Working Paper Series
Congressional Budget Office
Washington, D.C.

The Effects of Climate Change on GDP in the 21st Century

Chad Shirley
Congressional Budget Office
Chad.Shirley@cbo.gov

William Swanson
Congressional Budget Office
William.Swanson@cbo.gov

Working Paper 2025-02

February 2025

To enhance the transparency of the work of the Congressional Budget Office and to encourage external review of that work, CBO's working paper series includes papers that provide technical descriptions of official CBO analyses as well as papers that represent independent research by CBO analysts. Papers in this series are available at http://go.usa.gov/xUzd7.

For valuable comments, the authors thank Elizabeth Kopits of the Environmental Protection Agency, Ishan Nath of Harvard University's Kennedy School of Government, Brian Prest of Resources for the Future, Valerie Ramey of Stanford University, and James Stock of Harvard University. The authors also benefited greatly from comments by Christopher Adams, Nicholas Chase, Michael Falkenheim, Evan Herrnstadt, Joseph Kile, Jeffrey Kling, Junghoon Lee, and Hark Yoo. The authors gratefully acknowledge the editorial assistance provided by Christine Browne.

Abstract

This working paper provides an estimate of a probability distribution of changes in gross domestic product (GDP) in the year 2100 resulting from changes in temperature. To estimate that distribution, we perform a meta-analysis of the literature on the effects of climate change on GDP and combine those effects with forecast global temperature distributions for the year 2100. We fit Gaussian distributions to the underlying data and numerically estimate the joint distribution of GDP and temperature. Using that distribution, we project that, on average, future temperature increases will cause GDP to be 4 percent lower in 2100 than it would have been if temperatures remained unchanged after 2024. However, considerable uncertainty surrounds the long-run effects of temperature on output in the United States. There is a 5 percent chance that GDP in 2100 will be at least 21 percent lower than it would have been in the absence of additional changes in temperature. There is a similar chance that GDP will be at least 6 percent higher by 2100.

Keywords: climate change, economic growth

JEL Classification: O44, Q54

Contents

1. Introduction

Climate change is expected to affect the United States in a variety of ways in the 21st century. Although those effects will be positive in some ways or in certain areas of the country, the overall effect is expected to be negative: Temperatures will increase, the risk of damage from storms and wildfires will increase, and the productivity of outdoor workers will decline. Lawmakers have expressed an interest in understanding the range of possible outcomes from climate change. CBO recently released a report describing some of those effects.[1] In that report, CBO estimated that there is a 5 percent chance that future increases in temperature will cause U.S. gross domestic product (GDP) to be at least 21 percent lower in 2100 than it would be if temperatures remained unchanged. Similarly, there is a 5 percent chance that changes in temperatures will cause GDP in 2100 to be higher by 6 percent or more than it would have been otherwise. The distribution of GDP losses is skewed so that the probability of large negative GDP outcomes relative to the median is higher than the probability of small negative outcomes. The mean of the distribution is a 4 percent GDP loss from climate change.

In this working paper, we describe the modeling framework that CBO developed to generate those estimates. Though the methods build from an existing academic literature and from past work by the agency, our approach in this paper differs from past work in three respects. First, our goal is to characterize the distribution of possible outcomes from temperature changes under a set of emissions scenarios that broadly reflect current abatement policies instead of estimating the average or most likely effect or the effect of policies that could be adopted to reach certain climate goals. Second, our aim is to characterize the unconditional distribution of GDP outcomes, which is a departure from the literature that focuses on the distribution of GDP conditional on a specific amount of temperature change, such as 3 degrees Celsius (3°C). Finally, our focus is the effect of climate change specifically on U.S. GDP, rather than global impacts. Several innovative modeling features are developed in this paper to arrive at robust results that address our specific research goals.

We perform a meta-analysis on a set of studies that provide estimates for the effects of climate change on GDP. Those estimates are combined with forecasts of temperature changes out to 2100 to create a mixed probability density that is the weighted average of many separately estimated probability densities. Changes in temperature are calculated relative to our reference climate, defined as the prevailing climate between 1850 and 1900.[2] Each component distribution in the mixed density is weighted by a systematic measure of relevance. The result is a final joint density that averages together the many weighted component densities and describes the likelihood of any pair of outcomes of temperature changes and GDP effects. By integrating that

[1] Congressional Budget Office (2024).

[2] Temperature changes are reported relative to that 1850–1900 reference climate unless otherwise noted.

mixed joint distribution across possible temperature changes, we arrive at the marginal distribution of GDP losses from climate change. Those results can provide insights into the likelihood of a range of possible outcomes of climate change.

Our preferred set of results are robust to an array of sensitivity tests and alternative approaches for estimating the parameters of the final mixed density. We obtain those results using maximum likelihood estimation (MLE) to arrive at the parameters of the component normal distributions in our mixture, but the results change only modestly when using three other statistical approaches. Across all approaches, we explicitly account for the fact that our meta-analysis uses estimated rather than known variance parameters for GDP effects. Among the robustness checks, we review the sensitivity of our results to data outliers by reporting results for subsets of our dataset that consecutively omit each academic study. We also compare our final unconditional distribution of damage with distributions from other meta-analyses in the literature, such as Howard and Sterner (2022), Howard and Sterner (2017), and Nordhaus and Moffat (2017), and conclude that our results are similar. Our discussion of results includes the results of those and other sensitivity tests.

2. Related Literature

This paper is most closely related to the literature that estimates the relationship between climate change and economic growth. Papers on that topic generally use one of three approaches. First, GDP-econometric models use panel datasets with variation across time and geography to estimate historical relationships between variations in economic output and weather (for example, Kalkuhl and Wenz, 2020). Second, computable general equilibrium (CGE) models depend heavily on microeconomic theory to model how utility-maximizing consumers and profit-maximizing firms would react to the effects of climate change (for example, Fernando, Liu, and McKibbin, 2021). Third, build-up models quantify the impacts of climate change on narrowly defined sectors and then add them up to arrive at an overall estimate of damage (for example, Hsiang and others, 2017). Some researchers have also conducted meta-analyses and developed techniques to combine the results from multiple studies across all three approaches.

The approach we use in this paper is a meta-analysis. Our meta-analysis is similar to those that use random-effects panel regression models to combine estimates of the effects on GDP from climate change, such as Tol (2024), Barrage and Nordhaus (2024), Howard and Sterner (2022, 2017), and Nordhaus and Moffat (2017). CBO's previous working paper on the issue also uses a random-effects meta-analysis for climate damage coupled with hurricane-induced damage.[3] Like the authors of many papers in that literature, we rely on certain criteria for selecting the studies that we incorporate into our analysis. We use estimates that were published since 2016 and that

[3] Herrnstadt and Dinan (2020).

quantify the impact of climate change on U.S. GDP out to 2100. We do not restrict our attention to models that are considered the most efficient in their prediction methods.[4]

Most papers in the literature, across all of the approaches described above, estimate GDP outcomes conditional on changes in temperature. The literature has not yet consistently found that other effects of climate change, such as changes in precipitation, sea level, or hurricane intensity, have an economically significant effect on U.S. GDP growth apart from what is observable through temperature variation.[5] Therefore, similar to the literature, this paper focuses on rising temperatures as the key measure of climate change. The effects of hurricane-induced damage are included explicitly in two papers in our meta-analysis: Hsiang and others (2017) and Roson and Sartori (2016). Apart from including those papers in our meta-analysis, we do not separately estimate hurricane damage to include in our estimates.

To arrive at estimates of GDP outcomes from future temperature increases, we use mixtures of probability densities to combine the results from other studies in our meta-analysis. Mixed densities have been used in a variety of economic applications. For instance, Paçal and others (2023) uses Gaussian mixtures to identify unusually extreme temperatures, and Shin, Kang, and Kim (2022) applies them to forecast a future temperature comfort index. Mixed densities are also used to forecast crop yield risk from climate change in Tack, Coble, and Barnett (2018), Tolhurst and Ker (2015), and Woodard and Sherrick (2011); to forecast industrial demand in Chuang and Oliva (2014); and to forecast supply in Antle (2010). A small but growing literature applies Gaussian mixtures to questions about monetary policy. For example, Hall and Mitchell (2007) combines normally distributed forecasts of the inflation rate using a set of weights that minimize the distance between the predicted and observed inflation rates. Aastveit, Ravazzolo, and van Dijk (2018) provides a review of the literature.

Other approaches in the literature address the range of effects of climate change on people and society by consolidating those effects into a single economic value, which is typically characterized as the social cost of carbon or the social cost of greenhouse gases (GHGs).[6] This paper's focus is the effect of temperature change on U.S. GDP, though we recognize that GDP is an imperfect measure of the many consequences of a warming climate. GDP counts only the current production of goods and services within a country. Many effects of climate change that fall outside the scope of this paper, such as effects on health and national security, are addressed in Congressional Budget Office (2024).

---

[4] See Newell, Prest, and Sexton (2021) for an application of model selection based on out-of-sample model fit.

[5] See Tol (2024); Nath, Ramey, and Klenow (2024); Howard and Sterner (2022); and Newell, Prest, and Sexton (2021).

[6] See, for example, Environmental Protection Agency (2023).

3. Model

In this section and the next, we describe our approach for estimating the effect of temperature change on GDP. Here, we present our modeling framework and the theory behind it and describe the fat-tailed distribution used to model the possibility of extreme outcomes. Then, in the following section, we show how to practically apply this model to the data.

3.1. Modeling Framework

Most studies of the effect of climate change on economic activity, particularly meta-analyses, estimate the effects on GDP conditional on a climate outcome. Those studies generally provide point estimates of the average effect of temperature on GDP, along with either standard errors or confidence intervals, all of which are conditional on a temperature change. Suppose that $p(.)$ is any probability density function (PDF), Y is a the percentage change in GDP in the future from climate change, and T is the change in log temperature in degrees Celsius due to climate change.[7] The goal is to arrive at the unconditional distribution of GDP effects, $p(Y)$, by incorporating estimates of the future climate impacts on temperature, $p(T)$, together with estimates of the conditional GDP effects from the literature, $p(Y|T)$. We relate all three of those distributions, $p(Y)$, $p(Y|T)$, and $p(T)$, to one another by applying the definition of conditional probability:

$$p(Y) = \int p(Y|T)p(T)dT \tag{1}$$

The literature has many, often quite different answers for what $p(Y|T)$ and $p(T)$ are. Studies that report the marginal effects of temperature on GDP provide observations from the distribution of $p(Y|T)$, but the effects can vary widely in their magnitude and their degree of certainty. Observations of $p(T)$ come from climate scenarios like the ones we use in this working paper, but the range of forecast temperature changes is wide, from as low as zero degrees to as high as 5°C under different scenarios of future climate policy and other factors.

The true distributions for temperature and damage conditional on temperature, $p(T)$ and $p(Y|T)$, that appear in Equation (1) are never observed; the nearest alternative that *is* observed comes from the results of GDP studies and climate scenarios. Therefore, we assign each GDP study a distribution function that is indexed by i, $p_i(Y|T)$ and each climate scenario a distribution function that is indexed by j, $p_j(T)$. We can directly estimate the integral in Equation (1) and arrive at the target $p(Y)$ if we replace the true functions with flexible approximations fitted to the point estimates of GDP effects and temperature from each study and scenario.

[7] We use the log of temperature changes because the distribution of temperature changes is skewed and strictly positive relative to the 1850–1900 reference climate. See Section 4.1 for more discussion of the temperature data.

The PDFs, $p(T)$ and $p(Y|T)$, can be approximated using parameter vectors, $\boldsymbol{\omega}$ and $\boldsymbol{\theta}$, that weight the relative importance of each component study's density, $p_i(Y|T)$, and each scenario's density, $p_j(T)$, together with a flexible function, F, that maps the component densities into an overall density. There is not one right answer for what F should be, nor is there a single appropriate distribution to represent $p_j(T)$ and $p_i(Y|T)$. In similar contexts, studies such as Tack and others (2018) have established a precedent for using a Gaussian mixture approach, in which F is a weighted averaging operator with weights $\boldsymbol{\omega}$ and $\boldsymbol{\theta}$ and $p_j(T)$ and $p_i(Y|T)$ are each Gaussian PDFs. That can be written as follows:

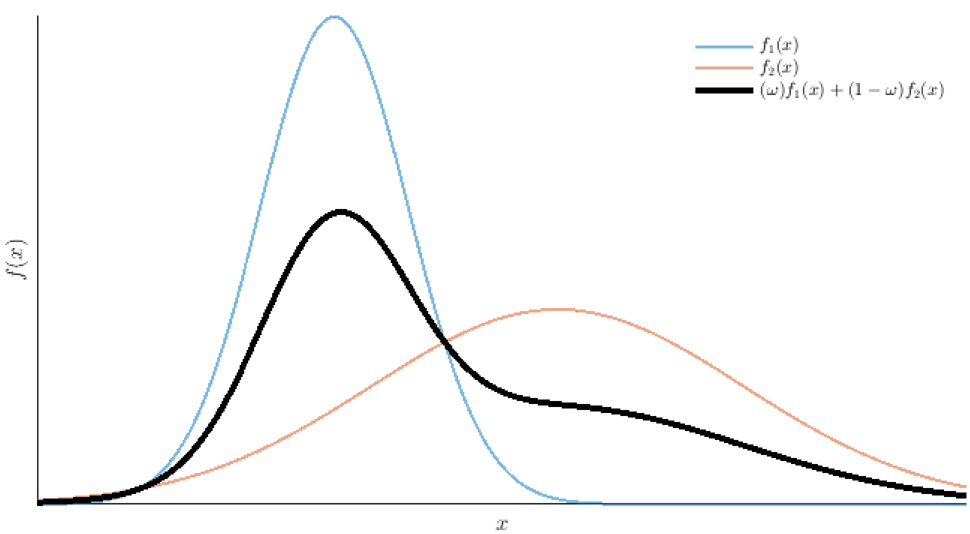
$$p(Y|T) \approx \sum_{i=1}^{I} \omega_i p_i(Y|T) \tag{2.1}$$

$$p(T) \approx \sum_{j=1}^{J} \theta_j p_j(T) \tag{2.2}$$

A useful feature of mixtures is that, although each of the component distributions is a symmetrical and elliptically shaped normal distribution, the weighted average of the densities is highly flexible and can be skewed, nonelliptical, and nonnormal (see Figure 1). That contrasts with the behavior of normal random variables, for which any linear combination is always normal.

Figure 1.

Illustration of a Gaussian Mixture



This is an illustrative example of a Gaussian mixture of two normal probability density functions. The black line represents the final mixed density.

Data source: Congressional Budget Office.

We can now recast Equation (1) as a Gaussian mixture. Using the definition of a conditional probability, $p(Y, T) = p(Y|T)p(T)$, and applying the definitions from Equations (2.1) and (2.2), Equation (3) is a weighted average across $I \times J$ bivariate normal distributions:

$$p(Y) \approx \int \sum_j^J \sum_i^I \omega_i \theta_j p_{ij}(Y, T) dT \tag{3}$$

Y and T are random variables that are jointly normally distributed for each study i and climate scenario j, with parameters for the means μ_{ij} and variances σ_{ij}^2:

$$Y, T \sim Normal\left[\begin{pmatrix}\mu_{ij,Y} \\ \mu_{ij,T}\end{pmatrix}, \begin{pmatrix}\sigma_{ij,YY}^2 & \sigma_{ij,YT}^2 \\ \sigma_{ij,TY}^2 & \sigma_{ij,TT}^2\end{pmatrix}\right] \text{ for all } i = 1, \dots, I \text{ and } j = 1, \dots, J \tag{4}$$

Each of the parameters in the bivariate normal distribution can be estimated from available data on forecast temperatures and the marginal GDP effects from each of the studies in our meta-analysis.

3.2. Incorporating Fat Tails Into the Modeling Framework

The possibility of extreme outcomes and uncertainty about the variance of the results from the approach described in Equation (4) is modeled by adopting a fat-tailed distribution. One characteristic of the normal distribution is that it has thin tails, meaning that there is a relatively low probability of extreme outcomes. Other common distributions such as the Student's *t* distribution and the Cauchy distribution are considered fat-tailed and have much more weight in the tails, reflecting a higher probability of extreme events. Peel and McLachlan (2000) shows that mixtures of Student's *t* distributions are an alternative to normal distributions that are more robust to outliers.

We therefore extend our framework so that each study's marginal GDP effects can be represented by a Student's *t* distribution. To do so, we create a scale mixture of normal distributions centered around each of the *ij* pairs of climate scenario and GDP study. A scale mixture is a weighted average of probability densities that may have different scale (variance) parameters but share the same location (mean) parameter. If the distributions in the scale mixtures have sample variance parameters $\sigma_{ij,YY}^2$, such that $\sigma_{ij,YY}^{-2}$ is a draw from the $\text{gamma}(\alpha, \beta)$ distribution, then the mixture of those normal distributions is a *t* distribution with $\alpha \times 2 = \nu$ degrees of freedom.

A benefit of using *t* distributions is that the degrees of freedom parameter, ν, explicitly accounts for uncertainty in the estimates of the sample variances. The dataset underlying our results pulls from a broad range of studies. For each study in our sample, there is some amount of natural variation in those reported statistics just by virtue of their being sample statistics rather than population statistics. Also, there are surely cases of specification error, and some models may extrapolate too far beyond the range of their data. Whatever the source of variation, a Student's *t* distribution is well suited to our approach because the fatness of the distribution's tails is scalable by the parameter ν. At one extreme, when ν is large and the sample size used to calculate the sample variance is large relative to the size of the population, the distribution approximates a normal distribution. At the other extreme, when $\nu = 1$ and the sample size is small, the distribution approximates a Cauchy distribution that is very fat-tailed.

A formal way to express that relationship between the normal and the *t* distribution is to let $p_{ij}(\sigma_{YY}^2)$ be the inverse gamma distribution and $p_{ij}(Y|T, \sigma_{YY}^2)$ be a normal distribution for GDP effects conditional on observing a particular sample variance. Then the marginal GDP effects, $p(Y)$, can be characterized by a Student's *t* distribution. Equation (5) is similar to Equation (1) but with $p(Y)$ written as a mixture of $I \times J$ densities that are each *t* distributions, rather than as a mixture of $I \times J$ densities that are each normal:

$$p(Y) = \int \int p_{ij}(Y|T, \sigma_{YY}^2) p_{ij}(T|\sigma_{YY}^2) p_{ij}(\sigma_{YY}^2) dT d\sigma_{YY}^2 \tag{5}$$

Using that specification, the bivariate distribution for Y and T in Equation (4) can be modified to reflect that Y and T are observed conditional on $\sigma_{ij,YY}^2$. That modification is captured in Equation (6) below. Also, here we define the distribution gamma$(\alpha_{ij}, \beta_{ij})$ that describes the probability of drawing any parameter, $\sigma_{ij,YY}^{-2}$. The parameters α_{ij} and β_{ij} are defined to ensure that the *ij* pair *t* distribution has the desired number of degrees of freedom, ν, and that the distribution is centered around the inverse of the sample variance, $\hat{\sigma}_{ij,YY}^{-2}$, for a large number of degrees of freedom. We define those parameters as $\alpha_{ij} = \nu/2$, and $\beta_{ij} = \alpha_{ij}^{-1} \hat{\sigma}_{ij,YY}^{-2}$:

$$Y, T|\sigma_{ij,YY}^2 \sim Normal\left[\begin{pmatrix}\mu_{ij,Y}\\ \mu_{ij,T}\end{pmatrix}, \begin{pmatrix}\sigma_{ij,YY}^2 & \sigma_{ij,YT}^2\\ \sigma_{ij,TY}^2 & \sigma_{ij,TT}^2\end{pmatrix}\right] \text{ for all } i = 1, \dots, I \text{ and } j = 1, \dots, J \tag{6}$$

$$\sigma_{ij,YY}^{-2} \sim \text{gamma}(\alpha_{ij}, \beta_{ij}) \tag{7}$$

We can now recast Equation (3) as a mixture of Student's *t* distributions by making several changes. We first replace $p_{ij}(Y|T)$ with $p_{ij}(Y|T, \sigma_{YY}^2)$, which is the distribution conditional on $\sigma_{ij,YY}^2$. Then, using the definition of conditional probability, we replace $p_{ij}(Y, T|\sigma_{YY}^2) = p_i(Y|T, \sigma_{YY}^2) p_{ij}(T|\sigma_{YY}^2)$. Finally, we model temperature distributions as invariant to the sample variance around the GDP effects, so $p_j(T) = p_{ij}(T|\sigma_{YY}^2)$. Using the definitions for *F*, $p_i(Y|T, \sigma_{YY}^2)$, and $p_j(T)$, Equation (1) becomes a weighted average across $I \times J$ bivariate normal distributions multiplied by their counterpart inverse gamma distribution for σ_{YY}^2, as shown in Equation (8):

$$p(Y) \approx \int \int \sum_i \sum_j \omega_i \theta_j p_{ij}(Y, T|\sigma_{YY}^2) p_{ij}(\sigma_{YY}^2) dT d\sigma_{YY}^2 \tag{8}$$

The distribution $p(Y)$ is a mixture of t distributions. In the limit, as ν approaches infinity, (Y, T) follows a bivariate normal distribution. Only when there is uncertainty in the sample variance for Y, expressed in the parameter ν, do we have a mixture of t distributions representing the marginal distribution for Y. The parameters in the normal distribution defined in Equation (6) are estimated using MLE to best fit the observed data on temperature and GDP effects for each of the studies in our dataset, as discussed in Section 4.

4. Empirical Application

To arrive at an unconditional distribution of GDP effects, the approach outlined in Equations (3) through (8) above can be grouped into the following six steps:

1. **Fitting Temperature Distributions**. Fit normal distributions to the data from the Intergovernmental Panel on Climate Change (IPCC) on the log of predicted temperature changes for each climate scenario.
2. **Fitting Conditional GDP Effects**. Fit normal distributions to predicted GDP effects conditional on a given temperature from each academic study.
3. **Estimating Joint Parameters.** Find the joint distribution that fits each combination of the distributions of temperature change and GDP effects.
4. **Incorporating Uncertainty About Variance**. Replace each bivariate normal distribution with a scale mixture of normal distributions.
5. **Weighting Across Studies**. Weight the bivariate scale mixtures by each study's relevance and average them together into a single, final mixed distribution.
6. **Creating the Unconditional Distribution of GDP Effects**. Simulate draws from the final mixed distribution to arrive at the marginal distribution for GDP effects.

4.1. Fitting Temperature Distributions

Projections of global temperature changes through 2100 come from the IPCC's Sixth Assessment Report (AR6; Byers and others, 2022). In that report, global emissions scenarios are coupled with climate emulators to project changes in global surface air temperature (GSAT).[8] We use a set of 21 scenarios that project global GHG emissions through 2100 under policies

[8] The emulators used are MAGICCv7.5.3 and FaIRv1.6.2. Appendix B provides details about the emissions scenarios, integrated assessment models, and emulators used for the temperature dataset in Table B-1. Emissions are plotted in Figure B-1.

implemented by 2020, which we take to reflect policies and trends that are close to current law.[9] Building on that distribution of emissions and temperatures, we make an explicit adjustment to emissions and temperatures to further account for the reconciliation act of 2022.

The IPCC couples each of the 21 scenarios with two distinct climate emulators to predict global warming outcomes, so there are 42 temperature distributions in our dataset. Climate emulators, also known as reduced-complexity climate models (RCMs), are simplified representations of more complex climate models. RCMs can be used to simulate the climate implications of emissions trajectories by being run hundreds or thousands of times, each time sampling from a probabilistic set of parameters that incorporates uncertainty about climate system. The emissions trajectories are often generated by general equilibrium macroeconomic energy models, such as integrated assessment models (IAMs). The distributions of temperature therefore reflect two sources of uncertainty. First, each RCM captures carbon cycle and climate system uncertainties by sampling from parameter distributions that represent possible changes in ocean heat content and effective radiative forcing from aerosols, GHGs, and methane.[10] Second, the temperature distributions reflect uncertainty in the IAM's parameters for economic interactions and emissions.

The AR6 database provides temperatures at several percentiles between the 5th and 95th for each of our 42 distributions.[11] We choose the mean and variance parameters for a log-normal distribution that minimizes the squared difference between the observed and predicted temperatures associated with each of the reported percentiles. So, if $p_j(T; \mu, \sigma)$ is the PDF for the jth log temperature distribution, and $P_j(T; \mu, \sigma)$ is the cumulative density function (CDF), then $T_{jk} = P_j^{-1}(k; \mu, \sigma)$ is the log of temperature corresponding to the kth percentile for the jth distribution as provided in the AR6 database. We choose $\hat{\mu}_j$ and $\hat{\sigma}_j$ to minimize the sum of the squared distances between $\hat{T}_{jk} = P_j^{-1}(k; \hat{\mu}_j, \hat{\sigma}_j)$ and T_{jk} across percentiles: $\sum_k \left(\hat{T}_{jk} - T_{jk}\right)^2$.

The marginal distribution for temperature is the weighted average of each $p_j(T; \mu, \sigma)$ across the 42 distributions for every possible value of T (see Figure 2). Log-normal distributions are chosen

[9] The 21 scenarios are identified in the AR6 Scenario Explorer and Database (International Institute for Applied Systems Analysis, 2022) as those in the Chapter 4 subset that model the trend from implemented policies and did not fail the IPCC vetting process. (The vetting process ensured that the emissions and energy data in the scenarios were within reasonable historical ranges. For further discussion, see Guivarch, Kriegler, and Portugal-Pereira, 2022.) Other scenarios used in the AR6 make projections using nationally determined contributions (NDCs)—that is, countries' pledged contributions to emissions reductions under climate action plans—and reflect effects from the full implementation of those pledged contributions. In recent years, successively lower estimates of emissions cited by the United Nations have generally been based on announcements of NDCs rather than changes to laws. Projections of both emissions and temperatures are lower when based on NDCs instead of laws.

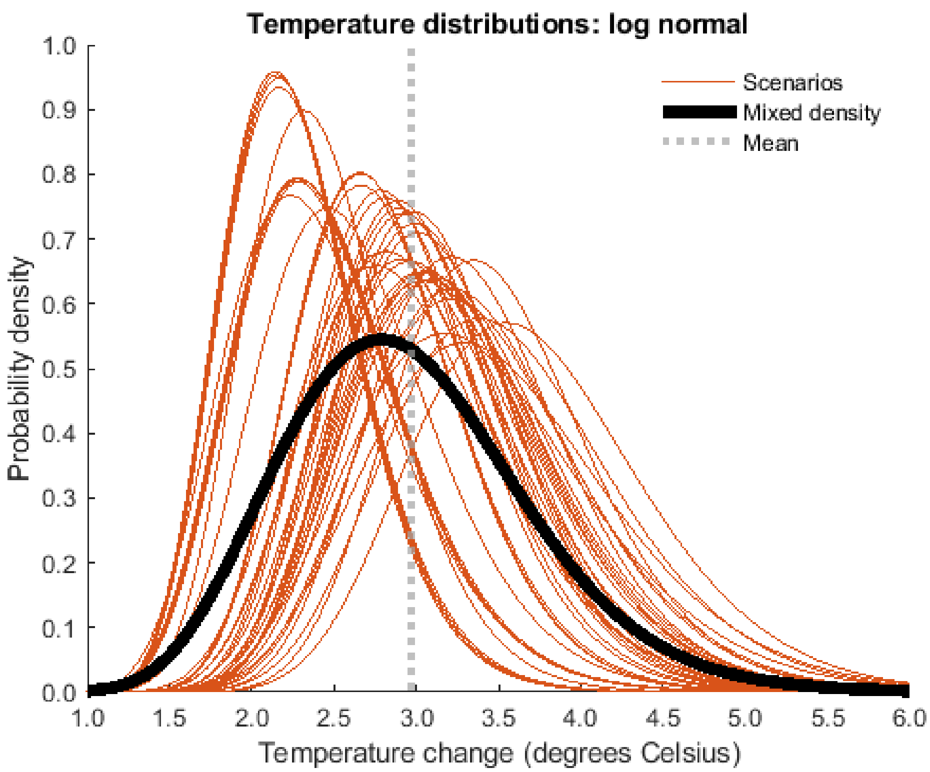
[10] For additional details, see Guivarch, Kriegler, and Portugal-Pereira (2022), p. 1880.

[11] International Institute for Applied Systems Analysis (2022).

because they are skewed with long right tails, a feature consistent with the data on temperature. They are also tractable and moderately fat-tailed. Because we do not know which temperature distribution is more credible than any other in our subset, weights for each component density in that mixture are all the same: $\theta_j = 1/42$. Equally weighting climate scenarios is common in the literature, although alternative weighting schemes exist.[12]

Figure 2.

Temperature Mixed Density



Red lines represent probability densities for temperature changes out to 2100 (relative to our 1850–1900 reference climate) and are fitted to the data from the AR6 Scenarios Database.

Although each scenario has a log-normal distribution, the mixed density, represented by the black line, generally does not.

Data source: Congressional Budget Office, using data from the AR6 Scenarios Database (Byers and others, 2022).

Each red line is a probability density function for one of the 42 projections of temperature change relative to our 1850–1900 reference climate.

The black line is the mixed density that represents the weighted average of all 42 temperature distributions. Each temperature distribution is the result of a simulated climate scenario from the IPCC's Sixth Assessment Report, which reflects energy use, climate, and economic projections based on recently implemented national policies. Table B-2 provides additional details about those scenarios.

Because the 2022 reconciliation act was enacted after the emissions scenarios and temperature forecasts were generated, we make an adjustment to the temperature distributions to account for

[12] For an example of a paper using equally weighted climate scenarios, see Shindell and others (2022). Weighting GCMs according to performance metrics is a growing literature; for example, see Merrifield and others (2023).

lower GHG concentrations in the atmosphere. Extending the Environmental Protection Agency's projected reductions in GHG emissions under the provisions of the reconciliation act out to the year 2100, after accounting for how carbon dioxide (CO_2) emissions accumulate and degrade in the atmosphere, the global CO_2 concentrations are 0.15 percent lower because of the reconciliation act.[13] Changes in the average temperature and the resulting effect on GDP from the reconciliation act are incorporated into our results.

Our mixed distribution for log temperature, $p(T)$, has global temperatures rising by around 3°C, on average, by 2100 relative to our reference climate, with a 90 percent probability of increasing between as little as 1.9°C and as much as 4.2°C (see Table 1). To put that in the context of commonly used climate scenarios from the IPCC, our distribution of temperatures has some similarities with the IPCC's SSP2-4.5 distribution, in which temperatures rise by 2.7°C by the end of the century. That scenario describes intermediate GHG emissions with global temperatures in a narrower "very likely" range of 2.1°C to 3.5°C by the 2081–2100 period. (In that context, the IPCC defines "very likely" as happening with a 90 percent probability.)

Table 1.

Distribution of Projected Temperature Changes by 2100

Degrees Celsius

Mean	Variance	5th percentile	33rd percentile	50th percentile	67th percentile	95th percentile
3.0	0.5	1.9	2.6	2.9	3.2	4.2

Data source: Congressional Budget Office, using data from the AR6 Scenarios Database (Byers and others, 2022).

Statistics in each column describe the marginal distribution of global surface air temperature changes by 2100 relative to the average temperature over the 1850–1900 reference period.

Other than SSP2-4.5, many IPCC climate scenarios reflect different pathways for social and environmental changes out to 2100. In more optimistic cases, such as SSP1-1.9, global surface temperature rises by roughly 1.5°C by 2100 relative to the benchmark climate. By contrast, in more pessimistic cases such as SSP5-8.5, global surface temperatures rise by an average of 4.4°C. Exploring the GDP consequences of those alternative scenarios is outside the scope of this working paper.

[13] For details about this estimate, see Environmental Protection Agency (2023). For the calculation for CO_2 concentrations, we applied to emissions the average fraction absorbed by carbon sinks over the past 50 years from ocean, land, and cement carbonation from Integrated Carbon Observation System (2024). For a discussion of the underlying approach, see Friedlingstein and others (2023).

4.2. Fitting Conditional GDP Effects

We observe point estimates of the average effect of temperature on GDP across 15 studies and either standard errors or confidence intervals, all of which are conditional on a temperature change. In total, we collect 196 point estimates, of which 35 have corresponding estimates for the standard errors or confidence intervals. (For a list of studies and a summary of observations, see Table B-2 in Appendix B.)

The approach to fitting normal distributions to the data on GDP effects is similar to the procedure for temperature data described above. For example, for the studies that report confidence intervals and medians—the 5th, 50th, and 95th percentiles—$p_{ij}(Y|T;\mu,\sigma)$ is the PDF for the ith-study's conditional distribution of GDP effects and $P_{ij}(Y|T;\mu,\sigma)$ is the CDF. We then choose $\hat{\mu}$ and $\hat{\sigma}$ to minimize the distance between $\hat{Y}_{ij} = P_{ij}^{-1}(k;\hat{\mu},\hat{\sigma},T)$ and Y_{ij} for every kth percentile.

Some GDP studies have an insufficient number of observations of $Y|T$ to compute all the parameters in Equation (6). Therefore, we collect those studies into one submodel and treat each of the studies in that composite submodel as if it were an independent observation of a single study. Table B-2 in Appendix B provides a list of the studies and the observations used to estimate the composite submodel.

Some observations in our dataset are adjusted to account for adaptation, with the rationale that economies may adapt to changing climate conditions given sufficient time. If a study does not explicitly incorporate adaptation, we draw on other models to adjust the projections. Previously, CBO estimated that adaptation was likely to reduce the effects of climate change by 25 percent in the long term, an approach that aligns with Deryugina and Hsiang (2017). We continue that approach in this paper.

For some studies in the dataset, only the mean or median is reported and the variance is unknown. In those cases, we follow Antle (2010, 1983) in imputing the missing error variances using information about similar studies for which the variance is known. The procedure starts by estimating a linear model for GDP effects from climate change across all studies i and study observations k, using a set of regressors $\mathbf{X}$ that includes temperature and a slate of binary variables that account for method-based differences between studies: $Y_{ik} = \mathbf{X}_{ik}\boldsymbol{\beta} + \epsilon_{ik}$. Defining the fitted values as $\hat{Y}_{ik}$, we also estimate the following regression to find $\hat{\boldsymbol{\gamma}}$:

$$\ln\left(Y_{ik} - \hat{Y}_{ik}\right)^2 = \mathbf{X}_{ik}\boldsymbol{\gamma} + u_{ik}$$

We then calculate the fitted variances as $\hat{\sigma}_{ik}^2 = \exp(\mathbf{X}_{ik}\hat{\boldsymbol{\gamma}})\bar{E}(\exp(\hat{\mu}_{ik}))$, where $\bar{E}(.)$ represents a simple average, to stand in for any missing observations.

Many studies in our dataset start accumulating GDP losses from temperature increases before 2025. In this paper, since we calculate GDP effects starting in 2025, we subtract out damage from each study in our meta-analysis in a way that is proportional to the rate of temperature change between that study's reference period and 2024. That adjustment is made before the joint distributions are estimated. Our approach to that feature of the meta-analysis data is different from the approach taken in CBO's earlier work on the GDP effects of climate change: The climate reference period in Herrnstadt and Dinan (2020) is centered around 1995, and GDP losses from rising temperatures accumulate to 1 percent between 2020 and 2050. Because the reference climate in that paper is prior to the starting period for the accumulation of GDP damage in this one, the estimated effect of future warming based on that paper is a loss of less than 1 percent. The decline in GDP growth caused by temperature changes between 1995 and 2020 continues to influence GDP growth between 2020 and 2050, so the effects on GDP growth from warming before 2020 must be subtracted away to make our papers' results comparable.[14]

4.3. Estimating Joint Parameters

There are five parameters in the bivariate normal probability density for each of the pairings of study and climate model (indexed by i and j, respectively). Those parameters, presented in Equation (6), are the means, $\mu_{T,ij}$ and $\mu_{Y,ij}$, and the covariances, $\sigma^2_{Y,ij}$, $\sigma^2_{YT,ij}$, $\sigma^2_{T,ij}$. From the climate scenarios and the procedure described in Section 4.1, we have already calculated $\sigma^2_{T,ij}$ and $\mu_{T,ij}$, and from the academic studies and the procedure described in Section 4.2, we have already calculated $\mu_{Y|T,i}$ and $\sigma^2_{Y|T,i}$. Therefore, the remaining parameters that we need to calculate are $\sigma^2_{Y,ij}$, $\sigma^2_{YT,ij}$, and $\mu_{Y,ij}$.

We arrive at estimates for these parameters by calculating ones that maximize the likelihood of observing the point estimates for GDP losses conditional on temperature from each of the studies in our meta-analysis. To do so, we use the definitions for the conditional mean and variance of $Y|T$ given in Equations (A.1.1) and (A.1.2) of Appendix A, together with the first-order conditions of the likelihood function with respect each of our target parameters, to solve for the unknown parameters. For further details about those calculations and alternative methods of estimating those parameters, see Section 6.2, Section 6.3, and Appendix A.

[14] Congressional Budget Office (2021) and Herrnstadt and Dinan (2020) estimate that of the 1 percent median total loss to GDP between 2020 and 2050 attributable to climate change, about 0.4 percent is from new climate conditions arising between 2020 and 2050. Using the approach described in this working paper, CBO now estimates that the mean reduction in GDP over a 30-year period is 0.9 percent.

4.4. Incorporating Uncertainty About Variance

To implement Equation (8) practically, we take N draws of σ_{YY}^{-2} from the density defined in Equation (7).[15] Letting $p_{ijk}(Y,T;\sigma_{YY}^2)$ represent the bivariate density that uses the kth draw for variance, $\sigma_{YY,k}^2$, we compute Equation (9) below and set N to 500.

$$\hat{p}_{ij}(Y,T) = \frac{1}{N}\sum_{k=1}^{N} p_{ijk}(Y,T;\sigma_{YY}^2) \tag{9}$$

The mixed distribution of $\hat{p}_{ij}(Y,T)$ can then be used in Equation (3) to compute the final marginal distribution. To our knowledge, there is not a closed-form representation of $\hat{p}_{ij}(Y,T)$, since it is neither purely normal nor purely a Student's *t* distribution but is, rather, a normal distribution in the *T* variable and a Student's *t* distribution in the *Y* variable.

An alternative setup would be to have a Student's *t* distribution in both the *Y* and the *T* dimensions by drawing the entire variance–covariance matrix from an inverse Wishart distribution. There are two reasons we do not use that setup: First, our approach keeps our results comparable to those of other papers in the literature that take the IPCC data as given; and second, the IPCC already accounts for some degree of parameter uncertainty in its results, so injecting additional uncertainty in temperature would be duplicative.

4.5. Weighting Across Studies

The studies in our dataset for GDP effects vary along three broad types of characteristics: their geographic scope, the persistence of their predicted effects on output, and their modeling approach.

Geographic Scope. Panel datasets for econometric analysis either can be specific to the United States, focusing on states, counties, or metropolitan areas, or can incorporate data from other countries (and their subregions) around the world. The same is true for CGE and build-up models. This study places greater weight on studies that focus only on the U.S. experience because we view those studies as having the greatest relevance for the United States, in terms of both its characteristics as a developed economy and its temperature range. As a practical matter, global studies that include U.S. subregions typically include many more international subregions. For example, Burke and Tanutama (2019) uses a panel of subregions that includes metropolitan areas in the United States, but the U.S. observations account for less than 5 percent of the subregion years in the data.

---

[15] These steps perform numerical integration across σ_{YY}^2. The implementation here could also be performed through a "quadrature" integration in which grid points are chosen more efficiently on the domain of σ_{YY}^{-2}. However, because the underlying distribution is smooth and well defined, 500 randomly spaced grid points are sufficient to ensure that the distribution $p_{ij}(Y,T)$ is well represented.

Persistence of the Effect on Output. Some studies model climate change as affecting the level of output; others model it as affecting the growth rates of output. Studies that model growth rate effects can also differ in whether they model effects that last indefinitely (permanent) or slowly dissipate over time (persistent). Studies that estimate a permanent effect on growth rates typically find much larger impacts over long time horizons than studies that estimate a single-year or persistent but nonpermanent effect. For example, Nath, Ramey, and Klenow (2024) uses impulse response functions to find that warming has persistent, but not permanent, effects on growth that last for several years; that paper also argues that common growth processes related to innovation and knowledge flows suggest that climate impacts would not permanently affect growth rates. CBO views both level effects and permanent growth effects as limiting and less plausible than specifications that allow for a tempered, more flexible impact. Therefore, this paper places greater weight on models that allow for persistent effects on GDP growth.

Modeling Approach. Some studies "build up" an estimate of the effect of climate change sector by sector, enumerating the impact through channels such as agricultural output, labor productivity, effects on coastal properties through disasters, and, in some cases, greater energy use and impacts on tourism. Other studies simulate the effects on output using CGE models, sometimes informed by the same sectoral damage estimates from the studies that build up an estimate. Finally, a third approach is to estimate the effects using econometric techniques on panel datasets with varying geographic scopes, temporal lengths, and levels of administrative disaggregation.[16]

Greater weight is given to models that use a panel regression-based approach to estimating climate change effects. Even though econometric models of GDP are dependent on historical data, as panel estimates, they use the high degree of variation in temperature between regions and across time to estimate parameters and, therefore, tend to be robust for estimating the effects of large changes in localized temperature. Less weight is given to models that build up to an estimate by aggregating results sector by sector, because they may underestimate the effect of climate change by missing important effects or interactions between effects. In addition, less weight is given to CGE models. Although they are valuable for capturing interaction effects, particularly the potential for substitution to reduce the economic effects, they are nonetheless dependent on the underlying values that are used to derive the results.

We systematically assign each study a weight (ω_i) that reflects its relevance. That approach is common among meta-analyses, in which weights might be assigned by a quality or credibility score; see, for example, Howard and Sterner (2022) and Nordhaus and Moffat (2017).

[16] Our meta-analysis does not include results from expert elicitation models.

The approach we take to weighting is to let θ_q^i be an indicator variable that is 1 when paper i has characteristic q and is 0 otherwise. There is thus a total of $n_q = \sum_i \theta_q^i$ papers with that characteristic. We can then assign some subjective valuation, μ_q, to that characteristic, with higher numbers connoting greater relevance or accuracy. Studies that have characteristics with higher values (higher μ_q) will have a higher overall weighting (ω_i) in the final mixed density. The overall weight for each paper i is as follows:

$$\omega_i = \sum_q \mu_q \theta_q^i / n_q \tag{10}$$

Our preferred set of valuations for study characteristics, μ_q, gives the most weight to studies that:

- Are focused on the United States,
- Model a persistent effect of temperature change on output, and
- Use an econometric approach to estimate the GDP effect (see Table 2).

Table 2.

Valuations, by Study Characteristic

Geographic scope	Effect on output	Modeling approach
U.S. GDP only: 0.8	Persistent: 0.7	Econometric: 0.8
Global GDP: 0.2	Permanent: 0.2	CGE or build up: 0.2
	Level: 0.1	

Data source: Congressional Budget Office.

This table presents the preferred set of values used to calculate weights according to Equation (10). Those weights convey the relevance of each of three types of characteristics for this paper. For example, studies that estimate effects on GDP growth for the United States separate from the rest of the world, model persistent effects on growth, and use an econometric approach will have a stronger effect on the results than papers without those characteristics.

CGE = computable general equilibrium; GDP = gross domestic product.

The weight for each study is determined by the characteristics of that study and the number of studies of each type. For example, Acevedo and others (2020) is a persistent-growth-effect econometric study that uses global data to identify the marginal effects of temperature on output growth. Therefore, the weight for that paper in the final mixed density is calculated as follows:

$$\omega_{Acevedo} = \left(\frac{\mu_{Global}}{n_{Global}} + \frac{\mu_{Persistent}}{n_{Persistent}} + \frac{\mu_{Econometric}}{n_{Econometric}} \right) \times \left(\frac{1}{\sum_i \omega_i} \right)$$

The values for each μ_q are pulled from Table 2, and the numbers of studies with each characteristic (n_q) are simply counted in the dataset. Also, ω_i is always rescaled by $\sum_i \omega_i$ so that it sums to 1 across studies. Applying the set of weights to Equation (10) yields our preferred weights for each individual study (see Table 3).

Table 3.

Weights Across Studies

Study	Preferred weight
Acevedo and others (2020)	0.08
Burke and Tanutama (2019)	0.07
Casey, Fried, and Goode (2023)	0.04
Colacito, Hoffmann, and Phan (2019)	0.13
Deloitte Economics Institute (2021)	0.08
Deryugina and Hsiang (2017)	0.14
Fernando, Liu, and McKibbin (2021)	0.02
Hsiang and others (2017)	0.08
Kahn and others (2021)	0.08
Kalkuhl and Wenz (2020)	0.04
Kompas, Pham, and Che (2018)	0.02
Kotz, Levermann, and Wenz (2024)	0.08
Nath, Ramey, and Klenow (2024)	0.08
Roson and Sartori (2016)	0.02
Takakura and others (2019)	0.02

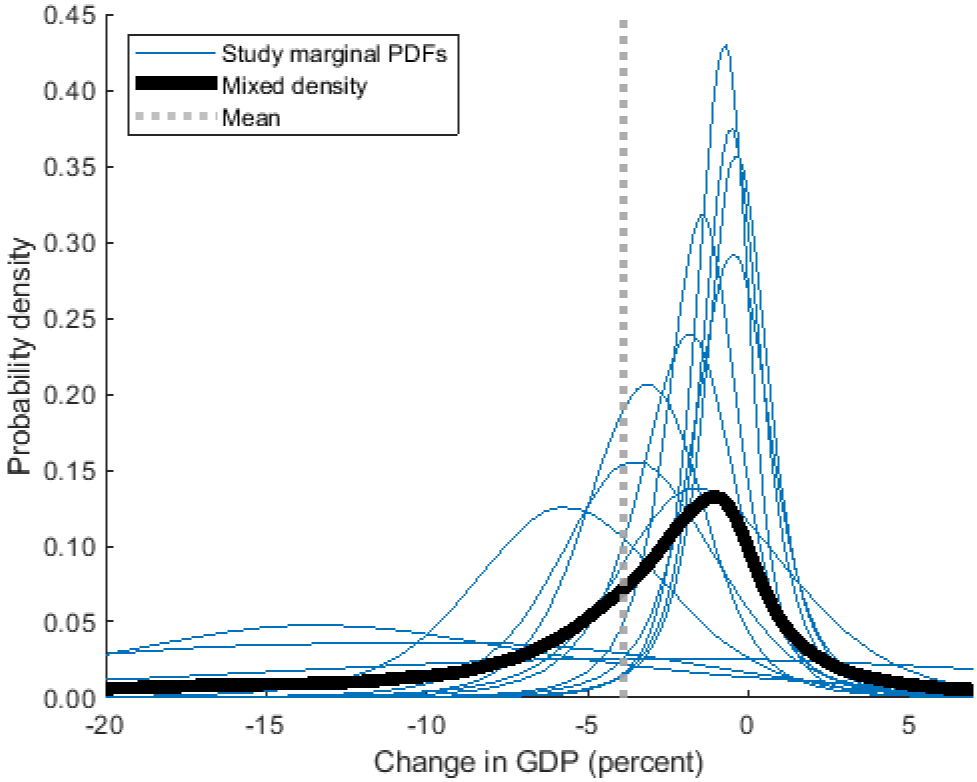
Data source: Congressional Budget Office.

These weights do not sum to exactly 1 because of rounding. For details about the dataset, see Table B-2 in Appendix B.

The weights are used to combine the PDFs for each of the studies into the overall marginal distribution of GDP effects. In Figure 3, the 15 studies are represented by 13 densities (blue lines) because we combine three studies with very few observations into one composite group. (See Table B-2 in Appendix B for details about that grouping and weighting within that group.)

Figure 3.

Mixture of Densities of GDP Effects



Each blue line represents a study (or group of studies). The black line is the weighted combination of those studies—the final marginal distribution.

Data source: Congressional Budget Office.

Twelve of the 13 blue lines represent the marginal distributions from each of the individual studies in the mixture model, and one represents the marginal distribution from a group of three studies with few observations. The curves are the probability densities of effects on GDP from temperature changes due to climate change.

For details about the studies included in each of the 13 groups, see Table B-2 in Appendix B.

GDP = gross domestic product; PDF = probability density function.

4.6. Creating the Unconditional Distribution of GDP Effects

Once the joint density for *Y* and *T* is estimated, we sample randomly from it 2 million times to generate a set of simulated data for both variables. Each draw in the sample is generated by a two-step process. In the first step, a draw (a_k, b_k) from a bivariate uniform density selects a component density. Component density *ij* is selected if, for the *k*th uniform draw, a_k is within $[\sum_{s\le i}^{i}\omega_s, \sum_{s\le i}^{i+1}\omega_s)$, and b_k is within $[\sum_{s\le j}^{j}\theta_s, \sum_{s\le j}^{j+1}\theta_s)$, where ω_s and θ_s are the mixture weights. In the second step, a random pair (*Y, T*) is drawn from the density that was selected in the first step. Both steps are repeated until the full simulated sample is generated. That sample is then used to calculate summary statistics (like those in Table 4) that provide insights into the likelihood of possible effects of temperature that are not the central estimate.

5. Results

This paper's principal result is the unconditional distribution of GDP effects from climate change (see Table 4). Our preferred result uses three degrees of freedom ($\nu = 3$) because the variance for Y is roughly twice as large as it would be using normal distributions, and three is the lowest integer value of ν for which both the mean and variance of Y are finite. We report the results for a range of values of ν to show the effects of uncertainty about that parameter.

Under our preferred approach for estimation, MLE with three degrees of freedom, GDP is projected to be 3.9 percent lower than it would be otherwise by the year 2100, but that is a central estimate surrounded by a great deal of uncertainty. The distribution of GDP effects is significantly skewed with a long left tail, which means that the probability of a large negative GDP outcome is much higher than the probability of a positive GDP outcome. In addition, under our preferred approach, there is a 5 percent chance that climate change could decrease GDP by 21.3 percent or more and, conversely, there is a 5 percent chance that GDP could increase by 6.1 percent or more.

Table 4.

Distribution of GDP Effects in 2100, by Degrees of Freedom

Percent

Statistic	Infinite (normal)	10 DF (Student's *t*)	4 DF (Student's *t*)	This paper's preferred: 3 DF (Students' *t*)	2 DF (Student's *t*)	1 DF (Cauchy)
Mean	-3.9	-3.9	-3.9	-3.9	-3.9	Undefined
Variance	56.1	64.4	91.4	132.6	Infinite	Undefined
5th percentile	-19.2	-19.9	-20.6	-21.3	-23	-33.5
33rd percentile	-4	-4.1	-4.2	-4.3	-4.4	-4.9
50th percentile	-2.3	-2.3	-2.3	-2.3	-2.3	-2.2
67th percentile	-1.1	-1.1	-1.0	-0.9	-0.8	-0.6
95th percentile	3.5	4.1	5.5	6.1	8.5	21.5

Data source: Congressional Budget Office.

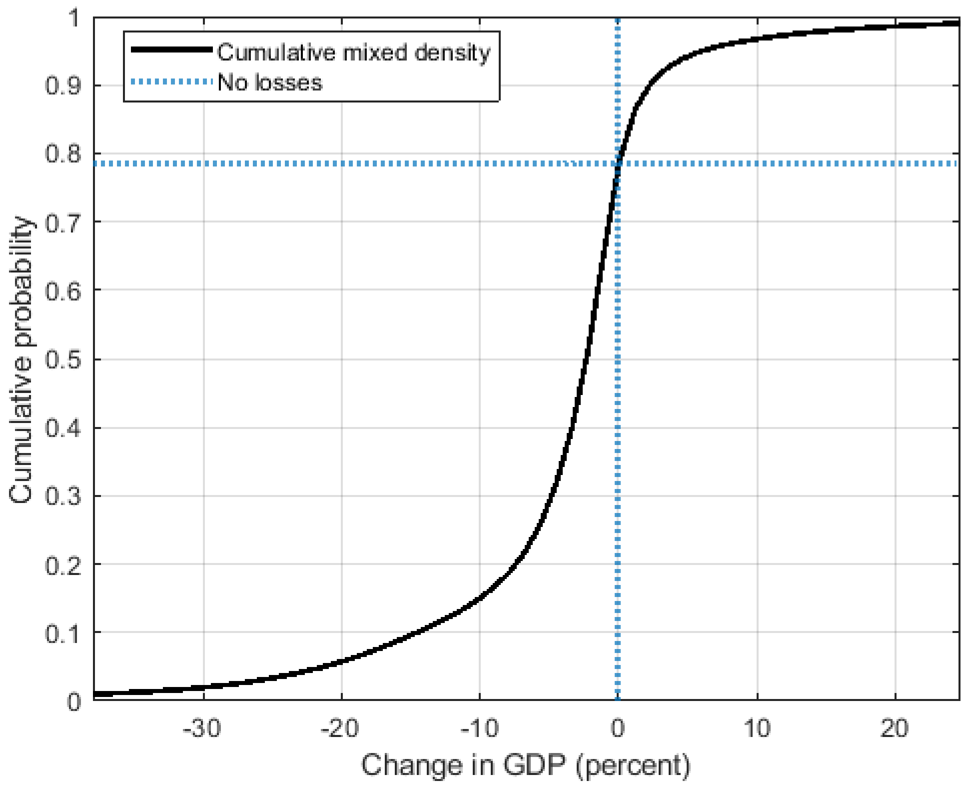
These statistics describe the marginal distribution of GDP effects from climate change in 2100 under different degrees of freedom for the multivariate Student's *t* distributions fitted to each academic study–climate model pairing. The columns present results for selected degrees of freedom, and the rows present statistics for the distributions.

DF = degrees of freedom; GDP = gross domestic product.

Overall, the distribution of GDP effects using three degrees of freedom results in a 79 percent chance that the effect of climate change on GDP in 2100 is negative (see Figure 4).

Figure 4.

Cumulative Distribution Function for GDP Effects in 2100



Data source: Congressional Budget Office.

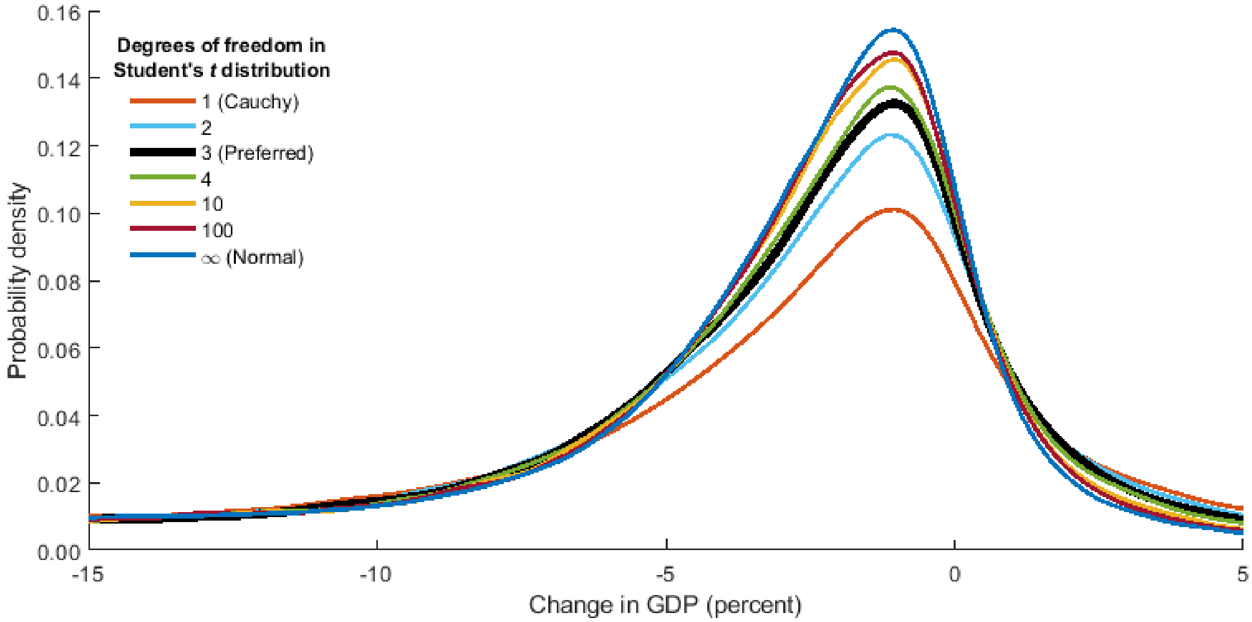
The horizontal blue line marks the cumulative probability that effects on GDP from rising temperatures will be negative, which is 79 percent. That line also corresponds to the area under the curve of Figure 3 to the left of the zero on the horizontal axis.

GDP = gross domestic product.

Some things stand out. Importantly, the curves get flatter as the degrees of freedom move from infinity to one, or as we move from a normal distribution to a Cauchy distribution (see Figure 5). With fewer degrees of freedom, we are expressing less certainty about the underlying data in our meta-analysis, and therefore the distribution of GDP effects is flatter and has greater variance.

Figure 5.

Sensitivity of Results to Degrees of Freedom



Data source: Congressional Budget Office.

The plotted distributions correspond to the statistics in Table 4. Moving from a normal distribution (blue line) to a Cauchy distribution (red line) suggests more uncertainty in the underlying data and therefore results in an increasingly flattened unconditional distribution of effects on GDP from climate change.

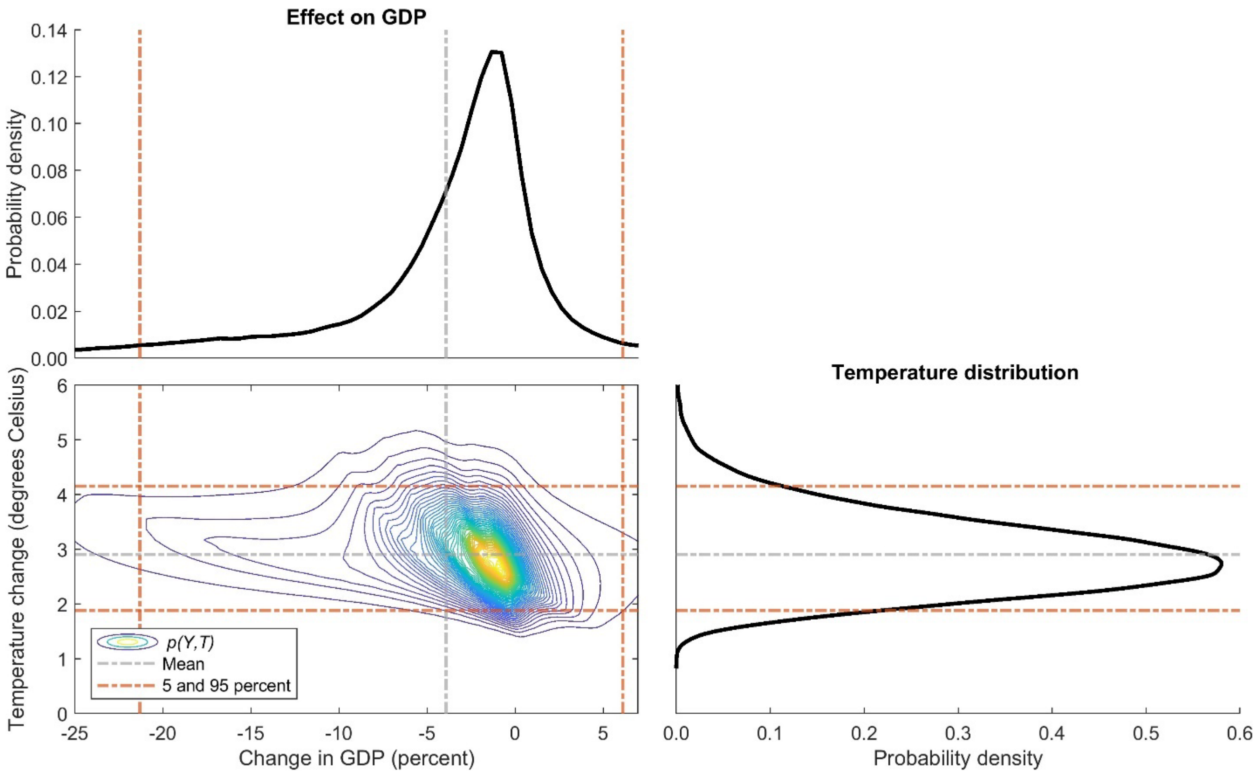
GDP = gross domestic product.

5.1. Joint and Marginal Distributions

In Figure 6, the joint PDF of Y and T (lower left panel) depicts the full landscape of probabilities for temperature and GDP effect pairs for our preferred specification. The probability of observing any single GDP effect (x-coordinate) and temperature (y-coordinate) is given by the height of the density function, indicated by the contour lines. That density peaks around a temperature increase of 2.9°C and a 2 percent decrease in GDP. Since the distribution is skewed with a long left tail in the Y direction, the mean GDP effects have larger magnitudes than either the mode or median effects, amounting to losses of about 3.9 percent of GDP. The marginal distribution of GDP effects (top panel) is our principal result. The marginal temperature distribution (right panel) is the one presented above (the black line in Figure 2).

Figure 6.

Joint and Marginal Distributions



Data source: Congressional Budget Office.

Top left panel: The marginal effect of temperature changes due to climate change on U.S. GDP in 2100.

Bottom left panel: The joint distribution of temperature changes and GDP effects in 2100 in the United States. The horizontal axis represents effects on GDP, and the vertical axis represents changes in temperature relative to the average temperature in the 1850–1900 period. The height of the joint distribution at each coordinate in the (*Y, T*) space indicates the probability of observing that pairing of GDP effect (*Y*) and temperature (*T*); brighter contour lines indicate higher probabilities.

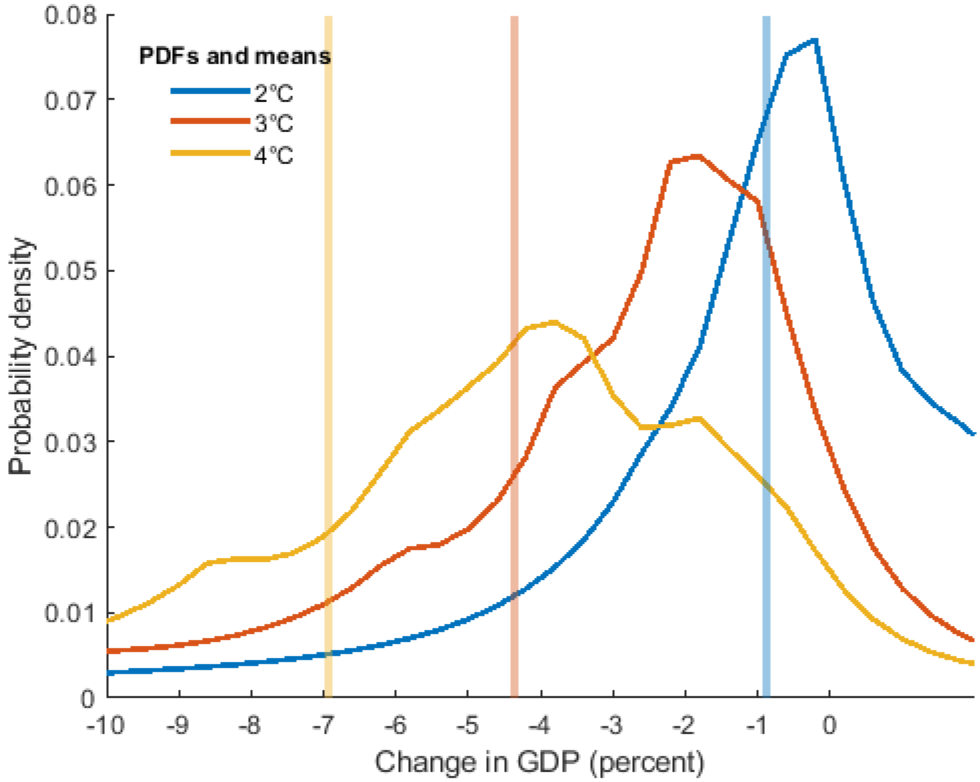
Bottom right panel: The marginal effect of climate change on global temperatures in 2100 relative to the 1850–1900 reference climate.

GDP = gross domestic product.

There appears to be a strong correlation between temperature and GDP effects, as suggested by the slanted elliptical contour lines near the peak of the PDF. We can get a better sense of what that means for GDP as temperature increases by pulling the conditional distributions for Y at discrete temperatures. For example, conditional on observing temperatures 2°C, 3°C, and 4°C above the reference climate, the mean GDP losses are 0.9 percent, 4.4 percent, and 6.9 percent (see Figure 7). Also, the distributions of GDP effects flatten slightly as temperatures rise, an indication that the variance is increasing with higher temperatures.

Figure 7.

Conditional Distributions at 2 Degrees, 3 Degrees, and 4 Degrees Celsius



As global temperature increases rise from 2°C to 3°C to 4°C, the average losses to GDP in 2100 grow from 0.9 percent to 4.4 percent to 6.9 percent.

Data source: Congressional Budget Office.

This figure shows the conditional PDF of GDP effects from global temperature increases of 2°C, 3°C, and 4°C. The horizontal axis represents the percentage change in GDP in 2100 relative to a baseline no-climate-change scenario. The vertical axis represents the rate of change in the cumulative distribution function for a small change in temperature.

GDP = gross domestic product; PDF = probability density function.

5.2. Comparison With Other Meta-Analyses in the Literature

To compare our results with those of other studies in the literature, we calculate the unconditional distribution of GDP effects using the marginal effects of temperature on global GDP from three other recent meta-analyses: Howard and Sterner (2022), Howard and Sterner (2017), and Nordhaus and Moffat (2017). To make that comparison, we combine those papers' estimated marginal effects of temperature on global GDP with CBO's mixed density for temperature changes in 2100.

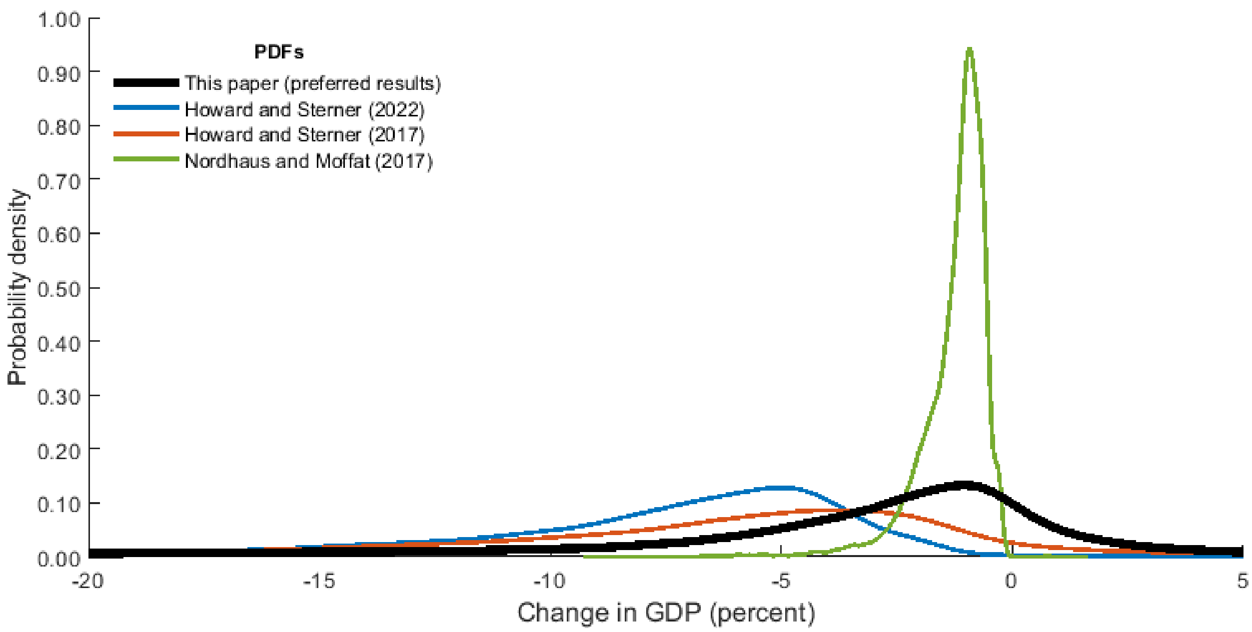
This paper's results differ from the results of those other meta-analyses in two important ways. First, our results represent the effects of temperature exclusively on U.S. GDP, whereas the other studies' results represent effects on global GDP. That is relevant because there is a consensus in the literature that rising temperatures will decrease global GDP growth by more than U.S. GDP growth. The mean loss estimates of 8 percent in Howard and Sterner (2022) and 9 percent in

Howard and Sterner (2017) reflect that consensus and are larger than our estimate of a 4 percent loss to U.S. GDP. Even though our meta-analysis includes many of the same studies, the overlapping studies tend to predict larger decreases in global GDP growth relative to what the United States is predicted to experience.

Second, our dataset includes some recent papers such as Takakura and others (2019) and omits older papers such as Burke (2015). The studies that appear in Nordhaus and Moffat (2017) overlap little with the ones we use; they include older studies, often from the 1990s, that tend to predict smaller global GDP effects from rising temperatures when compared with more recent studies. That accounts for the smaller predicted GDP loss of 1 percent in Nordhaus and Moffat (2017). Figure 8 and Table 5 compare our results with the results from those papers.

Figure 8.

Comparison of This Paper With Others in the Literature: GDP Effects



Data source: Congressional Budget Office.

Each line represents the unconditional effects on GDP from climate change in 2100. The black line represents CBO’s preferred estimate of U.S. GDP effects; the other lines are computed using estimates of the marginal effects on global GDP from Howard and Sterner (2022), Howard and Sterner (2017), and Nordhaus and Moffat (2017) combined with CBO’s mixed density for temperature changes in 2100.

GDP = gross domestic product; PDF = probability density function.

Table 5.

Comparison of This Paper With Others in the Literature: Statistics

Percent

Statistic	U.S. GDP effects	Global GDP effects		
	This paper's preferred	Howard and Sterner (2022)	Nordhaus and Moffat (2017)	Howard and Sterner (2017)
Mean	-3.9	-8.6	-1.3	-7.9
Variance	132.6	48.4	0.5	159.0
5th percentile	-21.3	-20.5	-2.6	-27.2
33rd percentile	-4.3	-8.9	-1.3	-8.5
50th percentile	-2.3	-6.9	-1.1	-5.7
67th percentile	-0.9	-5.4	-0.9	-3.7
95th percentile	6.1	-2.4	-0.5	4.2

Data source: Congressional Budget Office.

The cited papers provide estimates of the marginal effects of temperature on GDP; however, the distribution of changes in temperature was generated by CBO. Results for Nordhaus and Moffat (2017) were calculated using the coefficients and standard errors estimated in Howard and Sterner's (2022) replication of that paper's preferred result.

GDP = gross domestic product.

6. Sensitivity and Robustness

We perform three sensitivity and robustness checks: using alternative weighting schemes for the GDP studies, applying different adjustments for adaptation to control for omitted variables, and trying estimation techniques other than MLE (see Appendix A for details about those other techniques).

6.1. Comparison Across Weighting Schemes

Besides our preferred weighting scheme, we apply other weighting schemes to test the sensitivity of our results. The results are presented in Table 6. The second column of that table applies equal weights to all the papers, the third column drops all papers without a U.S. focus, the fourth column includes only papers that allow for persistent effects on GDP growth, and the final column includes only equally weighted econometric GDP studies.

Table 6.

Study Weights Under Alternative Weighting Schemes

Study	Preferred	Equal weights	U.S. GDP only	Persistent growth	Econometric
Acevedo and others (2020)	0.08	0.07	0	0.20	0.11
Burke and Tanutama (2019)	0.07	0.07	0	0	0.11
Casey, Fried, and Goode (2023)	0.04	0.07	0	0	0.11
Colacito, Hoffmann, and Phan (2019)	0.13	0.07	0.25	0	0.11
Deloitte Economics Institute (2021)	0.08	0.07	0.25	0	0
Deryugina and Hsiang (2017)	0.14	0.07	0.25	0.20	0.11
Fernando, Liu, and McKibbin (2021)	0.02	0.07	0	0	0
Hsiang and others (2017)	0.08	0.07	0.25	0	0
Kahn and others (2021)	0.08	0.07	0	0.20	0.11
Kalkuhl and Wenz (2020)	0.04	0.07	0	0	0.11
Kompas, Pham, and Che (2018)	0.02	0.07	0	0	0
Kotz, Levermann, and Wenz (2024)	0.08	0.07	0	0.20	0.11
Nath, Ramey, and Klenow (2024)	0.08	0.07	0	0.20	0.11
Roson and Sartori (2016)	0.02	0.07	0	0	0
Takakura and others (2019)	0.08	0.07	0	0	0

Data source: Congressional Budget Office.

Preferred weights in the first column can be calculated using values in Table 2 with Equation (10). For additional details about the sample of studies used in this paper, see Table B-2 in Appendix B.

GDP = gross domestic product.

The distribution of GDP effects varies by weighting scheme (see Table 7). When we analyze only the econometric studies, the loss to GDP from climate change is 4.9 percent, about 1 percentage point larger than our preferred result of 3.9 percent. That result is driven by Burke and Tanutama (2019) and by Kotz, Levermann, and Wenz (2024).

Table 7.

Distribution of GDP Effects in 2100, by Weighting Scheme

Percent

Statistic	Preferred	Equal weights	U.S. GDP only	Persistent growth	Econometric
Mean	-3.9	-3.3	-2.8	-5.1	-4.9
Variance	132.6	94.4	169.2	62.9	127.9
5th percentile	-21.3	-18.5	-17.0	-20.8	-23.0
33rd percentile	-4.3	-3.4	-4.6	-5.2	-5.4
50th percentile	-2.3	-1.8	-2.3	-3.1	-3.0
67th percentile	-0.9	-0.7	-1.0	-1.7	-1.4
95th percentile	6.1	3.9	11.0	1.6	5.4

Data source: Congressional Budget Office.

The statistics presented here describe the marginal distribution of effects of climate change on GDP by 2100 under each of the weighting schemes presented in Table 6. Each column represents one weighting scheme; the rows present statistics for the distributions.

GDP = gross domestic product.

The role of permanent- and persistent-growth-effect studies such as those is also evident when we rerun our preferred model after dropping one of the paper groupings (see Table 8). Without observations from either of two permanent-growth-effect studies, Burke and Tanutama (2019) or Colacito, Hoffmann, and Phan (2019), the 5th percentile moves from −21 percent to −19 percent. Without observations from the persistent-growth-effect study, Kotz, Levermann, and Wenz (2024), the 5th percentile moves to −17 percent, and the average moves a full percentage point to −3 percent.

Table 8.

Sensitivity of Results to Dropping a Study

Percent

Study dropped	Mean	Variance	5th percentile	33rd percentile	50th percentile	67th percentile	95th percentile
Burke and Tanutama (2019)	-3.3	121.7	-19.2	-3.8	-2.1	-0.8	6.1
Casey, Fried, and Goode (2023)	-4.0	133.0	-21.6	-4.4	-2.4	-1.0	6.5
Colacito, Hoffmann, and Phan (2019)	-4.0	59.6	-18.6	-3.9	-2.2	-1.0	2.7
Composite[a]	-4.5	157.0	-23.0	-5.0	-2.6	-1.1	7.4
Deryugina and Hsiang (2017)	-4.2	148.5	-22.6	-4.8	-2.4	-0.8	7.6
Fernando, Liu, and McKibbin (2021)	-3.9	132.3	-21.4	-4.3	-2.3	-0.9	6.4
Hsiang and others (2017)	-4.1	141.9	-22.0	-4.7	-2.6	-1.1	7.0
Kahn and others (2021)	-3.7	138.1	-21.9	-3.8	-2.0	-0.8	6.9
Kalkuhl and Wenz (2020)	-3.9	136.8	-21.6	-4.3	-2.2	-0.9	6.6
Kompas, Pham, and Che (2018)	-3.9	131.1	-21.4	-4.3	-2.3	-1.0	6.4
Kotz, Levermann, and Wenz (2024)	-3.0	118.4	-17.4	-3.7	-2	-0.8	6.5
Nath, Ramey, and Klenow (2024)	-3.9	143.4	-22.0	-4.2	-2.1	-0.8	6.9
Takakura and others (2019)	-3.9	128.2	-21.3	-4.3	-2.3	-1.0	6.4

Data source: Congressional Budget Office.

This table presents the results for our baseline approach, which uses MLE and three degrees of freedom. The mean results are the most sensitive to dropping Burke and Tanutama (2019) and Kotz, Levermann, and Wenz (2024).

MLE = maximum likelihood estimation.

a. The composite group combines three studies. For details, see row 13 of Table B-2 in Appendix B.

6.2. Wealth, Adaptation, and Omitted Factors

We account for temperature (T) and the distribution of the sample variance (σ^2_{YY}) in Equations (1) and (8), but there may be other omitted variables that condition the distribution of Y, and any omitted variables could have effects in either direction for our distribution of GDP effects from climate change. Wealth and income stand out as possible omitted variables. A robust literature documents how adaptation to a warmer climate will probably impose considerable costs and require considerable investments, which means that wealthier countries are better positioned to adapt to a warming climate than poorer countries.[17] Since wealth (W) is relevant for explaining the relationship between climate effects (Y) and changing temperatures (T), omitting wealth by modeling $p(Y|T,W)$ as being equivalent to $p(Y|T)$ has the potential to affect our results.

As an example, to showcase the problem and how it might affect our results, if W and Y are dependent, then our approximation for $p(Y)$ has calculated a distribution that is conditional on wealth in a particular period—for instance, in the year 2020. So, in this example, $W = W_{2020}$ (U.S. wealth in 2020). That is relevant because wealth moves over time and can significantly alter a country's ability to adapt to and mitigate the damage from climate change. Under the expectation that the United States will be wealthier in 2100 than it is in 2020, or $E(Y|W_{2100}) > E(Y|W_{2020})$, forgone GDP in 2100 will be smaller because adaptation will reduce the marginal effects of temperature changes.

To capture the potential effects of future wealth on the U.S. economy's ability to adapt to climate change, on the basis of estimates in Deryugina and Hsiang (2017), we reduce by 25 percent the climate damage for the United States for papers in our dataset that do not appear to account for adaptation in their analysis. We call that an "adaptation adjustment." The size of the reduction in the effect on GDP growth increases linearly each year, from zero to 25 percent, through 2100.

Results for different applications of that adaptation adjustment are reported in Table 9. In the "No adaptation" column, we do not apply the adjustment to any of our data. In the "Moderate adaptation" column, we apply our definition of adaptation, a 25 percent reduction in damage in 2100, only to Colacito and others (2019). And in the "Maximum adaptation" column, we apply the adjustment not only to Colacito, Hoffmann, and Phan (2019) but more broadly to Casey, Fried, and Goode (2023); Deloitte Economics Institute (2021); Fernando, Liu, and McKibbin (2021); Acevedo and others (2020); Burke and Tanutama (2019); Takakura and others (2019); Kompas, Pham, and Che (2018); and Roson and Sartori (2016). The adaptation adjustment was not applied to estimates indicating a positive effect of climate change on growth.[18]

If temperatures were very high, wealth could reasonably depend on the temperature, so W could depend on T. In that scenario, high enough temperatures might reduce wealth enough to diminish the United States' ability to adapt to climate change, thereby intensifying the negative impact of a warming climate. That channel would counteract the adaptation channel, so the net effect would be ambiguous. For the temperatures that we consider in this paper, however, that channel is unlikely to be relevant.

---

[17] See Kahn (2016).

[18] One of the specifications in Burke and Tanutama (2019) and one in Colacito, Hoffmann, and Phan (2019) predict positive effects on GDP growth from rising temperatures.

Table 9.

Distribution of GDP Effects in 2100, With and Without Adjustments to Account for Adaptation to Climate Change

Statistic	No adaptation	This paper's preferred: Moderate adaptation	Maximum adaptation
Mean	-3.9	-3.9	-3.6
Variance	181.4	132.6	121.5
5th percentile	-21.9	-21.3	-19.7
33rd percentile	-4.3	-4.3	-4.0
50th percentile	-2.3	-2.3	-2.1
67th percentile	-0.9	-0.9	-0.8
95th percentile	7.1	6.1	5.6

Percent

Data source: Congressional Budget Office.

The adjustment to Colacito, Hoffmann, and Phan (2019) in the "Moderate adaptation" and "Maximum adaptation" columns reduces the variance for that paper's unconditional GDP effects. That lower variance has broader effects on the variances for papers that have missing data, for which missing standard errors are imputed using the approach described in Section 4.2. Therefore, the lower variance in the "Moderate adaptation" and "Maximum adaptation" cases also causes values at the 95th percentile to be lower in those columns.

GDP = gross domestic product.

6.3. Comparison Across Estimation Approaches

In this extension, we add flexibility to the basic MLE approach by doubling the number of normal distributions fitted to each of the pairs of climate models and GDP studies. The added flexibility moderates any smoothing applied to the underlying data. We also test an alternative approach to estimating the parameters that minimizes the mean square error between the predicted and observed mean damage from each academic study. As a variation on that approach, we repeat that minimum mean square error (MMSE) estimation after reweighting observations by the inverse of their observed (or projected) sample variance.

MLE With Two Normal Distributions: "Double MLE." Rather than fitting only one normal distribution for each pairing of climate model and academic study, here we fit a mixture of two normal distributions that are averaged together by some weighting parameter ω. The rationale for that approach is to avoid oversmoothing the underlying data. Normal distributions are elliptically shaped and symmetrical, but the underlying data-generating process at the level of each pair of climate model and academic study may not be, so fitting an elliptical symmetrical distribution might smooth over legitimate signals in the data. However, *mixtures* of elliptical symmetrical distributions can be arbitrarily skewed and non-elliptical, so by fitting a *mixed* pair of distributions, we can relax the normality restriction. There would be evidence that a single normal distribution per *ij* pair was oversmoothing the data if the results under that approach were significantly different.

Fitting a cluster of two normal distributions per pairing will mitigate any inadvertent oversmoothing.[19] However, using two normal distributions comes with the cost of dramatically increasing the number of parameters in the overall mixed distribution. Under this approach, there are now seven free parameters per ij pair: three for each of the distributions ($\sigma^2_{1,YY}$, $\sigma^2_{1,YT}$, $\mu_{1,Y}$ and $\sigma^2_{2,YY}$, $\sigma^2_{2,YT}$, $\mu^2_{2,Y}$) and one parameter that weights the average of the two in the mixture (ω). That approach roughly doubles the computational cost of estimation, with most of the added complexity around solving for ω.

The double MLE approach yields results that are generally similar to the results of our preferred MLE approach (see Table 10). GDP losses are about 0.5 percentage points smaller by 2100 under the new approach for 3 degrees of freedom, and the other statistics of the distribution are only subtly changed. We interpret that as evidence that our preferred approach is not oversmoothing the data.

Minimizing the Mean Square Error. As an alternative to MLE, one can calculate the mean of the posterior distribution for each of the normal distribution's parameters, given the priors that we have already defined: the log-normal priors for temperature according to Section 5.1; and normal priors for GDP effects conditional on temperature and sample variances according to Section 5.2. The final mixed distribution will have the convenient property that the mean square prediction error between the observed data and the predicted data (from the fitted distribution) is minimized. Details about those MMSE calculations are provided in Sections A.2 and A.3 of Appendix A.

The effects of temperature on GDP tend to have a nonconstant variance in our dataset, so in an alternative approach (inverse variance weighted MMSE), we weight each within-study GDP observation by the inverse of the observation's variance. That approach deemphasizes observations with higher levels of uncertainty. Weighting by the inverse variance, or some proxy of it, is an increasingly common remedy for heteroskedasticity in the meta-analysis literature. For example, Howard and Sterner (2017) applies a fixed-effects estimator that sets precision-based weights for each observation. Howard and Sterner (2022), Herrnstadt and Dinan (2020), and Hsiang and others (2017) apply versions of the random-effects estimator that are similar to using fixed effects but allow for between-study heterogeneity. Section A.3 of Appendix A discusses the weights and gives equations used in estimation. Also, Table B-1 in Appendix B presents averaged versions of the weights, together with much of the underlying dataset used to construct them.

---

[19] Our baseline approach of using one distribution per pair mitigates that smoothing because we estimate bivariate distributions at 42 different values of (Y, T), expecting that the mixture of those 42 distributions will capture any unorthodox features of the data. Even so, some skewness and asymmetry may be missed.

Table 10.

Distribution of GDP Effects in 2100, by Estimation Procedure and Degrees of Freedom

Percent

Statistic	Infinite (normal)	10 DF (Student's *t*)	4 DF (Student's *t*)	3 DF (Student's *t*)	2 DF (Student's *t*)	1 DF (Cauchy)
			MLE			
Mean	-3.87	-3.88	-3.87	-3.93	-3.94	Undefined
Variance	55.3	64.42	91.44	132.62	Infinite	Undefined
5th percentile	-19.19	-19.87	-20.6	-21.3	-23.05	-33.47
33rd percentile	-4.00	-4.07	-4.19	-4.28	-4.44	-4.92
50th percentile	-2.29	-2.29	-2.27	-2.29	-2.28	-2.25
67th percentile	-1.10	-1.06	-0.97	-0.93	-0.85	-0.55
95th percentile	3.56	4.09	5.48	6.10	8.46	21.53
			Double MLE			
Mean	-3.4	-3.43	-3.45	-3.41	-3.41	Undefined
Variance	48.14	57.37	86.32	108.85	Infinite	Undefined
5th percentile	-16.78	-17.39	-17.98	-18.33	-20.03	-30.46
33rd percentile	-3.86	-3.92	-4.04	-4.08	-4.28	-4.63
50th percentile	-2.32	-2.31	-2.33	-2.3	-2.33	-2.28
67th percentile	-1.15	-1.12	-1.05	-0.99	-0.9	-0.64
95th percentile	4.36	4.94	5.87	6.64	8.44	21.04
			Inverse weighted MMSE			
Mean	-3.35	-3.37	-3.39	-3.45	-3.38	Undefined
Variance	64.81	77.26	116.07	176.42	Infinite	Undefined
5th percentile	-17.99	-18.65	-19.88	-20.84	-22.58	-34.15
33rd percentile	-3.41	-3.45	-3.53	-3.56	-3.66	-3.98
50th percentile	-2.02	-2.02	-2.03	-2.03	-2.04	-2.04
67th percentile	-0.98	-0.95	-0.91	-0.89	-0.84	-0.65
95th percentile	5.44	5.87	7.41	7.92	10.31	22.69
			MMSE			
Mean	-3.74	-3.77	-3.79	-3.87	-3.73	Undefined
Variance	99.98	118.59	176.82	263.42	Infinite	Undefined
5th percentile	-22.63	-23.4	-24.8	-25.61	-28.05	-42.35
33rd percentile	-3.86	-3.93	-4.06	-4.12	-4.26	-4.77
50th percentile	-2.15	-2.15	-2.14	-2.15	-2.17	-2.14
67th percentile	-0.94	-0.89	-0.82	-0.78	-0.72	-0.46
95th percentile	8.68	9.23	11.13	11.73	14.97	31.45

Data source: Congressional Budget Office.

These statistics describe the marginal distribution of the effects of climate change on GDP in 2100 under different degrees of freedom for the multivariate Student *t* distributions fitted to each academic study–climate model pairing. Each panel presents results for one of our four variations on the estimation procedure. The columns present results for selected degrees of freedom, and the rows present statistics for the distributions.

DF = degrees of freedom; GDP = gross domestic product; MLE = maximum likelihood estimation; MMSE = minimum mean square error.

The results under the MMSE and inverse variance weighted MMSE approaches generally have greater variance and fatter tails than the MLE results. That pattern arises in part because the priors we use for the temperature distribution are discretized to match the temperature observations from each paper, a feature of the estimation that we discuss in Sections A.2 and A.3 of Appendix A. For some academic papers in our dataset that report results for only two or three temperatures, the temperature's prior variance usually comes out higher than the nondiscretized temperature distribution, and that inflated variance contributes to the posterior variance of the GDP effects.

References

Aastveit, Knut Are, James Mitchell, Francesco Ravazzolo, and Herman K. van Dijk, *The Evolution of Forecast Density Combinations in Economics*, Discussion Paper TI 2018-069/III (Tinbergen Institute, 2018), https://hdl.handle.net/10419/185588.

Acevedo, Sebastian, and others, "The Effects of Weather Shocks on Economic Activity: What Are the Channels of Impact?" *Journal of Macroeconomics*, vol. 65 (September 2020), article 103207, https://doi.org/10.1016/j.jmacro.2020.103207.

Alder, Jay R., and Steven W. Hostetler, "National Climate Change Viewer (NVCC)" (U.S. Geological Survey, June 22, 2021), https://doi.org/10.5066/F7W9575T.

Antle, John M., "Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach," *Journal of Business and Economic Statistics*, vol. 1, no. 3 (1983), pp. 192–201, https://doi.org/10.2307/1391337.

Antle, John M., "Asymmetry, Partial Moments, and Production Risk," *American Journal of Agricultural Economics*, vol. 92, no. 5 (October 2010), pp. 1294–1309, https://doi.org/10.1093/ajae/aaq077.

Barrage, Lint, and William Nordhaus, "Policies, Projections, and the Social Cost of Carbon: Results From the DICE-2023 Model," *Proceedings of the National Academy of Sciences, United States of America*, vol. 121, no. 13 (March 2024), e2312030121, https://doi.org/10.1073/pnas.2312030121.

Boirard, Antoine, and others, *NGFS Climate Scenarios for Central Banks and Supervisors* (Network for Greening the Financial System, September 2022), https://tinyurl.com/5ew57kp2.

Burke, Marshall, and Vincent Tanutama, *Climatic Constraints on Aggregate Economic Output*, Working Paper 25779 (National Bureau of Economic Research, April 2019), www.nber.org/papers/w25779.

Byers, Edward, and others, "AR6 Scenarios Database" (Integrated Assessment Modeling Consortium and International Institute for Applied Systems Analysis, November 9, 2022), https://doi.org/10.5281/zenodo.5886911.

Casey, Gregory, Stephie Fried, and Ethan Goode, "Projecting the Impact of Rising Temperatures: The Role of Macroeconomic Dynamics," *IMF Economic Review*, vol. 71, no. 3 (June 2023), pp. 688–718, https://doi.org/10.1057/s41308-023-00203-0.

Chuang, Howard Hao-Chun, and Rogelio Oliva, "Estimating Retail Demand With Poisson Mixtures and Out-of-Sample Likelihood," *Applied Stochastic Models in Business and Industry*, vol. 30, no. 4 (July/August 2014), pp. 455–463, https://doi.org/10.1002/asmb.1986.

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan, "Temperature and Growth: A Panel Analysis of the United States," *Journal of Money, Credit and Banking*, vol. 51, no. 2–3 (March–April 2019), pp. 313–368, https://doi.org/10.1111/jmcb.12574.

Congressional Budget Office, *The Risks of Climate Change to the United States in the 21st Century* (December 2024), www.cbo.gov/publication/60845.

Congressional Budget Office, "Technical Information About How CBO Models the Effects of Climate Change on Output in Its Long-Term Economic Projections" (September 2021), www.cbo.gov/publication/57421.

Deloitte Economics Institute, *Turning Point: Technical Appendix* (August 2021), https://tinyurl.com/59v6r3fx.

Deryugina, Tatyana, and Solomon Hsiang, *The Marginal Product of Climate*, Working Paper 24072 (National Bureau of Economic Research, November 2017), https://www.nber.org/papers/w24072.

Environmental Protection Agency*, Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances* (November 2023), www.epa.gov/environmental-economics/scghg.

Fernando, Roshen, Weifeng Liu, and Warwick J. McKibbin, *Global Economic Impacts of Climate Shocks, Climate Policy, and Changes in Climate Risk Assessment. Climate Policy and Changes in Climate Risk Assessment*, Discussion Paper DP16154 (Centre for Economic Policy Research, July 14, 2021), https://tinyurl.com/2nrthset.

Friedlingstein, Pierre, and others, "Global Carbon Budget 2022," *Earth Systems Science Data*, vol. 14, no. 11 (November 2022), pp. 4811–4900, https://doi.org/10.5194/essd-14-4811-2022.

Guivarch, Céline, Elmar Kriegler, and Joana Portugal-Pereira, "Annex III: Scenarios and Modelling Methods," in Priyadarshi R. Shukla and others, eds., *Climate Change 2022: Mitigation of Climate Change—Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press, 2022), https://doi.org/10.1017/9781009157926.022.

Hall, Stephen G., and James Mitchell, "Combining Density Forecasts," *International Journal of Forecasting*, vol. 23, no. 1 (January–March 2007), pp. 1–13, https://doi.org/10.1016/j.ijforecast.2006.08.001.

Herrnstadt, Evan, and Terry Dinan, *CBO's Projection of the Effect of Climate Change on U.S. Economic Output*, Working Paper 2020-06 (Congressional Budget Office, September 2020), www.cbo.gov/publication/56505.

Howard, Peter H., and Thomas Sterner, *Between Two Worlds: Methodological and Subjective Differences in Climate Impact Meta-Analyses*, Working Paper 22-10 (Resources for the Future, June 2022), https://tinyurl.com/5b2x73st.

Howard, Peter H., and Thomas Sterner, "Few and Not So Far Between: A Meta-Analysis of Climate Damage Estimates," *Environmental and Resource Economics*, vol. 68 (2017), pp. 197–225, https://doi.org/10.1007/s10640-017-0166-z.

Hsiang, Solomon, and others, "Estimating Economic Damage From Climate Change in the United States," *Science*, vol. 356, no. 6345 (June 30, 2017), pp. 1362–1369, https://doi.org/10.1126/science.aal4369.

Hughes, Ifan G., and Thomas P. A. Hase, *Measurements and Their Uncertainties: A Practical Guide to Modern Error Analysis* (Oxford University Press, 2010).

Integrated Carbon Observation System, "Data Supplement to the Global Carbon Budget 2024" (accessed December 11, 2024), https://tinyurl.com/5b2bxbnz.

Kahn, Matthew E., "The Climate Change Adaptation Literature," *Review of Environmental Economics and Policy*, vol. 10, no. 1 (Winter 2016), pp. 166–178, https://doi.org/10.1093/reep/rev023.

Kahn, Matthew E., and others, "Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis," *Energy Economics*, vol. 104 (December 2021), article 105624, https://doi.org/10.1016/j.eneco.2021.105624.

Kalkuhl, Matthias, and Leonie Wenz, "The Impact of Climate Conditions on Economic Production: Evidence From a Global Panel of Regions," *Journal of Environmental Economics and Management*, vol. 103 (September 2020), article 102360, https://doi.org/10.1016/j.jeem.2020.102360.

Kompas, Tom, Van Ha Pham, and Tuong Nhu Che, "The Effects of Climate Change on GDP by Country and the Global Economic Gains From Complying With the Paris Climate Accord," *Earth's Future*, vol. 6, no. 8 (August 2018), pp. 1153–1173, https://doi.org/10.1029/2018EF000922.

Kotz, Maximilian, Anders Levermann, and Leonie Wenz, "The Economic Commitment of Climate Change," *Nature*, vol. 628, no. 8008 (April 17, 2024), pp. 551–557, https://doi.org/10.1038/s41586-024-07219-0.

Merrifield, Anna L., and others, “Climate Model Selection by Independence, Performance, and Spread (ClimSIPS v1. 0.1) for Regional Applications,” *Geoscientific Model Development*, vol. 16, no. 16 (August 23, 2023), pp. 4715–4747, https://doi.org/10.5194/gmd-16-4715-2023.

Mohaddes, Kamiar, and others, “Climate Change and Economic Activity: Evidence From U.S. States,” *Oxford Open Economics*, vol. 2, (2023), article odac010, https://doi.org/10.1093/ooec/odac010.

International Institute for Applied Systems Analysis, “AR6 Scenario Explorer and Database Hosted by IIASA” (2022), https://data.ece.iiasa.ac.at/ar6.

Nath, Ishan B., Valerie A. Ramey, and Peter J. Klenow, *How Much Will Global Warming Cool Global Growth?* Working Paper 32761 (National Bureau of Economic Research, July 2024), www.nber.org/papers/w32761.

Newell, Richard G., Brian C. Prest, and Steven E. Sexton, “The GDP–Temperature Relationship: Implications for Climate Change Damages,” *Journal of Environmental Economics and Management*, no. 108 (July 2021), article 102445, https://doi.org/10.1016/j.jeem.2021.102445.

Nordhaus, Wiliiam D., and Andrew Moffat, *A Survey of Global Impacts of Climate Change: Replication, Survey Methods, and a Statistical Analysis*, Working Paper 23646 (National Bureau of Economic Research, August 2017), www.nber.org/papers/w23646.

Paçal, Aytaç, and others, “Detecting Extreme Temperature Events Using Gaussian Mixture Models,” *Journal of Geophysical Research: Atmospheres*, vol. 128, no. 18 (September 27, 2023), e2023JD038906, https://doi.org/10.1029/2023JD038906.

Peel, David, and Geoffrey J. McLachlan, “Robust Mixture Modelling Using the *t* Distribution,” *Statistics and Computing*, vol. 10 (October 2000), pp. 339–348, https://doi.org/10.1023/A:1008981510081.

Pierce, David W. and others, “Future Increases in North American Extreme Precipitation in CMIP6 Downscaled With LOCA,” *Journal of Hydrometeorology*, vol. 24, no. 5 (May 2023), pp. 951–975, https://doi.org/10.1175/JHM-D-22-0194.1.

Richters, Oliver, and others, “NGFS Climate Scenarios Data Set,” version 5.0 (Network for Greening the Financial System, November 5, 2024), https://doi.org/10.5281/zenodo.13989530.

Roson, Roberto, and Martina Sartori, “Estimation of Climate Change Damage Functions for 140 Regions in the GTAP9 Database,” *Journal of Global Economic Analysis*, vol. 1, no. 2 (December 2016), pp. 78–115, https://doi.org/10.21642/JGEA.010202AF.

Shin, Ju-Young, Misun Kang, and Kyu Rang Kim, "Outdoor Thermal Stress Changes in South Korea: Increasing Inter-Annual Variability Induced by Different Trends of Heat and Cold Stresses," *Science of the Total Environment*, vol. 805 (January 2022), article 150132, https://doi.org/10.1016/j.scitotenv.2021.150132.

Shindell, Drew, and others, *Global Methane Assessment: 2030 Baseline Report* (United Nations Environment Programme/Climate and Clean Air Coalition, November 2022), https://tinyurl.com/3t9nsc5f.

Tack, Jesse, Keith Coble, and Barry Barnett, "Warming Temperatures Will Likely Induce Higher Premium Rates and Government Outlays for the U.S. Crop Insurance Program," *Agricultural Economics*, vol. 49, no. 5 (September 2018), pp. 635–647, https://doi.org/10.1111/agec.12448.

Takakura, Jun'ya, and others, "Dependence of Economic Impacts of Climate Change on Anthropogenically Directed Pathways," *Nature Climate Change*, vol. 9 (September 25, 2019), pp. 737–741, https://doi.org/10.1038/s41558-019-0578-6.

Tol, Richard S. J., "A Meta-Analysis of the Total Economic Impact of Climate Change," *Energy Policy*, vol. 185 (February 2024), article 113922,. https://doi.org/10.1016/j.enpol.2023.113922.

Tolhurst, Tor N., and Alan P. Ker, "On Technological Change in Crop Yields," *American Journal of Agricultural Economics*, vol. 97, no. 1 (January 2015), pp. 137–158,https://doi.org/10.1093/ajae/aau082.

Woodard, Joshua D. and Bruce J. Sherrick, "Estimation of Mixture Models Using Cross-Validation Optimization: Implications for Crop Yield Distribution Modeling," *American Journal of Agricultural Economics*, vol. 93, no. 4 (July 2011), pp. 968–982. https://doi.org/10.1093/ajae/aar034.

Appendix A: Alternative Approaches to Estimating Joint Distribution Parameters

This appendix presents four approaches to estimating the parameters in the distributions for each *ij* study–scenario pairing. For more discussion about the pros and cons of each approach, refer to Sections 6.3.1 and 6.3.2 of the main report. To summarize, our preferred results use the maximum likelihood approach described in Section A.1 of this appendix because it is well studied and efficient. To extend that approach and demonstrate its robustness to non-normality, we present a variation on the standard normal log-likelihood distribution by fitting a mixture of two normal distributions per *ij* pairing, as described in Section A.2. We also estimate the parameters with weighted and unweighted minimum mean square error (MMSE) approaches to further verify that the results are consistent across a variety of approaches.

A.1. Maximum Likelihood Estimation

This section describes how to estimate the parameters of the bivariate normal probability density, $p_{ij}(Y,T)$. The parameters in that density are the means, $\mu_{T,ij}$ and $\mu_{Y,ij}$, and the covariances, $\sigma^2_{Y,ij}$, $\sigma^2_{YT,ij}$, and $\sigma^2_{T,ij}$. From the climate scenarios and the procedure described in Section 5.1 of the main text, we have already calculated $\sigma^2_{T,ij}$, $\mu_{T,ij}$, and from the academic studies and the procedure described in Section 5.2, we have already calculated $\mu_{Y|T,i}$ and $\sigma^2_{Y|T,i}$. Therefore, the remaining parameters that we need to calculate are $\sigma^2_{Y,ij}$, $\sigma^2_{YT,ij}$, and $\mu_{Y,ij}$. The remainder of this section drops the *ij* subscripts to simplify the notation.

Using the definitions for the conditional mean and variance of $Y|T$ given in Equations (A.1.1) and (A.1.2), together with the first-order conditions of the likelihood function with respect to each of our target parameters (derived below), we can solve for the unknown parameters:

$$E(Y|T) = \mu_{Y|T} = \mu_Y + \rho \frac{\sigma_Y}{\sigma_T}(T - \mu_T) \tag{A.1.1}$$

$$Var(Y|T) = \sigma^2_{Y|T} = \sigma^2_Y - \sigma^2_Y \rho^2 \tag{A.1.2}$$

In those equations, ρ represents the correlation coefficient and is defined as $\rho = \sigma^2_{YT}/(\sigma_T \sigma_Y)$. The probability density function (PDF) for a random realization, Z_k indexed by k, arrives from the density $p(Y|T)$ given by Equation (A.1.3):

$$p(Z_k) = \left(\sigma_{Y|T,k}\right)^{-1}(2\pi)^{-1/2}\exp\left(-\frac{1}{2}\left(\frac{Z_k - \mu_{Y|T}}{\sigma_{Y|T,k}}\right)^2\right) \tag{A.1.3}$$

Substituting out the conditional mean by using Equation (A.1.1) in Equation (A.1.3), we arrive at the following:

$$p(Z_k) = \left(\sigma_{Y|T,k}\right)^{-1}(2\pi)^{-1/2}\exp\left(-\frac{1}{2}\left(\frac{Z_k-\mu_Y-\rho\frac{\sigma_Y}{\sigma_T}(T-\mu_T)}{\sigma_{Y|T,k}}\right)^2\right) \quad \text{(A.1.4)}$$

If we had observations of losses to gross domestic product (GDP) across randomly selected temperatures, the expected number of observations at each temperature would be proportional to the probability of observing that temperature. That can be written as $N \times P(T_k)$, where N is the sample size and $P(T_k)$ is the cumulative density function's (CDF's) value for temperature at T_k. But our sample of observations from the bivariate normal probability density $p(Y|T)$ is not random; rather, the authors of academic studies tend to select a few recognizably significant temperatures for which to report results. Therefore, the likelihood of observing our dataset given temperatures is $\prod_{k=1}^{N} p(Z_k)^{NP(T_k)}$ for N total observations of temperature. Applying that to Equation (A.1.4) gives Equation (A.1.5), which spans k observations that are all from the same ij pairing of academic study and climate model:

$$\prod_k p(Z)^{P(T_k)N} = \prod_k \left(\sigma_{Y|T,k}\right)^{-P(T_k)N}(2\pi)^{-P(T_k)N2}\exp\left(-\frac{NP(T_k)}{2}\left(\frac{Z_k-\mu_Y-\rho\frac{\sigma_Y}{\sigma_T}(T-\mu_T)}{\sigma_{Y|T,k}}\right)^2\right) \quad \text{(A.1.5)}$$

We then take the log of both sides of Equation (A.1.5):

$$\mathcal{L} = -\sum_k P(T_k)N\log\left(\sigma_{Y|T,k}\right) - \sum_k P(T_k)N2\log(2\pi) - \sum_k \left(-\frac{NP(T_k)}{2}\left(\frac{Z_k-\mu_Y-\rho\frac{\sigma_Y}{\sigma_T}(T-\mu_T)}{\sigma_{Y|T,k}}\right)^2\right) \quad \text{(A.1.6)}$$

And then we take the derivative of (A.1.6) with respect to μ_Y and set $\omega_k \equiv P(T_k)N/\sigma^2_{Y|T,k}$:

$$\partial\mathcal{L}/\partial\mu_Y = \sum_k \left(-NP(T_k)\left(\frac{Z_k-\mu_Y-\rho\frac{\sigma_Y}{\sigma_T}(T_k-\mu_T)}{\sigma_{Y|T,k}}\right)\right)\frac{-1}{\sigma_{Y|T,k}} = 0$$

$$= \sum_k \omega_k Z_k - \mu_Y \sum_k \omega_k - \frac{\sigma^2_{YT}}{\sigma^2_T}\sum_k \omega_k(T_k-\mu_T) = 0 \quad \text{(A.1.7)}$$

Simplifying Equation (A.1.67) gives us the following:

$$\mu_Y = \frac{\sum_i \omega_k Z_k}{\sum_i \omega_k} - \frac{\sigma^2_{YT}}{\sigma^2_T}\left(\frac{\sum_k \omega_k T_k}{\sum_i \omega_k} - \mu_T\right) \quad \text{(A.1.8)}$$

Next, we take the derivative of Equation (A.1.6) with respect to σ^2_{YT}:

$$\partial\mathcal{L}/\partial\sigma^2_{YT} = \sum_k \left(\frac{\omega_k 2}{2}\left(Z-\mu_Y-\frac{\sigma^2_{YT}}{\sigma^2_T}(T_k-\mu_T)\right)(T_k-\mu_T)\right) = 0$$

$$= \sum_i \omega_k (Z - \mu_Y)(T_k - \mu_T) - \frac{\sigma_{YT}^2}{\sigma_T^2} \sum_k \omega_k (T_k - \mu_T)^2 = 0 \tag{A.1.9}$$

Equation (A.1.10) simplifies Equation (A.1.9):

$$\sigma_{YT}^2 = \sigma_T^2 \frac{\sum_k \omega_k (Z_k - \mu_Y)(T_k - \mu_T)}{\sum_k \omega_k (T_k - \mu_T)^2} \tag{A.1.10}$$

Using the definitions for $\sigma_{Y|T}^2$ in Equation (A.1.2) and incorporating the definition for ρ, we have the following:

$$\sigma_{Y|T,k}^2 + \left(\frac{\sigma_{YT}^2}{\sigma_T}\right)^2 = \sigma_{Y,k}^2 \tag{A.1.11}$$

Finally, we define a set of parameters, α_k for all k, that accounts for the differences in the observed variance between observations:

$$\alpha_k \sigma_Y^2 = \sigma_{Y,k}^2 \tag{A.1.12}$$

Since we are using the normal distribution, there must be only true underlying σ_Y^2 for all the k observations, and idiosyncratic differences are explained by that α_k term. The only requirement that we put on α_k is that it must satisfy the following equation:

$$1 = \frac{\sum_k \omega_k \alpha_k}{\sum_k \omega_k} \tag{A.1.13}$$

Applying Equations (A.1.11) and (A.1.12) to Equation (A.1.13) and summing across k, we arrive at the following:

$$\sum_k \omega_k \left(\sigma_{Y|T,k}^2 + \left(\frac{\sigma_{YT}^2}{\sigma_T}\right)^2\right) = \sum_k \omega_k \alpha_k \sigma_Y^2$$

That equation can be simplified as follows:

$$\frac{\sum_k \omega_k \sigma_{Y|T,k}^2}{\sum_k \omega_k} + \left(\frac{\sigma_{YT}^2}{\sigma_T}\right)^2 = \sigma_Y^2 \tag{A.1.14}$$

We now have a system of three unknown variables, $\sigma_{YT}, \sigma_Y,$ and μ_Y, and the three equations: (A.1.8), (A.1.10), (A.1.14). The final weights are $\omega_k = P(T_k)/\sigma_{Y|T,k}^2$, since the N cancels out. The three equations are numerically solved simultantenously for each ij pairing.

A.2. Minimum Mean Square Error

We calculate the first and second moments of the jointly distributed data for Y and T and use those data to define a bivariate normal distribution for each ij pairing. The distribution will have the convenient property that the mean square prediction error between the observed data and the predicted data from the fitted distribution is minimized.

To keep track of which moments come from climate models and which come from GDP studies, we let X_s be a random variable that represents the academic study s being true, and the probability of that event is $p(X_s)$. Therefore, s is an index across studies of the effects of climate change on GDP. We then let c be an index across possible climate and emissions scenarios. Supposing that X_s and X_c are independent of each other, and building from Equation (1) as described in the main text, we arrive at Equation (A.2.1):

$$\begin{aligned} p(Y) &= \int p(Y|T)p(T)dT \\ &= \int \left(\sum_s \sum_c p(Y|T, X_s, X_c)p(T|X_s, X_c)p(X_s)p(X_c)\right)dT \\ &= \int \sum_s \sum_c p(Y, T|X_s, X_c)\theta_c\omega_s dT \end{aligned} \tag{A.2.1}$$

Equation (A.2.1) is equivalent to Equation (3) in the main text, except that we have interpreted $\omega_s = p(X_s)$ and $\theta_s = p(X_c)$ as parameters that represent model certainty: Higher weights convey more likelihood that the model s or c is correct. It is convenient and intuitive here to work with that interpretation of the mixture weights ω and θ.

Every observation from study s has a normal distribution conditional on observing temperature k from climate model c. We observe estimates of parameters for the distributions of $Y|T$ from GDP studies and of T from emissions scenarios, and we assume that those parameters are observed without error.

$$Y|T = T_k, X_s \sim N(\mu_{ks}^Y, \sigma_s^Y)$$

$$T|X_c \sim N(\mu_c^T, \sigma_c^T)$$

We need to estimate the parameters in that joint distribution for each climate model c and study s:

$$\binom{Y}{T} \sim N\left[\begin{pmatrix}\mu_{sc}^Y \\ \mu_{sc}^T\end{pmatrix}, \begin{pmatrix}(\sigma_{sc}^{YY})^2 & (\sigma_{sc}^{YT})^2 \\ (\sigma_{sc}^{TY})^2 & (\sigma_{sc}^{TT})^2\end{pmatrix}\right] \text{ for all } s = 1, \dots, S \text{ and } c = 1, \dots, C$$

GDP effects collected from climate studies are conditional on discrete temperatures T_k. We must then take an extra step of conditioning each distribution of T on the temperatures used in climate model c. We use the following discrete distribution, in which $\phi(.)$ is the normal PDF, for k observations in model s:

$$p(T = T_k|X_s, X_c) = \phi(T_k; \mu_c^T, \sigma_c^T) / \sum_k \phi(T_k; \mu_c^T, \sigma_c^T)$$

Then we use Equation (A.2.2) to calculate parameters in the joint distribution:

$$\begin{aligned}
\mu_{sc}^{Y} &= E(Y|X_s, X_c) \\
&= E(E(Y|T, X_s, X_c)|X_s, X_c) \\
&= \textstyle\sum_k E(Y|T = T_k, X_s, X_c)p(T = T_k|X_s, X_c) \\
&= \textstyle\sum_k \mu_{ks}^{Y} p(T = T_k|X_s, X_c)
\end{aligned} \tag{A.2.2}$$

And we use Equation (A.2.3) to arrive at the same for temperature:

$$\begin{aligned}
\mu_{sc}^{T} &= E(T|X_s, X_c) \\
&= \textstyle\sum_k T_k p(T = T_k|X_s, X_c)
\end{aligned} \tag{A.2.3}$$

The covariance is given by Equation (A.2.4):

$$\begin{aligned}
\sigma_{sc}^{YT} &= E(YT|X_s, X_c) - E(Y|X_s, X_c)E(T|X_s, X_c) \\
&= E(TE(Y|T, X_s, X_c)|X_s, X_c) - \mu_{sc}^{Y}\mu_{sc}^{T} \\
&= (\textstyle\sum_k T_k \mu_{ks}^{Y} p(T = T_k|X_s, X_c)) - \mu_{sc}^{Y}\mu_{sc}^{T}
\end{aligned} \tag{A.2.4}$$

The variance for temperature is given by Equation (A.2.5):

$$\begin{aligned}
\sigma_{sc}^{TT} &= E(T^2|X_s, X_c) - E(T|X_s, X_c)^2 \\
&= \textstyle\sum_k (T_k)^2 p(T = T_k|X_s, X_c) - (\mu_{sc}^{T})^2
\end{aligned} \tag{A.2.5}$$

And the variance for GDP effects is given by Equation (A.2.6);

$$\begin{aligned}
\sigma_{sc}^{YY} &= E(Y^2|X_s, X_c) - E(Y|X_s, X_c)^2 \\
&= \textstyle\sum_k E(Y^2|T = T_k, X_s, X_c)p(T = T_k|X_s, X_c) - (\mu_{sc}^{Y})^2 \\
&= (\textstyle\sum_k ((\sigma_{ks}^{YY})^2 + E(Y|T = T_k, X_s, X_c)^2)p(T = T_k|X_s, X_c)) - (\mu_{sc}^{Y})^2 \\
&= (\textstyle\sum_k ((\sigma_{ks}^{YY})^2 + (\mu_{ks}^{Y})^2)p(T = T_k|X_s, X_c)) - (\mu_{sc}^{Y})^2
\end{aligned} \tag{A.2.6}$$

Using Equations (A.2.2) through (A.2.6), we can calculate the parameters for each model–climate pairing (sc): μ_{sc}^{Y}, μ_{sc}^{T}, σ_{sc}^{YT} , σ_{sc}^{TT}, and σ_{sc}^{YY}.

A.3. MMSE and Inverse Variance Weighted MMSE

This section presents a variant of the approach outlined above, in which we downweight observations with a higher relative variance of GDP losses than other observations within an academic-study pair. Since the variance of losses tends to increase with temperature, higher damage estimates are down-weighted relative to lower temperate observations. The end result is that the covariance between temperature and GDP is lower than when estimated using our other approaches.

In some cases, the variance is also a random variable, as in the following equation:

$$Y|T = T_k, \sigma_{ks}^Y, X_s \sim N(\mu_{ks}^Y, \sigma_{ks}^Y)$$

In such cases, we make an adjustment to weight within-study observations by the inverse variance. Thus, we would calculate μ_{sc}^Y as follows:

$$\begin{aligned}
\mu_{sc}^Y &= E(Y|X_s, X_c) \\
&= E(E(Y|T, \sigma^Y, X_s, X_c)|X_s, X_c) \\
&= \textstyle\sum_k E(Y|T = T_k, \sigma = \sigma_{ks}^Y, X_s, X_c) p(T = T_k, \sigma = \sigma_{ks}^Y|X_s, X_c) \\
&= \textstyle\sum_k \mu_{ks}^Y p(T = T_k|X_s, X_c) p(\sigma = \sigma_{ks}^Y|T = T_k, X_s, X_c)
\end{aligned}$$

The last step is to use methods from Hughes and Hase (2010) to guide our choice for the conditional probability of observing σ_{ks}^Y. We set that probability to $\varphi_{ksc} = (\sigma_{ks}^Y)^{-2} / (\sum_k (\sigma_{ks}^Y)^{-2} \times p(T = T_k|X_s, X_c))$.

$$\tilde{\mu}_{sc}^Y = \textstyle\sum_k \mu_{ks}^Y \varphi_{ksc} p(T = T_k|X_s, X_c) \qquad \text{(A.3.1)}$$

The same weights are applied to estimate σ_{sc}^{YY} and σ_{sc}^{YT}.

$$\tilde{\sigma}_{sc}^{YY} = (\textstyle\sum_k ((\sigma_{ks}^{YY})^2 + (\mu_{ks}^Y)^2) \varphi_{ksc} p(T = T_k|X_s, X_c)) - (\tilde{\mu}_{sc}^Y)^2 \qquad \text{(A.3.2)}$$

$$\tilde{\sigma}_{sc}^{YT} = (\textstyle\sum_k T_k \mu_{ks}^Y \varphi_{ksc} p(T = T_k|X_s, X_c)) - \tilde{\mu}_{sc}^Y \mu_{sc}^T \qquad \text{(A.3.3)}$$

Using Equations (A.2.3), (A.2.5), (A.3.1), (A.3.2), and (A.3.3), we can calculate the parameters for each model–climate pairing (sc): $\tilde{\mu}_{sc}^Y$, μ_{sc}^T, $\tilde{\sigma}_{sc}^{YT}$, σ_{sc}^{TT} , and $\tilde{\sigma}_{sc}^{YY}$.

A.4. Double MLE: Clustering With Two Bivariate Normal Distributions

In this section, we perform a procedure similar to the one oulined in Section A.1 above; however, we now fit two normal distributions, $p(Z_k)$ and $q(Z_k)$, to the dataset of conditional means $\mu_{Y|T,k}$ and conditional variances $\sigma_{Y|T,k}^2$. In Equation (A.4.1), we take the product across discrete temperatures T_k, setting μ_{Y1} as the mean of p density and μ_{Y2} as the mean of q density:

$$\log \prod_k m(Z_k) = \log(\prod_k (\omega p(Z_k) + (1-\omega)q(Z_k))^{P(T_k)N})$$

$$= \sum_k P(T_k)N\log(\omega p(Z_k;\mu_{Y1}) + (1-\omega)q(Z_k;\mu_{Y2})) \qquad \text{(A.4.1)}$$

We take the derivative of (A.4.1) with respect to μ_{Y1}:

$$\frac{\log \prod_k m_k(Z_k)}{d\mu_{Y1}} = \sum_k P(T_k)N \frac{\omega}{(\omega p(Z_k;\mu_{Y1}) + (1-\omega)q(Z_k;\mu_{Y2}))} \frac{dp(Z_k;\mu_{Y1})}{d\mu_{Y1}} = 0$$

$$= \sum_k P(T_k)N \frac{\omega p(Z_k;\mu_{Y1})}{(\omega p(Z_k;\mu_{Y1})+(1-\omega)q(Z_k;\mu_{Y2}))} \left(\frac{Z_k-\mu_{Y1}-\rho\frac{\sigma_Y}{\sigma_T}(T_k-\mu_T)}{\sigma_{Y|T,k}}\right) \frac{1}{\sigma_{Y|T,k}} = 0$$

$$= \sum_i (\tilde{\omega}_k^1)\left(Z_k - \mu_{Y1} - \rho\frac{\sigma_Y}{\sigma_T}(T_k - \mu_T)\right) = 0$$

$$= \sum_k \tilde{\omega}_k^1 Z_k - \mu_{Y1}\sum_k \tilde{\omega}_k^1 - \frac{\sigma_{YT}^2}{\sigma_T^2}\sum_k \tilde{\omega}_k^1(T_k - \mu_T) = 0 \qquad \text{(A.4.2)}$$

Using Equation (A.4.2), the means for $j = 1, 2$ are calculated with Equation (A.4.3):

$$\mu_{Yj} = \frac{\sum_k \tilde{\omega}_k^j Z_k}{\sum_k \tilde{\omega}_k^j} - \frac{\sigma_{YT,j}^2}{\sigma_T^2}\left(\frac{\sum_k \tilde{\omega}_k^j T_i}{\sum_k \tilde{\omega}_k^j} - \mu_T\right) \qquad \text{(A.4.3)}$$

We then take the derivative of Equation (A.4.1) with respect to μ_{YTj} for $j = 1, 2$:

$$\sigma_{YTj}^2 = \sigma_T^2 \frac{\sum_k \tilde{\omega}_k^j(\mu_{Yj|T,k}-\mu_{Yj})(T_k-\mu_T)}{\sum_k \tilde{\omega}_k^j(T_k-\mu_T)^2} \qquad \text{(A.4.4)}$$

And the variance is as follows:

$$\sigma_{Yj}^2 = \frac{\sum_k \tilde{\omega}_k^j \sigma_{Yj|T,k}^2}{\sum_k \tilde{\omega}_k^j} + \left(\frac{\sigma_{j,YT}^2}{\sigma_T}\right)^2 \qquad \text{(A.4.5)}$$

We there define $\tilde{\omega}_k^1$ as follows:

$$\tilde{\omega}_k^1 = \frac{\omega p(Z_k;\mu_{Y1})}{(\omega p(Z_k;\mu_{Y1})+(1-\omega)q(Z_k;\mu_{Y2}))} \qquad \text{(A.4.6)}$$

And $\tilde{\omega}_k^2 = 1 - \tilde{\omega}_k^1$. With clusters of two normals, we have eight variables per pairing—$\mu_{Y1}, \sigma_{YT1}^2, \sigma_{Y1}^2, \mu_{Y2}$, σ_{YT2}^2, σ_{Y2}^2, $\tilde{\omega}_k^1$, and ω—but only seven conditions. Those seven conditions are defined by Equations (A.4.3), (A.4.4), and (A.4.5) for each *j*, together with Equation (A.4.6). The eighth condition comes from the likelihood function above that is maximized for our choice of ω. We use a nonlinear solver to find ω between 0 and 1.

Appendix B: Data From the Studies Providing Values for Temperature and GDP Effects

This appendix provides information on the data underlying the analysis in this paper.

Table B-1 provides details about the metadata for the emissions scenarios, integrated assessment models (IAMs), and emulators used for the temperature dataset. The emulators MAGICCv7.5.3 and FaIRv1.6.2 translate the 21 emissions scenarios into 42 temperature distributions.[1]

Table B-2 provides a list of the studies and the observations used for this paper. Temperatures have been adjusted to reflect increases relative to our 1850–1900 reference climate. For studies that used U.S. temperatures, we translate predicted U.S. temperature changes to global temperature changes. GDP effects reported in the table are not adjusted for a study's reference climate or forecast end year—that adjustment is performed during the parameter estimation. Results for Casey, Fried, and Goode (2023), Colacito, Hoffmann, and Phan (2019), and Burke and Tanutama (2019) are generated by applying the regression coefficients in those papers to state- and county-level temperature data from Pierce and others (2023) using code from Alder and Hostetler (2013). Results for Kotz, Levermann, and Wenz (2024) and Kalkuhl and Wenz (2020) were generated from their publicly available code repositories and from the NGFS scenarios databases from 2022 and 2024 in Boirard and others (2022) and Richters and others (2024), respectively.

Figure B-1 shows the emissions scenarios underlying the temperature projections out to 2100. Scenarios with higher emissions are associated with hotter temperature distributions. The two panels of the figure convey that with line shading going from black to tan, corresponding to gradually higher emissions and temperatures. The data presented in the right panel are identical to the data presented in Figure 2 in the main text.

[1] Details about the MAGICCv7.5.3 emulator are available at https://magicc.org/download/magicc7. Details about the FaIRv1.6.2 emulator are available at https://docs.fairmodel.net/en/v1.6.2.

Table B-1.

Description of Dataset on Temperature Changes in 2100

Temperature scenario	Integrated assessment model	Emissions scenario	Warming category	Year of peak GHG emissions	Median warming in 2100, by climate emulator (degrees Celsius)	
					MAGICCv7.5.3	FaIRv1.6.2
1	COFFEE 1.1	CO_CurPol	C6	2070	2.94	2.75
2	COFFEE 1.1	EN_NPi2100	C6	2070	2.93	2.74
3	GEM-E3_V2021	EN_NPi2100_COV	C7	2100	3.19	2.97
4	IMAGE 3.0	EN_NPi2100	C7	2100	3.51	3.30
5	IMAGE 3.0.1	ADVANCE_Reference	C7	2100	3.34	3.10
6	MESSAGE-GLOBIOM 1.0	ADVANCE_Reference	C6	2050	2.88	2.75
7	MESSAGEix-GLOBIOM 1.0	CD-LINKS_NPi	C7	2100	3.67	3.44
8	MESSAGEix-GLOBIOM_1.1	EN_NPi2100_COV	C7	2100	3.23	3.06
9	MESSAGEix-GLOBIOM_1.1	NGFS2_Current Policies	C7	2100	3.16	3.00
10	MUSE 1.0	PR_CP_Intensity	None	2020	2.35	2.24
11	REMIND 2.1	LeastTotalCost_NPi_brk LR15_SSP1_P50	C5	2035	2.39	2.23
12	REMIND 2.1	LeastTotalCost_NPi_brk SR15_SSP1_P50	C5	2035	2.40	2.24
13	REMIND 2.1	R2p1_SSP1-NPi	C5	2020	2.37	2.21
14	REMIND-MAgPIE 2.1-4.2	CEMICS_SSP1-Npi	C6	2035	2.57	2.40
15	REMIND-MAgPIE 2.1-4.2	EN_NPi2100	C7	2080	3.20	2.98
16	REMIND-MAgPIE 2.1-4.2	EN_NPi2100_COV	C7	2080	3.07	2.86
17	REMIND-MAgPIE 2.1-4.2	NGFS2_Current Policies - IPD-95th	C7	2035	3.17	2.90
18	REMIND-MAgPIE 2.1-4.2	SusDev_SSP1-NPi	C5	2035	2.38	2.22
19	REMIND-MAgPIE 2.1-4.2	SusDev_SSP2-NPi	C7	2080	3.34	3.08
20	WITCH 5.0	CO_CurPol	C7	2075	3.47	3.13
21	WITCH 5.0	EN_NPi2100	C7	2090	3.35	3.01

Data source: Congressional Budget Office, using data from the AR6 Scenarios Database (Byers and others, 2022).

This table presents metadata for the scenarios, IAMS, and climate emulators used to produce our data for temperature changes through 2100. The 21 scenarios are identified in the AR6 Scenario Explorer Database as those in the Chapter 4 subset that model the trend from implemented policies and did not fail the IPCC's vetting process. Guivarch, Kriegler, and Portugal-Pereira (2022) provides helpful additional context for those data.

Integrated assessment model: IAMs are energy models that are used to project the economic and emissions outcomes from each scenario. Those models vary widely in their level of detail, regional granularity, and mathematical representation of the economy.

Emission scenario: Scenarios are descriptions of alternative future developments in energy technology, policy, human economic activity, and GHG mitigation progress. Most scenarios were conceived to run in an IAM to generate projections of emissions and human activity that would be paired with a climate emulator.

Warming category: For category C5, median warming is between 2°C and 2.5°C; for category C6, median warming is between 2.5°C and 3°C; for category C7, median warming is between 3°C and 4°C. For temperature scenario 10, no formal warming category was reported in the IPCC metadata, so we do not report one here.

Year of peak GHG emissions: The year that GHG emissions peak in the study.

Median warming in 2100: Median temperature changes from each of the climate emulator results used in this working paper. Emulators are used to assess the climate implications of the GHG and other emissions trajectories that IAMs produce. These columns show the median temperature change from the 1850–1900 reference climate in each of the two climate emulators, MAGICC and FaIRv1. Emulators are used to assess the full range of uncertainty surrounding carbon cycles and climate responses.

GHG = greenhouse gas; IAM = integrated assessment model; IPCC = Intergovernmental Panel on Climate Change.

Table B-2.

Extended Summary of Dataset of Effects on GDP From Climate Change

Group	Paper	Change in temperature (degrees Celsius)	GDP loss		Weights		
			Mean (percent)	Standard deviation (percent)	Variance and temp. (average)[e]	Temp. only (average)	Relevance
1	Kompas, Pham, and Che (2018)	2.00	-0.39	1.49	0.13	0.22	0.02
		3.00	-0.62	0.96	0.56	0.56	
		4.00	-0.89	0.77	0.31	0.22	
2	Fernando, Liu, and McKibbin (2021)	1.61	-0.57	1.87	0.01	0.03	0.02
		2.41	-1.31	1.21	0.30	0.38	
		2.81	-1.98	1.02	0.52	0.49	
		4.31	-0.31	0.75	0.17	0.10	
3	Kotz, Levermann, and Wenz (2024)	2.07	-3.42	2.15	0.09	0.06	0.08
		2.80	-13.45	7.54	0.25	0.05	
		3.33	-21.15	10.37	0.24	0.03	
		2.95	-15.75	8.44	0.27	0.04	
		1.70	-0.66	0.42	0.03	0.18	
		2.01	-2.94	1.86	0.08	0.06	
		1.77	-0.47	0.30	0.04	0.57	
4	Kahn and others (2021)	1.61	-0.98	1.04	0.11	0.10	0.08
		1.61	-1.88	1.04	0.11	0.10	
		1.61	-2.84	1.04	0.11	0.10	
		4.31	-6.66	1.62	0.22	0.24	
		4.31	-10.52	1.62	0.22	0.24	
		4.31	-14.32	1.62	0.22	0.24	
5	Hsiang and others (2017)	1.70	-0.37	0.44	0.09	0.06	0.08
		2.20	-0.70	0.55	0.36	0.28	
		2.70	-1.10	0.66	0.44	0.46	
		3.70	-2.11	0.93	0.10	0.18	
		4.70	-3.41	1.25	0.01	0.02	
		5.70	-5.01	1.59	0.01 >	0.01>	
		6.70	-6.90	1.97	0.01 >	0.01>	
		7.70	-9.08	2.36	0.01 >	0.01>	
		8.70	-11.55	2.76	0.01 >	0.01>	
6	Nath, Ramey, and Klenow (2024)	2.50	-4.10	0.88	0.46	0.39	0.08
		2.50	-2.00	0.88	0.46	0.39	
		4.40	-4.80	1.72	0.04	0.11	
		4.40	-9.60	1.72	0.04	0.11	
7	Kalkuhl and Wenz (2020)	1.93	-1.14	0.38	0.10	0.07	0.04
		2.67	-2.73	0.48	0.31	0.26	
		3.25	-4.16	0.70	0.18	0.29	

		2.82	-3.11	0.58	0.24	0.29	
		1.56	-0.40	0.26	0.03	0.01	
		1.87	-1.01	0.35	0.09	0.06	
		1.64	-0.55	0.26	0.05	0.02	
8	Burke and Tanutama (2019)[a]	2.70	-29.2	5.04	0.24	0.23	0.07
		3.60	-33.46	4.86	0.16	0.15	
		4.40	-35.22	5.78	0.03	0.04	
		2.21	0.05	5.69	0.13	0.16	
		2.99	0.19	4.85	0.25	0.23	
		3.69	0.29	4.91	0.14	0.13	
		4.29	0.19	5.59	0.04	0.05	
9	Colacito and others (2019)[a]	2.70	-6.67	14.14	0.45	0.28	0.13
		3.60	-8.62	19.06	0.17	0.17	
		4.40	-9.93	22.7	0.04	0.05	
		2.70	3.75	18.89	0.25	0.28	
		3.60	6.35	26.48	0.09	0.17	
		4.40	9.03	32.49	0.02	0.05	
10	Takakura and others (2019)	1.70	-0.14	1.77	0.03	0.09	0.02
		2.70	-0.36	1.07	0.47	0.51	
		3.20	-0.44	0.90	0.45	0.37	
		4.50	-0.91	0.74	0.05	0.03	
11	Casey, Fried, and Goode (2023)	2.70	-0.42	0.94	0.79	0.57	0.04
		3.60	-0.99	1.68	0.18	0.34	
		4.40	-1.53	2.18	0.03	0.10	
12	Deryugina and Hsiang (2017)[b]	2.89	-2.51	0.90	0.03	0.02	0.14
		3.60	-0.61	1.10	0.01	0.01	
		3.89	-0.63	1.25	0.01	0.01	
13	Roson and Sartori (2016)	3.00	-0.16	0.96	0.01	0.39	0.01
	Acevedo and others (2020)	2.50	-1.00	0.88	0.77	0.35	0.08
		4.40	-3.00	1.72	0.06	0.07	
	Deloitte Economics Institute (2021)	3.00	-3.70	0.96	0.17	0.20	0.03

Data source: Congressional Budget Office.

Group: Groups of papers for which joint distributions are estimated for each climate scenario. All papers have their own group except for Group 13.

Temperature: The change in global surface air temperature in the year 2100 relative to the 1850–1900 reference climate.

Mean: Mean GDP loss in 2100 as a percentage change.

Standard deviation: Reported by each paper for the mean estimate.

Variance and temp. (average): Nonconstant-variance-adjusted temperature probability weights applied in the inverse weighted MMSE estimation. The weights are averaged across climate scenarios; values in this column correspond to $(1/42)\sum_c \varphi_{ksc} p(T = T_k|X_s, X_c)$, as defined in Appendix A.

Temp. only (average): Simple temperature probability weights that have not been adjusted for variance. The weights are averaged across climate scenarios, so values in this column correspond to $(1/42)\sum_c p(T = T_k|X_s, X_c)$.

Relevance: The preferred relevancy weight, defined in Table 3, scaled here to sum to 1.

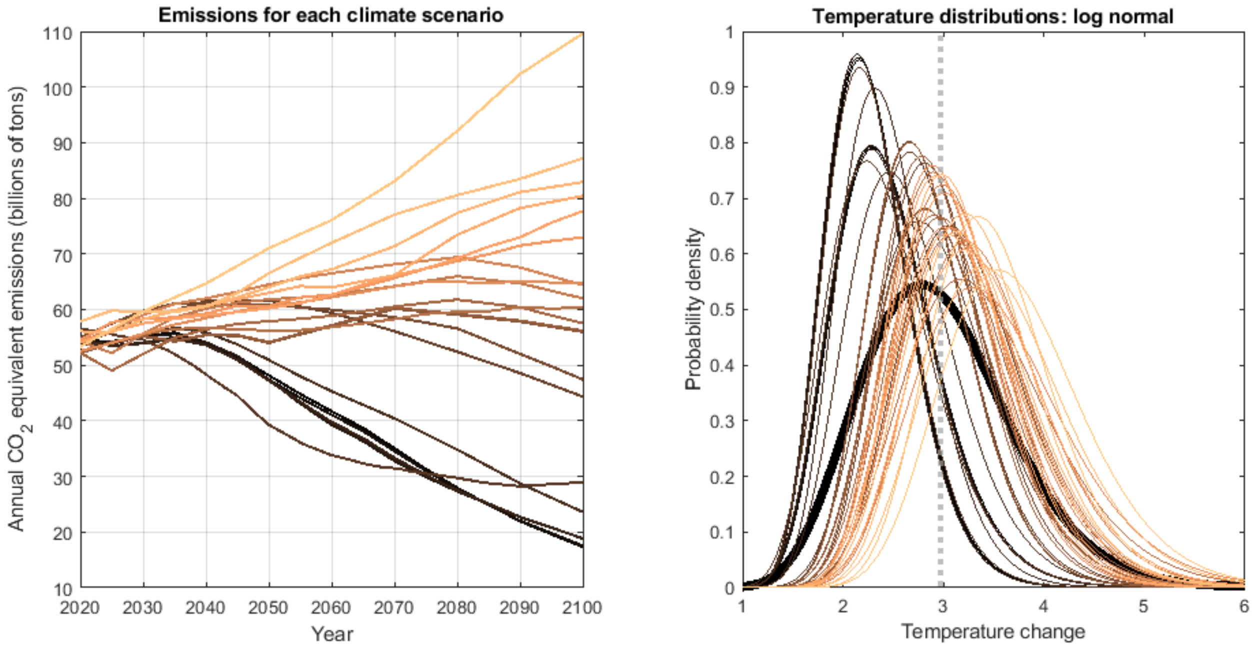
GDP = gross domestic product; MMSE = minimum mean square error; temp. = temperature.

a. Burke and Tanutama (2019) and Colacito and others (2019) have split samples.

b. Data for Deryugina and Hsiang (2017) are abbreviated here to only three observations. The full dataset contains 156 observations.

Figure B-1.

Global Emissions Under Emissions Scenarios



Data source: Congressional Budget Office, using data from the AR6 Scenarios Database (Byers and others, 2022).

Metadata for each of the 21 scenarios are presented in Table B-1.