. The Energy Journal, 40(4).

Bamber, J. L., & Aspinall, W. P. (2013). An expert judgement assessment of future sea level rise from the ice sheets. Nature Climate Change, 3(4), 424-427.

Bamber, J. L., Oppenheimer, M., Kopp, R. E., Aspinall, W. P., & Cooke, R. M. (2019). Ice sheet contributions to future sea-level rise from structured expert judgment. Proceedings of the National Academy of Sciences, 116(23), 11195-11200.

[BOEM,2015] Industrial Economics, Inc. (2015). Consumer Surplus and Energy Substitutes for OCS Oil and Gas production: The 2015 Revised Market Simulation Model (MarketSim). U.S. Department of the Interior, Bureau of Ocean Energy Management. OCS Study BOEM 2015-054.

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., & Tavoni, M. (2006). A world induced technical change hybrid model. The Energy Journal, (Special Issue# 2).

Bosello, F., Eboli, F., & Pierfederici, R. (2012). Assessing the economic impacts of climate change. FEEM (Fondazione Eni Enrico Mattei), Review of Environment, Energy and Economics (Re3).

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527(7577), 235-239.

Cai, Y., & Lontzek, T. S. (2019). The social cost of carbon with economic and climate risks. Journal of Political Economy, 127(6), 2684-2734.

Carleton, T., Hsiang, S. M., & Burke, M. (2016). Conflict in a changing climate. The European Physical Journal Special Topics, 225(3), 489-511.

Carleton, T. A., Jina, A., Delgado, M. T., Greenstone, M., Houser, T., Hsiang, S. M., ... & Zhang, A. T. (2020). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits (No. w27599). National Bureau of Economic Research.

Climate Action Tracker Data, 2020. "CAT_2020-12_PublicData_EmissionPathways.XLSX". Available at https://climateactiontracker.org/global/temperatures/.

Climate Action Tracker Data, 2021. "CAT_2021-05_PublicData_EmissionPathways.XLSX". Available at https://climateactiontracker.org/global/temperatures/.

Cooke, R. M. (2013). Uncertainty analysis comes to integrated assessment models for climate change … and conversely. Climatic change, 117(3), 467-479.

Cromar, K., Howard, P. H., Vásquez, V. N. and Anthoff, D. Public Health Benefits of Climate Mitigation in Social Cost of Carbon Estimates. Forthcoming in BioHealth.

Cropper, M. L., Freeman, M. C., Groom, B., & Pizer, W. A. (2014). Declining discount rates. American Economic Review, 104(5), 538-43.

De Bruin, K. C., Dellink, R. B., & Tol, R. S. (2009). AD-DICE: an implementation of adaptation in the DICE model. Climatic Change, 95(1), 63-81. Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66-95.

Dietz, S., Gollier, C., & Kessler, L. (2018). The climate beta. Journal of Environmental Economics and Management, 87, 258-274.

Downs, A. (1957). An economic theory of political action in a democracy. Journal of political economy, 65(2), 135-150. Drupp, M. A., Freeman, M. C., Groom, B., & Nesje, F. (2018). Discounting disentangled. American Economic Journal: Economic Policy, 10(4), 109-34.

Freeman, M. C., & Groom, B. (2015). Positively gamma discounting: combining the opinions of experts on the social discount rate. The Economic Journal, 125(585), 1015-1024.

Gerst, M. D., Howarth, R. B., & Borsuk, M. E. (2010). Accounting for the risk of extreme outcomes in an integrated assessment of climate change. Energy Policy, 38(8), 4540-4548.

Gigone, D., & Hastie, R . (1997). Proper analysis of the accuracy of group judgments. Psychological Bulletin, 121(1), 149.

Gollier, C., & Hammitt, J. K. (2014). The long-run discount rate controversy. Annu. Rev. Resour. Econ., 6(1), 273-295.

Gollier, C., & Zeckhauser, R. (2005). Aggregation of heterogeneous time preferences. Journal of political Economy, 113(4), 878-896.

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. Econometrica, 82(1), 41-88.

Hänsel, M. C., Drupp, M. A., Johansson, D. J., Nesje, F., Azar, C., Freeman, M. C., ... & Sterner, T. (2020). Climate economics support for the UN climate targets. Nature Climate Change, 10(8), 781-789.

Hausfather, Z., & Peters, G. P. (2020). Emissions–the 'business as usual'story is misleading. Nature 577, 618–620.

Heal, G. M., & Millner, A. (2014). Agreeing to disagree on climate policy. Proceedings of the National Academy of Sciences, 111(10), 3695-3698.

Ho, E., Budescu, D. V., Bosetti, V., van Vuuren, D. P., & Keller, K. (2019). Not all carbon dioxide emission scenarios are equally likely: a subjective expert assessment. Climatic Change, 155(4), 545-561.

Hope, C. (2011). The social cost of CO2 from the PAGE09 model. Economics discussion paper, (2011-39).

Houser, T., Hsiang, S., Kopp, R., Larsen, K., Delgado, M., Jina, A., ... & Wilson, P. (2015). Economic risks of climate change: an American prospectus. Columbia University Press.

Howard P. (2014). Omitted Damages: What's Missing from the Social Cost of Carbon. Cost of Carbon Project.

Howard, P. H. (2019). The social cost of carbon: capturing the costs of future climate impacts in US policy. In Managing Global Warming (pp. 659-694). Academic Press.

Howard, P. H., & Livermore, M. "Climate-Society Feedback Effects: Be Wary of Unidentified Connections" Forthcoming in International Review of Environmental and Resource Economics.

Howard, P. H., & Schwartz, J. (2021). About time: recalibrating the discount rate for the social cost of greenhouse gases. Institute for Policy Integrity. Available at https://policyintegrity.org/publications/detail/about-time.

Howard, P. H., & Sterner, T. (2017). Few and not so far between: a meta-analysis of climate damage estimates. Environmental and Resource Economics, 68(1), 197-225.

Howard, P. H., & Sterner, T. (2020). Between Two Worlds: Methodological and Subjective Differences in Climate Impact Meta-Analyses. AERE Summer Conference Paper.

Howard, P. H., & Sylvan, D. (2015). Expert Consensus on the Economics of Climate Change. Institute for Policy Integrity. Available at https://policyintegrity.org/publications/detail/expert-climate-consensus.

Howard, P. H., & Sylvan, D. (2020). Wisdom of the experts: Using survey responses to address positive and normative uncertainties in climate-economic models. Climatic Change, 162(2), 213-232.

Howard, P. H., & Sylvan, D. (2021). Gauging Economic Consensus on Climate Change. Institute for Policy Integrity. Available at https://policyintegrity.org/publications/detail/gauging-economic-consensus-on-climate-change.

IPCC, 2014: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2018: Global Warming of 1.5°C.An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R.Shukla, A.Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M.Tignor, and T. Waterfield (eds.)]. In Press.

[IWG, 2010] Interagency Working Group on Social Cost of Carbon. 2010. Social cost of carbon for regulatory impact analysis under Executive Order 12866. Washington, DC: U.S. government.

[IWG, 2013] Interagency Working Group on Social Cost of Carbon. 2010. Social cost of carbon for regulatory impact analysis under Executive Order 12866. Washington, DC: U.S. government.

[IWG, 2016] Interagency Working Group on Social Cost of Carbon. 2010. Social cost of carbon for regulatory impact analysis under Executive Order 12866. Washington, DC: U.S. government.

[IWG, 2021] Interagency Working Group on Social Cost of Greenhouse Gases, United States Government. 2021. Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990. Washington, DC: U.S. government.

Javeline, D., Hellmann, J. J., Cornejo, R. C., & Shufeldt, G. (2013). Expert opinion on climate change and threats to biodiversity. Bioscience, 63(8), 666-673.

Jouini, E., Marin, J. M., & Napp, C. (2010). Discounting and divergence of opinion. Journal of Economic Theory, 145(2), 830-859.

Jouini, E., & Napp, C. (2014). How to aggregate experts' discount rates: An equilibrium approach. Economic Modelling, 36, 235-243.

Kopp, R. E., Golub, A., Keohane, N. O., & Onda, C. (2012). The Influence of the Specification of Climate Change Damages on the Social Cost of Carbon. Economics, 6(13), 0_1.

Kopp, R. E., Shwom, R. L., Wagner, G., & Yuan, J. (2016). Tipping elements and climate–economic shocks: Pathways toward integrated assessment. Earth's Future, 4(8), 346-372. Koubi, V. (2019). Climate change and conflict. Annual Review of Political Science, 22, 343-360.

Kriegler, E., Hall, J. W., Held, H., Dawson, R., & Schellnhuber, H. J. (2009). Imprecise probability assessment of tipping points in the climate system. Proceedings of the national Academy of Sciences, 106(13), 5041-5046.

Lemoine, D. (2021). The climate risk premium: how uncertainty affects the social cost of carbon. Journal of the Association of Environmental and Resource Economists, 8(1), 27-57.

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., & Schellnhuber, H. J. (2008). Tipping elements in the Earth's climate system. Proceedings of the national Academy of Sciences, 105(6), 1786-1793.

Letta, M., & Tol, R. S. (2019). Weather, climate and total factor productivity. Environmental and Resource Economics, 73(1), 283-305.

Link, P. M., & Tol, R. S. (2004). Possible economic impacts of a shutdown of the thermohaline circulation: an application of FUND. Portuguese economic journal, 3(2), 99-114.

Lorenz, J., Rauhut, H., Schweitzer, F., & Helbing, D. (2011). How social influence can undermine the wisdom of crowd effect. Proceedings of the national academy of sciences, 108(22), 9020-9025.

Manne, A. S., & Richels, R. G. (2005). MERGE: an integrated assessment model for global climate change. In Energy and environment (pp. 175-189). Springer, Boston, MA.

Marcucci, A., & Turton, H. (2012). The MERGE-ETL model: model documentation. Marten, A. L., Kopits, E. A., Griffiths, C. W., Newbold, S. C., & Wolverton, A. (2015). Incremental CH4 and N2O mitigation benefits consistent with the US Government's SC-CO2 estimates. Climate Policy, 15(2), 272-298.

McKibben, B. (2007). Warning on warming [Review of the IPCC Fourth Assessment Report]. The New York Review of Books, 15, 44-45. http://www.nybooks.com/articles/19981.

Millner, A., & Heal, G. (2018). Discounting by committee. Journal of Public Economics, 167, 91-104.

Moore, F. C., Baldos, U, & Hertel, T. (2017a). Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models. Environmental Research Letters, 12(6), 065008.

Moore, F. C., Baldos, U., Hertel, T., & Diaz, D. (2017b). New science of climate change impacts on agriculture implies higher social cost of carbon. Nature communications, 8(1), 1-9.

Morgan, M. G., & Keith, D. W. (1995). Subjective judgments by climate experts. Environmental Science & Technology, 29(10), 468A-476A.

Morgan, M. G., Pitelka, L. F., & Shevliakova, E. (2001). Elicitation of expert judgments of climate change impacts on forest ecosystems. Climatic Change, 49(3), 279-307.

Murray, C. J., Lopez, A. D., & World Health Organization. (1996). The global burden of disease: a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 and projected to 2020: summary. World Health Organization.

[NAS, 2016] National Academies of Sciences, Engineering, and Medicine. (2016). Assessment of approaches to updating the social cost of carbon: Phase 1 report on a near-term update. National Academies Press.

[NAS, 2017] National Academies of Sciences, Engineering, and Medicine. (2017). Valuing climate damages: updating estimation of the social cost of carbon dioxide. Washington, DC: National Academies Press.

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: implications for climate change damages. Journal of Environmental Economics and Management, 108, 102445.

Nordhaus, W. D. (1994a). Expert opinion on climatic change. American Scientist, 45-51.

Nordhaus, W. D. (1994). Managing the global commons: the economics of climate change (Vol. 31). Cambridge, MA: MIT press.

Nordhaus, W. (2007). Accompanying Notes and Documentation on Development of DICE-2007 Model: Notes on DICE-2007. delta. v8 as of September 21, 2007. Miscellaneous publication, Yale University, New Haven, NE.

Nordhaus, W. (2014). Estimates of the social cost of carbon: concepts and results from the DICE-2013R model and alternative approaches. Journal of the Association of Environmental and Resource Economists, 1(1/2), 273-312.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. Proceedings of the National Academy of Sciences, 114(7), 1518-1523.

Nordhaus, W. (2019). Climate change: the ultimate challenge for economics. American Economic Review, 109(6), 1991-2014.

Nordhaus, W. D., & Boyer, J. (2000). Warming the world: economic models of global warming. MIT press.

Nordhaus, W. D., & Moffat, A. (2017). A survey of global impacts of climate change: replication, survey methods, and a statistical analysis.

Oppenheimer, M., Little, C. M., & Cooke, R. M. (2016). Expert judgement and uncertainty quantification for climate change. Nature climate change, 6(5), 445-451.

Oppenheimer, M., Oreskes, N., Jamieson, D., Brysse, K., O'Reilly, J., Shindell, M., & Wazeck, M. (2019). Discerning experts: The practices of scientific assessment for environmental policy. University of Chicago Press.

Oreskes, N., Oppenheimer, M., & Jamieson, D. (2019). Scientists have been underestimating the pace of climate change. Scientific American, 19(08), 2019.

Persson, T., & Tabellini, G. (2002). Political economics: explaining economic policy. MIT press. Pindyck, R. S. (2013). The climate policy dilemma. Review of Environmental Economics and Policy, 7(2), 219-237.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us?. Journal of Economic Literature, 51(3), 860-72. Pindyck, R. S. (2017). Coase lecture—taxes, targets and the social cost of carbon. Economica, 84(335), 345-364. Pindyck, R. S. (2017b). The use and misuse of models for climate policy. Review of Environmental Economics and Policy, 11(1), 100-114.

Pindyck, R. S. (2019). The social cost of carbon revisited. Journal of Environmental Economics and Management, 94, 140-160.

Rahmstorf, S., Cazenave, A., Church, J. A., Hansen, J. E., Keeling, R . F., Parker, D. E., & Somerville, R . C. (2007). Recent climate observations compared to projections. Science, 316(5825), 709-709.

Rahmstorf, S., Foster, G., & Cazenave, A. (2012). Comparing climate projections to observations up to 2011. Environmental Research Letters, 7(4), 044035.Revesz, R. L., Howard, P. H., Arrow, K., Goulder, L. H., Kopp, R. E., Livermore, M. A., ... & Sterner, T. (2014). Global warming: Improve economic models of climate change. Nature News, 508(7495), 173.

Rose, S., Turner, D., Blanford, G., Bistline, J., de la Chesnaye, F., & Wilson, T. (2014). Understanding the social cost of carbon: A technical assessment. EPRI technical update report (Electric Power Research Inst, Palo Alto, CA

Roughgarden, T., & Schneider, S. H. (1999). Climate change policy: quantifying uncertainties for damages and optimal carbon taxes. Energy Policy, 27(7), 415-429.

Schauer, M. J. (1995). Estimation of the greenhouse gas externality with uncertainty. Environmental and Resource Economics, 5(1), 71-82.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences, 106(37), 15594-15598.

Shepsle, K. A. (1979). Institutional arrangements and equilibrium in multidimensional voting models. American Journal of Political Science, 27-59.Stern, N., & Stiglitz, J. E. (2021). The social cost of

carbon, risk, distribution, market failures: An alternative approach (No. w28472). National Bureau of Economic Research.

Sunstein, C. R . (2005). Group judgments: Statistical means, deliberation, and information markets. NYU Law Review, 80, 962. http://www.nyulawreview.org/sites/default/files/pdf/NYULawReview-80-3-Sunstein.pdf.

Surowiecki, J. (2004). The Wisdom Of Crowds. Knopf Doubleday Publishing Group.

Tol, R. S. (1995). The damage costs of climate change toward more comprehensive calculations. Environmental and Resource Economics, 5(4), 353-374.

Tol, R. S. (2002a). Estimates of the damage costs of climate change. Part 1: Benchmark estimates. Environmental and resource Economics, 21(1), 47-73.Tol, R. S. (2009). The economic effects of climate change. Journal of economic perspectives, 23(2), 29-51.

Tol, R. S. (2002b). Estimates of the damage costs of climate change, Part II. Dynamic estimates. Environmental and Resource Economics, 21(2), 135-160.

Tol, R. S. (2014). Correction and update: The economic effects of climate change. Journal of Economic Perspectives, 28(2), 221-26.

Tol, R. S. (2018). The economic impacts of climate change. Review of Environmental Economics and Policy, 12(1), 4-25.

Tol, R. S. (2021). Estimates of the social cost of carbon have not changed over time. arXiv preprint arXiv:2105.03656.

U.S. Environmental Protection Agency, National Center for Environmental Economics. Report of the EPA Working Group on vsl meta-analysis. Report EE-0494. Washington, DC: EPA; 2006.

van Sluisveld, M. A., Harmsen, M. J., Van Vuuren, D. P., Bosetti, V., Wilson, C., & Van Der Zwaan, B. (2018). Comparing future patterns of energy system change in 2° C scenarios to expert projections. Global Environmental Change, 50, 201-211.

Walton T. Regulatory Impact Analysis: National Emission Standards for Hazardous Air Pollutants from the Portland Cement Manufacturing Industry. Research Triangle Park, NC: US Environmental Protection Agency; 2009.

Weitzman, M. L. (2001). Gamma discounting. American Economic Review, 260-271.

Yohe, G. W., & Tirpak, D. (2008). A research agenda to improve economic estimates of the benefits of climate change policies. Integrated Assessment, 8(1). Yumashev, D., Hope, C., Schaefer, K., Riemann-Campe, K., Iglesias-Suarez, F., Jafarov, E., ... & Whiteman, G. (2019). Climate policy implications of nonlinear decline of Arctic land permafrost and other cryosphere elements. Nature communications, 10(1), 1-11.

Zickfeld, K., Morgan, M. G., Frame, D. J., & Keith, D. W. (2010). Expert judgments about transient climate response to alternative future trajectories of radiative forcing. Proceedings of the National Academy of Sciences, 107(28), 12451-12456.

Appendices

Table 1. Social Cost of Carbon ($/metric ton of carbon dioxide in 2007 USD), Weighting Methodology, Discount Rate, and Year

Year	Rate	Weighted SCC - BAU	Weighted SCC - Paris	SCC	SCC BAU	SCC - 550
2010	5%	$9	$9	$10	$11	$7
2020	5%	$12	$13	$12	$12	$9
2030	5%	$17	$17	$16	$17	$12
2040	5%	$22	$22	$21	$22	$16
2050	5%	$27	$28	$26	$27	$21

Year	Rate	Weighted SCC - BAU	Weighted SCC - Paris	SCC	SCC - Avg 4 BAU	SCC - 550
2010	3%	$34	$36	$31	$33	$27
2020	3%	$44	$44	$42	$44	$34
2030	3%	$53	$54	$50	$53	$41
2040	3%	$63	$64	$60	$62	$49
2050	3%	$73	$74	$69	$72	$58

Year	Rate	Weighted SCC - BAU	Weighted SCC - Paris	SCC	SCC BAU	SCC - 550
2010	2.5%	$53	$54	$50	$54	$34
2020	2.5%	$65	$66	$62	$65	$52
2030	2.5%	$77	$78	$73	$76	$61
2040	2.5%	$89	$90	$84	$87	$71
2050	2.5%	$100	$101	$95	$98	$82

We calculated the social cost of carbon using five different weighting systems to the IWG (2016; 2021)'s five scenario specific SCC estimates before aggregation: "Weighted SCC – BAU" and "Weighted SCC – Paris" apply Ho et al. (2019)'s SSP weights conditional on a policy state consistent with BAU and the Paris Climate Treaty, respectively, to the EMF-22 scenarios; "SCC" is consistent with the equal weighting approach applied in IWG (2013; 2016; 2021); "SSC BAU" applies equal weighting to only the SCC estimates from the four BAU scenarios; and "SCC – 550" equals the SCC on the 550 ppm scenario.

Table 2. Enumerative and Expert Elicitation Damage Estimates, by Estimating Methods and Temperature

Method	Model	Estimate	Temperature					
			1.2	3	4.3	5	6	7
Meta-regression	DICE-2016R (Nordhaus, 2017)	5th	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
		Best	0.3%	2.1%	4.4%	5.9%	8.5%	11.6%
		95th	0.7%	4.2%	8.7%	11.8%	17.0%	23.1%
	Howard and Sterner (2017)'s non-catastrophic	5th	0.5%	3.3%	6.9%	9.3%	13.4%	18.2%
		Best	1.1%	6.7%	13.8%	18.6%	26.8%	36.4%
		95th	1.6%	10.0%	20.6%	27.9%	40.2%	54.7%
	Howard and Sterner (2017)'s Total	5th	0.2%	1.0%	2.0%	2.7%	3.9%	5.3%
		Best	1.4%	9.0%	18.6%	25.1%	36.1%	49.2%
		95th	2.7%	17.1%	35.1%	47.5%	68.4%	93.1%
	Tol (2018) - Approximating 5th and 95th percentile based on	5th	≈-2.5%	≈-1%	≈0.3%	≈1%	≈2%	3.0%
		Best	-0.5%	2.1%	3.9%	4.9%	6.3%	7.7%
		95th	≈2%	≈8.8%	≈13.6%	≈16.3%	≈20%	≈23.8%
Statistical	Burke approximated - Frequently Cited in IPCC's 1.5°C Report	5th	1.7%	10.6%	21.8%	-	-	-
		Best	1.8%	11.2%	23.0%	-	-	-
		95th	6.8%	42.5%	87.3%	-	-	-

Expert elicitation	Nordhaus (1994a) - Basis of Roughgarden and Schneider (1999) - Mean plus 10th and 90th percentiles	5th	-	0.7%	-	-		-
		Mean	-	3.6%	-	-	6.7%	-
		95th	-	8.0%	-	-	-	-
	Nordhaus (1994a) - Basis of Roughgarden and Schneider (1999) - Median plus 10th and 90th percentiles	5th	-	0.0%	-	-	-	-
		Median	-	1.9%	-	-	4.1%	-
		95th	-	5.5%	-	-	-	-
	Schauer (1995) - 2.5°C only	Median	-	2.6%	-	-	-	-
		Mean	-	5.2%	-	-	-	-
	Pindyck (2019) - All - 2066 and 2166	Median	-	10.0%	-	-	25.0%	-
		Mean	-	12.1%	-	-	29.2%	-
	Pindyck (2019) - Economists	Median	-	5.0%	-	-	20.0%	-
		Mean	-	10.0%	-	-	26.5%	-
	Howard and Sylvan (2020) - Observe damages for 0.9°C to 1°C and 3°C	Median	0.0%	5.0%	-	-	-	-
		Mean	0.0%	9.2%	-	-	-	-
	Howard and Sylvan (2021)'s median	5th	0.5%	2.0%	-	5.0%	-	7.0%
		50th	1.0%	5.0%	-	10.0%	-	20.0%
		95th	3.0%	10.0%	-	22.0%	-	40.0%
	Howard and Sylvan (2021)'s mean	5th	1.0%	3.5%	-	7.5%	-	12.2%
		50th	2.2%	8.5%	-	16.1%	-	25.2%
		95th	5.2%	17.4%	-	31.0%	-	45.1%

Table 3. Adjustments of Drupp et al. (2018)'s Elicited Social Discount Rate and Pure Rate of Time Preference for Structural Complications Arising in Intergenerational Contexts

Dependent Variable	Regression Type	Adjustment	Social Discount Rate	Statistical Significance of Coefficient
Minimum SDR	Mean	Constant	1.3	***
		Declining	0.7	***
		Substitution	0.2	***
		All	-0.4	***
	Median*	Constant	1.0	***
		Declining	0.5	
		Substitution	0.0	-
		Both	-0.5	***
SDR	Mean	Constant	2.4	***
		Declining	1.9	*
		Substitution	1.5	***
		Both	1.0	**
	Median*	Constant	2.0	***
		Declining	1.5	
		Substitution	1.0	**
		Both	0.5	***
Maximum SDR	Mean	Constant	4.4	***
		Declining	3.6	*
		Substitution	2.9	**
		Both	2.1	***
	Median*	Constant	4.0	***
		Declining	4.0	
		Substitution	2.0	***
		Both	2.0	***
Pure rate of time preference	Mean	Constant	1.2	***
		Declining	0.9	
		Substitution	0.3	***
		Both	0.0	***
	Median*	Constant	0.8	***
		Declining	0.8	
		Substitution	0.0	***
		Both	0.0	***

We regress social discount rate / pure rate of time preference on indicator variables for whether the expert commented on declining discount rates (Declining=1) or on issues related to relative prices including substitution

*(Substitution=1) using heteroskedasticity robust standard errors. When referring to the regression constant, we refer to the constant term only in the multivariate-regression in terms of both the social discount rate and its statistical significance. For Declining and Substitution, the social discount rate refers the net difference between the constant and the corresponding variable's coefficient, while the significance rate applies solely to the variable of interest. All refers to the results from the full regression and its joint significance. For statistical significance of individual and joint coefficients, *, **, and *** refer to statistical significance at the 10%, 5%, and 1% significance levels.*

Table 4. Adjustments of Drupp et al. (2018)'s Elicited Social Discount Rate for Structural Complications Arising in Intergenerational Contexts, by Normative or Prescriptive Assumption

Regression Type	Normative or Prescriptive	Adjustment	Social Discount Rate	Statistical Significance of Coefficient
Mean	Prescriptive	Constant	4.0	***
		Declining	1.7	**
		Substitution	1.3	**
		Both	-0.9	***
	Normative	Constant	1.3	***
		Declining	1.6	**
		Substitution	1.3	**
		Both	1.7	***
Median	Prescriptive	Constant	3.4	***
		Declining	0.0	***
		Substitution	1.0	
		Both	-2.4	***
	Normative	Constant	1.4	***
		Declining	2.0	***
		Substitution	1.0	
		Both	1.6	***

We regress the social discount rate on indicator variables for whether the expert commented on declining discount rates (Declining=1) or on issues related to relative prices including substitution (Substitution=1), the percentage weight that the expert placed on normative judgment (Normative), and the interaction of Normative with the two indicator variables using heteroskedasticity robust standard errors. When referring to the regression constant, we refer to the constant term only in the Prescriptive *results (Normative=0)* and constant plus *Normative* in the *Normative results (Normative=1) in terms of both the social discount rate and its statistical significance. For Declining and Substitution, the social discount rate refers the net difference between the constant and the*

corresponding variable's coefficients and its interactions with the Normative variable*, while the significance rate applies solely to the variable of interest and its interactions. All refers to the results from the full regression and its joint significance. For statistical significance of individual and joint coefficients, *, **, and *** refer to statistical significance at the 10%, 5%, and 1% significance levels.*

Figure 1: CO2 Emissions, Population, and GDP, by SSP Scenario and Weighting

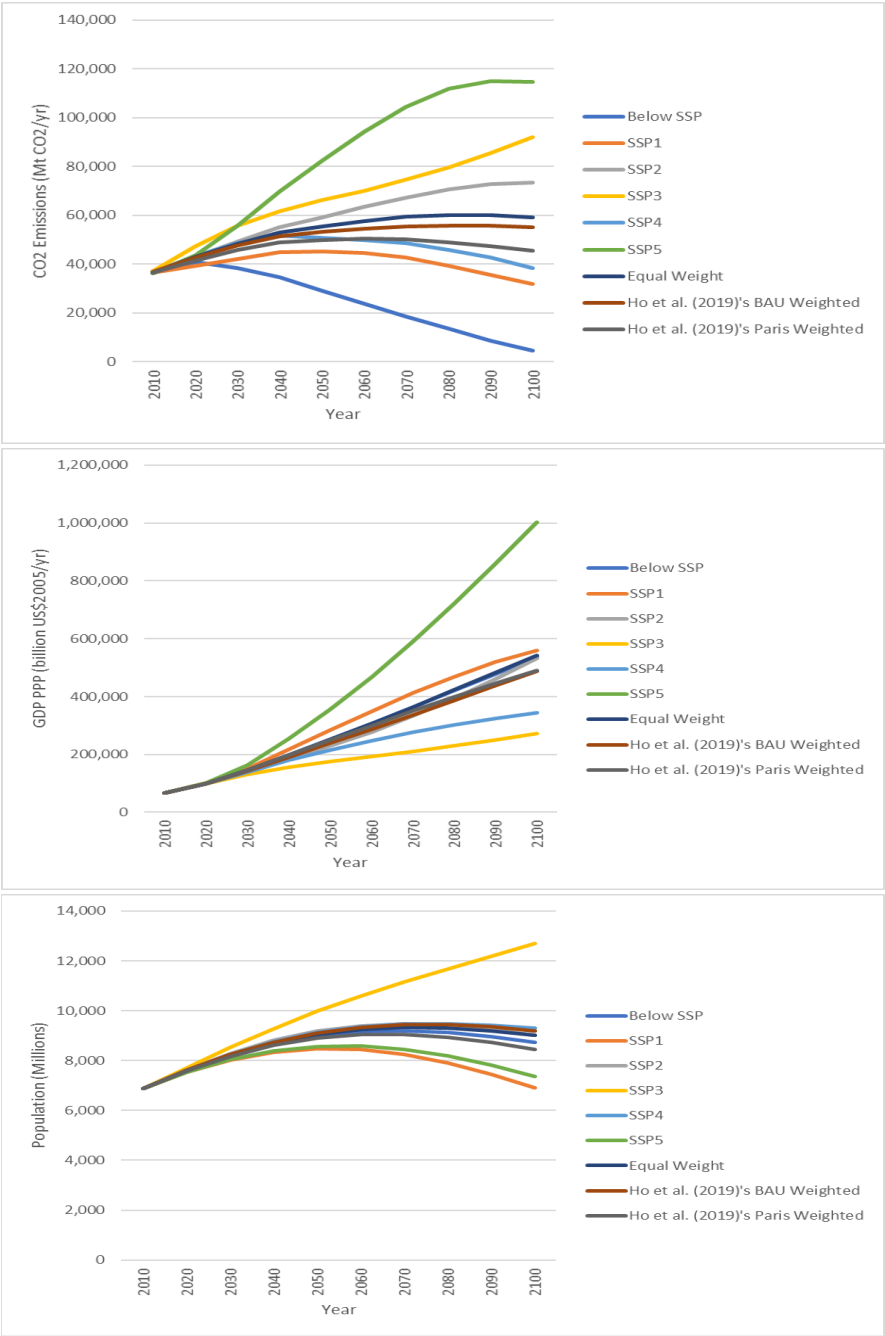
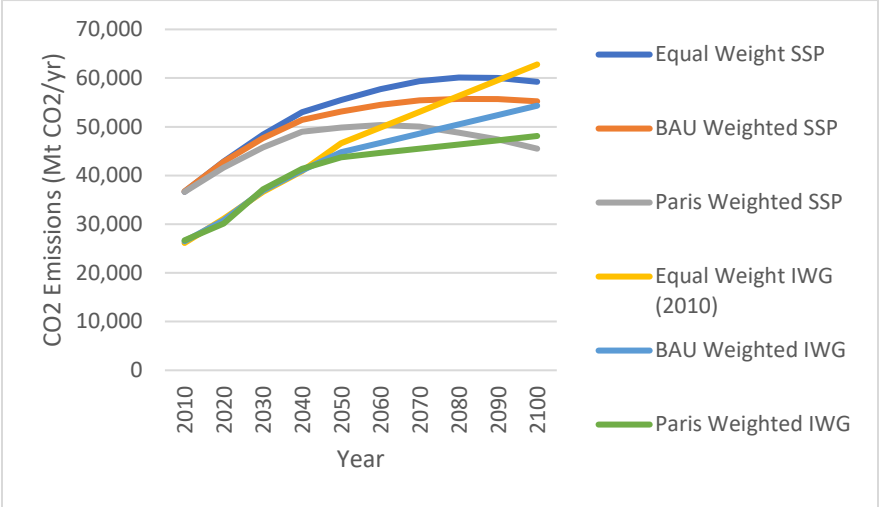
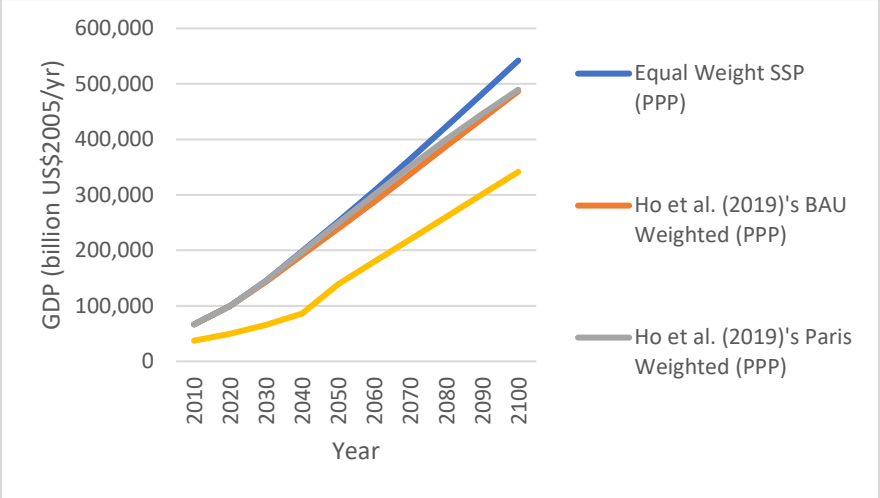


Figure 2: CO_2 Emissions, Population, and GDP for SSP and IWG's EMF-22 Scenarios, by Weighting





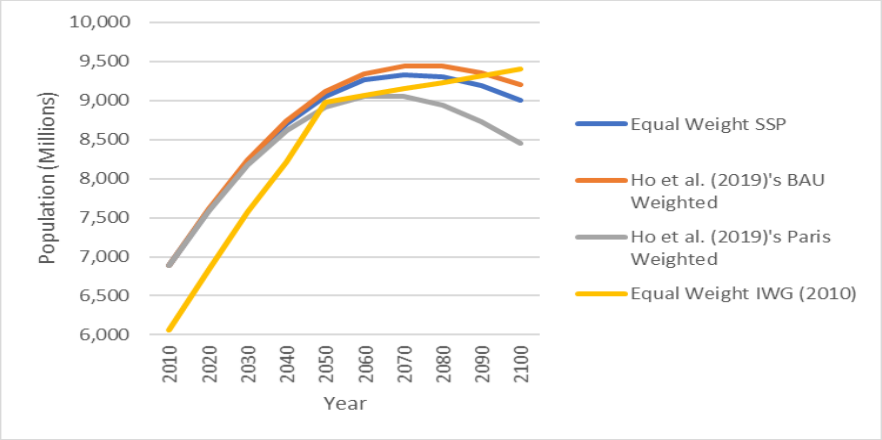
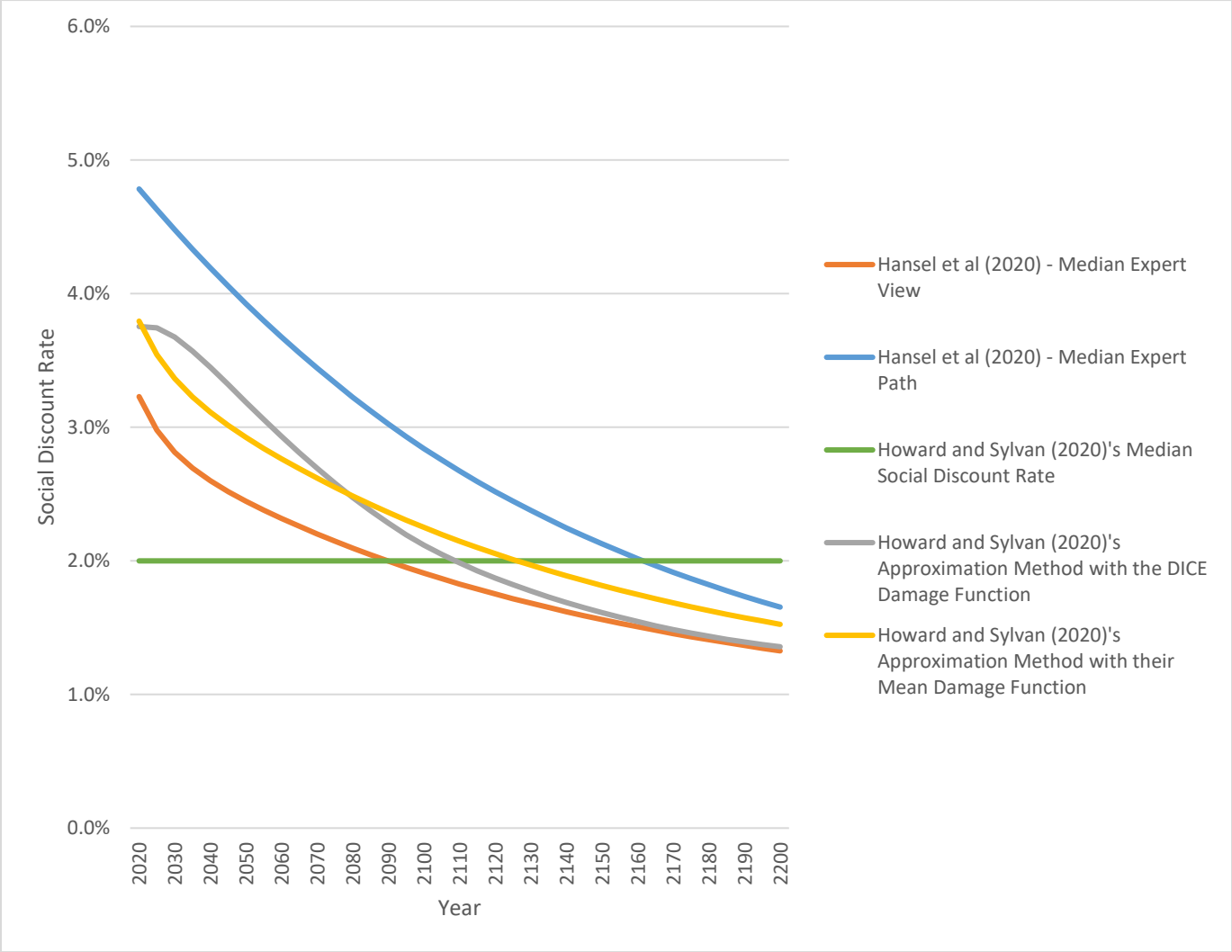
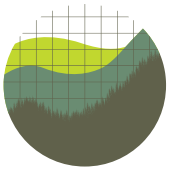


Figure 3: Discount Rates Calibrated to Drupp et al. (2018), by Calibration Methodology





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