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Economic Damages from Climate Change to U.S. Populations: Integrating Evidence from Recent Studies

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ABSTRACT: This paper takes a step forward in synthesizing recent evidence on estimating climate change damages specific to U.S. populations. We first present the findings from (1) existing global and U.S. models that take an enumerative approach to estimating market and nonmarket damages of climate change, (2) new impact-specific studies that have not yet been incorporated into the larger models, and (3) recent macroeconomic studies that empirically estimate the relationship between climate change and U.S. GDP. We then incorporate damage functions based on the results of these different lines of evidence into a consistent modeling framework to show what this literature implies for U.S. impact-specific social cost of greenhouse gas estimates under harmonized socioeconomic and emissions inputs, climate modeling, and discounting methods. We find that evidence on U.S.-specific damages from existing enumerative type models is still incomplete in the categories of impacts that are represented. Emerging research indicates that some missing categories, such as wildfire damages, are likely to be especially consequential to U.S. populations. Evidence from macroeconomic studies indicates that the U.S. GDP-based market damages from GHG emissions are also substantial. Combining lines of evidence on market and nonmarket damages based solely on the enumerative damage function approach provides preliminary results of U.S.-specific social cost of carbon (SC-CO_2) estimates on the order of $40 or more per metric ton of CO_2 for 2030 emissions. Combining evidence on GDP-based market damages with evidence on nonmarket health damages (heat- and cold-related mortality) yields U.S.-specific SC-CO_2 estimates ranging from $31-85 for 2030 emissions. We discuss the many categories of market and nonmarket impacts omitted from this analysis and highlight the need for more research on climate damages to U.S. populations, not only resulting from individual direct impacts of climate change occurring within U.S. borders, but also through interaction effects and international spillover impacts.

KEYWORDS: Integrated assessment models, benefit-cost analysis, economic damages, climate change

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1 Introduction

Elevated concentrations of greenhouse gases (GHGs) have been warming the planet, leading to changes in the Earth's climate that are occurring at a pace and in a way that threatens human health and well-being. Global average temperature has increased by about 1.1 °C (2.0 °F) in the 2011–2020 decade relative to 1850–1900 (IPCC 2021), and the last 10 years 2014–2023 have been the warmest 10 years in the 174-year instrumental record (Blunden and Boyer 2024). Global average sea level has risen by about 8 inches (about 21 centimeters (cm)) from 1901 to 2018, with the rate from 2006 to 2018 (0.15 inches/year or 3.7 millimeters (mm)/year) almost twice the rate over the 1971 to 2006 period, and three times the rate of the 1901 to 2018 period (IPCC 2021). The anthropogenic GHG emissions contributing to these changes include carbon dioxide (CO_2) emissions from fossil fuel combustion and industrial processes are the largest contributor to GHG emissions (totaling 64 percent of global net anthropogenic GHG emissions in CO_2 equivalent in 2019), followed by emissions of methane, CO_2 from land use change, nitrous oxide, and fluorinated gases (IPCC 2022). Because of the long-lived and well-mixed nature of GHGs in the atmosphere, they contribute to climate changes and consequent externalities on people and ecosystems both near and far from where they are emitted. Changes in temperature and other climate variables have substantially impacted global water availability and food production, health and well-being, infrastructure, and biodiversity and ecosystems, and these impacts are expected to increase over time (IPCC 2023).

Informed development of policies to address environmental externalities requires a way to assess the economic consequences of GHG emissions changes resulting from those policies. This includes understanding both the aggregate net impact to current and future generations and how these consequences will be distributed across regions and populations. One useful metric for providing an aggregate measure of how GHG emissions on the margin will affect society is the social cost of greenhouse gases (SC-GHG). The SC-GHG is the present value of global net damages from emitting one additional ton of a GHG into the atmosphere in a particular year.[1] In principle, it is a comprehensive measure that accounts for all future climate change impacts (both negative and positive), including, but not limited to, impacts to human health, net agricultural productivity, buildings and infrastructure, energy systems, and ecosystem services. In practice, the current global models used in the SC-GHG modeling are limited in their ability to represent all, or even many, of the physical, ecological, and economic impacts of climate change and their interactions. Thus, existing SC-GHG estimates remain a partial accounting of all climate change impacts and do not capture all the pathways through which climate change affects public health and welfare. Nevertheless, the scientific research community continues to make significant methodological advances in SC-GHG modeling capabilities (EPA 2023). SC-GHG estimates are widely applied in policy analysis at various levels of government, both in the U.S. and other countries. In particular, benefit-cost analysis (BCA) requires SC-GHG estimates to provide an aggregated measure of affected individuals' willingness to pay (WTP) for reduced climate change impacts associated with policy actions that impact GHG emissions. This allows the climate benefits (or disbenefits) of policies to be represented in the accounting of all the benefits and costs of a policy action.

[1] The SC-GHG varies based on the year that emissions are released into the atmosphere due to changes in concentrations of GHGs in the atmosphere and socioeconomic conditions. GHGs also differ in their lifetimes and the timing and magnitude of their effects on temperature and other environmental outcomes, and thus their impacts on society will be gas-specific. Collectively, these values – the social cost of carbon (SC-CO_2), social cost of methane (SC-CH_4), social cost of nitrous oxide (SC-N_2O), and social cost of hydrofluorocarbons (SC-HFC) – are often referred to as the "social cost of greenhouse gases" (SC-GHG).

Developing a complete understanding of how the consequences of GHG emissions are likely to be experienced across particular regions and populations is challenging because it requires a mapping between physical effects and their ultimate economic incidence through both direct and indirect effects. This is especially difficult in the case of a global pollutant in an increasingly globalized economy. How GHG emissions affect people in specific countries or regions depends on both the direct impacts occurring around them and those occurring through indirect channels from climate impacts in, and actions taken by, other countries (National Academies of Sciences, Engineering, and Medicine, 2017). Impacts occurring outside of U.S. borders can have significant impacts on U.S. interests due to the interconnectedness of the global economy and populations. There are direct effects on U.S. citizens and assets located abroad, as well as indirect effects on those within U.S. borders through international trade, tourism, and other spillovers, such as economic and political destabilization and global migration that can lead to adverse impacts to the U.S. economy and national security, public health, and humanitarian concerns. When assessing the benefits of U.S. GHG mitigation activities, information about how other countries respond with their own reciprocal reductions is also important since those international mitigation efforts provide equivalent climate benefits per ton of GHG reductions to U.S. citizens and residents due to the global nature of GHGs.[2]

This paper takes a step forward in synthesizing recent evidence on estimating climate change damages specific to U.S. populations in a consistent modeling framework. We first review the findings on U.S. specific damages from (1) existing global and U.S. models that take an enumerative[3] - or impact by impact - approach to estimating market and nonmarket damages, (2) two new impact-specific studies that have not yet been incorporated into the larger models, and (3) recent macroeconomic studies, primarily those that empirically estimate the relationship between climate change and U.S. GDP.[4] We then incorporate damage functions based on the results of these different lines of evidence into a consistent modeling framework to show what this literature implies for U.S. impact-specific estimates of the social cost of carbon (SC-CO_2)[5] and other greenhouse gases (methane and nitrous oxide), when estimated using harmonized socioeconomic and emissions inputs, climate modeling, and discounting methods. Finally, we discuss considerations for combining different lines of evidence and present preliminary combined results to the extent possible within a common analytical modeling framework.

We find that evidence on U.S.-specific damages from existing global and U.S. enumerative type models is still incomplete in the categories of impacts that are represented. Some missing categories are likely to be especially relevant in the U.S. For example, emerging research on health effects from wildfire smoke indicates that this missing impact category is likely especially consequential for U.S. populations. Evidence

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[2] As discussed in EPA (2023), economists and other scientific experts have emphasized this issue of international cooperation and reciprocity as support for assessing global damages of GHG emissions in domestic policy analysis (e.g., Kopp and Mignone 2013, Pizer et al. 2014, Howard and Schwartz 2017, Pindyck 2017, 2021, Revesz et al. 2017, Carleton and Greenstone 2022, Houser et al. 2023).

[3] We use "enumerative" in this paper to refer to the more disaggregated approach to damage function development that typically involves spatially explicit and sectoral or category-specific modelling of relevant processes and then aggregates regional or sectoral damages. This has also been described as a "bottom-up" or "impact-specific" approach for estimating climate damages in the literature.

[4] Macroeconomic studies that estimate the effect of temperature on GDP are sometimes characterized as providing a "top-down" approach to developing a climate damage function. However, we do not adopt this terminology since, as discussed in more detail in Section 4, these studies on their own are not able to provide a comprehensive accounting of climate damages.

[5] For the scope of this paper, U.S. impact-specific SC-CO_2 refers to the present value of the monetized future damages resulting from one or a few categories of climate impacts occuring within the United States as a result of an additional ton of CO_2 emissions in a given year.

from macroeconomic empirical studies indicates that the U.S. GDP-based market damages from GHG emissions are also substantial. In fact, the U.S. impact-specific SC-CO_2 estimates based on macroeconomic econometric damages functions are larger than the market damages based on any of the enumerative models. Combining lines of evidence on market and nonmarket damages based solely on the enumerative damage function approach provides preliminary results of U.S.-specific SC-CO_2 estimates on the order of \$40 or more per metric ton of CO_2 for 2030 emissions (under a 2 percent near-term Ramsey discount rate). We find that combining evidence on GDP-based market damages with evidence on just one category of nonmarket health damages (heat- and cold-related mortality) yields U.S.-specific SC-CO_2 estimates ranging from \$31-85 per metric ton of CO_2 for 2030 emissions (under a 2 percent near-term Ramsey discount rate). We emphasize that there are still many categories of nonmarket impacts omitted from this analysis, such as mortality and morbidity effects from many climate-mediated extreme weather events and various nonmarket impacts associated with the loss of ecosystem services, among others. The U.S.-specific damages from some market impacts are also not yet reflected, even in estimates based on macroeconomic econometric studies, as they can only account for net climate impacts on macroeconomic outcomes that have, to some extent, been experienced in the historical record. Our findings highlight the need for more research on both market and nonmarket climate damages to U.S. populations, not only resulting from individual direct impacts of climate change occurring within U.S. borders, but also through interaction effects and international spillover impacts.

The paper is organized as follows. Section 2 provides a brief overview of approaches used for modeling economic damages from climate change. Section 3 reviews evidence on U.S.-specific damages in the existing literature and presents U.S. impact-specific SC-CO_2 estimates based on the results of both enumerative damage models and macroeconomic empirical studies within a consistent modeling framework. Section 4 discusses considerations for combining different lines of evidence. Section 5 concludes.

2 Modeling economic damages from climate change

The economic consequences of global changes driven by projected GHG emissions are most often assessed using integrated assessment models (IAMs) of climate change.[6] These IAMs are typically global models that incorporate climate processes and economic systems into a single unified modeling framework. Climate change IAMs vary in their complexity, structure, geographic resolution, and the degree to which they capture feedbacks within and between natural and economic systems. The type of IAMs used to estimate the SC-GHG allow researchers to link physical impacts, such as global temperatures and SLR, to monetized measures of social and economic damages based on available evidence on the relationships between the two systems.[7] These relationships depend on projected economic growth, population, and

[6] Other methods to estimate the SC-GHG include expert elicitation methods or other survey techniques (e.g., Pindyck 2019, Hulshof and Mulder 2020, Moore et al. 2024). Economy-wide computable general equilibrium (CGE) models are often used to explore how market-based climate impacts propagate through the economy (e.g., Dellink et al. 2019, Takakura et al. 2019), but have not generally been used on their own to develop SC-GHG estimates.

[7] Other climate change IAMs include more structural representations of the global economy with a high level of regional and sectoral detail and were originally developed for analyzing the impact of policy and technology on GHG emissions. See NASEM (2017) for more discussion. These types of IAMs are often used to examine different climate change impact sectors and interactions between sectors and regions but do not yet comprehensively link physical impacts to monetized economic damages as needed for SC-GHG estimation (NASEM 2017).

technological change. The National Academies of Sciences, Engineering, and Medicine (NASEM) characterized climate change IAMs that are used in SC-GHG estimation as generally being comprised of four modules: socioeconomic, climate, damages, and discounting (NASEM 2017). The socioeconomic module consists of jointly estimated projections of economic growth, population, and GHG emissions, which feed into the climate module to project future earth system conditions such as global temperatures, ocean acidity, and sea level rise (SLR). The damage module translates these changes in climatic conditions into physical and monetized estimates of economic damages. These economic damages represent the amount of money those experiencing the changes would be willing to pay to avoid them. These damages can be experienced through impacts to goods and services traded in markets (e.g., changes in agricultural productivity, energy expenditures, or property damage) or nonmarket goods and services (e.g., changes in mortality and morbidity risks or ecosystem services) (EPA 2023). Lastly, the discounting module translates the stream of undiscounted economic damages from the damage module into the present value of net damages. This four-step procedure is modeled with both baseline emissions and with a small additional amount (a pulse) of GHG emissions in a particular year. The SC-GHG is the per-ton difference in present value of damages between the baseline and pulse models from the perspective of the year of the emissions pulse.

In December 2023, the U.S. Environment Protection Agency (EPA) published a set of SC-GHG estimates that reflect recent advances in the scientific literature on climate change and its global economic impacts and incorporate recommendations made by the National Academies (EPA 2023). Importantly, EPA's SC-GHG estimates use an updated methodology in which each of the four modules described above was developed by drawing on the latest research and expertise from the scientific disciplines relevant to that component. The socioeconomic module relies on a new set of probabilistic projections for population, income, and GHG emissions developed under the Resources for the Future (RFF) Social Cost of Carbon Initiative (Rennert et al. 2022a). The climate module is based on the Finite amplitude Impulse Response (FaIR) model (version 1.6.2) (Millar et al. 2017, Smith et al. 2018) as used by the IPCC (2021a, 2021b), a widely used Earth system model recommended by the National Academies for SC-GHG estimation (NASEM 2017). As discussed further below, EPA then uses a three-part damage module to estimate how projected temperature changes will translate into future monetized global economic damages. Finally, the discounting module uses an updated, dynamic discounting approach based on the Ramsey equation (Ramsey 1928) which allows the discount rate to vary over time consistent with changes in estimated global economic growth. These dynamic discount rates were calibrated based on multiple lines of evidence on observed real market interest rates following Newell et al. (2022), as applied in Rennert et al. (2022a, 2022b). Taken together, the updated methodology incorporates a more comprehensive quantitative consideration of uncertainty than past SC-GHG estimates used by EPA and others that captures the compounding uncertainties across the estimation process. Detailed discussion of each input, the modeling process, and modeling limitations, including the many categories of omitted climate impacts and associated damages, is provided in EPA (2023). Because the remainder of this paper focuses climate damages within the United States, we describe the damage module in greater detail below, and Appendix B provides information about the U.S.-specific aspects of the other three modules. Appendix B presents the U.S. projections of socioeconomic variables from the RFF-SPs; global mean surface temperature (GMST) projections from the FaIR 1.6.2 model downscaled to U.S. temperature; and Ramsey discounting parameters that are based on the EPA's SC-GHG methodology recalibrated using the U.S. growth rate of consumption.

One of the more involved components of SC-GHG estimation discussed above is the damage module. This module is often developed by calibrating to, or building up, disaggregated estimates of the damages resulting from various types of climate impacts. Two of the three global models underlying the damage module in EPA's current SC-GHG estimates rely on this enumerative approach to estimating damage functions (EPA 2023).[8] This approach typically involves spatially-explicit and sectoral- or category-specific modeling and aggregation of damages across sectors or impact categories.[9] Some types of climate impacts are straightforward to map into measures of welfare consequences (i.e., impacts on individuals' overall well-being) using standard producer and consumer theory. For example, the social welfare consequence of climate change impacts on crop yield can be estimated as the change in consumer and producer surplus between the unperturbed and the climate-impacted equilibria. In other cases, what is feasible to estimate, given data and methodological constraints, can serve as a lower bound on the theoretically correct welfare impact. For example, additional energy consumption from temperature-related changes is a defensive expenditure for climate change impacts. Bartik (1988) shows that defensive expenditures of this sort are a lower bound of the welfare loss associated with a reduction in environmental quality. There are also studies that econometrically estimate the relationship between temperature change and more aggregate measures of economic outcomes, such as national or regional gross domestic product (GDP). By definition, GDP is not an estimate of welfare, nor even an estimate of impacts on consumption, and does not account for nonmarket impacts. However, GDP is a readily available measure that captures a wide range of economic activity and is often viewed as a way to estimate many sectoral effects without the need to fully enumerate and estimate them.

In the following section, we review recent advances in the understanding of the effect of climate change on U.S.-specific outcomes based on both the enumerative approach to developing damage functions and recent macroeconomic econometric research. We focus on studies whose results are in a form that can be combined with the other components of the modeling framework (e.g., country-level annual socioeconomics and mean temperature projections) to estimate U.S. impact-specific SC-GHGs.

3 U.S. climate damages

Many of the economic impacts of climate change experienced by the rest of the world are also present in the U.S.: water supplies are being threatened by flooding, drought, and SLR; food production and distribution are being disrupted; homes and infrastructure are increasingly at risk from SLR, wildfires, and extreme weather events; temperature-related human health impacts are being exacerbated; and ecosystems are being stressed and transformed. These impacts are projected to worsen in the future as increased temperature, SLR, and extreme weather events are expected to increase the probability and intensity of future heatwaves, wildfires, droughts, floods, and crop failure (USGCRP 2023). The U.S. is

[8] The third damage function used in EPA's SC-GHG estimates was based on a meta-analysis (Howard and Sterner 2017) that estimates an aggregate global damage function directly.

[9] Consistent with the terminology used by the NASEM (2017) and many researchers in the academic literature on the SC-GHG, in this paper, "sector" is generally used to refer to climate impact categories, rather than specific industry sectors (e.g., agriculture, manufacturing, construction) of the economy. In the relatively few studies that rely on multisectoral, multiregional economic computable general equilibrium (CGE) models to build damage functions, the term may be used in the more traditional way to refer to economic sectors. CGE models calibrate to region-sector impact estimates but account for more interactions among regions, impacts, supply, and demand factors.

expected to warm faster than the global average because land areas warm faster than the oceans, and higher latitudes warm faster than lower latitudes. In the U.S., Alaska is expected to see the largest temperature increase over time, followed by areas in the Southwest, Northern Great Plains, and Northeast; the Northwest, Midwest, and Southern Great Plains; and the Southeast and Caribbean. Specific climate change impacts are also expected to be regionally heterogeneous. Extreme heat and human health impacts will likely affect all areas of the country, but water supply impacts are more likely in the Southeast, Great Plains, Northwest, and Southwest, while food security concerns are more likely in the Caribbean and Alaska (USGCRP, 2023). In this section, we pull together evidence on these types of U.S.-specific consequences of climate change to the extent that they are currently represented in modeling frameworks capable of providing U.S.-impact specific SC-GHG estimates.

a. Evidence from global and U.S. enumerative models

Currently, there are three leading models that provide an enumerative approach to monetizing damages resulting from climate impacts occurring within the United States: the Greenhouse Gas Impact Value Estimator (GIVE), the Data-driven Spatial Climate Impact Model (DSCIM), and the Framework for Evaluating Damages and Impacts (FrEDI). The first two, GIVE and DSCIM, are the two global models used to inform the damage module underlying EPA's SC-GHG estimates that have spatial resolution permitting some geographic disaggregation of future climate impacts across the world. This allows for the calculation of damages projected to physically occur within the United States for the climate impact categories included in those models. The third, FrEDI, is a reduced form model that was developed by EPA as an outgrowth of the extensive impacts-specific research generated under the Climate Change Impacts and Risk Analysis (CIRA) effort to project the physical and economic impacts of future temperature change and SLR within the continental U.S. (CONUS), under various temperature or emissions pathways. Tables A.1 through A.3 list the types of climate damages represented and the underlying peer-reviewed literature for the three models. We summarize each in turn below. A more detailed discussion can be found in EPA (2023).

GIVE. The GIVE damage module, developed under RFF's Social Cost of Carbon Initiative (Rennert et al. 2022b), includes country-level representation of monetized damages from four climate impacts: changes in mean temperature-related mortality risk, agricultural yields for staple crops, energy related expenditures, and SLR-induced mortality risk and physical capital loss in coastal areas. Each of these components is based on recent scientific advancements in the peer-reviewed literature, and the model is structured in a way that it can accommodate additional damage categories as they become available.[10]

The temperature-related health damage function in GIVE is based on a systematic review and meta-analysis of all-cause mortality estimates from increases in temperature using a random-effects pooling of studies (Cromar et al. 2022). Net changes in mortality were estimated for nine global regions, varying in their effect size and uncertainty, mapped to country-specific baseline mortality projections and rates for 184 countries. The energy damage component estimates the changes in building energy expenditure (net heating and cooling expenses) due to changes in local temperature and climate using a regional linear regression to estimate the net energy expenditures for each country (Clarke et al. 2018). Agricultural

[10] GIVE is built on the Mimi.jl platform, an open-source package for constructing modular integrated assessment models, www.mimiframework.org (Anthoff et al. 2017). GIVE (Rennert et al. 2022b) is written using the Julia programming language which allows for fast estimation times.

damages in GIVE relies on a meta-analysis of 1,010 temperature-yield responses from 56 published studies and the results from multiple global gridded crop models (GGCMs) from the Agricultural Model Intercomparison and Improvement Project as inputs in the open-source GTAP (CGE) model (Moore et al. 2017). The economic welfare impacts from the climate-induced net yield responses was reported as equivalent variation, accounting for changes in trade, production, and consumption in agricultural markets. GIVE's coastal damages are calculated using global mean sea level rise projections based on the BRICK SLR model (Wong et al. 2017) and corresponding local adaptation and associated costs based on the Coastal Impact and Adaptation Model (CIAM), a deterministic optimization model that chooses the least-cost adaptation strategy for each of 12,148 coastal segments (Diaz 2016).

DSCIM. The DSCIM damage module, developed by the Climate Impact Lab (CIL 2023, Carleton et al. 2022, Rode et al. 2021), currently estimates net damages resulting from similar health, energy, agriculture, and coastal impact endpoints as considered in GIVE. In addition, DSCIM includes representation of net disutility from labor supply responses to changes in temperature, particularly in high-risk weather-exposed industries. DSCIM monetizes climate damages for nearly 25,000 global impact regions (including U.S. counties) using econometric methods that account for local conditions, including adaptation investments. The model uses econometrically estimated sector-specific outcomes for each impact region based on the variation in short-run weather and long-run average climate and socioeconomic conditions. These sector-specific outcomes and associated monetized damages are projected into the future using a probabilistic ensemble of high-resolution downscaled climate projections from 33 global climate models (GCMs). The local damages are aggregated across impact regions to develop an estimate of damages as a function of GMST changes.

The health component in DCSIM is an estimate of the value of net changes in heat- and cold-related mortality risk. Age-specific mortality is estimated as a linear function of daily grid-level nonlinear temperature and precipitation data transformations and includes the effect of climate-driven adaptation (e.g., more cooling systems) and income growth (Carleton et al. 2022). The DSCIM energy model includes energy expenditures from temperature-related changes in electricity and direct fuel consumption by residential, commercial, and industrial end-uses. Energy consumption responses include the impact from income changes and climate adaptation (e.g., installation of air conditioning and more frequent operation of existing equipment) (Rode et al. 2021). The net impact of climate change on the agriculture production is estimated for six globally and regionally important staple crops: maize, wheat, rice, soybean, sorghum, and cassava. This estimate includes within-crop adaptations (e.g., varietal switching and changes in production methods), crop switching, trade protective effects, and fertilization benefits of CO_2 emissions on crop yields (Hultgren et al. 2022). The coastal component of DSCIM estimates damages resulting from SLR inundation in coastal regions. SLR projections are based on the probabilistic FACTS model used in IPCC's AR6 report (Kopp et al. 2016, Garner et al. 2021), and associated damages are estimated based on CIAM similar to the approach taken in GIVE. The labor productivity component of the model captures the value of labor losses from responses to daily temperature, estimated as an inverted U-shaped relationship, with lost labor occurring at extreme hot and cold temperatures (Rode et al. 2022).

FrEDI. U.S. focused modeling efforts such as FrEDI can help to increase understanding of modeled U.S. damages in a number of climate impact categories that are currently unrepresented in GIVE and DSCIM. FrEDI was developed by the U.S. EPA (EPA 2024) and draws on over 30 peer-reviewed studies and impact models, including EPA's CIRA project, to estimate the relationship between future degrees of warming and the net physical and economic impacts within the CONUS.[11] As the climate-related risks to a particular area or community will be determined both by the physical climate stressors (e.g., heat and precipitation) and by the sensitivities to adverse effects in each location, the EPA developed FrEDI to better understand and communicate these detailed impacts and risks across the CONUS.

As discussed in EPA (2023) and presented in Hartin et al. (2023), the FrEDI framework can also be used to estimate the future stream of net damages in the CONUS associated with adding one ton of a GHG to the atmosphere in a given year (i.e., U.S. impact-specific SC-GHGs). FrEDI currently includes representation of temperature and SLR-driven impacts to over 20 endpoints, listed in Table A.3, across many impact categories including human health, infrastructure, labor, electricity supply and demand, agriculture, and ecosystems and recreation.

Comparison. Table 1 summarizes the evidence on U.S.-specific climate damages from DSCIM, GIVE, and FrEDI. Specifically, Table 1 lists the current impact categories included in each model (first column) and shows the implied U.S. impact-specific SC-CO_2 estimates for 2030 emissions (second column) that are generated when combining each model with the probabilistic projections of U.S. population and GDP from the RFF-SPs, the FaIR 1.6.2 model temperature outputs, and the 2% near-term Ramsey discounting approach employed by EPA (2023) with Ramsey parameters calibrated using the U.S. growth rate of consumption (see Appendix B for more discussion of these inputs). Each model's damage functions are discussed above.

The results illustrate how monetized damages that physically occur within CONUS generally increase as additional impacts are included in the modeling framework. Specifically, some of the impacts not appearing in DSCIM or GIVE but that have large regional economic damages estimated in FrEDI include: premature mortality from climate-driven changes in ozone and $PM_{2.5}$, transportation related damages from hightide flooding, and road and rail infrastructure impacts from heat stress. However, in all damage models, omissions or partial representation of key impact categories remain. For example, while some mortality and morbidity impacts from $PM_{2.5}$ emissions associated with wildfire smoke and suppression costs are included in FrEDI, none of the models currently account for other market and nonmarket welfare effects of wildfires (e.g., property damage, impacts to ecosystem services, additional health risks from specific wildfire $PM_{2.5}$ mixtures, climate feedback effects from wildfire CO_2 emissions, etc.). Similarly, some of the models include damages from SLR such as property damage and traffic delays resulting from flooding, but do not yet to include other damages such as interruptions to business operations, costs for debris removal, or the damages associated with groundwater intrusion. In addition, none of the models have yet incorporated climate-mediated effects to ecosystem services, national security, and do not currently reflect damages to U.S. extraterritorial interests or spillover effects from climate impacts occurring abroad.[12]

To explore the sensitivity of the U.S. impact-specific SC-CO_2 values from each model to additional climate uncertainties, such as the effect of carbon feedbacks, the last column of Table 1 shows the impact of incorporating two additional carbon feedbacks into the estimation framework that are currently not represented in FaIR 1.6.2. That is, the GMST outputs from the climate module account for carbon feedback effects from permafrost thaw and Amazon dieback based on the Dietz et al. (2021) modeling of these feedbacks (see Appendix C for a detailed discussion of their implementation). As shown in Table 1,

[11] The results in this analysis use FrEDI v4.1. Available at: https://github.com/USEPA/FrEDI/releases/tag/v4.1.1

[12] See EPA (2023) for more discussion of the numerous pathways through which considerable international spillovers can occur.

accounting for these two carbon feedback effects increase the U.S. impact-specific SC-CO_2 by 9 to 50 percent. Using the DSCIM damage module, the introduction of carbon feedbacks increases the U.S. impact-specific SC-CO_2 from $14 per mt$CO_2$ to $21 per mt$CO_2$, a 50 percent increase. In GIVE, these feedbacks increase the U.S. impact-specific SC-CO_2 by a smaller margin, from $22 per mt$CO_2$ to $24 per mt$CO_2$. Finally, FrEDI estimates a U.S. impact-specific SC-CO_2 of $36 per mt$CO_2$ for damages physically occurring within CONUS for 2030 emissions, compared to $33 per mt$CO_2$ without incorporating these carbon feedbacks. U.S. impact-specific SC-GHG results for 2030 emissions of CH_4 and N_2O incorporating these feedbacks are presented in Table A.4 in Appendix A. As discussed in Appendix C, this increase represents the modeled temperature-driven damages in the U.S. from the additional carbon released from permafrost thaw and Amazon dieback. It does not reflect the value of other physical impacts from these feedbacks, such as lost ecosystem services and biodiversity loss from Amazon rainforest dieback and infrastructure damage from permafrost thaw. Importantly, even with the addition of these two carbon feedback effects, our climate module includes only a partial representation of 6 of the 11 earth systems feedbacks relevant to climate change identified in recent reviews (Dietz et al. 2021, Wang et al. 2023).

Table 1: Evidence on U.S. climate damages from current global and U.S. enumerative models

		U.S. impact-specific SC-CO_2 *(2030 emissions, 2% near-term Ramsey discount rate, 2020$/mt$CO_2$)*	
Model	Impacts represented	FaIR 1.6.2	FaIR 1.6.2 With Additional Carbon Feedbacks[c]
DSCIM	health, energy, agriculture, coastal, labor	$14	$21
GIVE [a]	health [b], energy, agriculture, coastal	$22	$24
FrEDI[a]	various impacts to human health, energy demand and supply, coastal and inland property (e.g., from SLR, flooding and storms), labor, transportation and other infrastructure, water resources, and winter recreation (CONUS only)	$33	$36

[a] *Discounting module follows Newell et al. (2022) with Ramsey parameters, ρ and η, recalibrated to the U.S. growth rate of consumption.*

[b] *To calculate the temperature-related mortality damages (based on Cromar et al. 2022), GMST projections from FaIR 1.6.2 are downscaled to U.S. temperature using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets). This downscaling approach, a historical period validation exercise of the approach, and resulting U.S. temperature projections are described in detail in Appendix B.*

[c] *Climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021).*

b. Evidence from additional impact-specific studies

As illustrated in the summary Table A.1 and discussed at length in EPA (2023), there are many categories of climate change impacts and associated damages that are not yet or only partially represented in GIVE, DSCIM, and FrEDI. Continued progress in filling data gaps and estimating the magnitude of many of these omitted impacts includes a large and growing body of research providing evidence on a wide range of U.S.-specific outcomes, such as heat-related kidney disease and other morbidity outcomes (see, e.g., Bell et al. 2024, Yang et al. 2024), human capital impacts (Park et al. 2020), flooding impacts on mortality (Mueller er al. 2024, Lynch et al. 2025), forestry impacts (Baker et al. 2023), long-term impacts to coastal wetlands

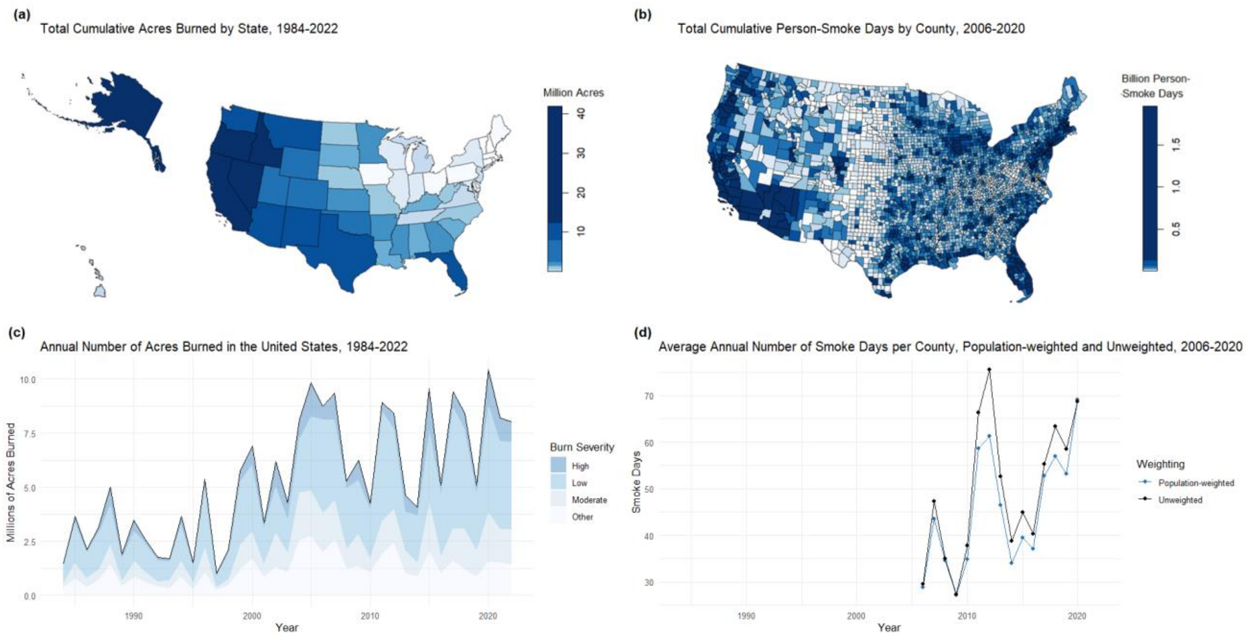
(Fant et al. 2022), net impacts on outdoor recreation (Willwerth et al. 2023), climate impacts on mental health (Obradovich and Minor 2022), and the distortionary effects of fiscal impacts (Barrage et al. 2023), to name a few. The U.S. National Climate Assessment offers a periodic overview of much of this literature, including examples of how changes in temperature and other climate variables have affected, and are projected to affect, various U.S. economic outcomes as estimated in particular studies (see, e.g., Table 19.1 in USGCRP (2023)). While the majority of this research has not yet been converted into damage functions of the kind needed for developing U.S. impact-specific SC-GHG estimates, two exceptions include emerging research on climate-driven wildfire-related health impacts (Qiu et al. 2024) and monetized damages from biodiversity loss (Wingenroth et al. 2024). We discuss each in turn.

i. Wildfire

One source of climate change damages receiving increasing attention in the academic literature, which may be especially relevant to assessing the climate damages experienced by U.S. citizens and residents, is wildfire. Wildland fires in the U.S., though a naturally occurring disturbance regime important to diverse ecosystems, are increasing in frequency, severity, burned area, and wildfire season length (Ostoja et al. 2023, EPA 2024c). Climate change is projected to exacerbate these trends, with increasing temperatures causing earlier spring melts and diminished snowpacks, which allow for drier summer conditions. The increasing frequency and longevity of droughts are predicted to further lengthen fire seasons and augment wildfire size (EPA 2024c). Figure 1 illustrates the increasing acreage of land burned by wildfire annually in the United States from 1984-2022 (panel (c)), and the geographic concentration of that burned area in the western part of the country (panel (a)).

U.S. populations' exposure to wildfire risks has increased with the expansion of the wildland-urban interface, as more Americans live near forests, grasslands, and other natural areas affected by fire (Mockrin et al. 2022, Guo et al. 2024). Additionally, U.S. populations exposed to wildfire smoke cover even larger areas of the country as the impact of wildfire smoke on U.S. air quality has increased in recent years (Gellman and Wibbenmeyer 2025). Burke et al. (2021) estimate that wildfires have accounted for up to 25 percent of $PM_{2.5}$ in the U.S. in recent years with even higher percentages in some Western U.S. regions. The majority of wildfire smoke spreads through atmospheric flows into areas outside of a wildfire's origin; Wen et al. (2023) estimate that 87 percent of wildfire $PM_{2.5}$ is experienced in counties outside of the fire's origin, and 60 percent comes from fires that started in other states. U.S. exposure to wildfire smoke also originates from wildfires in other countries. For example, Canadian wildfires in 2023 increased the incidence of respiratory illnesses-related visits to the emergency department in New York City (Thurston et al. 2023, CIL 2024). Figure 1 presents trends of increasing wildfire smoke exposure in the contiguous U.S. over 2006-2020, as measured by population-weighted smoke days. Childs et al. (2022) calculate smoke days (days when smoke was overhead) for each county in the contiguous United States from 2006 to 2020 using satellite imagery and simulated air trajectories. Smoke day calculation considers only the presence of smoke in an area, not the smoke's origin point, meaning that smoke from wildfires outside the contiguous U.S are included in the Childs et al. (2022) data. Panel (b) displays the spatial distribution of person-smoke days, counting each person in a county experiencing a smoke day, across this 15-year period. Panel (d) shows the average annual number of smoke days[13] per county over this time period, both unweighted and when weighted by the county population in each year. The close tracking of these two measures over the 15 years indicates that the increasing trend in the number of smoke days was not only concentrated in relatively unpopulated areas of the country.

Figure 1: Historic trends of wildfire burned area and wildfire smoke days across the U.S., 1984-2022



The data in panels (a) and (c) are taken from Monitoring Trends in Burn Severity (2024). The data in panels (b) and (d) are derived from Childs et al. (2022) and U.S. Census Bureau (2006-2020).

Wildfire events can result in many types of damages. Market-based damages can occur from the fire itself (e.g., property destruction, suppression costs, business productivity impacts, and energy supply disruptions), smoke exposure (e.g., labor market impacts[14]), and spillover effects (e.g., through trade and supply chain networks). Nonmarket damages can also occur through these mechanisms (e.g., mortality and morbidity effects from fire or smoke exposure, recreation impacts, population displacement, and changes to ecosystem services). See Gellman and Wibbenmeyer (2025) for a recent review of the various types of impacts of wildfire smoke on human health and economic activity. Current methods for estimating these damages for a given wildfire vary by impact or damage category. Estimating future marginal wildfire-related damages from GHG emissions also requires modeling of wildfire starts and severity and smoke exposure under climate change, which is currently not well modeled at the global level, and incompletely even for the U.S. (see review in CIL 2024). As discussed above, FrEDI incorporates some wildfire damages

[13] Given ongoing research into the health risks from even low-level $PM_{2.5}$ exposure (see e.g., Boogard et al. 2024) and other more toxic components of wildfire smoke (see discussion of related literature in CIL (2024)) we do not apply a smoke intensity threshold to the smoke days data presented in Figure 1.

[14] For example, recent research suggests that the welfare costs of lost earnings from smoke exposure is similar to or larger than the cost of increased mortality from wildfire smoke (Borgschulte et al. 2024).

for the U.S., but currently only includes response costs and mortality and morbidity from wildfire smoke generated in the Western U.S. (EPA 2024a, Neumann 2021a).

Emerging research is advancing the climate-wildfire linkage to associated damages in the U.S. for one category of wildfire related damages: climate-driven mortality risks of wildfire smoke exposure. A recent working paper by Qiu et al. (2024) uses an ensemble of region-specific statistical and machine learning models to project wildfire emissions as a function of climate and land-use variables over North America together with county-level mortality data from 2006-2019 to empirically estimate the effects of wildfire-specific $PM_{2.5}$ exposure on all-cause mortality rates. The authors then combine these empirical relationships with projected climate variables from 28 GCMs in CMIP6 to generate future projections of smoke $PM_{2.5}$ concentrations and the attributable mortality burden in each cell of a grid with 10km resolution over CONUS between 2046 and 2055 under different climate scenarios. For example, they estimate that between 2025 and 2055, the cumulative excess deaths from wildfire smoke $PM_{2.5}$ could exceed 700,000 additional deaths under a SSP3-RCP7.0 scenario. Their work lends itself to traditional damage function development that is compatible with climate change IAMs of the type used in SC-GHG estimation. See Appendix D for a detailed explanation of how we derive a reduced-form approximation of Qiu et al.'s (2024) results for use in a damage module of such an IAM.

ii. Biodiversity loss

Another area in which emerging research has advanced our knowledge of climate damages to U.S. populations is in the development of estimates of economic damages from climate-driven biodiversity loss. A full accounting of the damages from the loss of biodiversity ecosystem services would include consideration of both market impacts (e.g., crop pollination, nutrient cycling, tourism, and pharmaceutical innovations) and nonmarket impacts (e.g., existence and aesthetic values). Developing causal estimates of these types of impacts is challenging due to significant data and methodological limitations given the complexity of ecosystem changes, and biodiversity loss is likely to be associated with other ecological shocks (Druckenmiller 2022). A new working paper published by RFF (Wingenroth et al. 2024) has advanced the estimation of one category of nonmarket damages associated with climate-driven biodiversity loss: the loss of its nonuse value. Nonuse value of biodiversity includes individuals' WTP for knowing that a species exists, bequest values for future generations, and altruistic values for others' enjoyment of the species.

Wingenroth et al. (2024) develop a biodiversity loss damage function by combining a species loss function (relating GMST change to species loss) with a WTP function (relating species loss to nonuse value) to link changes in temperature to economic impacts from biodiversity loss. The functional form of the species loss function is derived from the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) model (Anthoff and Tol, 2014). Wingenroth et al. (2024) re-parameterize the temperature-effect coefficient of the species loss function using data from a more recent and globally comprehensive synthesis of studies on extinction rates (Urban et al. 2015) and found temperature to have a larger impact on species loss than previous parameterizations. For the WTP function, the authors employ the method developed by Brooks and Newbold (2014) for estimating WTP for avoided biodiversity loss from stated preference estimates. The preference for biodiversity parameter of the WTP function is calibrated following Kaushal and Navrud (2023), who estimate this parameter for the 16 regions used in the FUND model. Using country-level population and income forecasts from the RFF-SPs, Wingenroth et al. (2024) develop country-level WTP estimates for avoided species loss for 184 countries, including in the U.S. That is, it provides a damage function that reflects U.S. populations' nonuse damages from global species loss resulting from a change in GMST.

Table 2 presents the U.S. impact-specific SC-CO_2 estimates for 2030 emissions that result from combining the damage functions based on Qiu et al. (2024) and Wingenroth et al. (2024) with the same U.S.-specific socioeconomic and emissions inputs, climate modeling, and discounting methods used in Table 1 and described in Section 3a. The GMST projections, which are used as inputs to both the biodiversity loss and wildfire-related damage functions, are based on FaIR 1.6.2 and account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks.

The results in Table 2 show that wildfire $PM_{2.5}$-related mortality damages as estimated using the Qiu et al. (2024) damage function are found to be considerable. The U.S. impact-specific SC-CO_2 is estimated to be $15 per metric ton of CO_2 for 2030 emissions (under 2 percent near-term Ramsey discounting). This is of similar magnitude as the analogously estimated U.S. temperature-related mortality SC-CO_2 in DSCIM and GIVE, and significantly greater than the share of the FrEDI based damages attributable to smoke and other impacts from wildfires in U.S. Western states (Hartin et al. 2023, EPA 2024a). As discussed further in Section 4, it is reasonable to assume the partial SC-CO_2 based on Qiu et al. (2024) is not double counting the effect of temperature itself on mortality because Qiu et al. (2024) include temperature control variables in their empirical estimation. The results in Table 2 do not reflect any other type of nonmarket or market damages from wildfires, nor are the carbon feedback effects from wildfires (see e.g., Jerrett et al. 2022) accounted for in the climate module of our modeling framework.

The non-use value of biodiversity impacts also contributes to monetized U.S. economic damages from GHG emissions. For 2030 emissions, the U.S. impact-specific SC-CO_2 for this endpoint is similar in magnitude to coastal and energy use impacts represented in the DSCIM and GIVE damage modules, and on par with several other impact categories currently represented in FrEDI (Hartin et al. 2023, EPA 2024a). As discussed above, the results in Table 2 are a subset of the value of biodiversity-related ecosystem services. They do not reflect the value of any market and nonmarket use impacts of species loss (e.g., from hunting, commercial, and recreational activities). Analogous U.S. impact-specific SC-GHG results for 2030 emissions of CH_4 and N_2O are presented in Table A.4 in Appendix A.

Table 2: Evidence on U.S. climate damages from new impact-specific studies

Study	Impact represented	U.S. impact-specific SC-CO_2 *(2030 emissions, 2% near-term Ramsey discount rate, 2020$/mt$CO_2$)*
Qiu et al. (2024)	Mortality risk changes from climate-driven wildfire $PM_{2.5}$ exposure (CONUS only)	$15
Wingenroth et al. (2024)	Nonuse value from biodiversity loss	$1

Modeling conducted in a modified MimiGIVE framework: U.S. socioeconomic and emissions inputs taken from RFF-SPs (Rennert et al. 2022a); climate module temperature projections are based on FaIR 1.6.2 and account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks. Both use Ramsey-based discounting following Newell et al. (2022) updated to use U.S. growth with recalibrated ρ and η parameters. See Appendix B for details on each of these harmonized inputs.

The results presented in this section provide an overview of U.S.-specific damage estimates based on the categories of climate impacts currently represented in existing U.S. and global enumerative models. Importantly, not all climate impacts are currently incorporated in these models, and our inclusion of two additional impact-specific studies suggests that U.S-specific damages from omitted categories may be substantial. We expect that the results of other recent U.S. impact-specific studies (e.g., Bell et al. 2024, Yang et al. 2024, Fant et al. 2022, Barrage et al. 2023) could likewise soon be adapted for inclusion in an IAM modeling framework of the type used for SC-GHG estimation.

c. Evidence from macroeconomic econometric studies

In addition to the literature focused on estimating the impact of climate change on specific endpoints or sectors, another line of research has focused on econometrically estimating the effect of temperature and other climate variables on more aggregate measures of economic outcomes. These aggregate measures subsume many sectors without the need to fully enumerate them. Several studies in this strand of the academic literature can be used to provide projections of the effect of future climate change on U.S. macroeconomic outcomes. The most widely used measure is GDP, which is the total value of final goods and services produced in a country (without double counting the intermediate goods and services used to produce them). These methods are a reduced form approach to estimating the impact of changes in the climate on the combined set of market goods and services. That is, measured climate-driven changes in GDP are thought to reflect the value of net impacts on goods and services traded in markets (e.g., changes in agricultural crop yields or energy use) that have an associated market price. As noted earlier and discussed in greater detail in Section 4, aggregate measures of economic activity, such as GDP, are not measures of societal well-being and cannot be used to provide a comprehensive accounting of net damages to U.S. citizens and residents from GHG emissions. Nevertheless, GDP has been extensively studied as an indicator of the productivity of the economy as a whole, and thus, these macroeconomic econometric studies can help add to the understanding of the magnitude of net market-based climate damages.

In this section, we review a number of studies in this strand of the academic literature and synthesize the implications of their findings for projected end-of-century U.S. GDP losses from climate change and U.S. impact-specific SC-CO_2 estimates. We first discuss how the empirical methods used have evolved over time and summarize the different ways studies have addressed various econometric challenges in estimating a dynamic causal relationship between GDP and temperature or other climate variables. We then summarize the estimated dynamic effects and compare the response of U.S. GDP to a temporary temperature shock across the studies. Finally, we analyze the implications of each study for economic damages from climate change in the U.S. in a consistent modelling framework that allows for an apples-to-apples comparison across study results. Our review and analysis include studies using global panel data to estimate the effect of temperature and precipitation on economic growth and infer the economic impacts of climate change.[15]

[15] More specifically, we focus on studies in which the results can be converted into a damage function that can be combined with other components of our modeling framework (e.g., annual socioeconomic and mean temperature projections) to estimate U.S. GDP-based market damages from a pulse of GHG emissions in a given year. Incorporating the results of studies that investigate the economic growth impacts of changes in other aspects of the temperature distribution, or weather variables measured at finer geographic and/or temporal scales, would require additional extensions to our modeling framework. This includes, for example,

One important contribution of our analysis is an internally consistent comparison of the empirically estimated macroeconomic damage functions. While nearly all the papers we review use their estimates of the GDP-temperature relationship to develop projections of U.S. GDP impacts through 2100, our review found that there is considerable variation in the underlying temperature projections used in the papers, assumed socioeconomic and climate scenarios, and scope of their projections. Without a consistent framework to compare these studies, inferences comparing the magnitude of projected GDP losses across these papers can be misleading. For example, while the papers provide projections under similar climate change scenarios (including with an RCP8.5 radiative forcing scenario), we found that authors' temperature projections consistent with RCP8.5 are drawn from a variety of data sources, projections are made with different base years or measurements of baseline temperatures, or with different treatment of precipitation effects. The papers also use different aggregation methods and weighting schemes to recover country-level temperatures and have different assumptions on the shape of the path of warming. Thus, to synthesize and compare the implications of their findings under a consistent modeling framework, we develop a damage component based on each study's results and show the implications for both end-of-century projected damages to U.S. GDP from climate change and for U.S. impact-specific SC-CO_2 estimates under a harmonized set of U.S. socioeconomic and emissions inputs, climate modeling, and discounting methods used in Section 3a and 3b (Tables 1 and 2).

i. Overview of methods

While an association between temperature and GDP has been studied for some time (e.g., Gallup et al. 1999), the earliest empirical studies tended to use cross-sectional data that didn't control for other non-climate factors that may determine differences in incomes across countries. Beginning in the early 2010s, this literature looked toward identifying more plausibly causal relationships between climate and economic growth (i.e., growth in GDP) using panel data approaches. These methods allow researchers to study effects irrespective of time-invariant country-specific factors (e.g., topography, latitude) and country-invariant time-specific factors (e.g., global economic recessions). Researchers have also explored ways to address other empirical challenges, including assumptions about identification of climate effects from weather variation, functional forms of relationships between climate and economic outcomes, and serial correlation in historical temperature and other variables.

Two prominent early papers using global panel datasets that serve as a foundation for subsequent literature in this endeavor are Dell et al. (2012) and Burke et al. (2015). The source of identification in these studies comes from the measurement of fluctuations in annual mean temperature and precipitation, aggregated from gridded climate measurements to the country or region level, to study its effects irrespective of other factors. Arguing that IAMs should be informed by an empirically estimated GDP-temperature relationship, Dell et al. (2012) use a panel of 125 countries with at least 20 years of GDP data

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macroeconomic empirical studies that estimate the impact of temperature or precipitation on sectoral GDP (Conte et al. 2021), studies that use seasonal or daily temperature and precipitation data (Colacito et al. 2019, Deryugina and Hsiang 2014, Kotz et al. 2022), and those that include measures of annual temperature variability or extremes (Kotz et al. 2021, 2024, Schwarz and Pretis 2022, Waidelich et al. 2024). Similarly, we are unable to incorporate the results of papers investigating the effects of climate-driven changes in tropical cyclones and other natural hazards on economic growth (e.g., Hsiang and Jina 2014, Bakkensen and Barrage 2018) at this time. Finally, we have also not included studies using time-series methods that make it more challenging to control for time-varying confounders, including a recent study by Bilal and Känzig (2024) that estimates the economic effects of global temperature fluctuations and finds large statistically significant impacts on GDP.

and estimate economic growth in a given year as a linear function of population-weighted temperature and precipitation in that year and in previous years (i.e., lagged weather variables), controlling for country-specific effects and time trends. They find a one-time 1°C increase in temperature to have statistically significant negative impacts for poor countries (i.e., reducing economic growth in that year by about 1.3 percentage points), but imprecise smaller impacts for rich countries.[16] By including multiple lags of temperature (called a distributed lag (DL) model), the authors are able to examine whether these growth impacts persist over time. They find evidence of temperature changes affecting economic growth for at least 10 years.

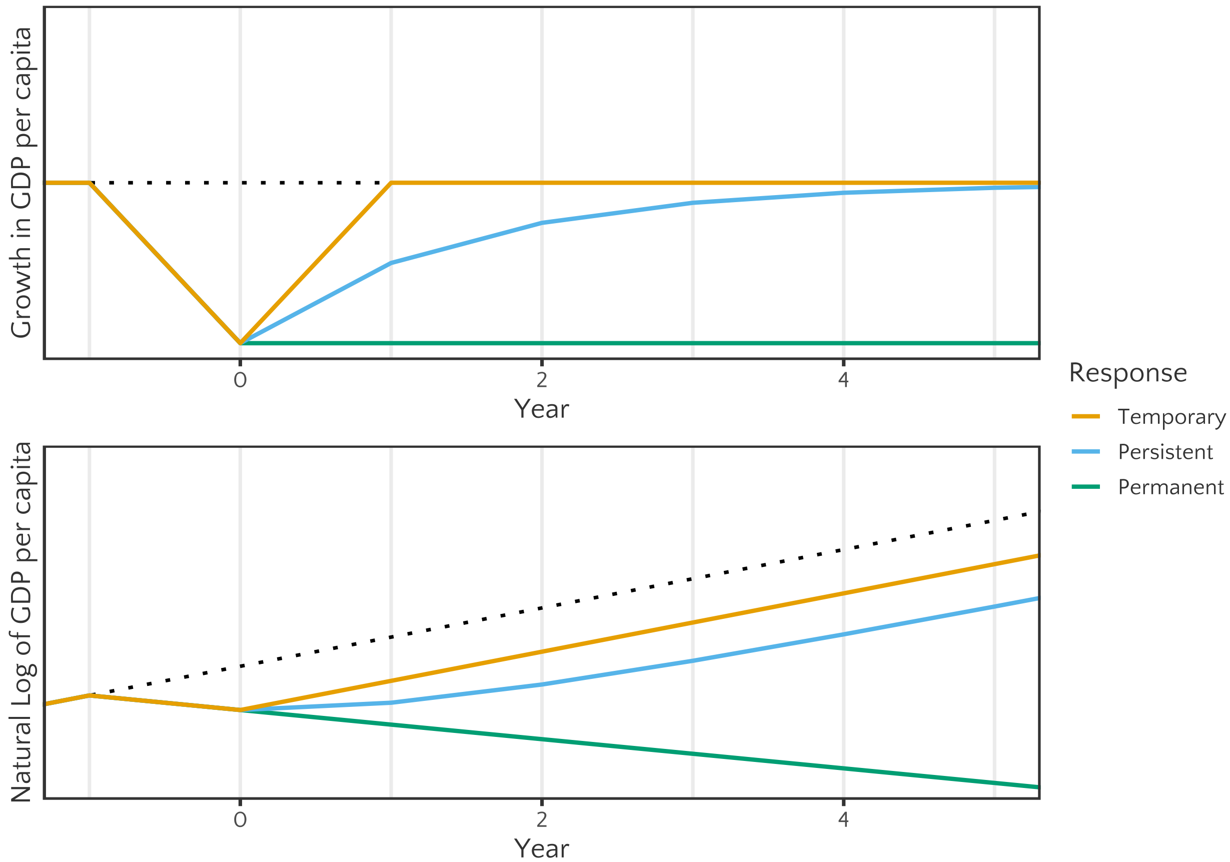
Burke et al. (2015) extend this framework by considering a nonlinear relationship between a country's economic growth and temperature. Using panel data from 166 countries over the period 1960–2010, they estimate economic growth as a quadratic function of temperature and find a statistically significant inverted U-shaped relationship with GDP peaking at approximately 13.1°C, with the response in rich countries not statistically different from that in poor countries. They find suggestive, but statistically ambiguous, evidence for permanent growth effects. Finally, Burke et al. (2015) develop a climate projection approach that applies their econometric results to estimate future GDP losses from climate change under a key assumption: that the long-run impact of changes in climate will be the same as the effect of short-run impacts from changes in weather. The resulting damages are estimated to be large globally, and substantial even for many high-income countries.

Following the early findings of Dell et al. (2012) and Burke et al. (2015), researchers began employing various empirical methods to further investigate the extent to which temperature changes have temporary, persistent, or permanent effects on economic growth. Understanding these dynamics has emerged as a key focus in this literature due to the important implications for estimating future damages from climate change. Figure 2 illustrates what an impact on GDP growth implies for the impact on the level of GDP, and vice versa. If a permanent change in temperature leads to a reduction in economic growth in the initial year of the change only (i.e., a temporary growth effect), it will still lead to a permanent change in the level of GDP, but that level effect will remain constant over time, holding all else equal. However, if a permanent change in temperature causes a permanent impact on GDP growth, then the impacts on the level of GDP continues to increase over time, leading to an indefinitely widening divergence between the level of GDP under a climate shock and the level of GDP without climate change. An impact on the growth rate of GDP with some persistence but eventual convergence back to the original growth rate represents an intermediate case.[17]

[16] In Dell et al. (2012), a country is categorized as "poor" if it has below median purchasing power parity-adjusted GDP per capita in the initial year of the data.

[17] The temporary and permanent responses illustrated in Figure 2 are often called "levels" and "growth" effects, respectively, in macroeconomic econometric studies of the relationship between temperature and GDP. However, there is inconsistency in terminology used across the literature.

Figure 2: Conceptual plot of the response of gross domestic product (GDP) to a permanent temperature increase



Source: Adapted from Nath et al. (2024).

Some studies have focused on examining the robustness of the Burke et al. (2015) results. For example, Newell et al. (2021) conducts a large cross-validation exercise in which they explore model uncertainty and estimate 800 plausible specifications of the relationship between temperature and GDP growth and test the out-of-sample performance of the models. They find that models estimating a relationship between temperature and economic growth exhibit significant model uncertainty leading to a wide range of forecasted climate impacts by the end of the century. In their conclusion, they argue that their results do not support a statistically significant marginal effect of temperature on global GDP growth. The authors emphasize that specifications estimating a relationship between temperature and GDP levels (i.e., a temporary effect on GDP growth) generally find a more robust and much narrower range of GDP losses by the end of the century.

Kalkuhl and Wenz (2020) also found evidence in support of temperature fluctuations only affecting the level of economic output using different sources of data. They measure economic activity using data from a variety of sources with increased resolution and detail of subnational regions, referred to as Gross Regional Product (GRP), for more than 1500 regions in 77 countries including U.S. states. In their preferred specification, a one-year distributed lag (DL) model, the authors find a strong nonlinear relationship between area-weighted annual temperature and GRP, but do not find the level of temperature to affect economic growth when the annual change in temperature is also included in the model. They interpret these findings to be consistent with permanent changes in temperature affecting the level of GDP but not the long-run growth rate of the economy. Aside from differences in the underlying data used, their projected damages are larger than those of Newell et al. (2021) in part because their results imply a lower optimal temperature, above which climate damages accrue.

Several recent papers have further advanced the examination of the extent of GDP effects using more flexible empirical methods and/or different measures of temperature variation that can better address common econometric challenges that arise in the analysis of temperature-GDP relationships. For example, Acevedo et al. (2020) use data from over 180 economies from 1950 – 2015 to examine the effects of weather on a large set of outcome variables, using more flexible empirical specifications than the distributed lag (DL) models used in earlier studies. In particular, the authors use the local projections (LP) method (Jordà 2005) to trace the impulse response function of GDP per capita to a change in population-weighted temperature and precipitation. The LP method is more flexible than a DL model because it imposes fewer restrictions on the dynamic process by directly estimating the cumulative impact of a current shock in each future horizon period.[18] In their main specification, Acevedo et al. (2020) estimate both the contemporaneous and medium term (7-year) change in per capita GDP as a quadratic function of temperature and precipitation, controlling for a one-year lag of the dependent and weather variables, and country and time fixed effects. The inclusion of the lagged variables importantly helps to address serial correlation in temperature and GDP growth over time that could lead to biased estimates. They find statistically significant negative effects of temperature on per capita output and that these effects continue for at least 7 years. However, they do not interpret these findings as evidence of permanent growth effects because they are statistically unable to reject that the contemporaneous and medium-term effects on output are identical. Using the same methodology, Acevedo et al. (2020) also estimate the impact of temperature on channels of impacts and find the largest impacts on crop production and the agricultural sector. They also find impacts on manufacturing but find no impacts on the services sector. The paper also estimates the impact of temperature increases on some of the basic determinants of GDP. The authors find that temperature reduces labor productivity in heat exposed industries but find no impact on labor productivity in non-heat exposed industries. Temperature also appears to have persistent impacts on investment. Acevedo et al. (2020) further find that temperature increases led to persistent increases in infant mortality and decreases in the Human Development Index. The authors apply their estimated coefficients to produce an illustrative, subnational mapping of conservative projected climate impacts on real per capita output by the end of the century, which suggests modest negative impacts in the United States on average.

Kahn et al. (2021) use a panel autoregressive distributed lag (ARDL) model[19] (with four lags). They attempt to address the econometric challenges with trended variables by focusing on a country's deviation in temperature relative to a moving historical average, rather than levels or squares of temperature. The authors argue that this measure allows for a more explicit modeling of changes in the distribution of

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[18] By estimating a collection of projections local to each forecast horizon, the authors can interpret the estimated effects in the 0-horizon regression as the contemporaneous impact and the estimated effects in subsequent regressions as reflecting the impact h years after the shock. The LP method produces less biased (but higher variance) forecasts at intermediate and long horizons than vector autoregression methods because it does not constrain the shape of the impulse response functions and is thus less sensitive to misspecification (Li et al. 2024).

[19] An ARDL model is a type of a DL model frequently used in analysis of macroeconomic data that includes lags of the dependent variable (autoregressive) and lags of an explanatory variable (distributed lag).

weather patterns and an implicit model of adaptation. The length of time over which their moving average is calculated is the assumed amount of time economies need to adapt to changes in climate, and thus the authors view the GDP impacts of the deviation from this moving average as the relevant temperature shock after accounting for adaptation. Under their preferred specification their results suggest a 1°C annual increase in the temperature above its 30-yr historical norm reduces a country's long-term real GDP per capita growth by 5.43 percent per year. The authors derive climate projections that incorporate the full long-run implications of their ARDL estimates under parametric assumptions on the distribution of future deviations of temperature from its historical norm.

Casey et al. (2023) further advance the examination of the extent of GDP growth effects by appealing to macroeconomic growth theory and exploring the mechanisms through which climate impacts on GDP growth could occur. The authors focus on the effect of climate variables on total factor productivity (TFP) as a way to help distinguish between temporary and persistent impacts of climate change on economic output. More precisely, they argue that even a one-time effect of a change in temperature on the level of GDP is likely to manifest over several time periods due to an endogenous capital response, while climate change effects on TFP ought to be more easily distinguishable as temporary or persistent. Under certain assumptions, growth theory implies that temporary effects on TFP lead to persistent but relatively short-lived effects on GDP, while persistent effects on TFP lead to longer-term growth impacts on GDP (since TFP is the key driver of the long-run growth rate of output). Guided by this reasoning, the paper empirically investigates how temperature shocks affect TFP. In regressions allowing for potential impacts both on the level and growth rate of TFP, they find temperature has a persistent effect on the level of TFP, but not its rate of growth. This result implies that a change in temperature's impact on GDP growth may still persist for several years (through temperature impacts on TFP and TFP's impact on investment and capital accumulation) but will not lead to permanent long-run growth impacts. Model-based climate change impacts on economic output are derived from reduced-form projections of country-level TFP using their empirically estimated coefficients.

Harding et al. (2024) use a reduced-form approach to align their empirical analysis more closely with theoretical models and methods used in the broader empirical macroeconomic growth literature by accounting for growth convergence when estimating the relationship between temperature and country-level economic growth. Similar to Casey et al. (2023), they argue that under neoclassical macroeconomic growth theory, the only way for climate change to have permanent effects on economic growth is if it permanently affects the determinants of long-run economic growth, such as the rate of innovation. By contrast, non-permanent climate-induced changes in productivity can only have a temporary effect on economic output because the economy will eventually converge back to the steady-state long-run growth rate. They empirically estimate this speed of convergence by regressing GDP growth on one lag of GDP in addition to the weather variables, including the same controls for time trends and country fixed effects as in Burke et al. (2015) and Newell et al. (2021). In their central specification, the authors find significant support for short-run effects on economic growth, but no statistically significant evidence of permanent long-term growth impacts. The authors emphasize that while including the convergence term has little impact on the estimated effects of weather variables on GDP growth, accounting for the convergence effect is important when projecting long-run damages from climate change; otherwise, any estimated effects of climate on growth, by construction, will be permanent.

Nath et al. (2024) also take models of economic growth as a starting point and argue that temperature can have persistent but not permanent growth effects because fundamental drivers of growth, specifically technological change, link countries' growth rates together. They present a range of evidence to support that international technology spillovers prevent countries from differing entirely in growth as global temperatures change. They then use 1960-2019 data from a panel of countries to empirically estimate the dynamic effects of temperature on GDP. Like other recent macroeconomic econometric papers discussed above, Nath et al. (2024) control for lagged GDP growth, but they also address econometric difficulties in estimating a dynamic causal relationship between GDP and temperature in additional ways. First, they emphasize that because temperature itself is serially correlated, it is important to include lags of both temperature and GDP to recover an unbiased coefficient on contemporaneous temperature. Second, they examine the impact of a temperature shock[20], rather than temperature itself, and explore an alternative specification to capture nonlinearities in the way that the temperature shock affects GDP, relative to the quadratic terms typical in many previous studies. Finding that a state-dependent model outperforms a quadratic function of temperature variables, in their main specification Nath et al. (2024) interact the temperature shock variable with mean temperature to investigate whether a shock to temperature has different effects on GDP depending on the country's mean historical temperature. Finally, the authors estimate a flexible impulse response function of GDP to temperature shocks using the LP approach, similar to Acevedo et al. (2020), while putting additional emphasis on the importance of accounting for the persistence in temperature when using their empirical results to project the effects of future increases in temperature on GDP. For instance, for a moderate temperature country (15 degrees Celsius) like the United States, the paper finds persistent effects of temperature shocks on GDP. The persistence in the effect of temperature shocks on GDP is partly driven by persistence in temperature (see Figure 6b in Nath et al. 2024). For example, for such a moderate temperature country, Nath et al. (2024) find 9 percent of a temperature shock persists 9 years later. Nath et al. (2024) account for this persistence in temperature by using a cumulative response ratio of GDP to temperature, defined as the ratio of the cumulative response of GDP to the cumulative response of temperature to a temperature shock, which accounts for the dynamic impact of the initial shock and the continuing impacts driven by its persistence.

Table 3 presents a summary of the empirical methods used in the main specification of the econometric papers discussed above. While each of these papers provides results of many alternative specifications and robustness checks, Table 3 focuses on the authors' stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. As discussed above, the main specification of the first four papers in the table (Dell et al. 2012, Burke et al. 2015, Kalkuhl and Wenz 2020, Newell et al. 2021) use a distributed lag (DL) model in which the growth rate of economic output is regressed on temperature and precipitation variables as well as several lags of these variables. The remaining studies in the table employ more flexible empirical methods (such as LP or ARDL models) to estimate the dynamic effects over time and include lags of the dependent variable (or GDP in the case of Harding et al. (2024)) as explanatory or control variables in the analysis. The papers also vary in their weather variables (temperature and precipitation) and in the functional form estimated for the economic growth-weather relationship. Most of the papers use the annual average temperature in each country, or the change in annual temperature from the previous year, whereas two papers, Kahn et al. (2021) and Nath et al. (2024), develop various measures of temperature

[20] Nath et al. (2024) define the shock to temperature as the innovation in a nonlinear autoregressive model of country temperature, a common practice in analysis of macroeconomic data which isolates current shocks from their relationship to past shocks in the presence of serial correlation. Specifically, they construct the temperature shock as the residual from a regression of temperature on lagged values of temperature and lagged temperature interacted with mean temperature.

deviations or shocks as the explanatory variable to better identify causal effects. Dell et al. (2012) and Kahn et al. (2021) consider a linear relationship between their temperature variables and GDP growth. Burke et al. (2015) and many of the papers that followed employ a quadratic specification, while Kalkuhl and Wenz (2020) and Nath et al. (2024) examine other forms of non-linearities through the use of interaction terms of weather variables to account for state dependence.

The last column of Table 3 qualitatively classifies what each paper projects about the impact of temperature on U.S. GDP growth. As expected, the papers employing distributed lag models to estimate long-run impacts project either permanent or temporary impacts on GDP growth. By contrast, the papers using more flexible estimation approaches and incorporating lagged dependent variables project some amount of persistence in the impact on GDP growth. This is further illustrated in Figure 3 which traces out the estimated U.S. GDP-temperature response function over time based on the econometric results of the main specification of each paper discussed above, evaluated at a projected U.S. average temperature for 2100 (16.3°C).[21] Specifically, the figure displays the GDP response to a temporary 1°C shock (increase in temperature) which is reversed in the following year. The Figure shows how the temperature shock affects GDP contemporaneously and each year following the shock. For papers using distributed lags methods and the temperature level (Dell et al. 2012, Burke et al. 2015), the cumulative GDP response is the sum of the marginal effects of the lags of temperature, up to the longest lag.[22] For papers using distributed lags methods and temperature change (Newell et al. 2021, Kalkuhl and Wenz 2020), the cumulative GDP response is simply equal to the marginal effects of the lags.[23] For the papers using local projections methods (Acevedo et al. 2020, Nath et al. 2024), the GDP response is the marginal effects of the lag of the temperature variables for each regression. For papers using autoregressive distributed lags or growth convergence methods, the cumulative GDP response is the sum of the marginal effects estimated using the dynamic multipliers (temperature level in Harding et al. (2024) and the change in temperature in Kahn et al. (2021)), computed by using the ARDL or growth convergence coefficients and repeated substitution of the lags of GDP (Harding et al. 2024) or GDP growth (Kahn et al. 2021). The response functions displayed in Figure 3 do not reflect how Nath et al. (2024) account for the serial correlation in temperature and its impact on projections over time, or how the temperature variable specification (assumed to reflect adaptation) in Khan et al. (2021) dampens the impacts of a permanent temperature shock over time.

[21] This 2100 U.S. temperature projection is consistent with the U.S. temperature projections presented in Figure C.2 and described in Appendix B. That is, it is based on the average of 10,000 Monte Carlo simulations of FaIR 1.6.2 (inclusive of two additional carbon feedbacks based on Dietz et al. (2021)) using the RFF-SP emission projections as inputs and FaIR 1.6.2 uncertainty to recover the increase of 2.67°C in U.S. temperature relative to 1980-2010 average and a 1980-2010 baseline U.S. temperature level of 13.62°C (Burke et al. 2015).

[22] The percentage change in the GDP response from the year before the shock to the year of the response is the sum of the response of GDP growth from the year of the shock to the year of the response. $\ln(GDP_h) - \ln(GDP_{-1}) = \sum_{j=0}^{h} \ln(GDP_j) - \ln(GDP_{j-1})$

[23] Papers that estimate the marginal effect of the change in temperature on the change in the natural log of GDP are estimating a first-differenced equation of the marginal effect of temperature on the natural log of GDP. Therefore, the parameters can be directly used to estimate the response of GDP.

Table 3: Summary of methods in recent macroeconomic econometric studies

Study (Empirical Specification)	Econometric Model[b]	Data	Weather Variables	Weather Variables Specification	Lags Included	Projected Temperature Impact on GDP Growth
Dell et al. (2012) (Table 3, col 4)	DL (10 lags)	Country	Level	Linear	Weather	N/A
Burke et al. (2015) (Ext. Data Table 1, col 1. ("base"/"main"))	DL (0 lags)	Country	Level	Non-linear (quadratic)	None	Permanent
Kalkuhl & Wenz (2020) (Table 4, col 5 ("preferred"))	DL (1 lag)	Subnational	Level, first difference	Non-linear (level & difference interactions)	Weather	Temporary
Newell et al. (2021) (Levels version of Burke et al.[c])	DL (0 lags)	Country	First difference	Non-linear (quadratic)	None	Temporary
Acevedo et al. (2020) (Table 1, col 5 ("baseline"/ "main"))	LP (0 horizons)	Country	Level	Non-linear (quadratic)	Weather, GDP growth	Temporary
Kahn et al. (2021) (Table 2, Spec 2, m=30(b) ("preferred"))	ARDL (4 lags)	Country	Absolute deviation from historical moving average	Linear	Weather, GDP growth	Persistent
Casey et al. (2023) (Table 1, col 2)	AR (1 lag) of TFP growth	Country	First difference	Non-linear (quadratic)	TFP growth	Persistent
Harding et al. (2024) (Table 1, col 5 "central"))	Convergence equation[d]	Country	Level	Non-linear (quadratic)	Natural Log of GDP	Persistent
Nath et al. (2024) (Full dynamics with FE (Figure 6c))	LP (9 horizons)	Country	Shock[e] and historical mean	Non-linear (shock and mean interactions)	Weather, weather interacted with their mean, GDP growth	Persistent

This table summarizes each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated.

[b] *DL – Distributed Lags, AR – Auto-regressive, LP – Local Projection*

[c] *Levels only specification analogous to main Burke et al. (2015) specification; See Table 2, GDP Level effect estimation with year fixed effects and 2-degree time trend, in Newell et al. (2021).*

[d] *The convergence equation (Acemoglu 2009) is similar to an AR model but controls for lagged GDP rather than lagged GDP growth.*

[e] *The temperature shock variable is the residual in an equation of temperature as a function of lags of temperature and lagged temperature interacted with mean temperature.*

Figure 3: Response of U.S. gross domestic product (GDP) to a temporary 1°C temperature increase at U.S. average temperature in 2100 (16.3°C).

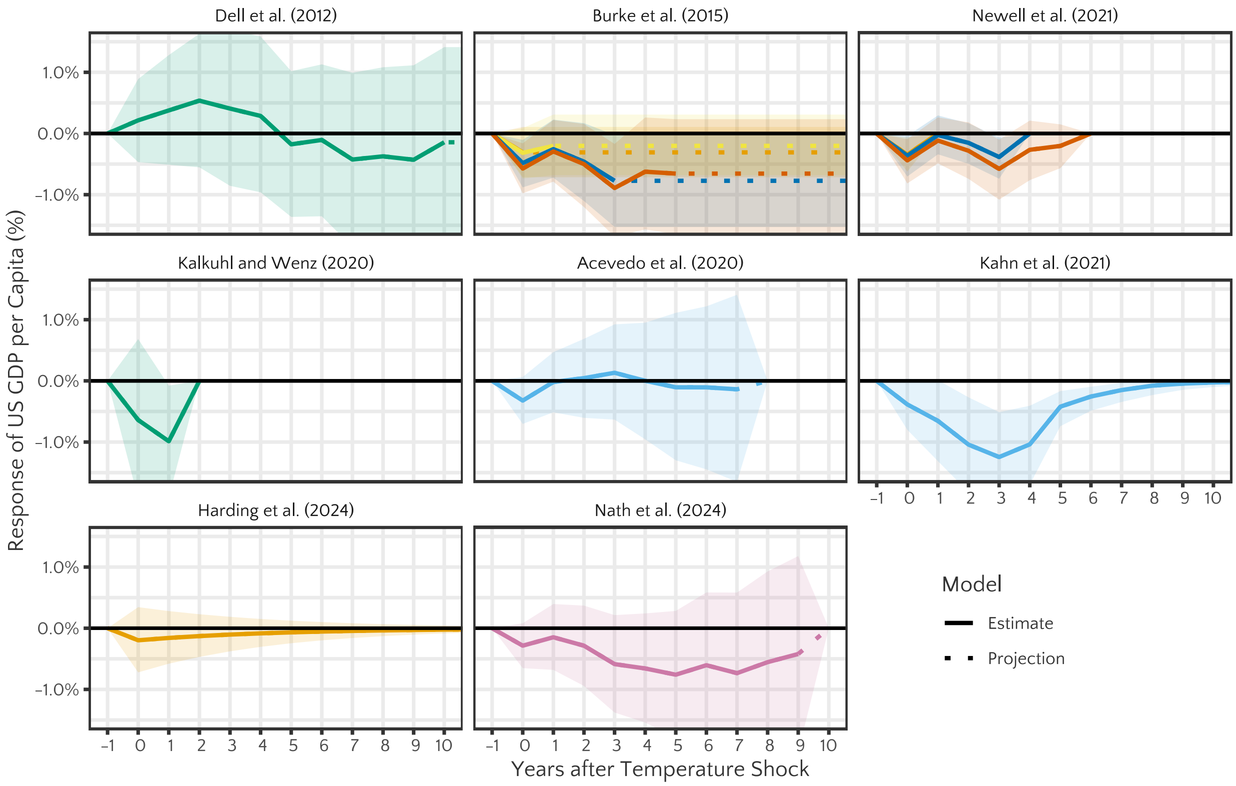


Figure shows the impulse response from the main specification for each paper (as described in Table 3) as well as some additional lags and horizons explored in the case of Burke et al. (2015), Newell et al. (2021), and Acevedo et al. (2020). The dotted line shows the implicit assumption about the response beyond the estimate lags or horizons based on the projections in the papers. The shaded ribbon represents the econometric uncertainty (95% confidence interval) from the corresponding specification in the paper.

ii. Projected U.S. climate damages based on recent macroeconomic econometric studies

While each of the macroeconomic econometric papers discussed above, except Dell et al. (2012),[24] present some projections of climate damages based on their estimated GDP-temperature relationships, the studies vary in the underlying temperature data used, assumed socioeconomic and climate scenarios, and scope of their projections. For example, most studies apply some form of population weighting to their temperature data using a single year of gridded population data and different baseline years, while Kalkuhl and Wenz (2020) apply area weighting at the U.S. state level (or subregion). Similarly, the authors differ in the ways they select the baseline temperature from which to develop their temperature projections under

[24] While Dell et al. (2012) developed an early framework for examining the relationship between changes temperature and precipitation and changes in a country's economic performance, they do not carry their framework through to project future damages, stating: "Given uncertainty over adaptation, international spillovers, technical change, and other issues, the estimates here—driven primarily from short-run fluctuations in temperature—alone cannot provide precise predictions about the estimated impacts of future climate change." Therefore, we also do not extend their framework into a damage function.

various climate change scenarios going forward. Several papers follow the approach of Burke et al. (2015) and use the mean country-level temperature observed over 1980-2010, while others use temperature from a single recent year as a starting point (2005, 2014, and 2010 in case of Acevedo et al. (2020), Kahn et al. (2021) and Casey et al. (2023), respectively), or the mean temperature over a shorter, more recent time period (2015-2019) in the case of Kalkuhl and Wenz (2020). Moreover, when projecting future climate impacts, even under the same emissions scenario, the papers use a variety of emissions-consistent temperature projections based on different global climate models. These and other differences in data inputs (see Table E.1 in Appendix E for a complete listing) make an apples-to-apples comparison difficult based on the projections presented in each paper (or based on the U.S.-specific results obtained from each paper's replication code). To synthesize and compare the results under a consistent modeling framework, we develop a damage component based on each study's results and show what it implies for U.S. impact-specific SC-CO_2 estimates under the same harmonized U.S. socioeconomic and emissions inputs, climate modeling, and discounting methods used in Tables 1 and 2 above. For each paper, the damage function was constructed to be consistent with the econometric results of the main specification and implemented according to the projection approach used in the paper.[25]

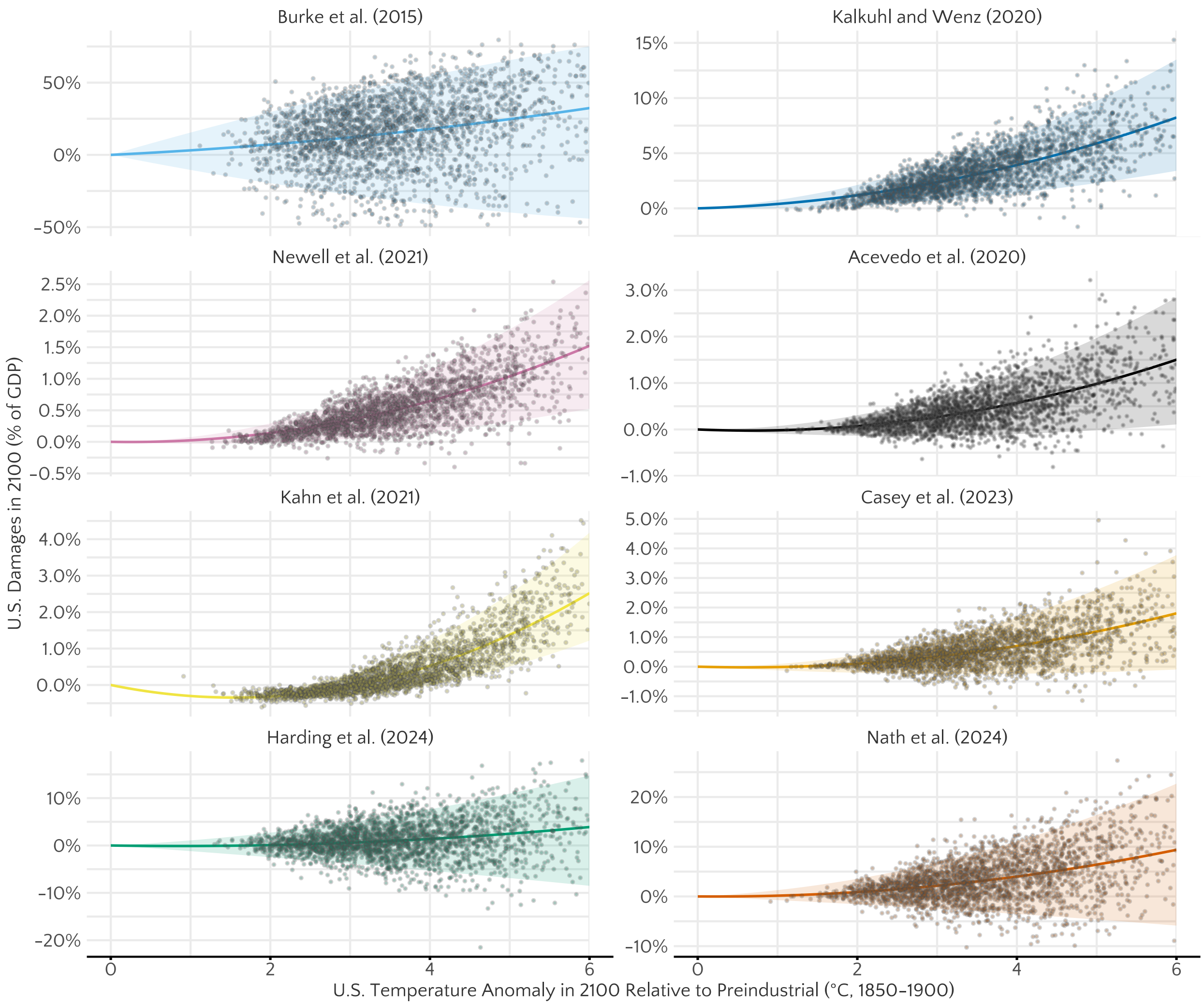
Figure 4 illustrates the shape of the resulting reduced-form damage function for each paper based on projections of U.S. GDP losses from climate change in 2100 as a function of U.S. temperature change. The points represent a random subset of the Monte Carlo simulation (2,500 of the 10,000 simulations) with consistent draws of U.S. RFF-SP socioeconomic projections and FaIR1.6.2 climate module parameters across all papers. The U.S.-specific damage functions shown here are generated using estimated GDP losses in 2100 (the points), and regressing GDP on temperature and temperature squared in 2100 at the mean (solid line), and quantile regressions at the 5th and 95th percentiles (shaded ribbons). Figure A.1 in Appendix A presents the solid lines from Figure 4 in a single figure to allow for an easier comparison across studies.

Figure 4 shows notable differences between the damage functions in their implied climate damages as a fraction of U.S. GDP in 2100. The only paper with explicit assumptions about adaptation, Kahn et al. (2021), assumes full adaptation after 30 years to climate change and has the lowest average damages to U.S. GDP in 2100 of 0.4 percent. The papers finding only contemporaneous effects of temperature on the level of GDP, Newell et al. (2021) and Acevedo et al. (2020), also have lower average damages of 0.5 percent in 2100. Casey et al. (2023) find some persistence in the impact of temperature on U.S. TFP (19 percent carry-over), and results from this damage component show slightly higher average annual damages in 2100 of 0.6 percent due to their modeling of the persistence of investment, capital, and output reductions following temperature changes. The damage component from Harding et al. (2024), who find higher level of persistence (81 percent carry-over) of temperature on U.S. GDP, shows larger average damages of 1.1 percent in 2100. Even with this high level of carry-over, the structural restrictions of this approach imply that the contemporaneous effect dissipates. When a more flexible damage function is estimated using local projections as in Nath et al. (2024), we find damages increase to 3.3 percent in 2100. This is the result of increasing damages in the short term and continued persistence in the medium term. Our estimates

[25] To validate that the damage component provides an accurate representation of each paper's findings, we confirmed that the U.S. damage projections based on our constructed damage function under an SSP5/RCP8.5 scenario through 2100 approximated the results from the U.S. damage projections in the replication code for the paper. While this SSP/RCP scenario is not used in the estimates we present in the main text, it is one that is generally available for each paper and assures consistency of the damage component with the paper results. See Appendix E for a detailed description and results of this multi-step validation exercise.

using the Kalkuhl and Wenz (2020) damage component are also higher and equal 3.5 percent in 2100. This paper finds much higher contemporaneous damages to U.S. GDP owing to the much lower global optimal temperature than other papers of 5.4°C, compared to 13.0°C in Nath et al. (2024), 13.2°C in Harding et al. (2024), and 13°C in Acevedo et al. (2021). We estimate the highest damages in 2100 of 15.3 percent for the Burke et al. (2015) damage component, which projects permanent growth effects of temperature.

Figure 4: Climate damages as a fraction of U.S. GDP in 2100 due to a change in annual global mean surface temperature under each of the 8 macroeconomic econometric damage functions



GDP loss functions are generated using estimated damages in 2100 (points) and regressing on temperature and temperature squared at the mean (solid line) and quantile regressions at the 5th and 95th percentiles (shaded ribbons). 2,500 of the 10,000 points for each module are randomly selected to simplify the presentation of damages. The IPCC (2021a) notes that present day global mean surface temperatures in the year 2020 are around 1.1°C above preindustrial (1850-1900) levels. Estimated damages in 2100 shown in this figure are based on each study's stated "preferred", "main", or "central" empirical specification of the temperature-GDP relationship and/or the method used to project climate damages. Each damage function requires a measure of current climate or baseline temperature; in all panels in this figure we use country-level population-weighted mean temperatures from 1980 to 2010 drawn from Burke et al. (2015) for this purpose. See Appendix E and Figure E.2 for more details.

Table 4 presents the resulting U.S. impact-specific SC-CO_2 estimates for 2030 emissions when we combine the constructed GDP damage component based on each paper's main specification with the same U.S.-

specific socioeconomic and emissions inputs, climate modeling, and discounting methods used in Sections 3a and 3b. Analogous U.S. impact-specific SC-GHG results for 2030 emissions of CH_4 and N_2O are presented in Table A.4 in Appendix A. As expected, the early studies that project permanent GDP growth effects from an increase in temperature (Burke et al. 2015) result in SC-CO_2 estimates that are more than an order of magnitude larger than those projecting only temporary or some intermediate persistence in the impacts on GDP growth. Among the studies projecting some persistence in U.S. GDP growth effects, the implied U.S. impact-specific SC-CO_2 for 2030 emissions ranges from $10 to $64 per metric ton CO_2 (under a 2 percent near-term Ramsey discounting rate). For this class of papers, one of the more recent studies that incorporates many recent advancements in the relevant literature, Nath et al. (2024), is at the high end of the range of estimates. More broadly, even the lower end of the range of estimates in Table 4 exceed the market damages based on the enumerative models using GIVE, DSCIM, and FrEDI presented in Table 1 (e.g., in FrEDI, market damages comprise approximately $7 of the $36/mt$CO_2$ in 2030). This finding further suggests that market-based damages are not fully represented in existing enumerative models.

Table 4: Evidence on U.S. climate damages from recent macroeconomic econometric studies

Study[b]	Impact represented	U.S. impact-specific SC-CO_2 *(2030 emissions, 2% near-term Ramsey discount rate, 2020$/mt$CO_2$)*
Burke et al. (2015)	Permanent U.S. GDP growth effects	$996
Kalkuhl and Wenz (2020)	Temporary U.S. GDP growth effects	$55
Newell et al. (2021)	Temporary U.S. GDP growth effects	$10
Acevedo et al. (2020)	Temporary U.S. GDP growth effects	$10
Kahn et al. (2021)	Persistent U.S. GDP growth effects	$10
Casey et al. (2023)	Persistent U.S. GDP growth effects	$14
Harding et al. (2024)	Persistent U.S. GDP growth effects	$27
Nath et al. (2024)	Persistent U.S. GDP growth effects	$64

Modeling was conducted in a modified MimiGIVE framework: U.S. socioeconomic and emissions inputs are taken from RFF-SPs (Rennert et al. 2022a); climate module temperature projections are based on FaIR 1.6.2, accounting for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks, and GMST projections are downscaled using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets); future damages are discounted using Ramsey-based discounting following Newell et al. (2022) updated to use U.S. growth rates and recalibrated ρ and η parameters. See Appendix B and C for details on each of these inputs. Due to sampling variation in the random draws of a Monte Carlo simulation, values presented in this table are rounded to the nearest dollar.

[b] Results shown in this table are based on each study's stated "preferred", "main", or "central" empirical specification of the temperature-GDP relationship and/or the method used to project climate damages. See Appendix E for more details.

A few common themes emerge from our analysis of these macroeconomic empirical studies. First, the impacts of temperature on GDP are likely to be nonlinear - this implies that temperature changes cause greater damages in hotter countries and greater damages as countries get hotter. Second, temperature shocks appear to have a persistent impact on a country's GDP. Empirical methods that allow for persistence are useful in tracing out the dynamic response of GDP to changes in temperature (Acevedo et al. 2020, Kahn et al. 2021, Casey et al. 2023, Harding et al. 2024, Nath et al. 2024). One potential mechanism for this persistence is through impacts on capital investment (Casey et al. 2023). Third, temperature shocks are themselves persistent, which partially explains the persistence of temperature's effect on GDP (Acevedo et al. 2020, Nath et al. 2024). Not accounting for the persistence of temperature can overestimate the dynamic impact of changes in current temperature on GDP. Recent literature has attempted to control for these using the lag of temperature as a control (Acevedo et al. 2020, Nath et al. 2024) and/or by filtering out the serial correlation of temperature to produce innovations to temperature (Nath et al. 2024). Despite controls that reduce temperature persistence, some level of persistence still appears present with these controls – additional care is necessary to account for temperature persistence and fully identify the persistence of GDP to temperature changes (Nath et al. 2024). Below, we carry forward the subset of macroeconomic econometric studies that try to address these issues in their empirical strategies.

4 Combining different lines of evidence

Section 3 presented a range of U.S. impact-specific climate damage estimates based on recent literature. In this section, we discuss considerations for the possibility of combining or comparing across these different lines of evidence. This includes the primary issue of overlap, or double counting of damages, as well as considerations of what different damage function estimation approaches are able to capture and communicate (e.g., with respect to adaptation and impacts from temperature variations unobserved in the historical record).

On the issue of double counting, as the enumerated damage models (discussed in Section 3a) continue to be developed and new impact categories are added, care must be taken to avoid double counting of impacts. With respect to the emerging research presented in Section 3b, there is no concern that the Wingenroth et al. (2024) based biodiversity loss damages overlap with other damages currently represented in GIVE, DSCIM, or FrEDI. Similarly, it is reasonable to assume there is little overlap between the estimated wildfire $PM_{2.5}$-related mortality impacts based on Qiu et al. (2024) and the heat- and cold-related mortality impacts represented in the three existing enumerative models. Importantly, Qiu et al. (2024) include temperature control variables in their empirical estimation of the effects of wildfire-specific $PM_{2.5}$ on all-cause mortality rates to ensure that they are not picking up confounding effects of temperature itself on mortality rates.[26]

Table 5 illustrates that adding the new wildfire and biodiversity loss damage functions to the GIVE damage module increases the U.S.-specific SC-CO_2 estimate to $40 per metric ton CO_2 for 2030 emissions (under a 2 percent near-term Ramsey discount rate). Analogous U.S.-specific SC-GHG results for 2030 emissions of CH_4 and N_2O are presented in Table A.5 in Appendix A. We have not yet been able to similarly amend and

[26] While the controls included in Qiu et al. (2024) isolate their mortality estimates from temperature-related confounders, it is possible that some of the studies underlying Cromar et al. (2022) could be partially capturing wildfire $PM_{2.5}$ related deaths. However, given that the U.S. studies included in the Cromar et al. (2022) meta-analysis use data primarily from less wildfire prone regions of the country, we expect that any contribution of wildfire $PM_{2.5}$ related deaths to the Cromar et al. (2022) temperature-related mortality estimates would likely be small.

re-estimate DSCIM and FrEDI with additional damage categories, but we expect the incremental impact on the U.S.-specific SC-CO_2, θ_D and θ_F, respectively, would be of similar magnitude as in GIVE.[27]

Table 5: Combined evidence on U.S. climate damages from existing enumerative models and new impact-specific studies

Enumerative models	U.S.-specific SC-CO_2 *(2030 emissions, 2% near-term Ramsey discount rate, 2020\$/mtCO_2)* Damage categories represented in existing models	Wildfire and biodiversity damages from new impact specific studies	Total
GIVE[a]	\$24	\$16	\$40
DSCIM	\$21	θ_D [b]	\$21+θ_D
FrEDI	\$36	θ_F [b]	\$36+θ_F

Discounting module uses U.S. growth with recalibrated ρ and η parameters. Climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks.
[a] To calculate the temperature-related mortality damages (based on Cromar et al. (2022)), GMST projections from FaIR are downscaled to U.S. temperature using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets).
[b] θ_D and θ_F represent the incremental impact on the U.S.-specific SC-CO_2 from incorporating the new evidence on wildfire and biodiversity loss-related damages in DSCIM and FrEDI, respectively, which has not yet been possible due to resource constraints.
Due to sampling variation in the random draws of a Monte Carlo simulation, values presented in this table are rounded to the nearest dollar.

To consider how to compare or combine the U.S. impact-specific SC-CO_2 estimates from the enumerative models with those based on the macroeconomic studies discussed in Section 3c, it is important to recall what the macroeconomic studies are measuring. The U.S. impact-specific SC-CO_2 estimates derived from these studies account for the net effect of all categories of CO_2-related impacts that are reflected in U.S. GDP. As discussed in Sections 2 and 3, GDP measures the monetary value of all goods and services produced in a country and is not a measure of economic well-being. While many researchers view GDP as sufficiently correlated with welfare to use it as a reasonable proxy (Jones and Klenow 2016), there are several key areas in which output and welfare diverge and the macroeconomic econometric studies fail to capture important climate impacts.

First, natural disasters result in significant reductions in welfare through health impacts and dislocation, but expenditures made responding to and rebuilding following natural disasters may increase local economic output. Similarly, expenditures on adaptation to and mitigation of climate change (such as on coastal protection or air purification) may temporarily increase economic output but are unlikely to increase welfare as they require the reallocation of resources from other productive activities. In environmental accounting, this type of expenditure is known as defensive expenditure because it is not

[27] In contrast to DSCIM and GIVE, FrEDI currently accounts for mortality and morbidity (e.g., hospitalization costs) damages from exposure to wildfire smoke, as well as response costs from wildfire suppression. These damages are based on the work published by Neumann et al. (2021) which includes impacts from changes in wildfire activity in the western CONUS only. Therefore, some adjustments would be needed in FrEDI to incorporate the new Qiu et al. (2024) based wildfire related health damage function to avoid any potential overlap with some wildfire damages already represented in FrEDI. That said, the share of the FrEDI U.S. impact-specific SC-CO_2 attributable to wildfire is ~1%, such that the FrEDI estimate without wildfires is ~\$35 (when rounded). For a discussion on the aggregation of impacts within FrEDI, see Section 2.2 of the FrEDI Technical Documentation (EPA 2024a).

intended to improve welfare but instead to prevent decreases in well-being. Aggregate measures of economic activity, such as GDP, do not reveal compositional changes in output and do not distinguish between defensive expenditures and welfare-increasing output.

Second, while U.S.-specific SC-CO_2 estimates derived from macroeconomic econometric damage functions in theory capture all market damages (inclusive of interaction effects) that affect U.S. GDP, they are only inclusive of market damages that have occurred in the historical record, and only those damages associated with the annual averages of climate variables at the geographic resolution used in the studies. Impacts of some changes such as expected large-scale SLR and Earth system feedback effects that have not been experienced in the historical record will not be reflected in the impulse response functions estimated in the econometric studies to date. Similarly, empirically estimated damage functions account for adaptation to the extent that this adaptation has occurred historically. Future projections of climate damages based on these studies implicitly assume that future adaptation to climate change occurs at the same rate that it has occurred historically.

Finally, U.S.-specific SC-CO_2 estimates derived from macroeconomic econometric damage functions only account for nonmarket damages to the extent that these damages have consequences for macroeconomic indicators. As discussed above, climate damages experienced through nonmarket pathways such as changes in net mortality rates, welfare resulting from household production or the value of time spent outside work, and changes in ecosystem services (including those provided by biodiversity) are notably absent from GDP calculations. As climate change progresses, these divergences between output and welfare are expected to increase as nonmarket damages increase and a higher percentage of spending is dedicated to adaptation and defensive expenditures instead of other productive investments. Some studies attempt to address this divergence by also estimating the effect of temperature on other outcomes such as political instability, the human development index, and infant mortality (Dell et al. 2012, Acevedo et al. 2020), but a complete econometric estimate of temperature on economic welfare would require a full environmental accounting framework which does not currently exist.

Given these considerations, it is clear that the macroeconomic empirically-based damage functions cannot be added to the full damage modules of GIVE, DSCIM, or FrEDI without some double counting as each of these models also contain representation of at least a few types of market damages that are likely to be captured in GDP measures (e.g., from net changes in crop yields, energy consumption, and labor productivity). However, it may be reasonable to combine one or more nonmarket damage functions from these enumerative models with the GDP-based market damage functions from the macroeconomic studies without concerns about double counting. Precedent for this type of combination within a damage module of an IAM used for SC-GHG estimation can be found in the PAGE model (see, e.g., Yumashev 2019, 2020). Others have also noted the importance of augmenting GDP impact estimates with nonmarket impacts for a comprehensive estimate of the full economic burden of climate change (e.g., Hsiang 2016), and there is a broader relevant literature that suggests nonmarket factors (e.g., leisure, lower inequality, and higher life expectancy) and GDP are additive when deriving social welfare (e.g., Jones and Klenow 2016).

Table 6 illustrates the U.S.-specific SC-CO_2 estimates resulting from adding one category of nonmarket damages from the peer-reviewed enumerative models to the GDP-based market damage function from several of the macroeconomic studies reviewed in Section 3c. Analogous U.S.-specific SC-GHG results for 2030 emissions of CH_4 and N_2O are presented in Table A.6 in Appendix A. Specifically, Table 6 shows the effect of combining the heat- and cold-related mortality damage function from Cromar et al. (2022) (used in GIVE and FrEDI) with the U.S. GDP damage functions derived from recent macroeconomic studies that project some persistence in the effect of temperature on GDP growth over time. As discussed in Section 3c, this includes the subset of the studies presented in Table 4 that use more flexible empirical methods that better allow for tracing out nonlinear dynamics in the temperature-GDP relationship and addressing serial correlation in temperature and GDP over time. Importantly, in this integrated modeling, we account for feedbacks from estimated GDP-based damages to monetization of health damages and to the discounting module.[28] Accounting for these feedbacks within our integrated modeling framework acts to slightly reduce monetized health damages and increase discounted damages, all else equal. As such, the specification with the highest market damages, Nath et al. (2024), has the lowest health damages when accounting for these feedbacks. Table 5 presents combined evidence which yields U.S.-specific SC-CO_2 estimates ranging from $31 to $85 per metric ton CO_2 for 2030 emissions (under a 2 percent near-term Ramsey discount rate). The two most recent papers, Harding et al. (2024) and Nath et al. (2024), are at the higher end of this range of estimates.

Table 6: Combined evidence on U.S. nonmarket health damages and U.S. GDP-based market damages from CO_2 emissions

	U.S.-specific SC-CO_2 *(2030 emissions, 2% near-term Ramsey discount rate, 2020$/mt$CO_2$)*		
Source of GDP-based market damages[b]	GDP-based market damages	Health nonmarket damages (Cromar et al. 2022)[c]	Total
Acevedo et al. (2020)	$10	$21	$31
Kahn et al. (2021)	$10	$21	$31
Casey et al. (2023)	$14	$21	$35
Harding et al. (2024)	$28	$20	$48
Nath et al. (2024)	$66	$19	$85

Modeling conducted in a modified MimiGIVE framework: U.S. socioeconomic and emissions inputs taken from RFF-SPs (Rennert et al. 2022a); climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks; U.S. temperature projections based on FaIR 1.6.2 GMST projections downscaled using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets); and uses Ramsey-based discounting following Newell et al. (2022) updated to use U.S. growth with recalibrated ρ and η parameters. Modeling accounts for feedbacks from estimated GDP-based damages to monetization of health damages and to the discounting module.

[b] *Results shown in this table are based on each study's stated "preferred", "main", or "central" empirical specification of the temperature-GDP relationship and/or the method used to project climate damages. See Appendix E for details.*

[c] *Results shown in this table are based on the mortality damage function in GIVE (Rennert et al. 2022b) due to modeling constraints in incorporating other health damage functions (e.g., Carleton et al. (2022) from DSCIM) into the MimiGIVE framework.*

Due to sampling variation in the random draws of a Monte Carlo simulation, values presented in this table are rounded to the nearest dollar.

[28] Specifically, projected changes in premature mortality in the U.S. are monetized using the same value of mortality risk reduction as in the EPA's regulatory analyses ($4.8 million in 1990 (1990USD)) and adjusted for income growth and inflation following current EPA guidelines and practice (EPA 2010) and consistent with EPA Science Advisory Board (SAB) advice (see e.g., EPA 2011), resulting in a 2020 value of $10.05 million (2020USD). See EPA (2023) for more discussion. In the case of combining market and nonmarket damages, the adjustment made for future income growth becomes based on the projected exogenous GDP per capita minus the GDP losses projected from the macroeconomic studies' damage functions.

5 Conclusion

This paper takes a step forward in synthesizing recent evidence on estimating climate change damages specific to U.S. populations. We first review findings on U.S.-specific damages from (1) existing global and U.S. models that take an enumerative approach to estimating market and nonmarket damages of climate change (GIVE, DSCIM and FrEDI), (2) new impact-specific studies on U.S. wildfire damages (Qiu et al. 2024) and biodiversity damages (Wingenroth et al. 2024) that have not yet been incorporated into the larger models, and (3) eight recent macroeconomic econometric studies that empirically estimate the relationship between climate change and U.S. GDP. We then incorporate damage functions based on the results of these different lines of evidence into a consistent IAM framework to show what this literature implies for U.S. impact-specific SC-CO_2 estimates under harmonized socioeconomic and emissions inputs, climate modeling, and discounting methods following the same approach as in EPA (2023). Our climate modeling also accounts for two additional carbon feedback effects based on Dietz et al. (2021) that have not been incorporated into most SC-GHG estimates to date. Finally, we discuss considerations for combining different lines of evidence and present preliminary combined results to the extent possible within a unified IAM framework.

Our findings suggest that evidence on U.S.-specific damages currently represented in existing global and U.S. enumerative models is still incomplete in the categories of climate impacts and associated economic damages that are represented. We estimate that incorporating just two additional carbon feedback effects in the climate modeling – the additional carbon emissions from dieback of the Amazon rainforest and the thawing of permafrost – increases the U.S. impact-specific SC-CO_2 from these models by 9 to 50 percent. We find that incorporating the latest damage functions accounting for some nonmarket health damages from climate-driven wildfire $PM_{2.5}$ exposure and nonmarket damages from biodiversity loss further increases the U.S. impact-specific SC-CO_2. Combining all available lines of evidence on market and nonmarket damages based solely on the enumerative damage function approach provides preliminary results of U.S.-specific SC-CO_2 estimates on the order of $40 or more per metric ton of CO_2 for 2030 emissions.

A second contribution of this paper stems from our review of recent macroeconomic studies that empirically estimate the relationship between temperature and GDP. Although aggregate measures of economic activity, such as GDP, cannot be used to provide a comprehensive accounting of net damages to U.S. citizens and residents from GHG emissions inclusive of nonmarket impacts, these studies can help add to the understanding of the magnitude of net market-based climate damages. Consistent with the developments in this body of literature over time, we focus primarily on recent studies that use flexible empirical strategies to estimate the dynamic responses of GDP to temperature and address common econometric challenges that arise in the analysis of temperature-GDP relationships. These studies generally find temperature changes to have persistent but nonpermanent effects on economic growth. Making an apples-to-apples comparison of the GDP loss projections presented by the authors of these studies is nontrivial due to the considerable variation in the underlying temperature projections used in the papers, assumed socioeconomic and climate scenarios, and aggregation methods and weighting schemes applied to recover country-level temperatures. To synthesize and compare the papers' findings under a consistent modeling framework, we develop a damage function based on each study's estimated dynamic temperature-GDP relationship and show what it implies for U.S. GDP estimates under the same harmonized U.S. socioeconomic inputs, climate modeling, and discounting methods used in the enumerative models. We find that the U.S. GDP-based market damages from CO_2 emissions across all these macroeconomic studies to be larger than the market damages accounted for in U.S.-specific SC-CO_2 estimates based on the enumerative models. Further, we find that combining evidence on GDP-based market damages with evidence on just one category of nonmarket health damages (heat- and cold-related mortality) yields U.S.-specific SC-CO_2 estimates ranging from \$31-85 per metric ton of CO_2 for 2030 emissions.

The results presented in this paper point to several next steps in developing a more comprehensive accounting of how the consequences of GHG emissions are likely to be experienced by U.S. populations. First, additional research is needed on various categories of market and nonmarket impacts omitted from enumerative modeling of climate damages. In some areas, there may be opportunities to convert existing U.S. impact-specific studies (e.g., existing estimates of temperature-driven impacts to some morbidity endpoints) into damage functions of the kind needed for developing U.S. impact-specific SC-GHG estimates. In other areas, new research is needed. For example, damages currently absent from enumerative models include many categories of market and nonmarket impacts associated with the loss of ecosystem services, national security impacts, displacement and migration impacts, impacts to water resources, among others. Moreover, damage categories that have been included in the estimates presented in this paper may be a partial representation of those impacts. For example, agricultural damages include only net yield impacts (inclusive of CO_2 fertilization) from GMST but omit impacts from changes in temperature extremes and variability (e.g., Calel et al. 2020) or impacts from hydroclimate volatility (Swain et al. 2025). Furthermore, our climate module includes only a partial representation of six feedbacks out of the eleven feedbacks identified in recent reviews of earth system feedback effects of climate change (Dietz et al. 2021, Wang et al. 2023).

Second, there is a need for a more explicit articulation of what is reflected in the empirically estimated GDP-temperature relationships found in the macroeconomic literature to more fully compare and combine the results of these studies with evidence from enumerative damage approaches. For example, it is unclear how well these studies fully account for revealed adaptation and its costs. Empirically based estimation of revealed adaptation must rely on what has been observed in the historical record, and it remains challenging to project how the ability of societies to adapt to climate change and how the costs of adaptation will change at higher levels of warming. Similarly, results from macroeconomic studies may not reflect the market-based damages of slow to manifest changes such as expected large-scale SLR, earth system feedbacks, or other damages that have not occurred historically.

Third, more research is needed to quantify how climate impacts occurring outside of U.S. borders affect U.S. interests. Due to the interconnectedness of the global economy and populations, climate impacts occurring abroad may impact U.S. citizens and assets located in other countries as well as lead to significant supply chain disruptions that may affect local economies. Geopolitical impacts from climate change such as political unrest, war, humanitarian crises, and increased global migration are also likely to affect U.S. populations. When assessing the benefits of U.S. GHG mitigation activities, information about how other countries respond with their own reciprocal reductions is also important since those international mitigation efforts provide equivalent climate benefits per ton of GHG reductions to U.S. citizens and residents due to the global nature of GHGs. More research is needed on these key omitted damage categories and the spillover effects on U.S. populations from climate damages abroad to develop a more comprehensive estimate of the economic damages from climate change to U.S. populations.

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Appendix A: Additional Tables and Figures

Table A.1: Representation of U.S.-specific climate damages in existing global and U.S. models

Impacts and Associated Damages	Represented in global models (GIVE, DSCIM)	Reflected in U.S. models (FrEDIv4.1)
Human Health and Well-being		
Heat and cold related mortality	Yes	Yes
Mortality and morbidity from extreme weather events (e.g., storms, wildfire, flooding), and SLR-	Partial	Partial
Mortality and morbidity from climate mediated changes in the formation of criteria air pollutants (e.g., ozone, $PM_{2.5}$)		Partial
Infectious diseases (e.g., vibriosis, lyme)		Partial
Other mortality (e.g., suicides) and morbidity (e.g., malnutrition, allergies)		Partial
Displacement and migration		
Labor		
Labor supply (i.e., hours worked)	Partial	Partial
Labor productivity (i.e., output per hour worked)		
Human Capital		
Energy		
Energy consumption (e.g., heating, cooling)	Yes	Yes
Energy production and provision (e.g., hydroelectric, thermal power generation)		Partial
Water		
Water consumption (residential, industrial, commercial)		
Provision of safe drinking water		
Water storage and distribution		
Land		
Coastal land loss from SLR	Partial	Partial
Buildings, transportation, and infrastructure		
SLR	Partial	Partial
Intensity or frequency of coastal storms		Partial
Extreme weather inland (e.g., storms, wildfire, flooding)		Partial
Environmental conditions (e.g., thawing permafrost, air temperature and moisture)		Partial
Food and Agriculture		
Agriculture/Crop production	Partial	Partial
Animal and livestock health and productivity		
Fisheries and aquaculture production		Partial
Forestry		
Timber, pulp, and paper production		
Tourism, recreation, aesthetics		
Visitation, locations, and opportunities (e.g., recreational fishing, winter sports, scuba diving, scenic views)		Partial
Ecosystem services		
Availability and quality of natural capital used in the production of marketable goods		
Biodiversity and wildlife habitat (e.g., aquatic environments, breeding grounds)		
Other provisioning and regulating services (e.g., water filtration, wildfire and flood mitigation, medicinal resources, pest control, pollination)		
Cultural services		
Crime (property, violent)		Partial
National Security		
Military base impacts		
Military mission impacts from international civil conflict		
International development, humanitarian assistance		
Trade and logistics		
Supply chain disruption (e.g., from extreme weather)		
Supply chain transitions (e.g., altering trade routes)		

Source: Adapted from Table 3.2.1 EPA (2023) together with information about FrEDI version 4.1 from EPA (2024a).

Table A.2: Impact categories in leading global models

Impact Category	DSCIM (CIL 2023)	GIVE (Rennert et al. 2022b)
Health	Heat- and cold-related mortality *(Carleton et al. 2022)*	Heat- and cold-related mortality risk *(Cromar et al. 2022)*
Energy	Expenditures for electricity and other direct fuel consumption *(Rode et al. 2021)*	Expenditures for space heating and cooling in buildings *(Clarke et al. 2018)*
Agriculture	Production impacts for six crops: maize, rice, wheat, soybeans, sorghum, and cassava *(Hultgren et al. 2022)*	Welfare changes from temperature driven changes in production of four crops: maize, rice, wheat, and soybeans *(Moore et al. 2017)*
Coastal	Impacts of SLR as realized through inundation, migration, protection, dry and wetland loss; mortality and physical capital loss from SLR *(Kopp et al. (2016), Garner et al. (2021) for SLR; Diaz (2016), Depsky et al. (2023) for damages)*	Impacts of SLR as realized through inundation, migration, protection, dry and wetland loss; mortality and physical capital loss from SLR *(Wong et al. (2017) for SLR; Diaz (2016) for damages)*
Labor	Labor disutility costs from labor supply responses to increased temperature *(Rode et al. 2022)*	

Source: Adapted from EPA (2023)

Table A.3: Impact categories in FrEDI, version 4.1 (EPA 2024a)

Impact Category	FrEDI v4.1	Underlying study
Health	Heat- and cold-related mortality	Cromar et al. (2022)
	Climate driven O_3 and PM-related mortality	Fann et al. (2021)
	Wildfire PM exposure mortality and morbidity impacts (hospitalization costs and lost productivity) and some suppression costs	Neumann et al. (2021a)
	Southwest region dust mortality and morbidity impacts	Achakulwisut et al. (2019)
	Valley fever mortality and morbidity impacts	Gorris et al. (2021)
	Suicide incidence	Belova et al. (2022)
	Vibriosis mortality and morbidity impacts	Sheahan et al. (2022)
Energy	Electric power sector costs (e.g., capital, fuel, variable operation and maintenance (O&M), and fixed O&M costs) for heating and cooling (demand) and required capacity expansion (supply)	McFarland et al. (2015)
	Stress to electricity transmission and distribution infrastructure (e.g., leading to system failure, changes in infrastructure health/lifespan, efficiency/capacity). Replacement or repair costs, O&M costs, costs from efficiency or capacity losses, and interruption costs to consumers	Fant et al. (2020)
Agriculture	Effects of changes in temperature, precipitation, and CO_2 fertilization on yields of cotton, maize, soybean, and wheat.	Hsiang et al. (2017), citing Hsiang et al. (2013); McGrath and Lobell (2013); Schlenker and Roberts (2009)
Coastal and Infrastructure	Coastal Properties – Costs related to armoring, elevation, nourishment, structure repair, and abandonment (including storm surge impacts)	Neumann et al., 2021b) & (Lorie et al., 2020
	High Tide Flooding – Coastal property damage/adaptation costs, traffic delays, and adaptation costs due to high tide flooding	Fant et al. (2021)
	Hurricane Wind Damage – Property damage from hurricane winds	Dinan (2017) with CBO (2016) and Marsooli et al. (2019)
	Urban Drainage – Costs of proactive urban drainage infrastructure adaptation (construction costs and annual maintenance costs of temporary storage or infiltration to manage runoff volumes)	Price et al. (2016), Neuman et al. (2015)
	Inland flooding – Residential property damages from riverine flooding	Wobus et al. (2021, 2019)
	Rail impacts – Costs of replacing tracks and costs of delays associated with temperature-induced track buckling.	Neumann et al. (2021b), citing Chinowsky et al. (2019)
	Road impacts – Temperature-driven damage to paved and unpaved road surfaces including road repair costs and road user costs (travel time delays and vehicle operating costs).	Neumann et al. (2021b), citing (Neumann et al., 2015)
Labor	Impacts on hours worked in weather-exposed industries (e.g., agriculture, construction, manufacturing)	Neidell et al. (2021)
Ecosystems and Recreation	Fisheries impacts – value of change in weight of landings due to changes in thermally available habitat (no additional adaptation) (16 US fisheries that account for 56% of US commercial fishing revenues)	Moore et al. (2021) and Morley et al. (2018)
	Water quality impacts – recreation-related WTP for changes in water quality	Fant et al. (2017) with (Boehlert et al., 2015; Yen et al., 2016)
	Winter recreation impacts – Lost snowmobiling, alpine skiing, and cross-country skiing revenues (some adaptation captured – i.e., snow blowing), only some regions	Wobus et al. (2017)
Crime	Property (robbery, burglary, larceny, and motor vehicle theft) and violent (murder, rape, and assault) crime impacts from temperature change	Hsiang et al. (2017), citing Heaton P., (2010), Jacob et al., (2007), and Ranson (2014)

Table A.4: U.S. impact-specific SC-CH_4 and SC-N_2O,
2030 emissions, 2% near-term Ramsey discount rate

Model	Impacts represented	U.S. impact-specific SC-CH_4 *(2020\$/mtCH_4)*	U.S. impact-specific SC-N_2O *(2020\$/mtN_2O)*
DSCIM	health, energy, agriculture, coastal, labor	\$130	\$6,000
GIVE	health[a] energy, agriculture, coastal	\$400	\$7,700
FrEDI[b]	various impacts to human health, energy demand and supply, coastal and inland property (e.g., from SLR, flooding and storms), labor, transportation and other infrastructure, water resources, and winter recreation (CONUS only)	\$590	\$11,000
Qiu et al. (2024) [a]	mortality risk changes from climate-driven wildfire $PM_{2.5}$ exposure (CONUS only)	\$590	\$6,300
Wingenroth et al. (2024)	nonuse value from biodiversity loss	\$4	\$180
Burke et al. (2015)[a]	permanent U.S. GDP growth effects	\$16,000	\$330,000
Kalkuhl and Wenz (2020)[a]	temporary U.S. GDP growth effects	\$850	\$17,000
Newell et al. (2021) [a]	temporary U.S. GDP growth effects	\$140	\$3,100
Acevedo et al. (2020) [a]	temporary U.S. GDP growth effects	\$120	\$3,000
Kahn et al. (2021)[a]	persistent U.S. GDP growth effects	\$210	\$3,300
Casey et al. (2023)[a]	persistent U.S. GDP growth effects	\$170	\$4,100
Harding et al. (2024)[a]	persistent U.S. GDP growth effects	\$310	\$8,100
Nath et al. (2024)[a]	persistent U.S. GDP growth effects	\$880	\$20,000

U.S. socioeconomic and emissions inputs taken from RFF-SPs (Rennert et al. 2022a); climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks (except in the case of FrEDI); discounting module follows Newell et al. (2022) with Ramsey parameters, ρ and η, recalibrated to the U.S. growth rate of consumption (except for the DSCIM-based results). As discussed in EPA (2023), the health damages represented in GIVE, DSCIM, and FrEDI do not account for non-climate mediated effects of CH_4 and N_2O emissions experienced by U.S. populations. For example, they do not capture the monetized increase in U.S. respiratory-related human mortality risk from the ozone produced from a marginal pulse of CH_4 emissions (which recent research estimates to be on the order of \$320/mtCH_4 for methane emissions in 2030 (McDuffie et al. 2023) or the U.S. health risks from stratospheric ozone destruction from N_2O emissions (Kanter et al. 2021).

[a] To calculate the U.S. temperature inputs needed for these damage functions, GMST projections from FaIR 1.6.2 are downscaled to U.S. temperature using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets). This downscaling approach, a historical period validation exercise of the approach, and resulting U.S. temperature projections are described in detail in Appendix B.

[b] FrEDI results presented in this table are based on FrEDI version 3.4 and do not yet account for the carbon feedback effects from permafrost thaw and Amazon dieback.

Table A.5: Combined evidence from existing enumerative models and new impact-specific studies on U.S. climate damages from CH_4 and N_2O emissions

Panel A	U.S.-specific SC-CH_4 *(2030 emissions, 2% near-term Ramsey discount rate, 2020\$/mtCH_4)*		
Enumerative models	Damage categories represented in existing models	Wildfire and biodiversity damages from new impact specific studies	Total
GIVE[a]	\$400	\$590	\$990
DSCIM	\$130	θ_D [b]	\$130+θ_D
FrEDI	\$590	θ_F [b]	\$590+θ_F

Panel B	U.S.-specific SC-N_2O *(2030 emissions, 2% near-term Ramsey discount rate, 2020\$/mtN_2O)*		
	Damage categories represented in existing models	Wildfire and biodiversity damages from new impact specific studies	Total
GIVE[a]	\$7,700	\$6,300	\$14,000
DSCIM	\$6,000	θ_D [b]	\$6,000+θ_D
FrEDI	\$11,000	θ_F [b]	\$11,000+θ_F

U.S. socioeconomic and emissions inputs taken from RFF-SPs (Rennert et al. 2022a). The climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks (except in the case of FrEDI); FrEDI results presented in this table are based on FrEDI version 3.4 and do not yet account for the carbon feedback effects from permafrost thaw and Amazon dieback.

[a] The discounting module follows Newell et al. (2022) with Ramsey parameters, ρ and η, recalibrated to the U.S. growth rate of consumption. To calculate the temperature-related mortality damages (based on Cromar et al. (2022)), GMST projections from FaIR are downscaled to U.S. temperature using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets).

[b] θ_D and θ_F represent the incremental impact on the U.S.-specific SC-CO_2 from incorporating the new evidence on wildfire and biodiversity loss-related damages in DSCIM and FrEDI, respectively, which has not yet been possible due to resource constraints.

Table A.6: Combined evidence on U.S. nonmarket health damages and U.S. GDP-based market damages from CH_4 and N_2O emissions

Panel A	U.S.-specific SC-CH_4 *(2030 emissions, 2% near-term Ramsey discount rate, 2020\$/mtCH_4)*		
Source of GDP-based market damages[b]	GDP-based market damages	Health nonmarket damages (Cromar et al. 2022)[c]	Total[d]
Acevedo et al. (2020)	\$120	\$350	\$470
Kahn et al. (2021)	\$210	\$350	\$560
Casey et al. (2023)	\$170	\$350	\$520
Harding et al. (2024)	\$310	\$340	\$660
Nath et al. (2024)	\$900	\$330	\$1,200

Panel B	U.S.-specific SC-N_2O *(2030 emissions, 2% near-term Ramsey discount rate, 2020\$/mtN_2O)*		
Source of GDP-based market damages[b]	GDP-based market damages	Health nonmarket damages (Cromar et al. 2022)[c]	Total
Acevedo et al. (2020)	\$3,100	\$6,700	\$9,700
Kahn et al. (2021)	\$3,300	\$6,700	\$10,000
Casey et al. (2023)	\$4,200	\$6,600	\$11,000
Harding et al. (2024)	\$8,300	\$6,400	\$15,000
Nath et al. (2024)	\$20,000	\$6,100	\$26,000

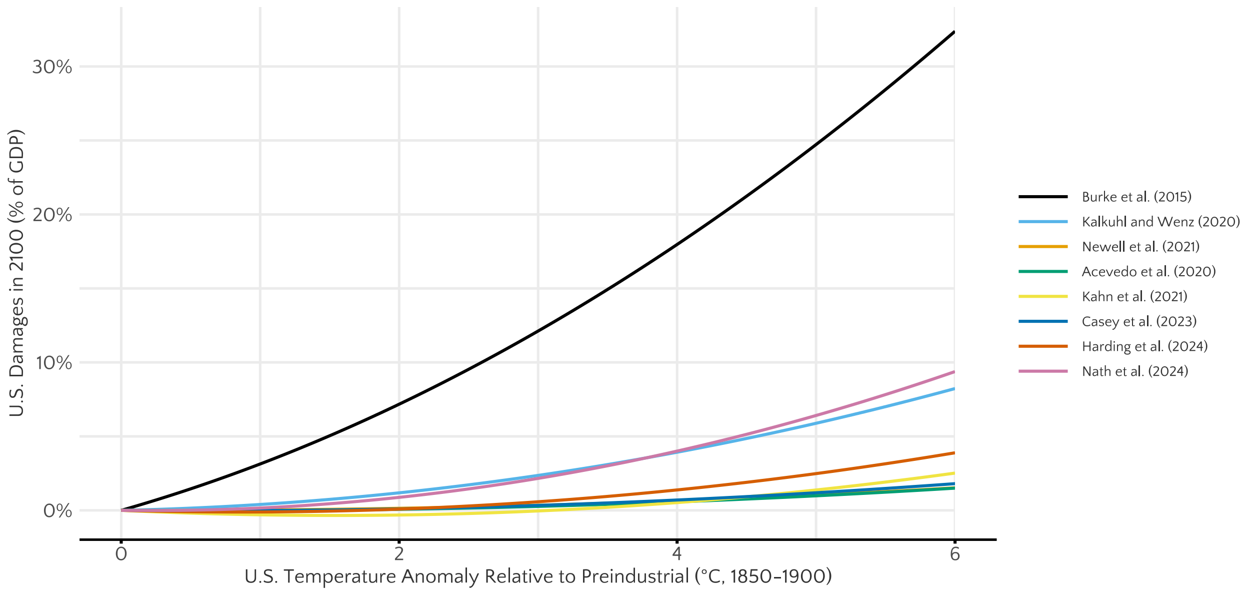
Modeling conducted in a modified MimiGIVE framework: U.S. socioeconomic and emissions inputs taken from RFF-SPs (Rennert et al. 2022a); climate module temperature projections account for carbon feedback effects from permafrost thaw and Amazon dieback based on Dietz et al. (2021) modeling of these feedbacks; U.S. temperature projections based on FaIR 1.6.2 GMST projections downscaled using a pattern-scaling approach (in which CONUS GCMs are paired with FaIR parameter sets); and uses Ramsey-based discounting following Newell et al. (2022) updated to use U.S. growth with recalibrated ρ and η parameters. Modeling accounts for feedbacks from estimated GDP-based damages to monetization of health damages and to the discounting module.

[b] *Results shown in this table are based on each study's stated "preferred", "main", or "central" empirical specification of the temperature-GDP relationship and/or the method used to project climate damages. See Appendix E for details.*

[c] *Results shown in this table are based on the mortality damage function in GIVE (Rennert et al. 2022b) due to modeling constraints in incorporating other health damage functions (e.g., Carleton et al. (2022) from DSCIM) into the MimiGIVE framework.*

[d] *Columns are individually rounded to two significant digits and, as such, may not add to be equal to the total column. Unrounded results are available in the paper's public repository.*

Figure A.1: Average climate damages as a fraction of U.S. GDP in 2100 due to a change in annual global mean surface temperature under each of the 8 macroeconomic econometric damage functions



Average (mean) GDP loss functions are generated using estimated damages in 2100 for the 10,000 Monte Carlo simulations and regressing on temperature and temperature squared (solid lines). The IPCC (2021a) notes that present day global mean surface temperatures in the year 2020 are around 1.1°C above preindustrial (1850-1900) levels. Estimated damages in 2100 shown in this figure are based on each study's stated "preferred", "main", or "central" empirical specification of the temperature-GDP relationship and/or the method used to project climate damages. Each damage function requires a measure of current climate or baseline temperature; in this figure we use country-level population-weighted mean temperatures from 1980 to 2010 drawn from Burke et al. (2015) for this purpose. See Appendix E for more details.

Appendix B: Technical Documentation for U.S. Socioeconomic and Climate Projections and U.S. Ramsey-based Discounting

Figure B.1 and Figure B.2 present the RFF-SP probabilistic projections of population and economic growth for the U.S. through the year 2300. These figures also include a comparison to the SSPs for years 2020 to 2100. The SSPs have been used in IPCC reports and other applications.[29] The SSP projections presented in the figure for years beyond 2100 are based on two extrapolation methods recently used in the literature—Benveniste et al. (2020) for SSP1, SSP2, and SSP3 (dashed lines), and CIL (2023) for SSP2, SSP3, and SSP5 (dashed-dotted lines)—illustrating the sensitivity to various extrapolation assumptions.

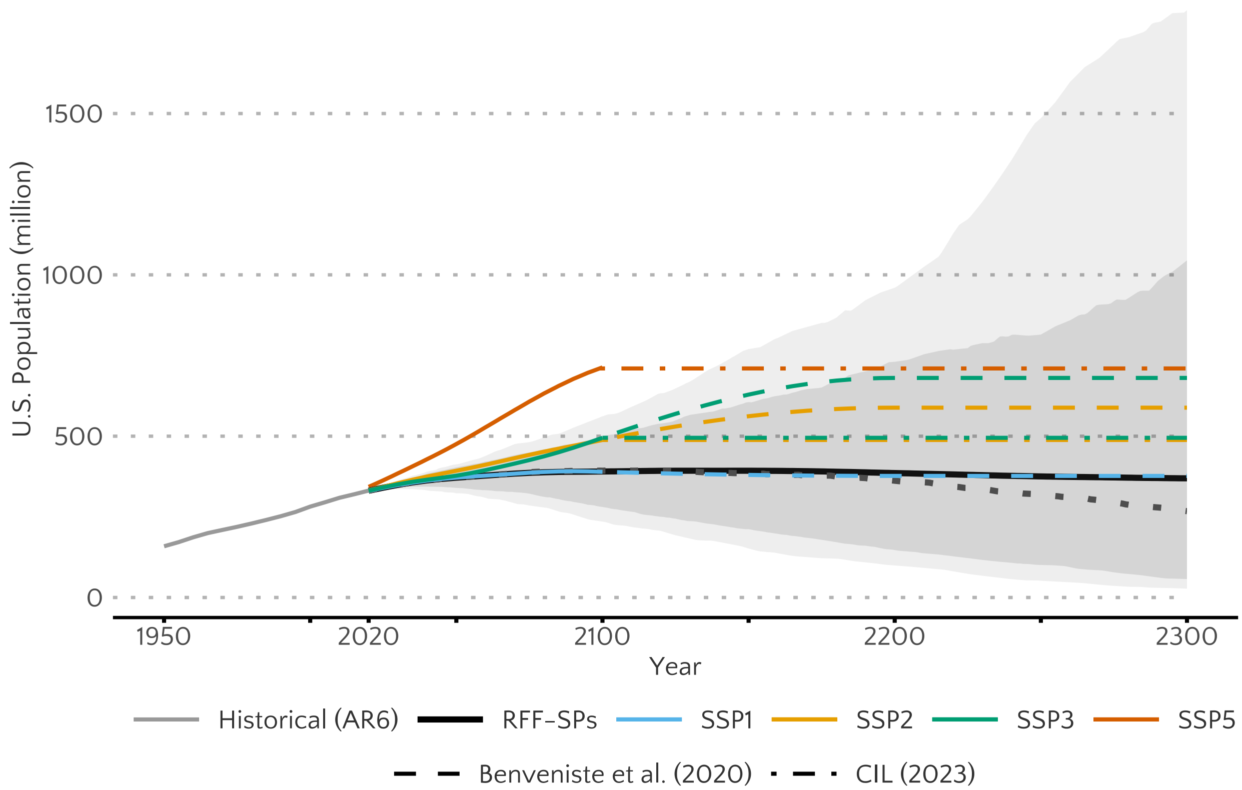
The mean (black solid line) and median (black dotted line) of the RFF-SP population projections follow a fairly flat trajectory through 2100, in-line with SSP1, peaking at 392 million people in the year 2150. This is followed by a slow decline to under 370 million by 2300. SSP2 and SSP3 follow the upper tail of the RFF-SPs through 2100 and, depending on the extrapolation method, drop within the 99th or 95th percentile of the RFF-SP distribution by 2300. While the SSP-based projections shown in Figure B.1 generally fall within or near the range of the RFF-SP probabilistic distribution for U.S. population, they are limited in providing a comparison to the full RFF-SP distribution. The SSPs were intentionally developed to reflect a range of reasonably likely scenarios corresponding to different storylines rather than a more comprehensive range of plausible scenarios like the RFF-SPs. Furthermore, the SSP-based projections are sensitive to the extrapolation method used. For example, the SSP3 projections displayed in Figure B.1 show U.S. population in 2300 rising to about 500 million under the CIL (2023) extrapolation, and 680 million under the Benveniste et al. (2020) extrapolation.

Figure B.2 presents the U.S. economic growth projections from the RFF-SPs along with comparisons to the SSPs in AR6.30 The mean (black solid line) economic growth rates start at 1.7 percent in 2021, slowly decline to 1.5 percent between 2030 and 2100 and then continue to decline through-out the next century. The mean economic growth rate levels off again after 2200 at 1 percent. The RFF-SP U.S. economic growth projections are lower but most consistent with SSP1 and SSP5 scenarios. All the SSP-based projections displayed in Figure B.2 lie within the long-run RFF-SP distribution.

[29] Figures B.1 and B.2 contain all Tier 1 SSPs from IPCC AR6. Tier 2 scenarios, such as SSP4, were not considered.

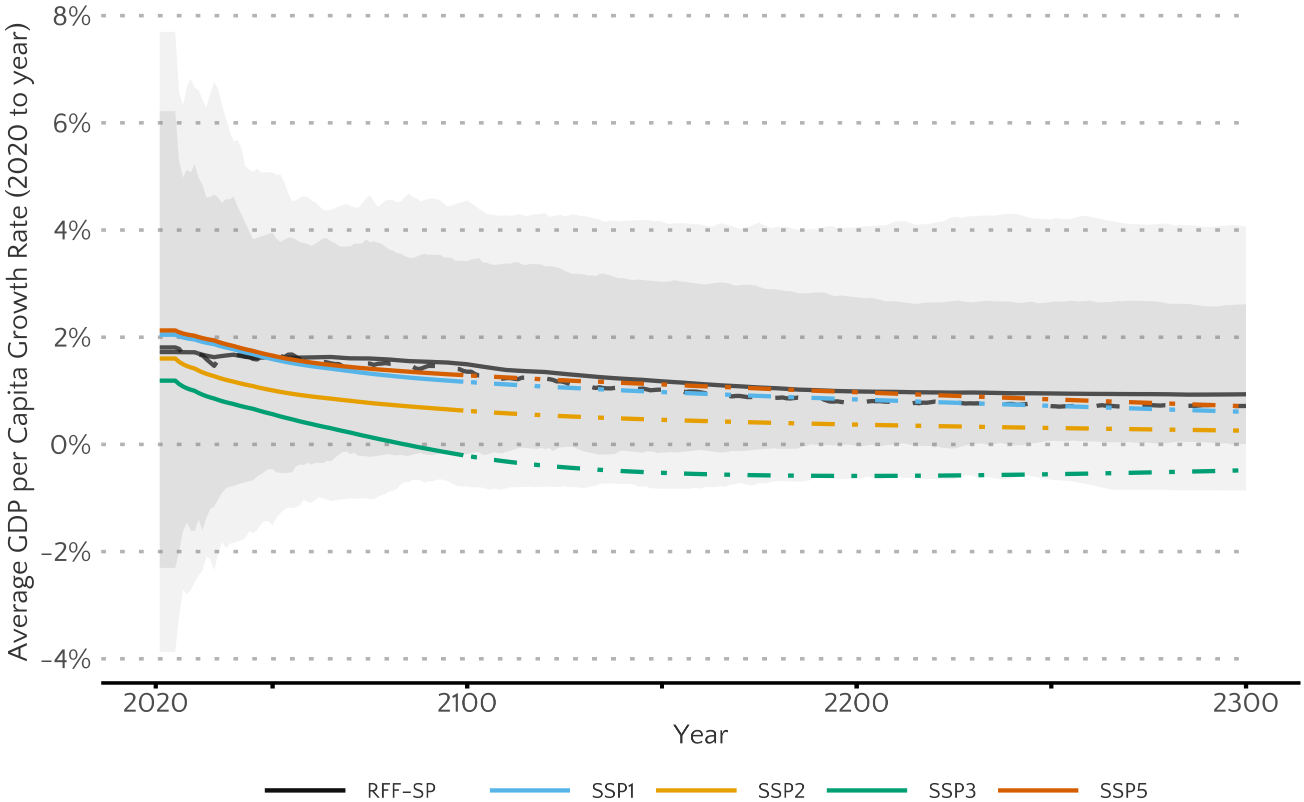
[30] The growth rates (and the uncertainty bounds around the RFF-SPs) shown in Figure B.2 are plotted in a time-averaged manner to accurately present the underlying year-on-year correlations that exist within each scenario/storyline.

Figure B.1: Projections of U.S. population from the RFF-SPs and SSPs, 1950-2300



RFF-SP probabilistic projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent the mean (solid) and median (dotted) along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. Historical data from Benveniste et al. (2020) using UN World Population Prospects 2019 (UN 2019). SSP1, SSP2, and SSP3 data through 2100 from Benveniste et al. (2020) using population growth rates from the International Institute for Applied Systems Analysis (IIASA) SSP Database (Riahi et al. 2017). SSP5 data through 2100 are from the IIASA database (Riahi et al. 2017). SSPs beyond 2100 (dashed) are based on two recent extrapolation methods: Benveniste et al. (2020), and CIL (2023).

Figure B.2: Projections of U.S. growth in income per capita from the RFF-SPs and SSPs, 2020-2300



RFF-SP probabilistic projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent mean (solid) and median (dotted) U.S. growth rates along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. Historical data from Benveniste et al. (2020) using World Bank WDI (World Bank 2019). SSP data through 2100 from International Institute for Applied Systems Analysis (IIASA) SSP Database's OECD Env-Growth model (Riahi et al. 2017). SSPs beyond 2100 (dashed) are based on two recent extrapolation methods: *Benveniste et al. (2020), and CIL (2023). The growth rates (and the uncertainty bounds around the RFF-SPs) are plotted in a time-averaged manner to accurately present the underlying year-on-year correlations that exist within each scenario.*

U.S. temperature projections. The damage module of many climate change IAMs takes GMST as an input to translate changes in climate into changes in physical impacts, such as SLR, and then associated monetized damages, or directly into economic outcomes. Other damage functions, however, are estimated using measures of local mean surface temperature (LMST). In this section we describe our process for transforming GMST into LMST for the U.S., and in Appendix C we present the resulting U.S. temperature paths underlying our estimations.

Reduced complexity climate models, such as the FaIR model, typically only provide GMST and other spatially aggregated climate variables (e.g., global ocean pH, or global SLR) as outputs. More computationally intensive earth system models (ESMs) or GCMs can provide more spatially resolute climate projections, such as LMST, but are less suited to fit the needs of climate IAMs that use many, sometimes tens of thousands, of possible emissions scenarios in a probabilistic setting. However, approximating LMST from GMST can be done using a pattern-scaling approach that pairs the spatial patterns of ESMs/GCMs with the GMST output from reduced complexity models (Kravitz et al. 2016, 2022, Lynch et al. 2017, EPA 2024b).[31]

The FaIR model provides explicit representation of many uncertainties, including effective heat capacities of the surface and deep ocean layers, deep ocean heat uptake efficacy, the integrated airborne fraction of CO_2 over the pre-industrial period, the strength of different forcing agents, a climate feedback term, and other key model parameters (Millar et al. 2017, Smith et al. 2018). From over 1 million initial combinations of a total of 44 random parameters, FaIR model developers selected 2,237 unique parameter sets through a model calibration process as part of the IPCC AR6 (IPCC 2021a, 2021b). These parameter sets, each consisting of a unique set of values for the 44 random parameters are calibrated to match historical observations, future GCM responses, and IPCC determined probabilities for transient climate response (TCR) and equilibrium climate sensitivity (ECS) model parameters. TCR and ECS are emergent properties in FaIR and are not directly recoverable from the model.

To recover the spatial patterns of LMST from ESMs/GCMs with GMST, we pair patterns from ESMs/GCMs with FaIR parameter sets that are more similar in their climate response. That is, a "hotter" ESM/GCM pattern is paired with a "hotter" FaIR parameter set, and vice versa. Because TCR and ECS are not directly recoverable from FaIR, one way to pair the spatial patterns of ESMs/GCMs with FaIR parameter sets is to examine the relative hotness of the FaIR model runs with the relative hotness of the ESMs/GCMs. The relative hotness of the 2,237 FaIR parameter sets were ranked based on the projected GMST in 2100 that resulted from running the model using SSP-RCP storyline scenarios (SSP245 and SSP585).

To rank the relative hotness of ESMs/GCMs, we use the TCR and ECS of the models directly. Tokarska et al. (2020) provide an overview of the TCR and ECS underlying each of the ESMs/GCMs considered in CMIP6 (Table B.1). Because both the TCR and ECS contribute to the model's response and relative hotness, we create a combined index to rank the set of models. This is done by summing the TCR and ECS and weighting the sum by the mean of each parameter. This results in a weighted sum of the TCR and ECS such that both are given an equal weight in the ranking. A higher number suggest a hotter model, and vice versa. Of the 21 available GCMs, 18 were evaluated in Tokarska et al. (2020) (Table B.1). US EPA's Climate Science and Impacts Branch (CSIB) has also examined the set of ESM/GCMs models and identified 5 ESM/GCMs for use as a minimum set, based on three criteria: matching historic temperature and precipitation metrics either globally (Brunner et al. 2020) or for the CONUS/North America region (Ashfaq et al. 2022, Zhang et al. 2024); independence from the other selected models (Brunner et al. 2020, Zhang et al. 2024); and availability in the LOCA and STAR-ESDM statistical downscaling datasets. Of these 5, 4 are reflected in the set of 18 (Table B.1, shaded rows, and Table B.2).

Pairing FaIR parameter sets with ESM/GCM patterns was done by simply pairing the relative hotness of each. That is, the 2,237 FaIR parameter sets were ranked into 18 groups from "cool" to "hot" based on their resulting GMST in the year 2100. These groups were then paired with the ESM/GCMs based on their ranked weighted sum, from 1 to 18 (Figure B.3). This exercise was repeated based on the 4 ESM/GCMs from CSIB's model prioritization exercise. That is, the 2,237 FaIR trials were ranked into 4 uniformly sized groups (i.e., 559 in the three hottest, and 560 in the coolest group) from cool to hot and paired with the weighted sum ranking of the four ESM/GCMs (Figure B.4). These relationships are further presented in

[31] Another possible approach is that of Tebaldi et al. (2020). They show that a time-shift approach to emulating earth futures and climate indices could, in some cases, outperform that of simple pattern scaling.

Figures B.5 and B.6, showing the full time-series of GMST under each SSP and colored according to their paired ESM/GCM.

Table B.1: Ranking of GCMs based on underlying TCR and ECS

Model (ESM/GCM)	TCR	ECS	Weighted Sum	TCR rank	ECS rank	Weighted Sum rank
INM-CM5-0	1.39	1.92	1.21	1	1	1
NorESM2-LM	1.48	2.6	1.43	2	4	2
MIROC6	1.55	2.57	1.46	5	3	3
CAMS-CSM1-0	1.75	2.29	1.48	9	2	4
MIROC-ES2L	1.55	2.68	1.49	4	6	5
GFDL-ESM4	1.61	2.62	1.5	6	5	6
BCC-CSM2-MR	1.5	3.01	1.55	3	8	7
MPI-ESM1-2-HR	1.65	2.97	1.62	8	7	8
MRI-ESM2-0	1.64	3.14	1.66	7	9	9
GFDL-CM4	2.01	3.87	2.04	11	10	10
CNRM-ESM2-1	1.9	4.7	2.2	10	14	11
EC-Earth3	2.32	4.2	2.28	14	11	12
CNRM-CM6-1	2.13	4.83	2.35	13	15	13
CESM2	2.06	5.19	2.41	12	16	14
EC-Earth3-Veg	2.61	4.3	2.45	15	12	15
NESM3	2.79	4.68	2.64	18	13	16
UKESM1-0-LL	2.75	5.34	2.8	17	17	17
CanESM5	2.66	5.62	2.83	16	18	18

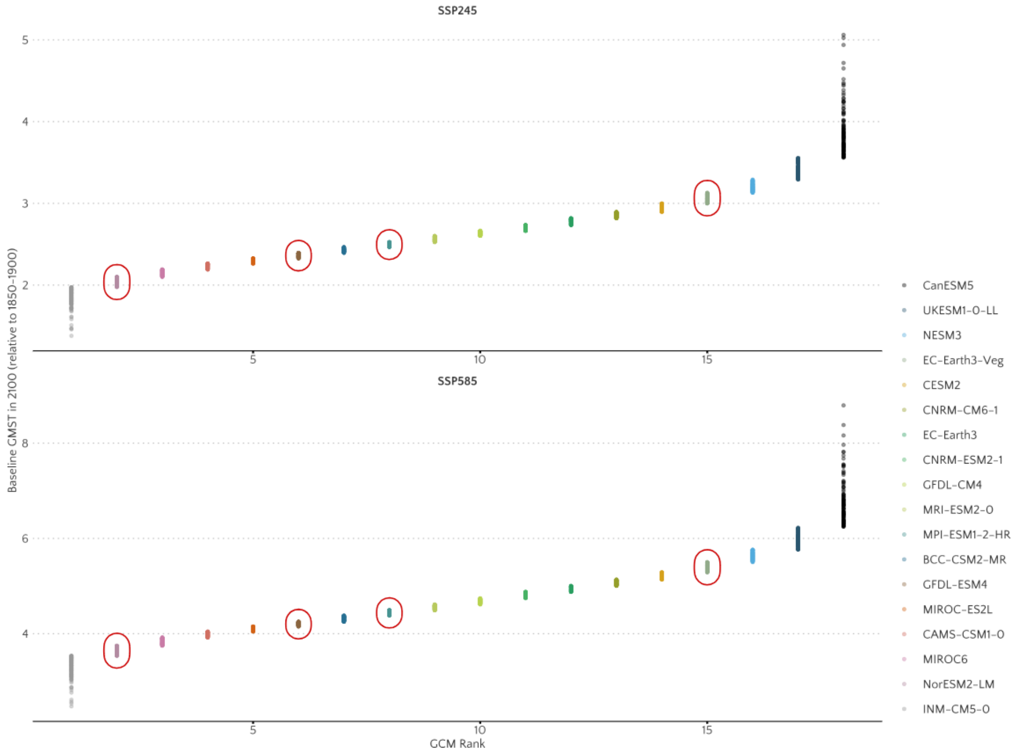
Data on TCR and ECS comes from Tokarska et al. (2020). Weighted sum is created by weighting the TCR and ECS by their means. Ranking of 1 denotes relatively "cool", while a ranking of 18 means relatively "hot". Shaded rows correspond to the 4 GCMs prioritized for CONUS by EPA CSIB.

Table B.2: Ranking of GCMs based on the minimum set for U.S.

Model (ESM/GCM)	TCR	ECS	Weighted Sum	TCR rank	ECS rank	Weighted Sum rank
NorESM2-LM	1.48	2.6	1.43	1	1	1
GFDL-ESM4	1.61	2.62	1.5	2	2	2
MPI-ESM1-2-HR	1.65	2.97	1.62	3	3	3
EC-Earth3-Veg	2.61	4.3	2.45	4	4	4

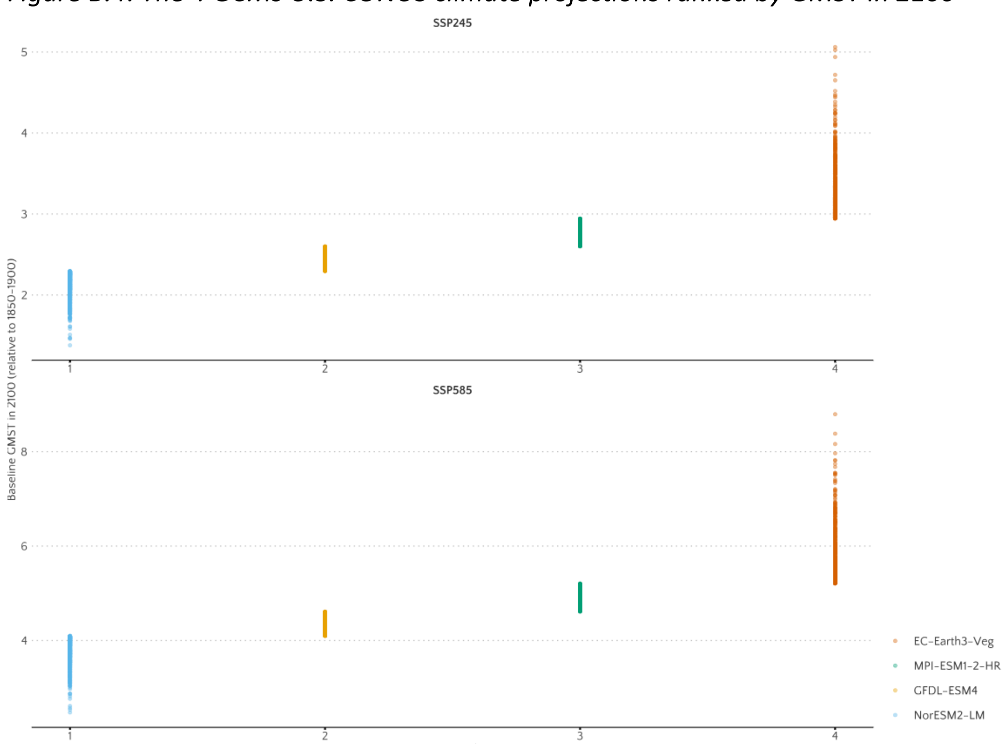
Data on TCR and ECS comes from Tokarska et al. 2020. Weighted sum is created by weighting the TCR and ECS by their means. Ranking of 1 denotes relatively "cool", while a ranking of 18 means relatively "hot".

Figure B.3: The 18 GCMs ranked by GMST in 2100



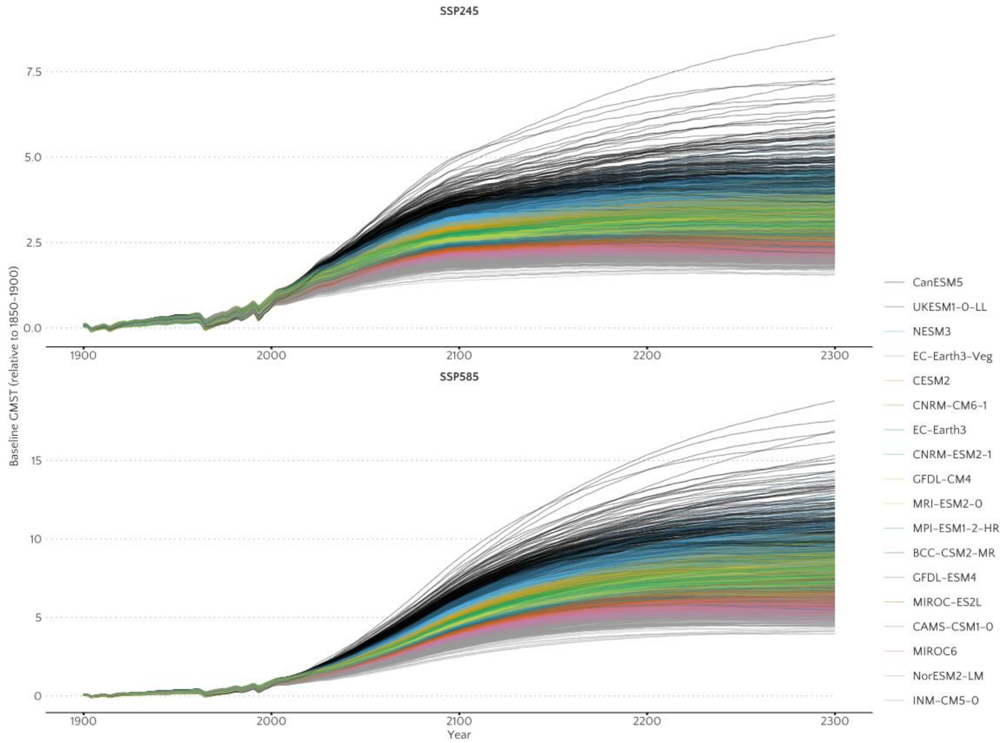
GCMs are ranked (x-axis) according to their projected GMST in the year 2100 (y-axis). Red circles correspond to the 4 GCMs identified by EPA CSIB as meeting the minimum set criteria.

Figure B.4: The 4 GCMs U.S. CONUS climate projections ranked by GMST in 2100



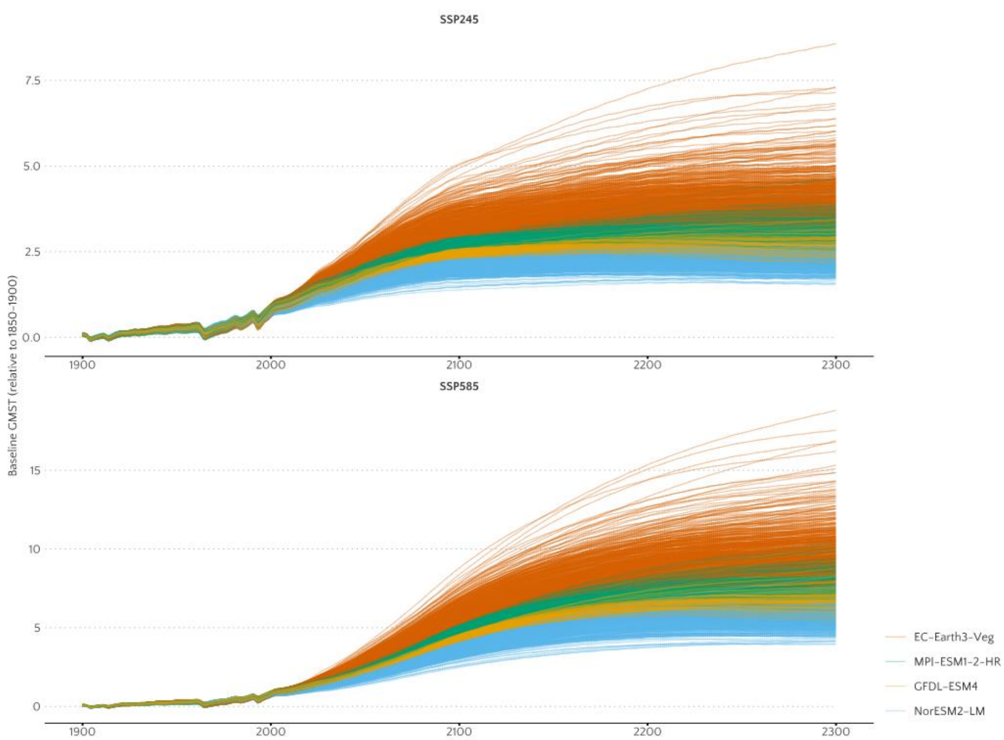
GCMs are ranked (x-axis) according to their projected GMST in the year 2100 (y-axis).

Figure B.5: Baseline GMST from FaIR and corresponding rankings for 18 GCMs



GCMs are ranked (x-axis) according to their projected GMST in the year 2100 (y-axis).

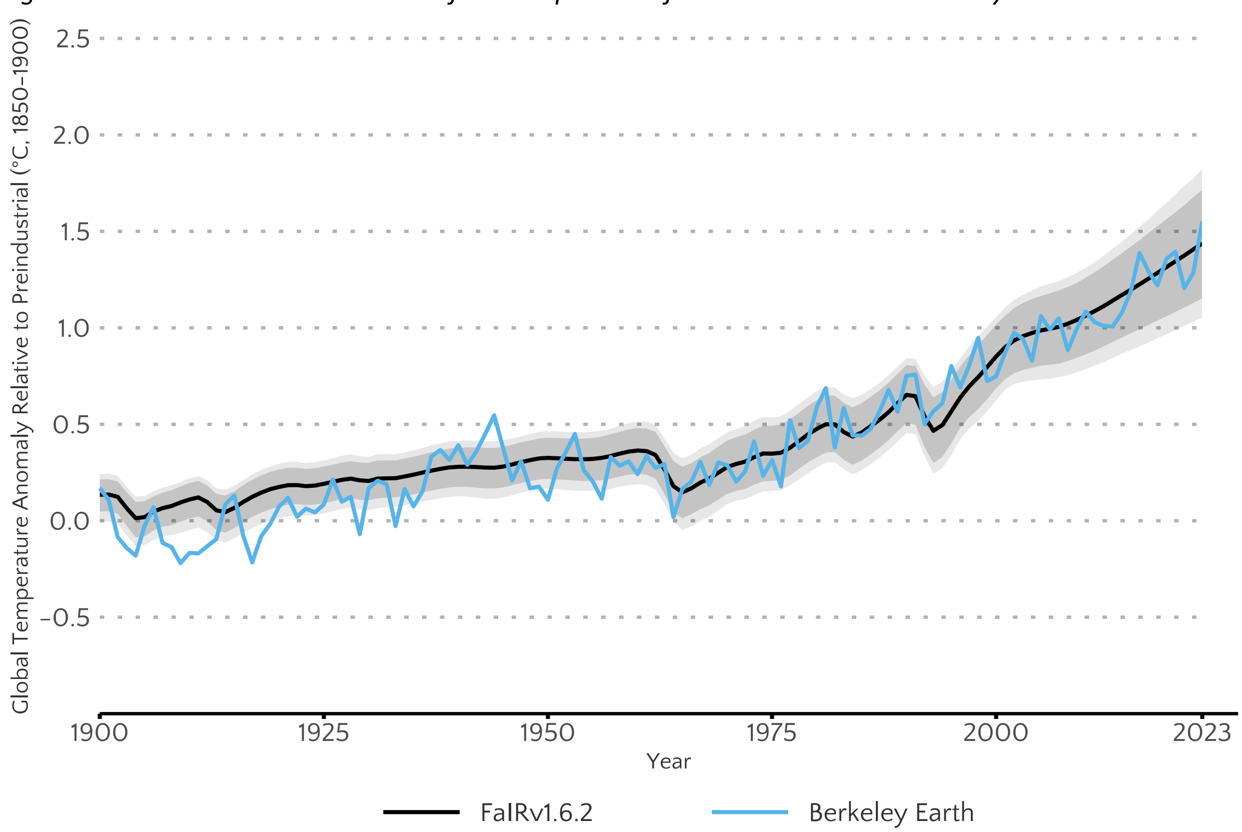
Figure B.6: Baseline GMST from FaIR and corresponding rankings for 4 CONUS GCMs



GCMs are ranked (x-axis) according to their projected GMST in the year 2100 (y-axis).

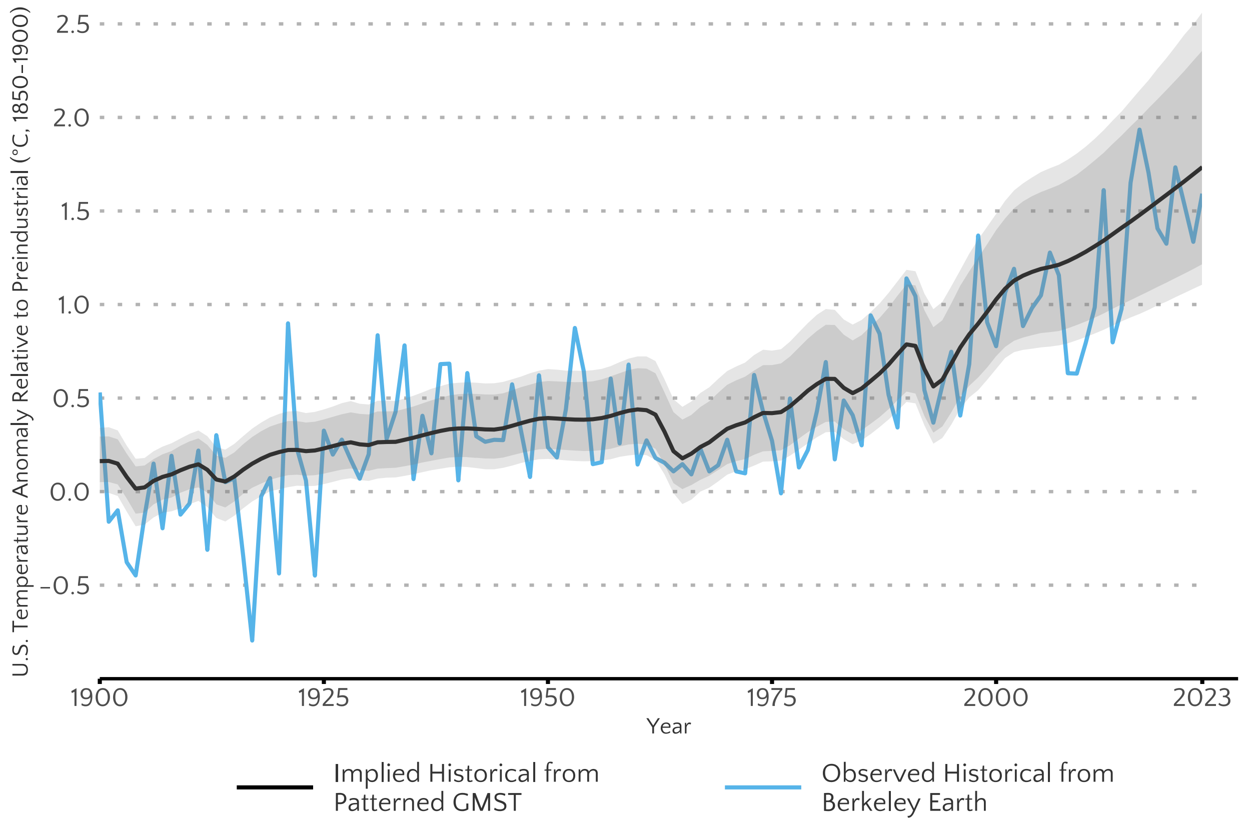
Validation of the pattern scaling approach. The pattern scaling approach described above is used to translate the FaIR model's annual GMST projections to annual average U.S. temperature. To explore how closely the patterns take historical observations of GMST and translate them into historical observations of U.S. mean surface temperature, we use a time-series of global gridded data from Berkeley Earth (Berkeley Earth, 2024). Figure B.7 compares the historical GMST observation from this dataset against the GMST coming from FaIR 1.6.2. Figure B.8 compares the result of using the CONUS patterns discussed above to recover U.S. mean surface temperature from FaIR against the observed historical record from the gridded Berkeley Earth dataset. Both show that the GMST and U.S. temperatures closely match the historical record, suggesting the pattern scaling approach used in this paper reasonably recovers U.S. temperatures from GMST as estimated by FaIR 1.6.2. In Appendix C, we present the result of our pattern scaling methods on U.S. temperature projections through the year 2300 (Figure C.2).

Figure B.7: Historical Global Mean Surface Temperature from FaIR 1.6.2 and Berkeley Earth



Black lines represent mean (solid) GMST from FaIR 1.6.2 along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges that are a result of the uncertainty underlying FaIR 1.6.2. Blue line represents the historical record from Berkeley Earth.

Figure B.8: Historical U.S. mean surface temperature from patterned GMST (FaIR 1.6.2) with CONUS patterns and observations from Berkeley Earth



Black lines represent mean (solid) U.S. mean surface temperature from combining FaIR 1.6.2 GMST and CONUS population-weighted patterns, along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges that are a result of the uncertainty underlying FaIR 1.6.2. Blue line represents the population-weighted U.S. historical record from Berkeley Earth.

U.S. Ramsey-based discounting. Following the approach used in EPA (2023), the discounting module in this paper uses dynamic discounting based on the Ramsey equation (Ramsey, 1928):[32]

$$r_t = \rho + \eta g_t \qquad (B.1)$$

where r_t is the consumption discount rate in year t, ρ is the pure rate of time preference, η is the elasticity of marginal utility of consumption, and g_t is the growth rate of consumption in year t. As explained in EPA (2023), this approach provides internal consistency within the modeling and a more complete accounting of uncertainty consistent with economic theory (Arrow et al. 2013, Cropper et al. 2014). The approach also follows the National Academies' (2017) recommendation to employ a more structural, Ramsey-like approach to discounting that explicitly recognizes the relationship between economic growth and discounting uncertainty.

Ramsey-based discounting implies that future states of the world with lower consumption will be discounted less than states of the world with higher consumption. The use of the Ramsey formula in our

[32] A detailed discussion of the discounting methodology can be found in EPA (2023).

IAM framework also appropriately addresses consumption risk. That is, the discount rate varies over time consistent with changes in estimated economic growth and, therefore, explicitly accounts for the correlation between consumption growth and climate change damages when discounting.[33]

The parameters of the Ramsey equation, ρ and η, are calibrated following the approach of Newell et al. (2022), so that: (1) the decline in the certainty-equivalent[34] discount rate matches the latest empirical evidence on interest rate uncertainty estimated by Bauer and Rudebusch (2020, 2023), and (2) the average of the certainty-equivalent discount rate over the first decade matches a near-term consumption rate of interest. Consistent with EPA (2023), we use a 2 percent near-term target rate for this calibration. This is based on multiple lines of evidence on observed the average real return on 10-Year Treasury securities and academic research on real interest rates, which support a risk-free 2 percent rate when discounting climate damages (Bauer and Rudebusch 2020, 2023; CBO 2022, 2023; Drupp et al. 2018; Giglio et al. 2015, 2021; Howard and Sylvan 2020; Pindyck 2019). See EPA (2023) for a more detailed discussion of these lines of evidence. For this U.S.-focused paper, we make two minor modifications to the implementation of the Newell et al. (2022) approach used in recent SC-GHG studies (Rennert et al. 2022a, 2022b; EPA 2023): (1) we use U.S. economic growth projections from the RFF-SPs, as opposed to global economic growth projections, in the calibration of ρ and η, which yields $\rho = 0.41\%$ and $\eta = 1.02$,[35] and (2) when discounting climate damages we assume a U.S. representative agent and, therefore, g_t in the Ramsey formula is a measure of the U.S. consumption growth rate (net of baseline climate damages to the U.S.) instead of the global consumption growth rate (net of baseline climate damages globally).

[33] The covariance between marginal climate change damages and future consumption growth is often referred to as the climate beta (see Dietz et al. 2018 or Gollier 2014 for a discussion). The climate beta can similarly be viewed as the covariance between returns to investments in climate mitigation and consumption growth. Because each Monte Carlo trial has a separate discount rate path that varies with consumption growth, the climate beta is internally determined within our IAM framework, and therefore, our discounting approach is also internally risk-adjusted.

[34] The certainty-equivalent discount rate is the discount rate that corresponds to the expectation of uncertain discount factors.

[35] In Rennert et al. (2022a, 2022b) and EPA (2023), parameter calibrations for a 2 percent near-term target discount rate following this approach but using global consumption growth rates are $\rho = 0.20\%$ and $\eta = 1.24$.

Appendix C: Technical Documentation for Estimation of Carbon Feedback Effects

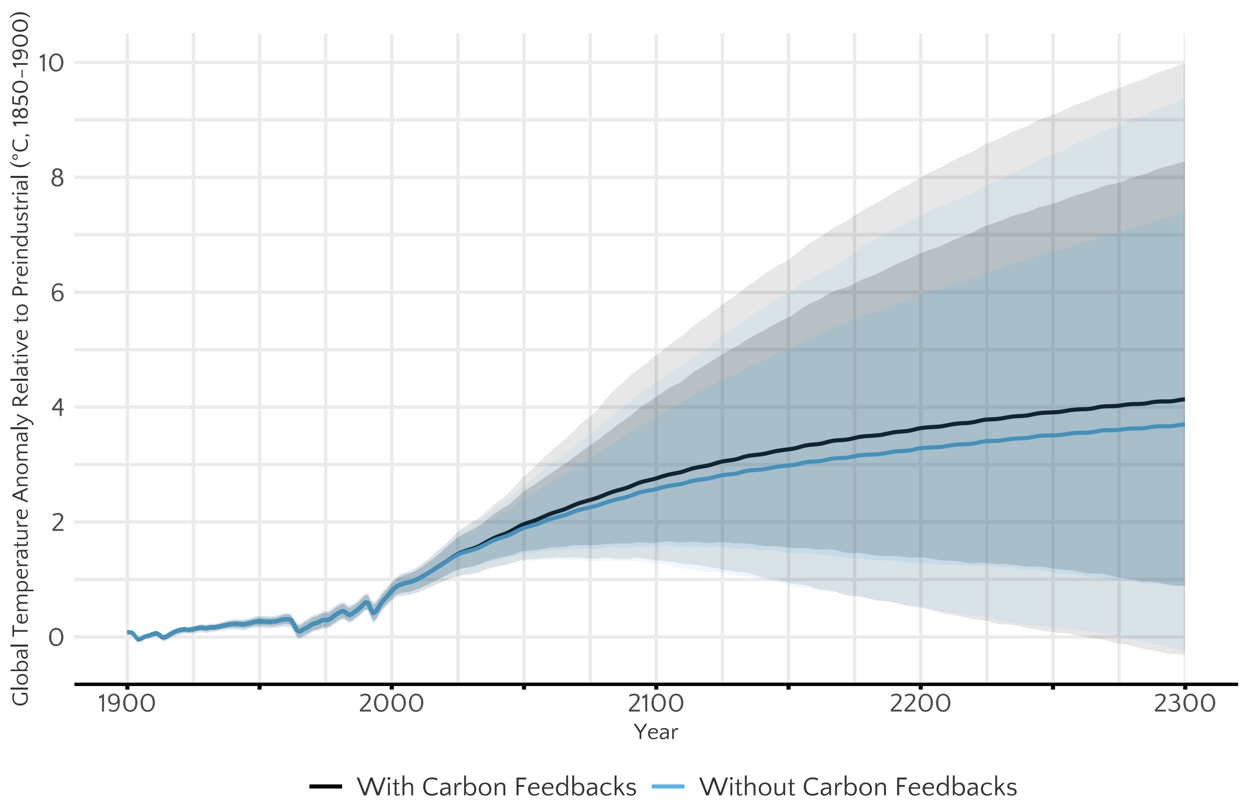
In this paper, the climate module's temperature projections incorporate two additional carbon feedback effects that are not accounted for in the FaIR 1.6.2 climate model: permafrost thaw and the dieback of the Amazon rainforest. These two feedbacks have been identified in recent reviews of Earth system feedbacks and tipping points as ones not yet represented in FaIR and which have sufficient scientific and methodological basis to be reliably incorporated in our modeling framework at this time (RFF 2024, Dietz et al. 2021, 2023). RFF (2024) assessed the eight feedbacks included in Dietz et al. (2021) and three others identified by Wang et al. (2023). Of these eleven, three are already accounted for in the modeling of temperature and associated SLR described in Section 3: (1) the rate of disintegration of the Antarctic ice sheet, (2) the rate of disintegration of the Greenland ice sheet, and (3) the surface albedo feedback. RFF (2024) find five additional feedback systems require more physical science and/or economic research to permit an adequate representation in the SC-GHG modeling framework. These include: (1) the slowdown of the Atlantic Meridional Overturning Circulation (AMOC), (2) the release of ocean methane hydrates, (3) shifts in boreal ecosystems, (4) the breakup of the low-latitude stratocumulus cloud deck, and (5) the die-off of tropical coral reefs. It is therefore important to note that our carbon feedback module is only a partial representation of the magnitude of U.S.-specific impacts from earth system feedbacks and tipping points identified in the academic literatures. For example, climate modeling indicates that one of the many global and regional consequences of a weakened AMOC is accelerated SLR on the eastern coast of North America, which would impact highly populated cities of the United States (Wang et al. 2023).

RFF (2024) develop code to model the three remaining mechanisms using approaches closely tied to those in Dietz et al. (2021): (1) the carbon feedback from permafrost thaw, (2) the carbon feedback from Amazon rainforest dieback, and (3) damages to the Indian economy from the disruption of the Indian summer monsoon (ISM). Since Dietz et al.'s modeling of the ISM is limited to the direct effect on the Indian economy, it is not relevant to the damage module used in this U.S.-focused paper. Therefore, in this paper we incorporate only the carbon feedbacks from permafrost thaw and Amazon rainforest dieback, based on the methods in Dietz et al. (2021) as described below. As shown in Table 1 of Section 3a, accounting for these two carbon feedback effects increases the U.S.-specific SC-CO_2 by 9 to 50 percent in existing global and U.S. models that take an enumerative approach to estimating climate damages. This increase represents the temperature-driven damages from the additional carbon released from permafrost thaw and Amazon dieback. It does not reflect the value of other physical impacts from these feedbacks, such as lost ecosystem services and biodiversity loss from Amazon rainforest dieback (Dietz et al. 2021, 2023) and infrastructure damage from permafrost thaw (Huntington et al. 2023). We briefly describe the modeling of the Amazon rainforest dieback and permafrost thaw below and then present the impact of these two carbon feedback effects on the GMST and U.S. temperature projections used in this paper. Specifically, Figures C.1 and C.2 show how the inclusion of these carbon feedbacks impact the GMST and the U.S. mean surface temperature, respectively.

Amazon rainforest dieback. Dieback of the Amazon rainforest due to climate change is expected to add billions of additional tons of CO_2 to the atmosphere, which will amplify warming. Other important damages associated with the Amazon rainforest dieback, including the loss of biodiversity and ecosystem services, are not incorporated in this module. To implement this feedback in our framework, we follow the approach of Dietz et al. (2021). The input into this module is GMST change, and the output is added CO_2 released, which is added to the emissions inputs to the FaIR climate model in the subsequent year. The probability that the Amazon dieback begins in any year after 2010 increases in global mean surface temperature. A uniform [0,1] random variable is drawn for each Monte Carlo draw and the feedback is triggered if the value is less than this probability. Following Dietz et al. (2021), it is assumed that there is a total of 183 gigatons of CO_2 is released over time. The amount of time that the carbon is released is sampled from a triangular distribution with a minimum of 10 years, a maximum of 250 years, and a central value of 50 years.

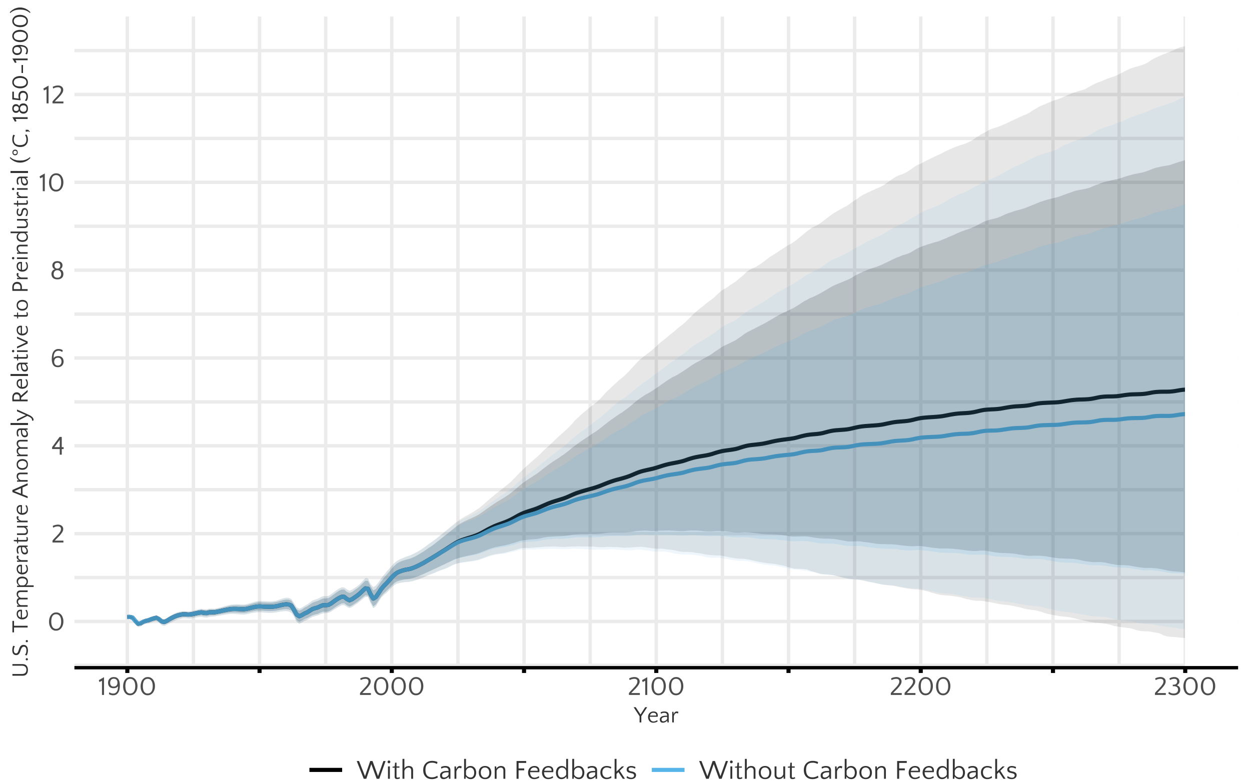
Permafrost carbon feedback. Similar to the modeling of Amazon rainforest dieback, we represent the permafrost carbon feedback following the approach of Dietz et al. (2021). The module uses GMST as an input, and as temperatures rise, thawing of the permafrost is expected to release additional CH_4 and CO_2 into the atmosphere, which are the output variables of the module that are input back into the FaIR climate model in the subsequent year. Other damages associated with permafrost thawing, such as infrastructure damage and soil erosion, are not included in this module. There are five uncertain variables that are sampled according to a normal distribution with the same parameter values as those used in Dietz et al. (2021) with an adjustment of truncating the normal distribution at zero. The equations for the relationships between these uncertain variables are presented in the supplemental materials of Dietz et al. (2021) and govern the stock of organic carbon in the permafrost, the proportion of the permafrost that thaws with increased temperatures, how quickly the thawed carbon decomposes into CO2 and CH4, and the proportion of the thawed carbon that is released into a passive reservoir.

Figure C.1: Global mean surface temperature anomaly with and without additional carbon feedbacks



Global mean surface temperature anomaly (GMST) (solid line) from FaIR 1.6.2, along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges that are a result of the joint uncertainty underlying FaIR 1.6.2 and the RFF-SPs.

Figure C.2: U.S. mean surface temperature anomaly with and without additional carbon feedbacks



U.S. mean surface temperature (solid line) from combining FaIR 1.6.2 GMST and CONUS population-weighted patterns (EPA 2024b), along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges that are a result of the joint uncertainty underlying FaIR 1.6.2 and the RFF-SPs.

Appendix D: Technical Documentation for the Implementation of Qiu et al. (2024)

This appendix describes the steps we take to implement a wildfire health damage function based on Qiu et al. (2024) within a modified MimiGIVE framework to estimate the U.S. impact-specific SC-CO_2 presented in Table 2. Because Qiu et al. (2024) do not provide an explicit damage function for direct implementation in a climate change IAM such as GIVE, we use the output $PM_{2.5}$ attributable all-cause mortality data from their paper to approximate a reduced form damage function based on their work.

Qiu et al. (2024) develop a framework that estimates changes in excess mortality that is attributable to $PM_{2.5}$ exposure from wildfire smoke. The authors use an ensemble of region-specific statistical and machine learning models to project wildfire emissions as a function of climate and land-use variables over North America and use county-level mortality data from 2006-2019 to empirically estimate the effects of wildfire-specific $PM_{2.5}$ on all-cause mortality rates in the CONUS. These empirical relationships are combined with projected climate variables from 28 GCMs in CMIP6 to generate future projections of wildfire smoke $PM_{2.5}$ and mortality burden in each cell of a grid with 10km resolution. For this paper, we received data from the authors that was GCM-specific national mortality projections under three SSP-RCP combinations (SSP1-2.6, SSP2-4.5, SSP3-7.0) for three future time periods (2026-2035, 2036-2045, and 2046-2055), for a total of 252 unique data points.

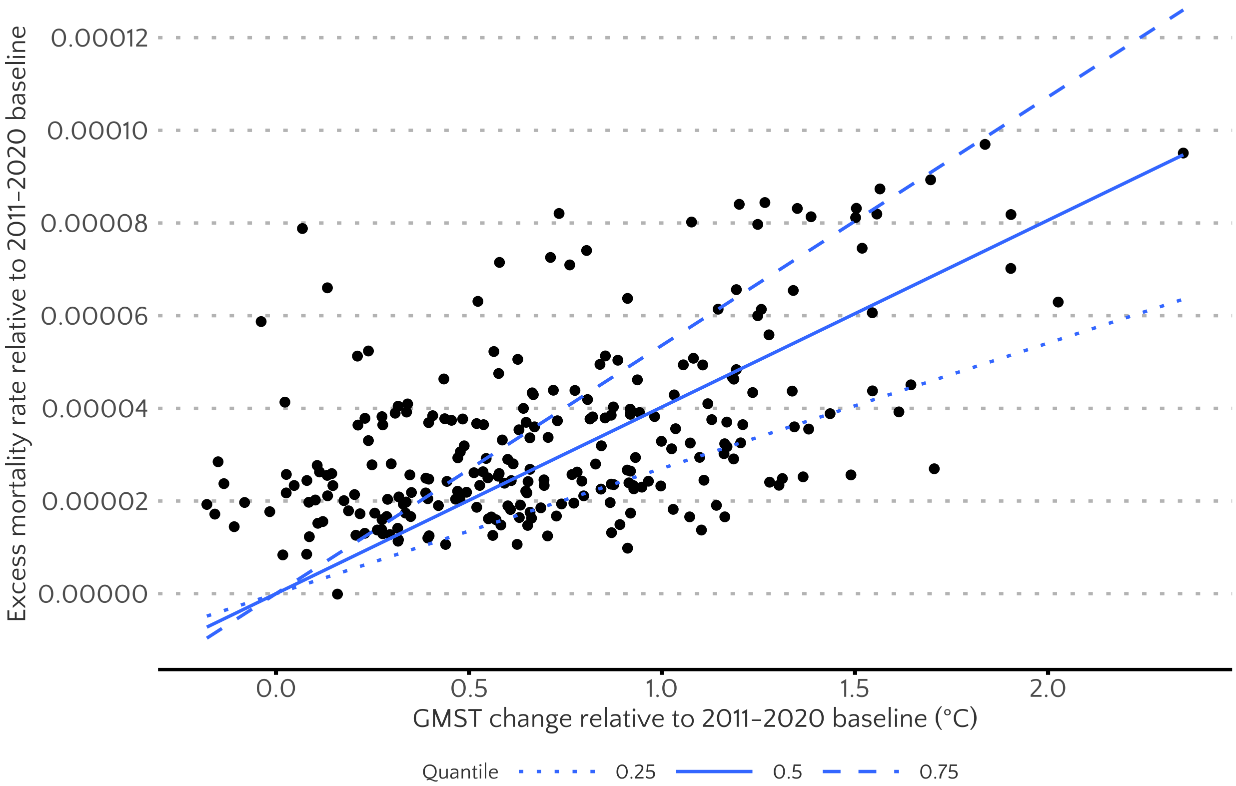
The authors calculate the average annual mortality for each of the three time periods assuming a U.S. population of 351,764,939—a result of scaling their gridded U.S. population in 2022 (CIESIN 2022) by U.S. Census projections of population and population growth to the year 2050 (U.S. Census, 2023).[36] Therefore, to maintain consistency with their methodology, we calculated the national average annual mortality rate in each observation by dividing by this total population. We then subtracted the wildfire mortality rate in the 2011-2020 baseline (6.74 per 100,000) for a measure of excess mortality above that baseline. To recover the GMST change relative to the 2011-2020 baseline for each of the 252 observations, we subtracted each observation's GMST change above the pre-industrial baseline by the average GMST change in 2011-2020 from the FaIR outputs (~1.16 °C). Finally, we estimate quantile regressions of excess mortality on temperature with no intercept (using the 25^{th}, 50^{th}, and 75^{th} quantiles) to generate slope parameters that are used in a modified MimiGIVE damage module, using the range of the estimated quantile regression coefficients to characterize the uncertainty in GMST-driven changes in wildfire smoke-related mortality. Table D.1 and Figure D.1 present the results of these regressions.

Table D.1: Quantile regression summary statistics

Quantile	Estimated slope	Standard error	t-value	p-value
25	2.70E-05	8.63E-07	23.6	< 2E-16
50	4.03E-05	9.72E-07	27.7	< 2E-16
75	5.36E-05	1.00E-06	35.8	< 2E-16

[36] GCM-specific output data, mortality rates, and population estimates were received directly from the authors (Personal communication with Minghao Qiu, December 4, 2024, January 7, 2025).

Figure D.1: Quantile regressions of GMST change on excess mortality from wildfire-related $PM_{2.5}$ emissions



Each point represents a GCM x SSP-RCP x epoch pairing for a total of 252 unique points. Quantile regression was used to recover the median (solid), 5th (dotted), and 95th (dashed) bounds of the wildfire damage function approximation from Qiu et al. (2024). The slopes of the lines were then used to define a triangular distribution of the wildfire damage coefficient, from which a value was randomly sampled for each of the 10,000 Monte Carlo simulations.

We construct a MimiGIVE damage component in which the slope parameter of the wildfire mortality rate function was drawn from a triangular distribution with parameters corresponding to the slopes of the quantile regressions above. To avoid making projections that extend further into the future than what is attempted by Qiu et al. (2024), we hold the mortality rate fixed at its 2055 level in each trial. Consistent with other health-related damage functions used in this paper, the projected changes in premature mortality are monetized using a U.S. population-average measure of willingness to pay for mortality risk reductions. [37]

[37] Specifically, projected changes in premature mortality in the U.S. are monetized using the same value of mortality risk reduction as in the EPA's regulatory analyses ($4.8 million in 1990 (1990USD)) and adjusted for income growth and inflation following current EPA guidelines and practice (EPA 2010) and consistent with EPA Science Advisory Board (SAB) advice (see e.g., EPA 2011, OMB 2003), resulting in a 2020 value of $10.05 million (2020USD). See EPA (2023) for more discussion.

Appendix E: Technical Documentation for Implementation of Macroeconomic Econometric Studies

For each of the macroeconomic econometric studies discussed in Section 3c, we construct a damage component that replicates the econometric results and projection methods in the paper and that can be implemented in the MimiGIVE modeling framework to estimate a U.S. impact-specific SC-CO_2 reflecting the GDP-based market damages from CO_2 emissions changes. For each paper, we focus on the authors' stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. This Appendix provides (1) a summary of key differences in data used for the econometric estimation and projections presented in each study, (2) a description of central end-of-century damage estimates for the U.S. from our modelling results and from each study, and (3) a description of how we validated that each damage component replicates the authors' empirical results.

E.1 Summary of data underlying the estimation and projections in each study.

Table E.1 presents a summary of the data used in each macroeconomic econometric study discussed in Section 3c. It lists both the sources of data and measurement applied in the econometric estimation of the relationship between weather variables and economic growth, as well as the data used for the GDP loss projections presented in each paper.

Table E.1: Source data used in the 8 macroeconomic econometric studies

A. Temperature					
Paper	Estimation Data	Estimation Sample Years	Estimation Temperature Weighting and Base Year	Projection Baseline	Projections[a]
Burke et al. (2015)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	mean 1980-2010	Ensemble mean warming of models in CMIP 5, RCP 8.5
Kalkuhl et al. (2020)	CRU gridded (Harris et al., 2014)	1900-2014	Area weighted	mean 2015-2019	Princeton Earth System Model GFDL-ESM2M, RCP 8.5 (Warszawski et al., 2014)
Newell et al. (2021)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	mean 1980-2010 (Burke data)	Ensemble mean warming of models in CMIP 5, RCP 8.5
Acevedo et al. (2020)	CRU gridded (Harris et al., 2014)	1950-2015	Population weighted, 1950	2005	Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) mean of all models, RCP 8.5 and 4.5
Kahn et al. (2021)	UDel gridded (Matsuura and Willmott, 2015)	1960-2014	Population weighted, 2010	2014	Author-calculated parametric forecasts using estimation data, RCP 8.5 and 2.6
Casey et al. (2023)	UDel gridded (Matsuura and Willmott, 2018)	1960-2010	Population weighted, 2000	2010 (Burke data)	World Meteorological Organization (WMO), RCP 8.5
Harding et al. (2024)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	mean 1980-2010 (Burke data)	Ensemble mean warming of models in CMIP 5, RCP 8.5
Nath et al. (2024)	Global Meteorological Forcing Dataset (Sheffield et al., 2006)	1960-2015	Population weighted, annual	mean 1980-2010 (Burke data)	Ensemble mean warming of models in CMIP 5, RCP 8.5

This table summarizes the source temperature data for each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. Burke et al. (2015): Table 1, col 1. Kalkuhl and Wenz (2020): Table 4, col 5. Newell et al. (2021): Levels version of Burke et al. (2015). Kahn et al. (2021): Table 2, spec 2 (m=30). Casey et al. (2023): Table 1, col 2. Harding et al. (2024): Table 1, col 5. Nath et al. (2024): Full dynamics with time FEs (Fig 6c).

[a] The Projections column describes the source of RCP-consistent temperature projections used in the papers. Aside from Kalkuhl and Wenz (2020), most papers link directly to a web interface for data request and collection (where citation is relatively clear). Papers using CMIP 5 models and WMO data draw from the KNMI Climate Explorer. Acevedo et al. (2020) draw from the NASA Center for Climate Simulation.

B. Precipitation					
Paper	Estimation Data	Estimation Sample Years	Estimation Precipitation Weighting and Base Year	Projection Baseline	Projections
Burke et al. (2015)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	NA	NA
Kalkuhl et al. (2020)	CRU gridded (Harris et al., 2014)	1900-2014	Area weighted	NA	NA
Newell et al. (2021)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	NA	NA
Acevedo et al. (2020)	CRU gridded (Harris et al., 2014)	1950-2015	Population weighted, 1950	NA	NA
Kahn et al. (2021)	UDel gridded (Matsuura and Willmott, 2015)	1960-2014	Population weighted, 2010	NA	NA
Casey et al. (2023)	UDel gridded (Matsuura and Willmott, 2018)	1960-2010	Population weighted, 2000	2010	Assumed constant growth at mean historical rate (with and without climate change)
Harding et al. (2024)	UDel gridded (Matsuura and Willmott, 2012)	1960-2010	Population weighted, 2000	mean 1980-2010 (Burke data)	Ensemble mean of models in CMIP 5, RCP 8.5 (inferred based on replication code)
Nath et al. (2024)	NA	NA	NA	NA	NA

This table summarizes the source precipitation data for each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. Burke et al. (2015): Table 1, col 1. Kalkuhl and Wenz (2020): Table 4, col 5. Newell et al. (2021): Levels version of Burke et al. (2015). Kahn et al. (2021): Table 2, spec 2 (m=30). Casey et al. (2023): Table 1, col 2. Harding et al. (2024): Table 1, col 5. Nath et al. (2024): Full dynamics with time FEs (Fig 6c). Projection data using CMIP 5 models draw from the KNMI Climate Explorer.

C. Socioeconomics					
Paper	Estimation Data	Estimation Sample Years		Projection Base Year	Projections
Burke et al. (2015)	World Bank WDI	1960-2010	-	2010	SSPs 1-5, OECD group (O'Neill et al., 2014)
Kalkuhl et al. (2020)	Author-compiled Gross Regional Product	1900-2014	-	2015	SSP 2 (O'Neill et al., 2014)
Newell et al. (2021)	World Bank WDI	1960-2010	-	2010	SSPs 1-5, OECD group (O'Neill et al., 2014)
Acevedo et al. (2020)	IMF World Economic Outlook and World Bank WDI	1950-2015	-	NA	NA
Kahn et al. (2021)	World Bank WDI	1960-2014	-	NA	NA
Casey et al. (2023)	Penn World Tables 10.0 (Feenstra et al., 2015)	1960-2010	-	2010	Author-calculated parametric projections of socioeconomics
Harding et al. (2024)	World Bank WDI	1960-2010	-	2010	SSPs 1-5, OECD group (O'Neill et al., 2014)
Nath et al. (2024)	World Bank WDI	1960-2015	-	2010	SSPs 1-5, OECD group (O'Neill et al., 2014)

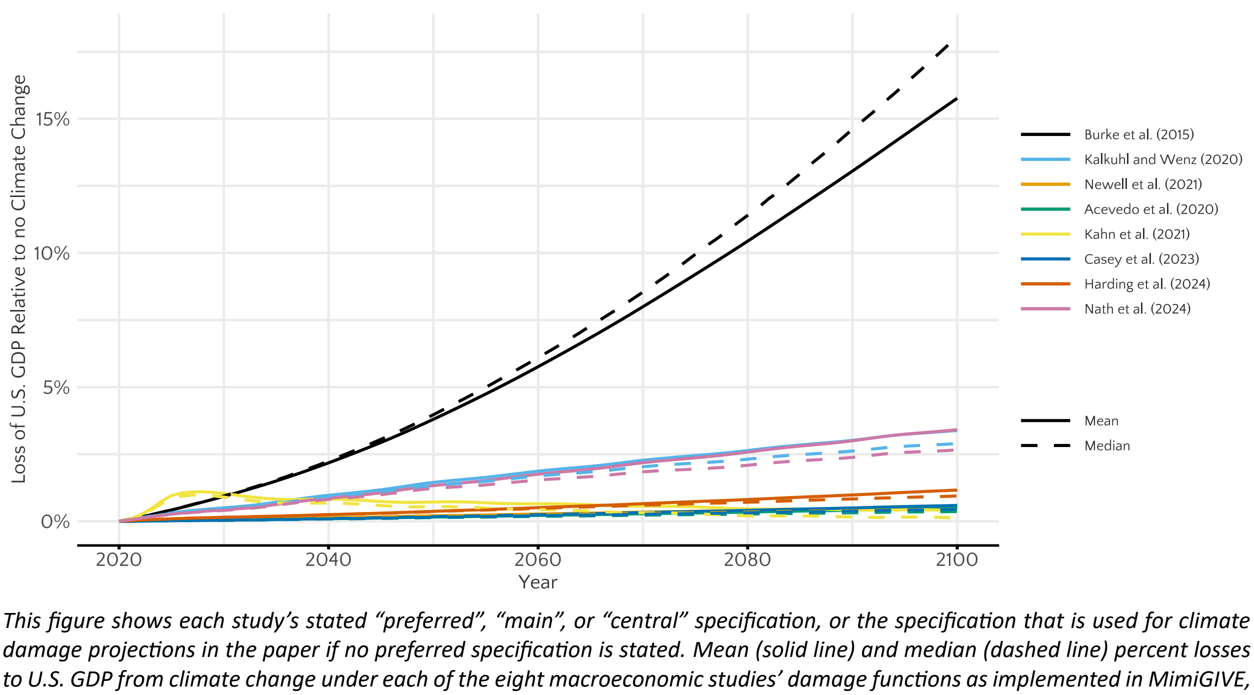
This table summarizes the source socioeconomic data for each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. Burke et al. (2015): Table 1, col 1. Kalkuhl and Wenz (2020): Table 4, col 5. Newell et al. (2021): Levels version of Burke et al. (2015). Kahn et al. (2021): Table 2, spec 2 (m=30). Casey et al. (2023): Table 1, col 2. Harding et al. (2024): Table 1, col 5. Nath et al. (2024): Full dynamics with time FEs (Fig 6c).

E.2 Projected U.S. GDP Loss from MimiGIVE Implementation of Macroeconomic Econometric Damage Functions

Figure E.1 presents projections of U.S. GDP loss from climate through 2100 resulting from the MimiGIVE implementation of each study's constructed damage function together with the U.S. projections of socioeconomic variables from the RFF-SPs and the U.S. temperature projections described in Appendix C. The Figure displays both the mean (solid lines) and the median (dashed lines) of estimated damages across the 10,000 Monte Carlo simulations in each year, where the socioeconomic and climate module parameters are consistent across the studies (i.e., the first trial of Burke et al. (2015) damage function takes the same socioeconomic pathways and climate parameters as the first trial of Kalkuhl and Wenz (2020, Newell et al. (2021) and so forth).

Consistent with the discussion in Section 3c, earlier papers in the literature such as Burke et al. (2015) that project permanent growth impacts from temperature change imply large damages to the U.S. economy over the next century (i.e., reductions in GDP of more than 15 percent relative to a scenario without climate change). Papers finding temperature to have temporary effects on GDP growth project modest impacts no more than a few percentage point reduction in U.S. GDP, and recent papers modeling varying degrees of persistence reflect an in-between case.

Figure E.1: Projections of U.S. GDP loss from climate change, MimiGIVE implementation of recent macroeconomic econometric studies



This figure shows each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. Mean (solid line) and median (dashed line) percent losses to U.S. GDP from climate change under each of the eight macroeconomic studies' damage functions as implemented in MimiGIVE, accounting for U.S. socioeconomic, climate, and damage parameter uncertainty across 10,000 Monte Carlo simulations. Each damage function requires a measure of current climate or baseline temperature; for all damage functions we use country-level population-weighted mean temperatures from 1980 to 2010 drawn from Burke et al. (2015). All GDP losses are relative to no climate change (i.e. no temperature anomalies above current climate) except Kahn et al. (2021), which is relative to a continuation of their country-level estimated historic warming trend from 1960 to 2014. U.S. damages include Puerto Rico.

E.3 Validation of MimiGIVE Implementation of Macroeconomic Econometric Damage Functions

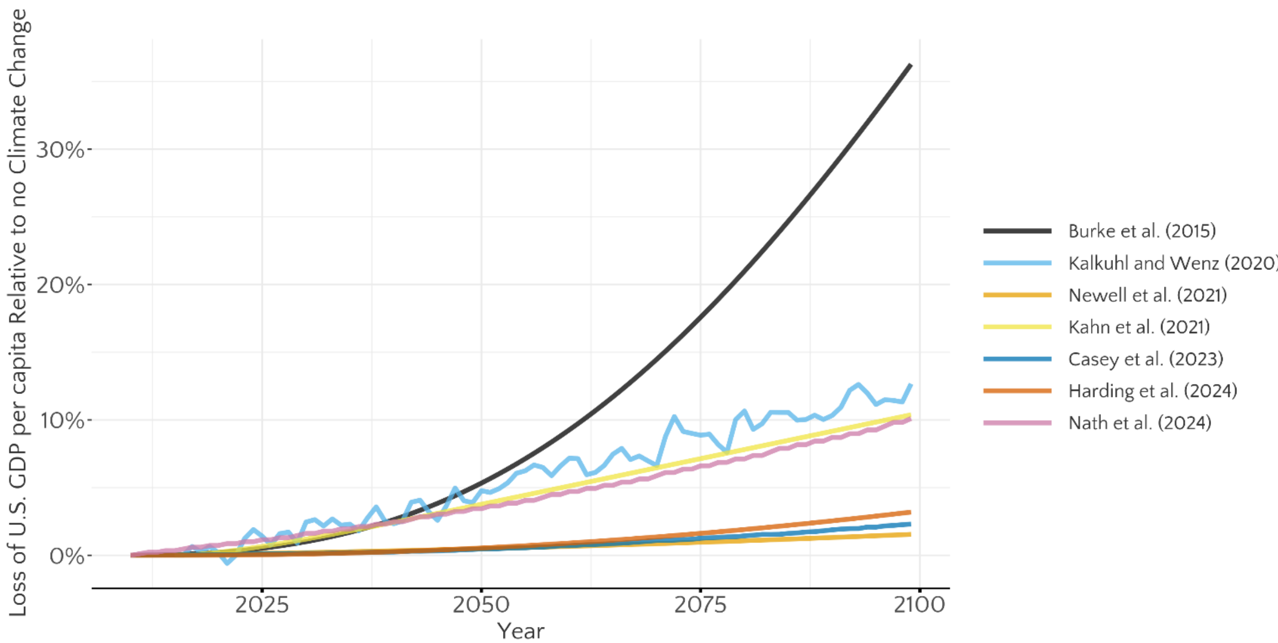
To validate that the damage component constructed for use in MimiGIVE provides an accurate representation of each paper's findings, we confirmed that U.S. GDP per capita loss projections based on our constructed damage functions under an SSP5/RCP8.5 scenario through 2100 approximates the U.S. GDP per capita loss projections from a similar RCP8.5 radiative forcing scenario generated using the replication code for each paper. There are two main advantages to this validation approach. First, the comparison is an intuitive one because all the papers we analyze provide projections consistent with an RCP8.5 scenario through 2100. Second, this approach allows us to focus attention on validating the damage component implementation: the projected GDP per capita loss comparison requires no discounting, marginal analysis, or explicit treatment of uncertainty.

Figure E.2 plots the U.S. GDP per capita losses projected under the RCP8.5-consistent scenario that were extracted from running the replication code available for each paper.[38] For the purposes of the validation exercise, we exclude damages to Puerto Rico, which are commonly estimated separately. The figure shows relative differences across papers under this scenario consistent with the patterns found in Figure E.1, and in Figure 4 in Section 3c. Earlier literature such as Burke et al. (2015) that projects permanent growth impacts from temperature change imply much larger damages to the U.S. economy over the next century than papers finding temperature to have temporary effects on GDP growth (e.g., Newell et al. 2021). Papers modeling varying degrees of persistence reflect an in-between case (e.g., Nath et al. 2024).

The projections displayed in Figure E.2 reflect not only differences in econometric methods used to estimate the effect of climate variables on economic output, but also differences in the underlying data used in the estimation and projection methods. As seen in Table E.1 above, temperature projections consistent with RCP8.5 across the papers are drawn from a variety of sources, projections are made with different base years or measurements of baseline temperatures, or with different treatment of precipitation effects. Therefore, the next steps of the validation procedure required harmonizing the diverse set of year coverage, exogenous inputs, and model assumptions until an apples-to-apples comparison could be made between damage paths from paper replication codes and the MimiGIVE implementation of each paper's damage function.

[38] We obtained replication codes for most of the published papers from publicly available replication packages, listed in the references. For the working papers and Newell et al. (2021), which do not have publicly available replication packages, we obtained the relevant replication codes and data via correspondence with the authors. Additionally, Acevedo et al. (2020) is not listed in this appendix – although the code is publicly available, the damage projections are not included in the replication package. We confirmed our projection approach via correspondence with the authors but are unable to show a quantitative comparison with paper results for this study.

Figure E.2: Projections of U.S. GDP per capita loss under RCP8.5 climate scenario, from replication code of macroeconomic econometric studies



This figure shows each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. Burke et al. (2015): Table 1, col 1. Kalkuhl and Wenz (2020): Table 4, col 5. Newell et al. (2021): Levels version of Burke et al. (2015). Kahn et al. (2021): Table 2, spec 2 (m=30). Casey et al. (2023): Table 1, col 2. Harding et al. (2024): Table 1, col 5. Nath et al. (2024): Full dynamics with time FEs (Fig 6c). All GDP losses are relative to no climate change (i.e. no temperature anomalies above current climate) except Kahn et al. (2021), which is relative to a continuation of their country-level estimated historic warming trend from 1960 to 2014. U.S. GDP per capita losses in the figure exclude Puerto Rico.

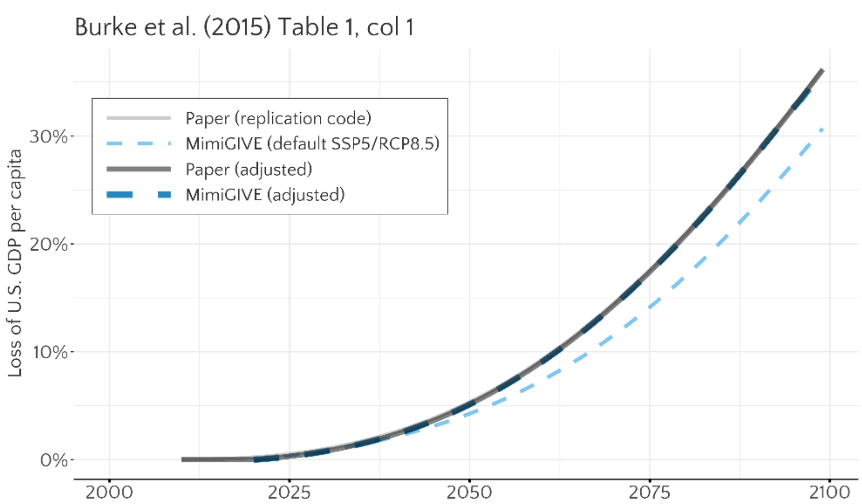
Figure E.3 below illustrates these steps. Each panel of the figure shows four (sometimes overlapping) damage paths under an RCP8.5-consistent scenario, plotted with time on the x-axis. The two solid lines are outputs produced with paper replication codes, and the two dashed lines display outputs from damage function implementations in the MimiGIVE IAM. An initial comparison between the paper replication outputs and the MimiGIVE implementation is represented by the lighter-colored lines. The solid light grey line displays the same GDP loss projections as the summary Figure E.2 above (the raw replication code outputs), while the light-colored dashed line shows results from the MimiGIVE damage component implementation under default SSP5 and RCP8.5 scenarios.[39] For most papers, this initial comparison yields damage paths of similar shape and order of magnitude, with some exceptions. We then explore to what extent the remaining differences are driven by model inputs and assumptions described above.

The outcome of our input adjustments (required to create an apples-to-applies comparison) is represented by the darker lines in each panel. The solid dark grey line shows paper replication outputs with adjustment to the replication codes. For example, for all papers we dropped any damages prior to 2020, the base year of the MimiGIVE IAM. Other adjustments are described beside each panel. Finally, the dark-colored dashed line displays MimiGIVE damage component results after substituting relevant information from each paper (such as country-level temperature projections), again extracted using replication codes, into the damage

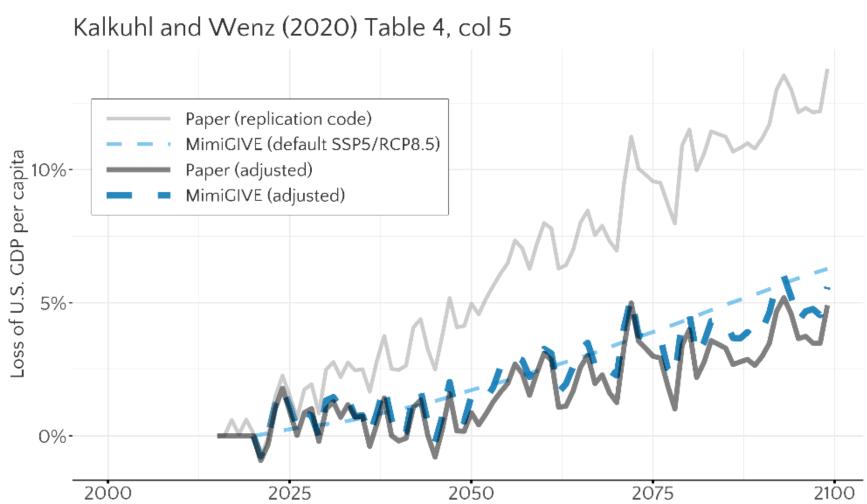
[39] For more details on SSP and RCP implementation in the Mimi framework see: https://github.com/anthofflab/MimiSSPs.jl.

components. In general, we considered a damage component to be validated when the solid dark grey line and the dark-colored dashed line coincided, indicating that under equivalent (baseline and RCP8.5) temperature assumptions the MimiGIVE implementation yielded the same U.S. GDP per capita losses as the paper's projections. Substitutions and other issues specific to each paper are explained alongside the relevant panel of Figure E.3.

Figure E.3: Illustration of validation procedure for MimiGIVE damage function implementations

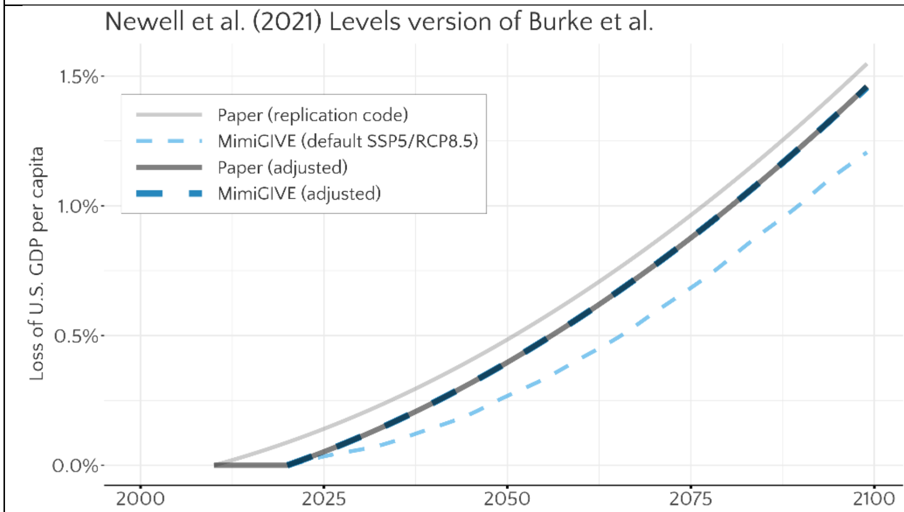
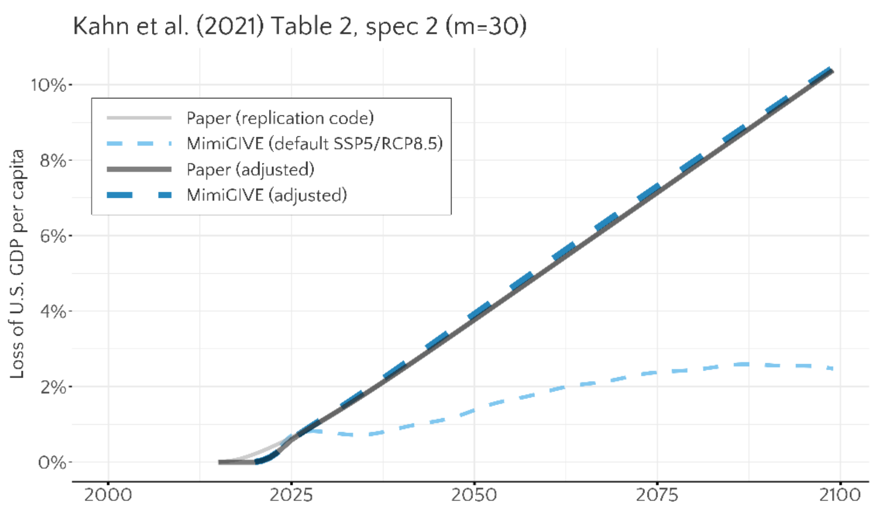
<table>
<tr>
<td>
</td>
<td>Burke et al. (2015):

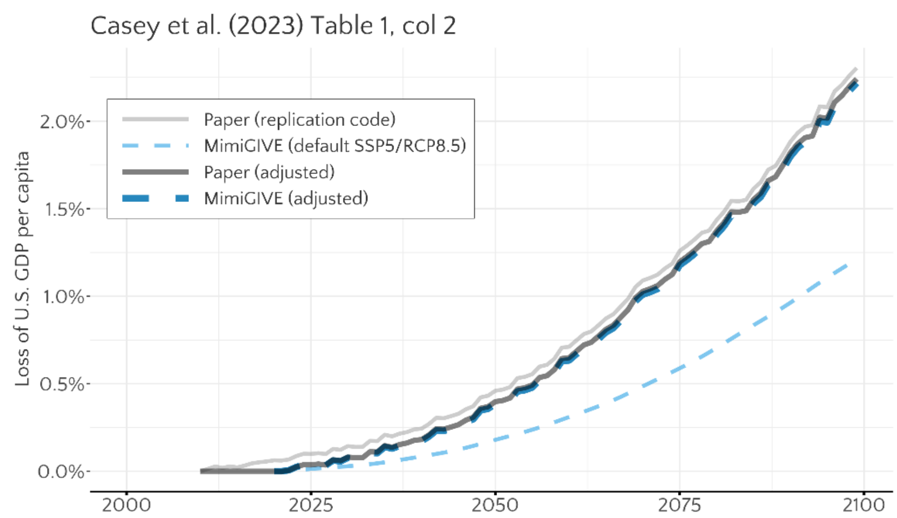
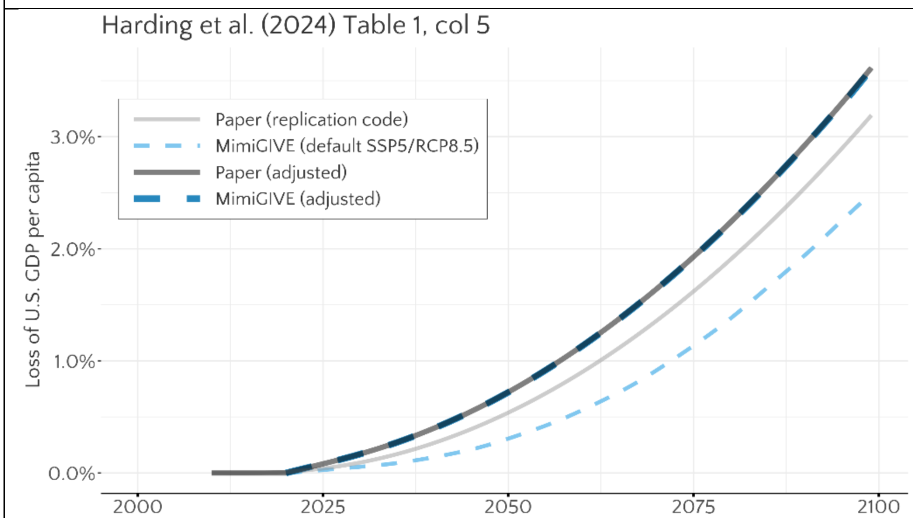
Paper (adjusted):
Drops damages prior to 2020 from the replication code.

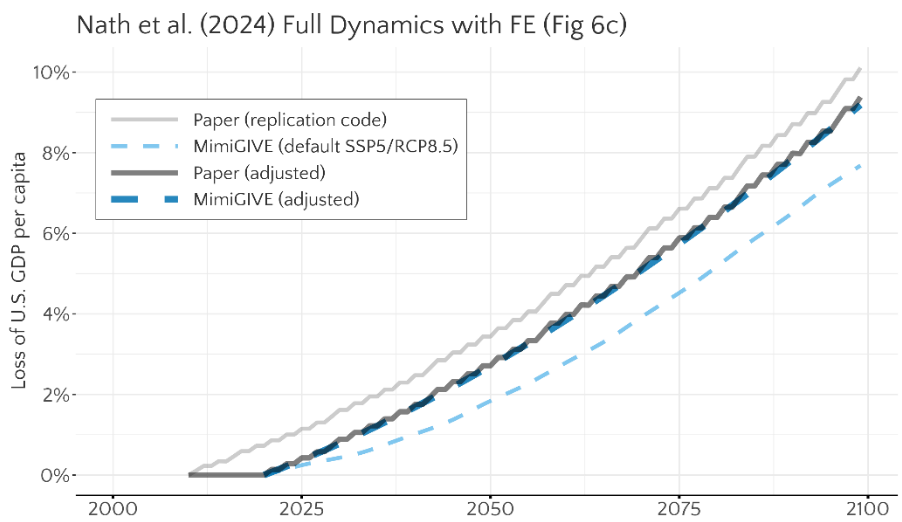
MimiGIVE (adjusted):
Substitutes country-level projected temperature paths consistent with RCP8.5 from the paper into the MimiGIVE climate component.</td>
</tr>
<tr>
<td>
</td>
<td>Kalkuhl and Wenz (2020):
MimiGIVE estimate of U.S. damages was compared with an output-weighted sum of state-level damages from the paper.

Paper (adjusted):
Drops damages prior to 2020 from replication code and edits the damage computations to be consistent with the econometric lags and empirical estimates presented in the paper text.

MimiGIVE (adjusted):
Substitutes population-weighted sum of state-level temperature projections from the paper into MimiGIVE. (The adjusted lines do not exactly coincide because paper damages for the U.S. are an output-weighted sum of nonlinear</td>
</tr>
</table>

	damages estimated at the state level, whereas MimiGIVE damages are estimated at the country level.)
	Newell et al. (2021): Damage estimation is a variant of the Burke et al. (2015) implementation. Paper (adjusted): Same as in Burke et al. above. MimiGIVE (adjusted): Same as in Burke et al. above.
	Kahn et al. (2021): Damage estimation uses a recursive computation of long-run damages combined with parametric assumptions on expected future variations in temperature. Paper (adjusted): Drops damages prior to 2020 from replication code. MimiGIVE (adjusted): Substitutes paper climate assumptions into MimGIVE. (The paper's parametric assumptions imply a high degree of U.S. warming relative to publicly available country-level projections of future temperatures.)

	Casey et al. (2023): Temperature affects TFP and GDP per capita losses are derived from a Solow-model-based computation. Paper (adjusted): Drops damages prior to 2020 from replication code. MimiGIVE (adjusted): Substitutes paper's inputs into MimiGIVE, including the paper's reduced-form socioeconomic projections, baseline capital stocks, temperatures, and projected future temperatures.
	Harding et al. (2024): Damage estimation is a variant of the Burke et al. (2015) implementation, modified with a convergence term. Paper (adjusted): Drops damages prior to 2020 from replication code. MimiGIVE (adjusted): Substitutes paper's temperature and precipitation projections into MimiGIVE.

	Nath et al. (2024): Damage estimation is a variant of the Burke et al. (2015) implementation. MimiGIVE implementation uses a smooth approximation of their state-dependent step function. Paper (adjusted): Drops damages prior to 2020 from replication code. MimiGIVE (adjusted): Substitutes paper's country-level projected temperature paths into MimiGIVE.

To summarize, we validated our MimiGIVE implementation of the damage functions from seven macroeconomic econometric studies by comparing U.S. GDP per capita loss projections based on our constructed damage function under an RCP8.5-consistent scenario with the projections generated using the replication code for each paper. We showed that when year coverage, exogenous model inputs, and model assumptions are harmonized, the MimiGIVE implementations yield similar results to the paper replication codes. Table E.2 summarizes the projected end-of-century U.S. GDP per capita losses from the validation exercise. The first column shows U.S. GDP per capita loss in 2099 drawn directly from unadjusted replication codes, the second column shows paper replication code damages including our adjustments to the replication codes (described above), and the third column shows damages from our MimiGIVE implementations under climate assumptions used in the papers. Thus, the comparison relevant for assessing error in the MimiGIVE implementations is between the second and third columns of the table.

Table E.2: U.S. GDP per capita lost in 2099 under RCP 8.5 (relative to no climate change), from paper replication codes and MimiGIVE results

Paper and Specification	Paper (Replication code)	Paper (Adjusted)	MimiGIVE (Adjusted)
Burke et al. (2015) Table 1, col 1	36.28%	36.14%	36.02%
Kalkuhl and Wenz (2020) Table 4, col 5	13.79%	4.91%	5.59%
Newell et al. (2021) Levels version of Burke et al. (2015)	1.55%	1.46%	1.46%
Kahn et al. (2021) Table 2, spec 2 (m=30)	10.38%	10.38%	10.45%
Casey et al. (2023) Table 1, col 2	2.30%	2.24%	2.22%
Harding et al. (2024) Table 1, col 5	3.19%	3.62%	3.60%
Nath et al. (2024) Full dynamics with FE (Fig 6c)	10.11%	9.38%	9.18%

This table shows validation results for each study's stated "preferred", "main", or "central" specification, or the specification that is used for climate damage projections in the paper if no preferred specification is stated. All GDP losses are relative to no climate change (i.e. no temperature anomalies above current climate) except Kahn et al. (2021), which is relative to a continuation of their country-level estimated historic warming trend from 1960 to 2014. U.S. GDP per capita losses in the table exclude Puerto Rico.