June 21, 2021

Dominic J. Mancini
Deputy Administrator
Office of Information and Regulatory Affairs
Office of Management and Budget
Executive Office of the President

Re: Notice of Availability and Request for Comment on "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates Under Executive Order 13990"

Dear Deputy Administrator Mancini,

On behalf of the two dozen climate scientists, economists and engineers at the Climate Impact Lab, it is our pleasure to submit the attached comments on OMB's Notice of Availability and Request for Comment on "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates Under Executive Order 13990" (Docket ID: OMB-2021-0006).

Sincerely,

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Climate Impact Lab

Introduction

The Office of Management and Budget (OMB), on behalf of the co-chairs of the Interagency Working Group (IWG) on the Social Cost of Greenhouse Gases (SC-GHG), is requesting comment on the "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990," released on February 26, 2021 (referred to from here forward as "Interim TSD"). As called for in Executive Order (E.O.) 13990, the IWG seeks to publish updated SC-GHG estimates—including for the social cost of carbon (SCC), the social cost of nitrous oxide (SCN), and the social cost of methane (SCM) no later than January 2022, noting that "an accurate social cost is essential for agencies to accurately determine the social benefits of reducing greenhouse gas emissions when conducting cost-benefit analyses of regulatory and other actions."[1]

Towards that end, E.O. 13990 instructs the IWG to "consider the recommendations of the National Academies of Science, Engineering, and Medicine as reported in Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide (2017) and other pertinent scientific literature" and to provide recommendations to "revise methodologies for calculating the SCC, SCN, and SCM, to the extent that current methodologies do not adequately take account of climate risk, environmental justice, and intergenerational equity."

Following the Supreme Court's decision in U.S. EPA vs. Massachusetts (2007), the U.S. government has been required to issue at least some regulations to reduce greenhouse gas emissions, but it lacked consistent SC-GHG estimates with which to inform its judgments. In 2009, therefore, the Obama administration issued a temporary SCC, formed the IWG and tasked it with developing a robust SCC, based on the best available science and economics. The work was completed in 2010 and then successively updated in 2013.[2] The same methods were used to develop an SCM and SCN in 2016.[3]

Rapid scientific and economic advances in the last decade mean that there is now an urgent need to update SC-GHGs, as called for in both the 2017 National Academies of Science, Engineering and Medicine (NASEM) report[4] and E.O. 13990. The IWG was given 30 days to provide interim SC-GHG estimates, and as a result was unable to incorporate these advances. The Interim TSD states "while the IWG works to assess how best to incorporate the latest, peer reviewed science to develop an updated set of SC-GHG estimates, it is setting interim estimates to be the most recent estimates developed by the IWG prior to the group being disbanded in 2017."[5] Section 5 of the Interim TSD correctly identifies the following four components of the Interim SC-GHGs that need updating, consistent with the recommendations in the NASEM report:

1. **Socioeconomic and emission projections:** The population, economic activity and GHG emission projections used in the Interim SC-GHGs were developed around 2007 and need to be updated to align with the projections now more commonly used by the scientific community.
2. **Climate system representation:** Estimates of the equilibrium climate sensitivity (ECS) used in the Interim SC-GHGs comes from the IPCCs Fourth Assessment Report, published in 2007. More recent IPCC Assessment Reports, reports from U.S. Global Change Research Program (USGCRP) and the National Academies, and new peer-reviewed studies have significantly advanced our understanding of

[1] Exec. Order No. 13990 (2021).

[2] Interagency Working Group, "Technical Support Document" (2013).

[3] Interagency Working Group, "Technical Support Document" (2016).

[4] NASEM, "Valuing Climate Damages."

[5] Interagency Working Group, "Technical Support Document" (2021).

how the climate system responds to changes in atmospheric concentrations of carbon dioxide and other GHGs. In addition, as noted by NASEM report, the simple climate models used in the three Integrated Assessment Models (IAMs) that underly the IWG's Interim SC-GHGs fail to adequately capture the temporal evolution of the climate response, including the climate response to a pulse of emissions, such as that used to calculate SC-GGHs.

3. **Damage functions**: As the Interim TSD notes, at the core of the Interim SC-GHG estimates are damage functions that "map global mean temperature changes and other physical impacts of climate change into economic (both market and nonmarket) damages". These damage functions have not been updated in more than a decade and often rely on unverifiable assumptions. Fortunately, there has been an explosion of econometric research on the relationship between the climate and a wide range of social and economic outcomes. A number of these new, empirically grounded studies indicate that the damage functions in the Interim SC-GHGs are no longer valid in terms of, for example, their projected impacts on mortality rates, energy demand, and agricultural productivity.[6]

4. **Discounting**: The Interim TSD correctly highlights recent empirical evidence that consumption interest rates are now below the 3 percent estimate used in OMB Circular A-4, as well as the need to consider discount rate uncertainty and the use of a Ramsey-like approach to discounting.

In addition to these four core elements, there are three other important factors the IWG should consider in developing final SC-GHG estimates:

5. **Global damages:** The Interim SC-GHGs correctly consider global damages, not just those occurring within the United States, and this decision should be carried forward to the final SC-GHGs. As the Interim TSD notes, "The global nature of GHGs means that damages caused by a ton of emissions in the U.S. are felt globally and that a ton emitted in any other country harms those in the U.S." Conversely, U.S. climate policy informed by SC-GHGs that reduces emissions within the U.S. leads to reciprocal action by other countries that also benefits U.S. residents through avoided climate damage. For example, research by Trevor Houser and Kate Larsen at the Rhodium Group finds that under the Paris Agreement, other countries pledged to reduce 6.1 to 6.8 tons for every ton pledged by the U.S.[7]

6. **Valuing uncertainty about climate risk:** E.O. 13990 calls on the IWG to "revise methodologies for calculating the SCC, SCN, and SCM, to the extent that current methodologies do not adequately take account of climate risk." The Interim TSD presents a range of possible SC-GHG outcomes (Figures 2-4), but the valuation method selected for the Interim SC-GHGs ignores both the economic theory and empirical evidence (see, for instance, the general existence of the insurance industry) that shows people dislike risk and are willing to pay to reduce their exposure to it. The final SC-GHGs should reflect this risk premium.

7. **Equity:** E.O. 13990 also calls on the IWG to revise methodologies to adequately take account of environmental justice as well as climate risk. This is not possible in the three simplified integrated assessment models (IAMs) used for the Interim SC-GHGs because of their coarse geographic resolution (ranging from one to 16 regions globally). Fortunately, the recent growth in high-resolution climate

[6] Carleton et al., "Valuing the Global Mortality"; Rode et al., "Estimating a Social Cost of Carbon for Global Energy Consumption"; Diaz & Moore, "Quantifying the Economic Risks"; Moore et al., "New Science of Climate Change Impacts".

[7] Houser and Larsen, "Calculating the Climate Reciprocity Ratio for the US."

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econometric research has made it possible for the IWG to both assess the disparate impacts of climate change both within countries and across countries[8], and to factor that into the SC-GHGs. Research increasingly shows that climate change disproportionately impacts the poor, both within the U.S. and across the world,[9] and an additional dollar is worth more to a poor person than a wealthy one.

The Climate Impact Lab (CIL) is a collaboration between climate scientists, economists and engineers at the University of Chicago, University of California, Berkeley, Rhodium Group and Rutgers University dedicated to advancing climate economics research globally. Founded in 2015 to expand the U.S.-focused research advances combining high resolution climate models and econometric climate impact research outlined in Hsiang et al. (2017)[10], the CIL has developed granular, empirically based, global SC-GHG estimates that satisfy all seven of the objectives outlined above. In these comments, CIL collaborators provide an overview of our method for producing the IWG's consideration. A web-based model for producing custom SC-GHGs using this approach (the CIL SC-GHG Tool) will be available this summer at https://www.impactlab.org/sc-ghg-tool.

[8] Hsiang, Oliva, and Walker. "The distribution of environmental damages." Review of Environmental Economics and Policy 13.1 (2019): 83-103.

[9] Houser, "Climate Convexity: The Inequality of a Warming World."

[10] Hsiang et al., "Estimating Economic Damage from Climate Change in the United States."

1. Overview

We begin with an outline of the socioeconomic and emissions pathways, which allow us to understand what the economy will be like in the future (Section 2), and the climate module, which allows us to understand what the climate will be like in the future (Section 3). Since 2010, there have been major scientific advancements in the estimation of both these modules and we recommend that both be updated to reflect those advances. Specifically, for the climate module, we use the Finite Amplitude Impulse Response (FaIR) to project changes in temperature, since (as noted by NASEM) it satisfies all the SC-GHG use criteria set out by NASEM.[11] For the socioeconomics and emissions pathways module, we use Shared Socioeconomic Pathways (SSP), which can be linked to standardized emissions scenarios, such as the Representative Concentration Pathways (RCP). Due to the difficult nature of predicting long run population and economic growth these are far from perfect but better capture possible future scenarios and are more widely used than the Stanford Energy Modeling Forum (EMF-22) pathways included in the Interim SC-GHGs. In Section 4, we outline our updated approach to estimating a damage function, which translates changes in climate like temperature increases into monetized impacts on the economy, with examples from two sectors: Energy and Mortality. Moving past the assumption-based and simplified damage functions in the Interim SC-GHGs, our updated damage functions are plausibly causal with respect to the relationship between weather events on socioeconomic outcomes, account for future adaptation, and are able to capture local level non-linearities on for the entire global population. Section 5 outlines our approach to valuation and discounting and Section 6 provides an overview our plans for updating the CIL SC-GHG Tool as new research becomes available.

2. Socioeconomic and emissions projections

2.1 Socioeconomic projections

The income and population projections used in the Interim SC-GHGs were developed in 2007 by the Stanford Energy Modeling Forum (EMF-22). The IPCC and many researchers have moved towards using the Shared Socioeconomic Pathways (SSPs, built collaboratively by a group of climate researchers over the last several years) as benchmark scenarios, and these serve as the baseline socioeconomic scenarios in our SC-GHG development. More specifically, we use the Organization for Economic Co-operation and Development (OECD) Env-Growth model and the International Institute for Applied Systems Analysis (IIASA) GDP model variants of the SSPs. While there are many models within the SSP database, only the IIASA GDP model and OECD Env-Growth model provide Gross Domestic Product (GDP) per capita projections for a wide range of countries. The SSPs propose a set of plausible scenarios of socioeconomic development over the 21st century in the absence of climate impacts and policy, with the IIASA GDP model describing per-capita incomes that are lower than the OECD Env-Growth model. The CIL produces results for both of these models to capture the range of outcomes within each socioeconomic scenario.

To construct annual estimates, we smoothly interpolate between the time series data in the SSP database, which are provided in 5-year increments. For each 5-year period, we calculate the average annual growth rate, and apply this growth rate to produce each year's estimate of GDP per capita. OECD estimates of income are provided for 184 countries and IIASA's GDP projections cover 171 countries. For the remaining countries, we

[11] NASEM, "Valuing Climate Damages."

apply the average GDP per capita from the available countries for the baseline period and allow this income to grow at the globally averaged growth rate.

2.2 Emissions projections

Much like income, the future emissions of key greenhouse gases must be projected under different scenarios that represent different atmospheric concentrations in the coming centuries. The emissions scenarios in the Interim SC-GHGs also come from the EMF-22. There are more recent and more widely used projections from the Coupled Model Intercomparison Project (CMIP).[12] The Representative Concentration Pathways (RCPs), associated with CMIP Phase 5 (CMIP5), trace out possible emissions scenarios that range from cases with ambitious mitigation of CO_2 to ones in which emissions continue to grow throughout this century.[13] Our damage functions are calculated using the CMIP5 RCPs (which were the most current until very recently; e.g., RCP 4.5, RCP 8.5).

CMIP Phase 6 introduces a new set of emissions scenarios,[14] which, like the RCPs, are defined by a range of climate forcing at the end of the century, from ones with ambitious mitigation of CO2 to ones of sustained emissions growth. In CMIP6, these are labeled as "SSP scenarios", because they are paired with different SSPs (e.g., SSP2-4.5, SSP3-7.0). The CIL SC-GHG Tool is calibrated to CMIP6 RCPs. For clarity, because we pair different forcing levels with multiple different compatible SSPs, we refer to these forcing levels as RCPs (e.g., SSP2-RCP4.5, SSP2-RCP6.0, SSP2-RCP7.0, SSP3-RCP4.5, etc.).

3. Climate system representation

Developing an estimate of the SC-GHG requires a climate module that converts emissions of greenhouse gases and other forcing agents--outputs of the socioeconomic module--into changes in the global climate. To accomplish this, the climate module converts greenhouse gas (GHG) emissions to atmospheric GHG concentrations, and in turn to radiative forcing and resulting changes in the climate, including warming and sea level rise. The CIL approach of estimating local impacts necessitates dividing the climate module into two separate but related components: a) highly spatially and temporally resolved damage estimates derived from a suite of global climate models (GCMs) under a range of projections of changing climate and socioeconomics on which empirically-derived global damage functions can be estimated (described in Appendix I), and b) global mean temperature projections of a baseline climate and a response to a marginal emission of CO_2 or other GHG that represent the full probability distribution of climate uncertainty with a large ensemble of simulations (discussed below).[15]

[12] IPCC, "Climate Change 2014: Synthesis Report."

[13] Moss et al., "The next generation of scenarios for climate change research and assessment."

[14] O'Neill, "Multi-Century Scenario Development."

[15] In principle, one could compute an SC-GHG estimate by perturbing each global climate model (GCM) in the suite with a pulse of CO_2 or other GHG and projecting damages for each location in both the original and perturbed simulations. However, in practice, such a procedure would prevent the calculation of an SC-GHG for any climate trajectory that did not exactly coincide with one of the GCMs, and would also be prohibitively costly from a computational standpoint. Instead, we rely on a probabilistic, simple climate-carbon cycle model, in combination with our empirically-derived damage functions, to construct SC- estimates.

3.2 SC-GHG calculations using the FaIR simple climate model

The Finite Amplitude Impulse Response (FaIR) simple climate model satisfies key criteria for a simplified climate module used to estimate SC-GHGs, including those outlined by NASEM, and was highlighted by NASEM as an example of a simple climate model that fulfills these criteria. These criteria include a climate module that is transparent, simple, and able to accurately and probabilistically represent climate and carbon cycle systems and their uncertainties. FaIR is a significant improvement over the climate modules used in the Interim SC-GHGs, which did not accurately replicate the climate and carbon cycle dynamics in more complex models. For example, these modules failed to capture the scientific understanding that peak warming associated with a pulse emission of CO_2 happens most likely happens within one to two decades of emissions and that the large majority of the associated warming endures for many centuries.[16] A detailed description of the model formulation is given in Millar et al. (2017) and of the software implementation in Smith (2018). Usage in calculating the partial SCCs for mortality and energy are described in detail in Carleton et al. (2021) and Rode et al. (2020a).

We fork the latest release of the FaIR model (v1.6.0 at the time of computation) and update it to include the most recent emissions pathways developed for CMIP6 and the IPCC's Sixth Assessment Report (AR6).[17] Three baseline climate scenarios from CMIP6 are provided: SSP2-4.5, SSP4-6.0, and SSP3-7.0. These scenarios represent widely divergent emissions and climatic pathways, especially in years beyond 2050. Following the method used in previous estimates of the SC-GHG, projections start in the current period (here defined as 2020) and run through the year 2300. In order to estimate the marginal effect of CO2 emissions in a given pulse year, a 1GtC (3.67 Gt CO_2) pulse of fossil CO2 emissions is added in that year to each of the "baseline scenarios" listed above. The FaIR model is then run again for these pulse scenarios, resulting in a new time series of concentrations, forcing, and temperature anomalies.

3.2 Methodology for capturing climate sensitivity uncertainty in FaIR

A key criteria of the climate module is to probabilistically represent the uncertainty in the carbon-climate system. To satisfy this, probability distributions for key FaIR climate input parameters are developed – including the joint probability distribution of the equilibrium climate sensitivity (ECS) and transient climate response (TCR), and short thermal and carbon uptake timescale parameters, d2 and τ3 – with constraints drawn from the IPCC Fifth Assessment Report (AR5) and other peer-reviewed literature. We efficiently and jointly sample these four distributions 3,000 times using Latin hypercube sampling, varying them in the FaIR model such that the represented climate uncertainty conforms to the literature after applying a post-simulation filter that removes simulations with ECS values less than the first percentile and greater than the 99th percentile. We confirm that the final 2,960 climate parameters satisfactorily represent uncertainty in the response to a pulse, as well as the transient response to cumulative emissions. The median values (17 – 85% "likely range") across our uncertainty distributions for each core model parameter are as follows: ECS is 2.7°C (1.6 – 4.5°C) per CO2 doubling, TCR is 1.6°C (1.0 – 2.5°C) per CO2 doubling, d2 is 3.7 years (2.3 – 5.9 years), and τ3 is 4.0 years (2.4 – 5.7 years). Throughout our implementation, all other parameters in FaIR are held fixed at their default values.

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[16] Ricke, K. L., and Caldeira, K. "Maximum warming occurs about one decade after a carbon dioxide emission"; Joos et al., "Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: A multi-model analysis."

[17] Available at https://github.com/ClimateImpactLab/FAIR/tree/cmip6_scenarios. A tagged release is forthcoming.

4. Damage functions

A "damage function" translates changes in the physical climate (e.g., temperature and sea level rise) into monetized impacts on the economy. In some climate damage models, a single damage function is calibrated to represent all categories of climate impact (e.g., PAGE), while in others, separate damage functions are modeled for individual impact categories (e.g., FUND). In the DICE model used for the Interim SC-GHGs a single damage function is used and individual impacts cannot be traced.[18]

At least two problems have plagued the climate damage model functions that underly the Interim SC-GHG estimates. First, they are primarily derived from ad-hoc assumptions and simplified relationships, not large-scale empirical evidence. Further, the damage functions in these models have tended to treat the world as nearly homogeneous, dividing the globe into at most 16 regions. This aggregation misses a great deal, especially because there are important nonlinearities in the relationship between temperature and human well-being that are obscured by substantial aggregation. For example, a given increase in temperature will have very different impacts in Arizona than it will in northern Minnesota. For both of these reasons, these damage functions have been heavily criticized in recent years.

4.1 The essential attributes of a modern damage function

In the last dozen years, there have been great advances in computing power, access to data from around the world, and econometric methods designed to quantify climate change impacts. A result has been an explosion of empirical research that has greatly deepened science's understanding of the economic impacts of climate change.[19] Relative to 2009, there is almost an embarrassment of riches, with, for example, at least 110 empirical studies on climate change's economic impacts published between 2010 and 2016 alone.[20]

So how should one choose among all of these studies when developing an updated damage function? To make full use of scientific advances, any modern damage function must now meet three criteria:

1. **Empirically derived and plausibly causal:** Damage functions should be derived from empirical estimates that reflect plausibly causal impacts of weather events on socioeconomic outcomes. Because the climate has remained stable throughout modern human history, it is difficult to isolate experimental variations in the long-run climate. However, a large and growing empirical literature leverages modern econometric methods to uncover causal impacts of short-run weather events on a host of socioeconomic outcomes, from agricultural output to mortality rates to energy use.[21] When combined with empirical estimates of differences in populations' responses to weather events (discussed in criterion three below), this literature provides a strong foundation for understanding the socioeconomic effects of weather, and its approach should be reflected in a new IWG's damage function. The damage functions from the three models used by the IWG do not meet this criterion. They

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[18] Nordhaus, "The 'DICE' Model: Background and Structure of a Dynamic Integrated Climate-economy Model of the Economics of Global Warming."

[19] Carleton and Hsiang, "Social and Economic Impacts of Climate"; Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "What Do We Learn from The Weather? The New Climate-Economy Literature." Journal of Economic Literature 52, no. 3 (2014): 740-98; Auffhammer, Maximilian. "Quantifying economic damages from climate change." Journal of Economic Perspectives 32.4 (2018): 33-52. Diaz, Delavane, and Frances Moore. "Quantifying the economic risks of climate change." Nature Climate Change 7.11 (2017): 774-782..

[20] Carleton and Hsiang, "Social and Economic Impacts of Climate."

[21] Id.; Dell et al., "What Do We Learn from the Weather?"

are only loosely calibrated to empirical evidence and/or rely on outdated estimates that fail to isolate the role of changes in the climate from economic variables such as income and institutions.[22]

2. **Capture local-level nonlinearities for the entire global population**: Damage functions should be estimated with data that represent the entire global population (not just high-income, temperate regions). Further, damage functions should account for "nonlinear" effects of climate variables at a local level. Dramatic reductions in computing costs and increased data availability have enabled researchers to identify the effects of climate change on social and economic conditions at local scale across the globe. This body of work has uncovered that many socioeconomic outcomes display a strongly nonlinear relationship with climate variables—that is, the effects of climate change are not identical everywhere, but are instead sensitive to prior socioeconomic and climatic conditions.[23] For example, both extreme cold and extreme heat increase mortality rates, while moderate temperatures have little impact.[24] In addition, this research has documented large differences in climate impact relationships between rich and poor,[25] hot and cold,[26] and agricultural and non-agricultural[27] regions. The significant differences in the results across different places imply that the additional damage caused by a given increment of warming may lead to substantially different outcomes around the globe, depending on the characteristics of the local economy, demographics, and region. The damage functions underlying the current SCC estimates fail to adequately characterize nonlinearities, to disaggregate local impacts around the world, or to include information from lower-income, hotter regions of the globe. Moreover, these models divide the globe into at most sixteen distinct regions, missing important spatial detail. A failure to capture globally representative, locally varying, nonlinear relationships is a grave threat to the validity of damage functions. While further advances in data collection and computing power are needed to derive damage functions for all sectors in all countries at high spatial resolution, substantial improvements over the existing climate damages models are feasible. Further, recent research has developed methods for estimating worldwide climate impacts by inferring damages in data-poor regions based on data-rich regions that have similar characteristics.[28]

3. **Inclusive of adaptation**: Damage functions should reflect that people, firms, and governments make defensive investments that provide protection against climate-related risks, and that these investments are costly. As climate change unfolds, individuals, governments, and firms will make innumerable decisions and investments to respond to the gradually changing environment. Damage functions within the models that underly the current SCC involve very different assumptions about such compensatory investments and their costs, the majority of which are not based on real-life observations of adaptation.[29] The damage function should include both the estimated benefits and costs of future adaptive investments. While earlier empirical studies failed to account for the benefits of

[22] Carleton and Greenstone, "Updating the United States Government's Social Cost of Carbon."

[23] Carleton and Hsiang, "Social and Economic Impacts of Climate."

[24] Gasparinni et al., "Mortality Risk Attributable to High and Low Ambient Temperature;" Deschnes and Greenstone, "Climate Change Mortality, and Adaptation."

[25] Davis and Gertler, "Contribution of Air Conditioning Adoption."

[26] Heutel et. al., "Adaptation and the Mortality Effects of Temperature."

[27] Cai et al., "Climate Variability and International Migration."

[28] Carleton et al., "Valuing the Global Mortality Consequences."

[29] Diaz and Moore, "Quantifying the Economic Risks of Climate Change."

adaptation,[30] a growing literature covering multiple sectors is developing damage estimates that reflect the benefits of adaptation.[31] However, these compensatory investments are not free—any updated damage function should also account for costs of adaptation.[32] Some progress has been made to infer these costs from available data,[33] but this is an active area of research. Damage functions should capture adaptation costs wherever possible.

Estimated damage functions that meet the above criteria lead to dramatically different understandings about the economic impacts of climate change, compared to the older damage functions. Research that meets the three criteria described here will fundamentally alter prior estimates of the economic impacts of climate change.

4.2 CIL's approach to estimating climate damages

Our approach to estimating damages begins with collecting globally representative, detailed datasets of socioeconomic outcomes, such as death rates and electricity demand, and matching them with high-resolution historical data on weather.[34] We analyze these data using sophisticated econometric techniques, which account for the many geographic, institutional, and cultural differences between regions, in order to estimate causal, rather than correlative, relationships between weather and our outcomes of interest.[35] Typically, the result of this analysis is at least one "dose response" function: a description of the nonlinear effect of changes in temperature (and other weather variables for some sectors) for each key sectoral outcome. To capture the potential for adaptation and dynamic vulnerability, we include climate and socioeconomics in this estimation process, allowing the effects of weather to vary with income levels and climatic adaptation.

Next, we apply this set of dose-response functions to the projected climate data from a combination of 21 global climate models (GCMs) participating in the IPCC AR5 and 12 surrogate models making up a surrogate mixed model ensemble (SMME).[36] We perform projections across the multiple drivers of uncertainty in future projections, consisting of: (1) different emissions scenarios, (2) different modeled changes in climate across GCMs, (3) different socioeconomic scenarios drawn from the SSPs, (4) different modeled country-level incomes (across economic models), and (5) different values of the parameters describing the dose-response functions, reflecting their statistical uncertainty. Our projections of climate change impacts isolate the role of a warming climate from changes in vulnerability driven by socioeconomics. To do so we apply the dose-response functions to a scenario without additional climate change, but with the same projected economic development as in the

[30] See, for example, Deschenes and Greenstone, "The Economic Impacts of Climate Change."

[31] See, for example, Auffhammer, "Climate Adaptive Response Estimation;" Deryugina and Hsiang, "The Marginal Product of Climate;" Heutel et al., "Adaptation and the Mortality Effects of Temperature."

[32] Estimates of adaptation costs are essential when computing the total damages of climate change. In contrast, under a strict set of assumptions, the marginal benefits and marginal costs of additional adaptation cancel each other out in the calculation of the damages from a marginal ton of CO2 emissions, making adaptation cost estimates unnecessary for the SCC when these assumptions are taken.

[33] Carleton et al., "Valuing the Global Mortality Consequences."

[34] For more details on the sources of our historical income data and historical climate data see Appendix 1.

[35] Deschenes and Greenstone, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the United States"; Hsiang et al., "Estimating Economic Damage from Climate Change in the United States"; Carleton and Hsiang, "Social and Economic Impacts of Climate."

[36] For more details on our future climate projections see Appendix 1.

climate change scenario. We then subract this counterfactual (in which the climate remains at historical levels while economies continue to develop) from the full projected outcomes.

The resulting impacts are typically in physical units, such as changes in death rates and agricultural yields. To translate these into economic damages, we apply a “valuation” scaling. For example, the U.S. Environmental Protection Agency (EPA) value of a statistical life (VSL) has the units of dollars per death. By multiplying projected changes in death rates from climate change with population, we estimate total changes in premature deaths, which we then multiply with the VSL to estimate economic losses in dollar terms. The valuation approach is specific for each sector.

We also estimate the costs of adaptation, based on the observed changes in vulnerability that are represented in the dose-response functions. The total economic losses combine direct losses from climate change and indirect costs of adaptation to avoid further climate change losses. Finally, we use these valued losses to estimate a “damage function.” The damage function describes the economic losses for average changes in climate. We do this by indexing each of the economic losses for each year to the average climate change around that year, from each GCM. Since these different data points describe notably different economies and different levels of vulnerability (the effect of high temperatures upon present-day populations will not match the effect of those temperatures on end-of-century populations), we split the data points into collections for five-year increments across the century. These data points typically describe a smoothly increasing and nonlinear relationship: at high temperatures, there are more economic losses. We approximate this relationship with a simple curve for each 5-year period.

Below are examples for how we implement this method for two climate impact categories – heat-related mortality and energy costs. We are completing similar studies for labor productivity, agricultural production, coastal property and infrastructure this summer, with other impact categories to follow.

4.2.1 Mortality

We use comprehensive historical mortality records to quantify how death rates across the globe have been affected by observed climate changes. We compile the largest sub-national vital statistics database in the world, detailing 232.9 million deaths across 40 countries accounting for 38 percent of the global population. These mortality records are combined with decades of detailed daily and local temperature observations.

We econometrically estimate the effects that extreme cold and extreme heat have on death rates, separately for each of three age groups. We find a U-shaped relationship in which both extreme heat and cold increase mortality rates, particularly for those over 65 years old. A single hot day (35C/95F) increases mortality rates by 4 deaths per 1 million people, while cold days (-5C/23F) increase the mortality rate by 3 deaths per 1 million people. However, these relationships are strongly modified by the climate and income levels of the affected population and demonstrate that adaptation has important influence over the sensitivity of a population to extreme temperatures. This leads to substantial differences between places, depending on how wealthy the population is and how warm the climate is.

We use these empirical mortality-temperature relationships to generate projections of the future impacts of climate change on mortality rates for areas across the globe, dividing the world into 24,378 distinct regions (each containing roughly 300,000 people, about the size of a U.S. county) up to 2099. We develop a technique to estimate the total cost of adaptive behaviors and technologies. These projections capture the full mortality risk of climate change, for the first time accounting for both adaptation benefits and costs, in addition to direct mortality impacts. Projected impacts of climate change on mortality rates are then monetized and used to determine the costs of excess mortality risk in a given year. This monetization uses the U.S. EPA value of a statistical life (VSL).[37] These projections include three scenarios for future income and population growth, two trajectories of future greenhouse gas emissions, and simulations from 33 climate models, allowing for an assessment of the uncertainty surrounding any particular projection. The full estimates also reflect statistical uncertainty related to the underlying economic and health data. See Carleton et al 2020 for more detail.

4.2.2 Energy

We match globally representative, longitudinal data on energy consumption with harmonized historical climate data. Energy consumption data are derived from International Energy Agency (IEA) data files that describe electricity and direct fuel consumption across residential, commercial, industrial, and agricultural end-uses (excluding transportation) in 146 countries during 1971-2010.

We econometrically estimate the effect of historical temperature distributions on national annual per capita energy consumption using random year-to-year variation, and measure how this energy-temperature response differs across energy types (electricity and other fuels), income levels, and climate zones. We then project impacts of climate change in 24,378 globally comprehensive geographic regions (roughly the size of US counties) through 2099 by combining the econometric results with a probabilistic ensemble of downscaled climate projections. When projecting these impacts, we account for how the energy-temperature response will evolve as populations become richer and exposed to warmer climates.

We monetize and pool the empirically derived impact projections, aggregating damages across locations 355 and indexing them against the global mean surface temperature anomaly expressed in each climate model realization. To monetize the projected impacts of climate change on energy consumption, we apply country-specific real prices for electricity and other fuels to the projected quantity impacts, thus reflecting differential costs across geographies and fuels. To extrapolate prices into the future, we use US average annual price growth rates for electricity and other fuels between 2020 and 2050, as projected by the US Energy Information Administration's Annual Energy Outlook 2021 (AEO). We apply these growth rates up to the year 2099 to the baseline country × fuel prices described above. Specifically, based on AEO projections, we allow electricity prices to decline by 0.27% per year and other fuels prices to rise by 0.82% per year.[38]

4.2.3 Valuation

As discussed above, and correctly highlighted in both the Interim TSD and NASEM report, the SC-GHG should include global damages as climate change is a uniquely global challenge. Thus SC-GHG estimates generated with the CIL SC-GHG Tool all include global damages. SC-GHG valuation also should also reflect the economic theory and empirical evidence that indicate people are averse to risk and willing to pay to reduce their exposure. The CIL's high-resolution, probabilistic approach makes this possible in a more robust way that was previously available, satisfying E.O. 13990's call for incorporating methodologies that take account of climate risk. Our approach also reveals deep disparities in the impact of climate change both within the U.S. and around the world, in and of itself going a long way towards satisfying E.O. 13990's call for incorporating methodologies

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[37] U.S. EPA's VSL amounts to $10.95 million in 2019 USD. This VSL is from the 2012 U.S. EPA Regulatory Impact Analysis (RIA) for the Clean Power Plan Final Rule, which provides a 2020 income-adjusted VSL in 2011 USD, which we convert to 2019 USD. This VSL is also consistent with income- and inflation-adjusted versions of the VSL used in the U.S. EPA RIAs for the National Ambient Air Quality Standards (NAAQS) for Particulate Matter (2012) and the Repeal of the Clean Power Plan (2019), among many other RIAs.

[38] The electricity price growth rate is of a consumption-weighted average electricity price across residential, commercial, and industrial sectors. The other fuels price growth rate is of a consumption-weighted average price across multiple fuels in residential, commercial, and industrial sectors.

that take account of environmental justice. In addition, the CIL SC-GHG Tool also the IWG to go even further, if they chose, incorporating that inequality in SC-GHG valuation (see section 5.2).

5. Discounting

Discounting is the process by which each year's future values are reduced to enable comparison with current costs or benefits to society. The "discount rate" determines the magnitude of this reduction. Because CO_2 emissions persist in the atmosphere and lead to long-lasting climatological shifts, small differences in the choice of discount rate can compound over time and lead to meaningful differences in the SCC in particular.

5.1 Discounting choices

There are two possible approaches to discounting in SC-GHG calculations. First, a fixed discount rate can be used, as was implemented in the Interim SG-GHG. The Interim SC-GHG set a 3 percent discount rate as the central case, the same as the IWG's 2010 and 2016 TSDs, to be consistent with guidance from the Office of Management and Budget (OMB) regarding the interest rate on U.S. government bonds.[39] This decision was also motivated by the assumption that climate damages were projected to be uncorrelated with overall market returns (eliminating the 7 percent rate, derived from equity markets) and thus used insights from asset pricing theory that the riskless interest rate was appropriate.[40] As the Interim TSD correctly notes, there have been profound changes in global capital markets since the publication of Circular A-4 in 2003 that make it extraordinarily challenging to justify 3 percent as an accurate estimate of the return on riskless investments. The Council of Economic Advisors (CEA) and Carleton and Greenstone (2021) demonstrate that this evidence leads to the conclusion that it is difficult to defend a 3 percent discount rate for climate investments, and there is now a compelling case for a riskless discount rate of no higher than 2 percent.[41]

There is also the possibility, however, that the riskless rate itself is not appropriate as the central discount rate due to the unique risk properties of climate change and uncertainty about future interest rates. Because discount rates reflect the returns to investments that mitigate climate change, Americans are best served by using an interest rate associated with investments that match the structure of payoffs from climate mitigation. Capital asset pricing models recommend low discount rates in scenarios where investments (in this case CO_2 mitigation) pay off in "bad" states of the world—that is, if climate damages are likely to coincide with a slowing overall economic growth rate that for example could be due "tipping points" or large-scale human responses to climate change, including mass migration. If on the other hand climate damages act as tax on the economy (i.e., total damages are larger when the economy grows faster), then higher discount rates like the average return in equity markets would be merited.

A second potential approach to deriving a discount rate is to explicitly account for future economic growth using the so-called Ramsey equation, [42] which is often referred to as the prescriptive approach. This approach has been recommended by the NASEM as a "feasible and conceptually sound framework" and was correctly identified by the Interim TSD as an important alternative approach. Rather than rely on observed interest rates,

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[39] OMB, "Circular A-4: Regulatory Analysis."

[40] Greenstone et al., "Developing A Social Cost of Carbon"

[41] CEA, "Benefits of Competition and Indicators of Market Power;" Carleton and Greenstone, "Updating the United States Government's Social Cost of Carbon."

[42] Ramsey, "A Mathematical Theory of Saving."

it derives a discount rate from assumptions about three parameters: the pure rate of time preference, the growth rate of consumption, and a parameter capturing the decreasing marginal utility of consumption. Values for the first and third parameters have been estimated in a large literature, while the consumption growth rate will depend on the set of socioeconomic scenarios developed in the socioeconomic and emissions module described above.

5.2 CIL SC-GHG Tool options

The CIL SC-GHG Tool allows users to choose either discounting approach. If the user selects Ramsey discounting, they have an additional option of accounting for inequality in SC-GHG valuation.

Option 1: Predetermined discount rates

The first option allows users to set a fixed or other pre-defined discount rate schedule, was done in the Interim SC-GHG. The SC-GHG is then calculated using the following procedure:

Step 1: Generate Monte Carlo draws of local climate damages for the all CIL impact categories using the empirically derived projections for 25,000 approximately county-sized "impact regions" around the world in each future year for each socioeconomic scenario.

Step 2: Calculate the local welfare loss of climate change. Take local baseline GDP per capita in each impact region as consumption without climate change. Calculate consumption with climate change in each Monte Carlo draw of damage realizations (GDP per capita - climate damages). Take the certainty equivalent across Monte Carlo draws to calculate expected welfare with climate change.[43] Climate damages, including the risk premium over uncertainty in damage realizations, are calculated as consumption without climate change minus the certainty equivalent of consumption with climate change.

Step 3: Aggregate local climate damages by adding up to the global level to form a damage function for each future year and scenario. Use projections from different emissions trajectories and 33 climate models with different temperature change projections to cover the support of GMST in the damage function. Estimate a quadratic damage function that best fits the pattern of calculated damages across the range of GMST anomalies.

Step 4: Use FaIR to generate Monte Carlo draws representing the probabilistic distribution of the change in GMST and GMSL under a given emissions trajectory, with and without the marginal pulse of emissions.

Step 5: For each Monte Carlo draw, use the estimated damage function to calculate climate damages with and without the pulse of emissions. In each future year for each Monte Carlo draw, calculate the realization of global consumption as global GDP minus climate damages. Calculate expected global welfare under climate change as the certainty equivalent of global consumption across Monte Carlo draws. Subtract the certainty equivalent from baseline global GDP to calculate climate damages. Calculate marginal climate damages in each future year as the difference in climate damages with and without the pulse of emissions.

[43] This approach is consistent with the NASEM guidance to evaluate the change in expected welfare (p 55), calculated as the change in social welfare in each state of the world weighted by the probability of that state.

Step 6: Discount the stream of damages caused by the pulse of emissions using a predetermined discount rate schedule (with constant or declining term structure). Use the long-term risk-free rate observed in financial markets as a guide to the choice of discount rate.

Step 7: Divide the discounted damages caused by the pulse of emissions by the number of tons of GHGs in the pulse to calculate the social cost per ton of a given GHG.

Option 2: Ramsey discounting

The second option employs Ramsey discounting, as called for in the NASEM report and highlighted as an important alternative framework in the Interim TSD. The CIL SC-GHG Tool employs Ramsey discounting using the following procedure.

Steps 1-5 proceed as in Option 1, with one exception. Consumption in the no climate change scenario now consists of the certainty equivalent of future consumption across the SSPs so that the valuation procedure can also account for uncertainty in the baseline path of economic growth.[44]

In Step 6, apply a Ramsey discounting procedure to calculate the discount rate. The Ramsey equation is given by $r = \rho + \eta g$, where ρ represents the pure rate of time preference, and η represents the intertemporal elasticity of substitution (or the curvature of the utility function). In this formulation, g is taken as the growth rate of the certainty equivalent of global consumption across economic growth scenarios and Monte Carlo draws from FAIR under the chosen emissions pathway, in the simulation without the extra marginal pulse of emissions.[45]

Critically, this procedure fulfills the NASEM recommendation that "The Interagency Working Group should develop a discounting module that explicitly recognizes the uncertainty surrounding discount rates over long time horizons, its connection to uncertainty in economic growth, and in turn, to climate damages." (p 174)

Option 2a: Ramsey discounting accounting for inequality

If the user choses Ramsey discounting, they have the additional option of explicitly accounting for the inequality of climate impacts in SC-GHG valuation. The purpose of this option is to account for greater marginal utility of dollar losses to lower income agents. This option proceeds as in Option 2, with the exception of Step 3. When aggregating from local to global damages for each year in the future, instead of adding up losses across impact regions we use the Jones and Klenow (2016) welfare metric[46] of taking the certainty equivalent across regions with and without climate change. This calculation captures the effect of climate change on the expected utility across regions, thereby giving greater weight to losses faced by lower income agents with a higher marginal utility of consumption.

Steps 3-7 proceed exactly as in Option 2, except that global consumption is redefined as the certainty equivalent of consumption across regions times the global population, rather than total GDP as in Option 2.

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[44] Note that the valuation procedure in Option 2 can also be applied within a given SSP omitting the incorporation of uncertainty in economic growth.

[45] This implementation is very similar to the procedure considered in the NAS report (p 174-176) in which each Monte Carlo draw is discounted separately, and the SCC is calculated as the average of SCCs across Monte Carlo draws. A primary difference is that the procedure recommended here allows for explicit calculation of the discount rate implied by the incorporation of growth and climate uncertainty.

[46] Jones and Klenow, "Beyond GDP? Welfare across Countries and Time." Hsiang et al 2017 also explore the impact of inequality aversion on SC-GHG

6. Updating

E.O. 13990 calls on the IWG to develop recommendations for reviewing and updating the SC-GHGs on an ongoing basis to reflect new scientific and economic research. The CIL has built a dynamic platform that allows for the incorporation of new damage functions meeting the criteria outlined in section 4 as they become available. Such research will be incorporated in into the web-based CIL SC-GHG Tool to the IWG and other users can produce updated SC-GHG estimates with the same climate, socioeconomic, valuation and discounting assumptions.

Appendix 1 – Historical income and climate data

Highly resolved damages: historical income data

One of the most important measures of sensitivity to weather and climate in our analyses is due to the wealth or incomes of those affected. This means that in order to capture the differential sensitivity to climate change in our empirical estimates, we need detailed subnational measures of income. In order to obtain income data for each subnational region in our empirical analyses, we draw subnational incomes from three main sources, using a combination of subnational GDP datasets as well as globally comprehensive national GDP data.

- **Penn World Tables (PWT) national GDP.**[47] This dataset provides national level incomes from 1950 to 2014 for most of the countries in the world. We use Penn World Tables version 9.0 to obtain national level income for all countries in our analyses.

- **European Union subnational GDP.**[48] This dataset provides national and sub-national level income data for the European countries in our datasets. We use this dataset to obtain subnational income at the NUTS2 level of aggregation.

- **First administrative division (ADM1) subnational GDP from national sources.** This dataset provides national and sub-national income data for 1,503 administrative regions from 83 countries. We use this dataset to obtain subnational level income data for all countries outside the EU.

Using these data, we construct a consistent multi-country panel of subnational incomes at the ADM1 level. To do so, we use the subnational data sources to downscale the PWT national-level incomes. We prefer this approach to using the subnational data directly, as there are known inconsistencies in measurement of subnational GDP across countries. Thus, we make the assumption that the within-country distributions of GDP in the subnational accounts are accurate, but the exact levels may not be. We rely on the PWT data as a consistent measure of GDP levels for all countries; thus, our subnational GDP estimates sum to national GDP from PWT for all countries in the sample. All subnational income data are in constant 2019 dollars PPP.

Subnational data collected by Gennaioli at al 2014 are drawn from disparate sources, often using census data, which are typically not annual, leading to an unbalanced panel. To construct annual values of income per capita using these data, we linearly interpolate between years, before constructing the Bartlett kernel and taking averages across all years. Full details of our construction of these data are provided in Carleton et al 2020.

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[47] Penn World Tables (PWT) database: https://www.rug.nl/ggdc/productivity/pwt/.

[48] Eurostat database: http://ec.europa.eu/eurostat/data/database.

Highly resolved damages: historical climate data and future GCM simulations

To create damage estimates at a highly resolved spatial and temporal resolution, CIL's method requires historical climate data and future climate projection data for multiple emissions scenarios at a high spatial and temporal resolution. We use historical climate data to estimate the relationship between temperature and impacts within a sector (e.g. the mortality-temperature relationship), and we use projected data on future climate to produce climate change damage estimates under several possible emissions trajectories.

For historical climate data, we primarily use the Global Meteorological Forcing Dataset (GMFD).[49] GMFD includes surface temperature and precipitation data, and was derived from observational weather data, reanalysis data and a weather forecasting model. The forecasting model was used to interpolate temporally and spatially, where observations did not exist, to create a gridded dataset of meteorological variables. GMFD data is available at a 1/4 degree resolution from 1948-2010. CIL used daily average temperatures and monthly average precipitation from GMFD. To investigate and ensure the consistency of estimated response surfaces across differing climate datasets, we used several other historical climate data sources.[50]

For future climate projections, a high-resolution (1/4 degree) dataset of global, bias-corrected climate projections produced by NASA's Earth Exchange program (NEX) is used, the Global Daily Downscaled Projections (GDDP).[51] This dataset includes projections downscaled from the output of 21 GCM runs that are part of the CMIP5 archive. The NEX-GDDP dataset was downscaled using the Bias Correction Spatial Disaggregation (BCSD) statistical downscaling method, which uses daily maximum and minimum temperature and daily precipitation data from the Global Meteorological Forcing Dataset (GMFD, 1950-2005) for bias correction using a traditional quantile mapping bias correction approach.[52] Quantile mapping is used to adjust the GCM outputs for historical and future time periods, and then the bias-corrected output is downscaled to a 1/4-degree resolution using a delta method that interpolates the daily bias corrected changes relative to GMFD climatologies.

Because the CMIP5 ensemble of GCMs is not representative of a probabilistic distribution but instead is an "ensemble of opportunity," it fails to adequately represent tail outcomes. Consequently, we use the surrogate mixed model ensemble (SMME) method to assign probabilistic weights to the GCM climate projections and also to improve representation of the tails of the distribution.[53] To accomplish this, the SMME approach uses a weighting scheme that is based on projections of GMST from a simple climate model and a form of linear pattern scaling to construct model surrogates to fill in the tails of the probability distribution that are not fully represented by the GCMs. The latter part of the SMME approach provides an additional 12 surrogate models used.

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[49] Sheffield et al., "Development of a 50-Year High-Resolution Global Dataset of Meteorological Forcings for Land Surface Modeling"

[50] For surface temperature, we used the Berkeley Earth Surface Temperature (BEST) dataset. For precipitation, we used the University of Delaware (UDEL) climate dataset. BEST includes surface temperatures from up to 37,000 station records using a kriging methodology that allows for including 130 stations with shorter time series that would otherwise be excluded. Gridded daily average 2-meter air temperature from 1957-2014 at a 1-degree resolution is used (over land) from BEST for this analysis. The UDEL dataset includes gridded, interpolated precipitation data that draws on station observations at a monthly frequency from 1900–2014. Gridded monthly precipitation at a 1/2 degree resolution is used from UDEL.

[51] Thrasher et al., "Technical note: Bias correcting climate model simulated daily temperature extremes with quantile mapping."

[52] Id.

[53] Rasmussen et al., "Probability-weighted ensembles of U.S. county-level climate projections for climate risk analysis."

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