Congressional Budget Office
Nonpartisan Analysis for the U.S. Congress

Technical Information About How CBO Models the Effects of Climate Change on Output in Its Long-Term Economic Projections

September 2021

Contents

Overview

Why CBO Changed Its Method of Incorporating the Effects of Climate Change Into Its Long-Term Economic Projections

Climate change has many effects on the U.S. economy that are expected to reduce the growth of real gross domestic product (that is, GDP adjusted to remove the effects of inflation), on net.

Before publishing *The 2020 Long-Term Budget Outlook*, the Congressional Budget Office used a long-term forecasting approach that accounted for the future effect of climate change on GDP by carrying forward trends in economic measures that were already influenced by climate change.[1]

Recent research suggests that the effects of climate change on GDP growth rates will be larger in the future than in recent years, indicating that the approach CBO used before 2020 would underestimate future effects.

CBO's projection of long-term economic growth now explicitly accounts for the increasing effect of climate change on GDP growth, modeled as a reduction in the growth rate of total factor productivity in the nonfarm business sector.

[1] For a less technical overview of the estimate, see Herrnstadt and Dinan (2020).

Components of the Overall Estimate Under the Method CBO Adopted in 2020

The method CBO adopted in 2020 projects how real GDP growth would be affected by two dimensions of climate change:

- Projected changes in average weather patterns (temperature and precipitation), and
- Projected increases in expected hurricane damage due to changes in hurricane intensity and frequency and rising sea levels.

For each of those dimensions, CBO separately identifies two components:

- The continuation of recent effects of recent trends in weather and hurricane damage on economic growth rates (the amount previously incorporated in the agency's baseline projections), and
- Additional effects on growth of future projected changes in weather and hurricane damage.

Because of climate change, real GDP is projected to grow more slowly each year than it would have under the "benchmark" climate of the late 20th century, reaching a 1.06 percent reduction in the projected level of real GDP in 2050.

The Methodology CBO Adopted in 2020

The methodology CBO adopted in 2020 has five steps:

First, CBO collects several econometric estimates of the relationship between temperature and precipitation patterns and output. It then applies those estimates to climate-change scenarios from various climate models. That process yields multiple projections of the effect of weather patterns on the level of real GDP in 2050.

Second, the agency uses those multiple projections to develop a single central estimate of the effects of changes in weather patterns on the level of real GDP in 2050.

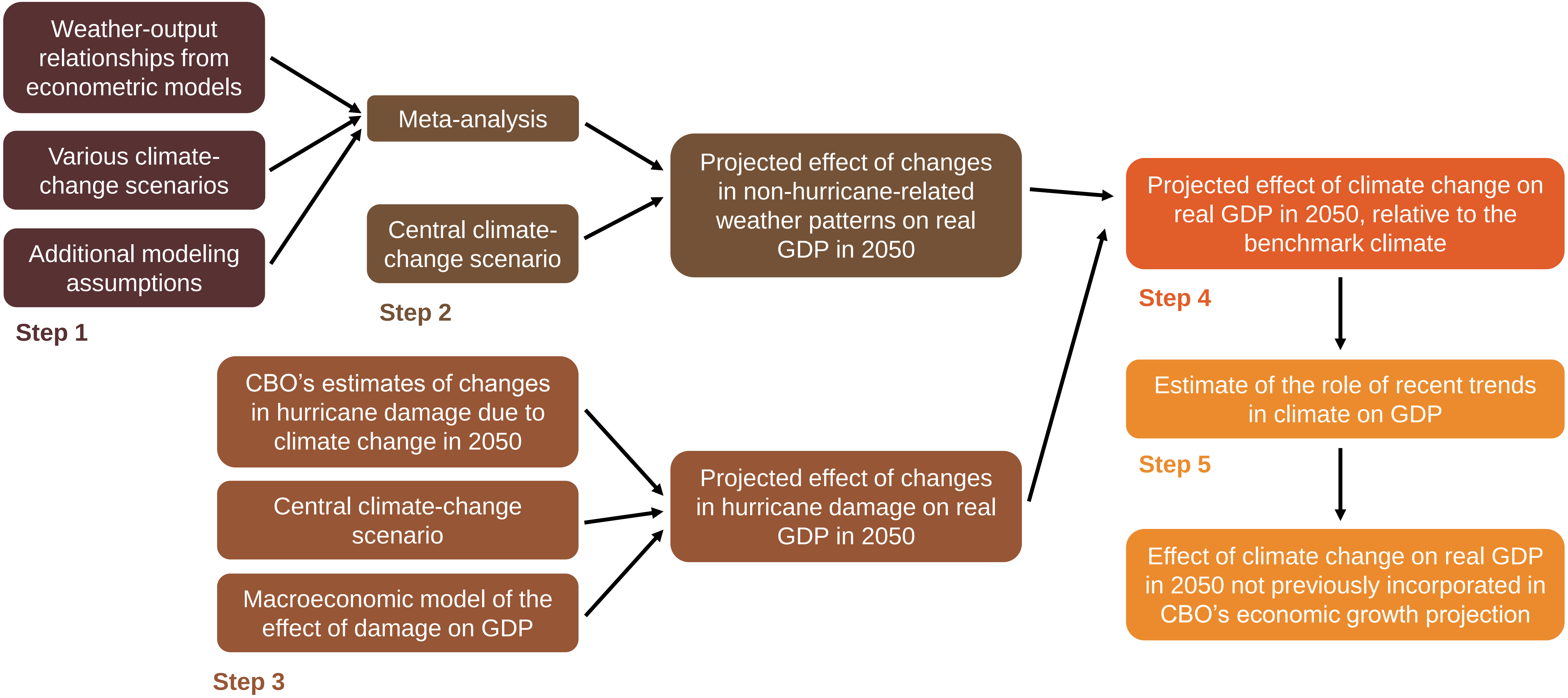
The Methodology CBO Adopted in 2020 (Continued)

Third, CBO applies its previous estimate of changes in expected hurricane damage due to projected climate change to the results of a structural macroeconomic model. That model translates direct hurricane damage in a given year into effects on GDP in subsequent years.

Fourth, CBO sums the effects of changes in weather patterns and hurricane damages.

Fifth, CBO adjusts its estimate of the effect of climate change on GDP to account for recent changes in climate that were already captured in its long-run growth estimates through economic trends. That adjustment prevents CBO from double-counting the effects of climate change previously incorporated in the agency's baseline projections.

Schematic of CBO’s Methodology



CBO's Central Climate-Change Scenario

Climate-Change Projections Used in CBO's Estimates

The methodology CBO adopted in 2020 requires, as an input, a standard set of projections of the physical effects of climate change.

CBO uses climate-change projections that are based on representative concentration pathways (RCPs) developed for the Intergovernmental Panel on Climate Change's most recent synthesis assessment report (IPCC, 2014). Each RCP describes a different projected time path for atmospheric concentrations of greenhouse gases and the associated radiative forcing.[2]

To inform the IPCC's report, climate scientists modeled climate outcomes under those RCP scenarios using a set of atmospheric-ocean coupled general circulation models (AOGCMs) known as the Coupled Model Intercomparison Project Phase 5 (CMIP5).

CBO draws on projections that adapt those AOGCM outcomes, which are global in scale, to smaller geographies. Specifically, the agency draws on a range of projections of temperature, precipitation, hurricane frequency, and sea level for specific regions, such as states or counties.

[2] Radiative forcing is the difference between the amount of energy entering and exiting the Earth's atmosphere. For example, RCP 4.5 is a scenario in which radiative forcing is approximately 4.5 watts per square meter greater in 2100 than it was in 1750.

CBO's Central Climate-Change Scenario in Context

In most cases, CBO's estimates use a combination of climate projections under RCPs 4.5 and 8.5, which the IPCC described as consistent with relatively low and high levels of emissions in the absence of climate policy, respectively (van Vuuren and others, 2011). However, the IPCC and CMIP5 analyze many scenarios and do not project a single climate path as most likely.[3]

CBO's use of the results associated with RCPs 4.5 and 8.5 does not indicate that the agency projects either specific scenario as more or less likely.

Instead, the agency combined results from the two RCPs to arrive at a central case consistent with expert emissions and forcing projections. For example, Landry and others (2019) projected that, without additional policy action or with action that achieves the Paris Agreement goals, radiative forcing in 2050 would fall roughly halfway between RCPs 4.5 and 8.5.

RCPs 4.5 and 8.5 have also been used as scenarios in many recent climate-economic impact studies, such as the National Climate Assessment (Environment Protection Agency, 2017).

[3] CMIP Phase 6 (CMIP6) will inform the IPCC's next synthesis assessment report, which is expected in 2022. The physical science basis for the upcoming assessment report (IPCC, 2021a) used multiple lines of evidence, including the results of CMIP6, to determine that the best estimate of the increase in global average temperature by 2041–2060 ranges from 1.6 degrees Celsius to 2.4 degrees Celsius relative to the 1850–1900 average, depending on the scenario. According to Hsiang and others (2017a), the global average temperature from 1981 to 2010 was roughly 0.6 degrees Celsius higher than the 1850–1900 average. Therefore, the IPCC's range of best estimates is 1.0 degrees Celsius to 1.8 degrees Celsius above the 1981–2010 average. That is consistent with CBO's use of projections based on RCPs 4.5 and 8.5, for which the median temperature changes are 1.2 degrees Celsius and 1.6 degrees Celsius above the 1981–2010 average, respectively.

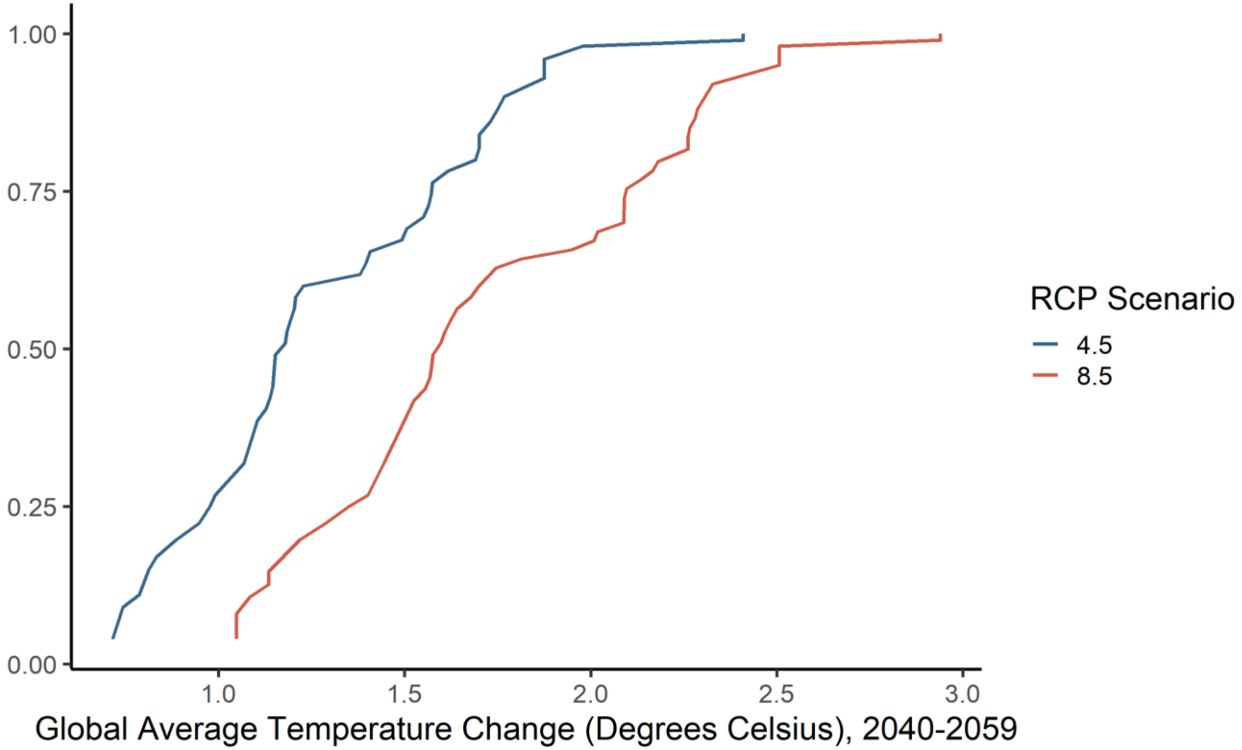
Projections of Changes in Average Weather Patterns

CBO's projections draw on the work of Rasmussen, Meinshausen, and Kopp (2016), which scaled global projections down to the county level and constructed probability distributions over those projections (see the figure).[4]

For both RCP 4.5 and RCP 8.5, CBO projects the median change in global average temperature across models, relative to the average climate of 1981–2010. The agency then estimates the effect of those median changes in weather on output and calculates the average of the two effects.

Distribution of Global Temperature Scenarios Under RCPs 4.5 and 8.5, Relative to 1981–2010 Average Temperature

Cumulative Probability



Data source: Congressional Budget Office analysis of data from Rasmussen, Meinshausen, and Kopp (2016). RCP = representative concentration pathway.

[4] CBO used Rasmussen, Meinshausen, and Kopp's projections because they reflect the most recent fully completed CMIP phase available, provide the fine level of geographic detail that the estimate required, and are specifically intended for estimating economic impacts. All temperature changes are expressed relative to 1981–2010 averages. For each climate projection, CBO further projects that average weather patterns would change linearly from 1981–2010 averages in 1995 to 2040–2059 averages in 2050, as is typical in the literature.

Projections of Changes in Hurricane Intensity and Sea-Level Rise

CBO's projection of the effects of hurricane damage on GDP incorporates projections of changes in hurricane intensity and sea-level rise used in the agency's 2016 report, *Potential Increases in Hurricane Damage in the United States: Implications for the Federal Budget.*

The projected change in hurricane intensity was based on draws from distributions of potential outcomes under RCPs 4.5 and 8.5.

The projected change in sea levels used in estimating hurricane damage was based on draws from distributions of potential outcomes under RCPs 4.5 and 8.5, as well as under RCP 2.6, which was the lowest emissions scenario that the IPCC considered.

Projections of Changes in Hurricane Intensity and Sea-Level Rise (Continued)

The hurricane damage estimate incorporated RCP 2.6 because CBO's underlying 2016 report relied on distributions of sea-level rise obtained from Risk Management Solutions. Those distributions were based on alternative assumptions about RCPs and the sea-level rise associated with any given RCP. Because CBO did not have access to RCP-specific distributions for each state and decade, it relied on distributions that combined the three RCP scenarios.[5]

Compared with temperature and precipitation, sea levels respond relatively slowly to changes in emissions; they are, therefore, less sensitive to differences in emissions scenarios over the next few decades, so the inclusion of RCP 2.6 as one possible scenario for sea-level rise had a small effect on the overall estimate.[6]

[5] See Dinan (2016) and CBO (2016) for more details about the projected changes in hurricane intensity and sea levels.

[6] See IPCC (2021b), FAQ 9.2, for information about the low sensitivity of sea-level rise through 2050 to various emissions scenarios.

How CBO Estimates the Effect of Changes in Average Weather Patterns on Economic Output

Econometric Studies of Weather Patterns and Economic Output

CBO's estimate of the effect of changes in weather patterns on GDP is based on four academic studies that examined the historical relationship between weather and economic output in the United States:

- Deryugina and Hsiang (2017) modeled the effect of the distribution of daily temperature and precipitation on county-level income between 1969 and 2011.
- Burke and Tanutama (2019) modeled the effect of annual average temperature and precipitation on GDP at the level of metropolitan statistical areas between 2002 and 2016.
- Colacito, Hoffmann, and Phan (2019) modeled the effect of annual average seasonal temperature on gross state product (GSP) between 1957 and 2012.
- Kahn and others (2019) modeled the effect of annual deviations from long-run average temperatures and precipitation on GSP between 1963 and 2016.

Meta-analysis Used to Summarize Econometric Estimates

CBO uses those four studies to develop projections of the effects of changes in weather patterns on economic output in counties, regions, and states.

The agency then uses those projections to develop a single set of estimates in a random-effects meta-analysis.[7] That approach can integrate results from studies that differ in their settings, data, and modeling approaches, and it yields a "grand mean" estimate of the effect of climate change on regional output.

The estimate of the grand mean is effectively a weighted average across the projections associated with different studies, where the weights are determined by the different projections ($\hat{\theta}_s$) and the precision of those projections ($\hat{\sigma}_s^2$):

- If one study-specific projection is very different from the others, it typically receives additional weight because it is assumed to capture additional information.

- If a study-specific projection is more imprecise, it typically receives less weight because it could be very far from the true effect by chance.

[7] For examples of random-effects meta-analyses applied to climate impacts, see Hsiang, Burke, and Miguel (2013) and Hsiang and others (2017a).

A Formal Description of the Meta-analyses

The random-effects meta-analysis framework models a grand mean effect of climate change on real GDP in 2050, μ, for each climate-change scenario.

In the model, each study is associated with a different “true effect,” which is assumed to come from a normal distribution, reflecting inherent differences across the studies. That is, $\theta_s \sim N(\mu, \tau^2)$. The assumption that the models’ true effects are distributed around the grand mean μ is the source of the term “random effects.”

Each $\hat{\theta}_s$ is a noisy estimate of some true effect θ_s. Those estimates are modeled as having a normal distribution $\hat{\theta}_s \sim N(\theta_s, \hat{\sigma}_s^2)$, where $\hat{\sigma}_s^2$ represents variance due to statistical uncertainty, model uncertainty, and uncertainty about the persistence of the economic effects over time.

CBO uses a Bayesian approach to fit the model to the inputs that were based on the four econometric studies $\{\hat{\theta}_s, \hat{\sigma}_s^2\}$ and obtain an estimate of the grand mean $\hat{\mu}$.[8] A frequentist approach produces similar results.

[8] The prior distribution for μ is uniform, and the prior distribution for τ^2 is half-Cauchy (Gelman, 2006), but the results are not sensitive to those choices. CBO uses the median of the posterior distribution of μ as its Bayesian estimate of $\hat{\mu}$. CBO also uses the frequentist restricted maximum likelihood estimator as a robustness check (Veroniki and others, 2016). CBO estimates the model using the “metafor” package for *R* (Viechtbauer, 2010).

How CBO Incorporates Econometric Studies Into the Meta-analysis

The inputs for the meta-analysis are the means $\hat{\theta}_s$ and variances $\hat{\sigma}_s^2$ of the projections that were based on each study. CBO uses computer code and data provided by the studies' authors to reconstruct the historical relationships reported in the econometric studies and the associated standard errors and covariances of the parameters. In CBO's estimation, parameters from different studies are statistically independent.[9]

In applying those historical relationships to climate projections, CBO follows the treatment in the original study as closely as possible. For example, if the original study found that precipitation effects were small or insignificant and omitted them from the study's climate impact projection exercise, CBO does so as well.

The studies differed in their treatment of the persistence of effects on output and of adaptation. If a study did not explicitly incorporate persistence, CBO tries to follow the authors' intent by relying on robustness checks and the study's exposition. However, if a study did not explicitly incorporate adaptation, CBO draws on other models to adjust the projections.

[9] The studies use similar variables measured at various levels of geographic resolution across the United States and over similar time periods. The partial overlap in the studies' data suggests that the studies and their estimated parameters may be statistically dependent. However, incorporating that dependence into the meta-analytic framework was not feasible.

Modeling the Persistence of Effects: Growth Versus Levels

One important model feature is the persistence of the effect of a shock to weather.

An unusually hot year may reduce output only in that year, leaving output in future years unaffected. That is referred to as a level effect.

By contrast, that hot year might persistently affect output in following years. That is referred to as a growth effect, which can compound over time.

Researchers have not yet determined whether climate-induced changes in output will be predominately level or growth effects.[10]

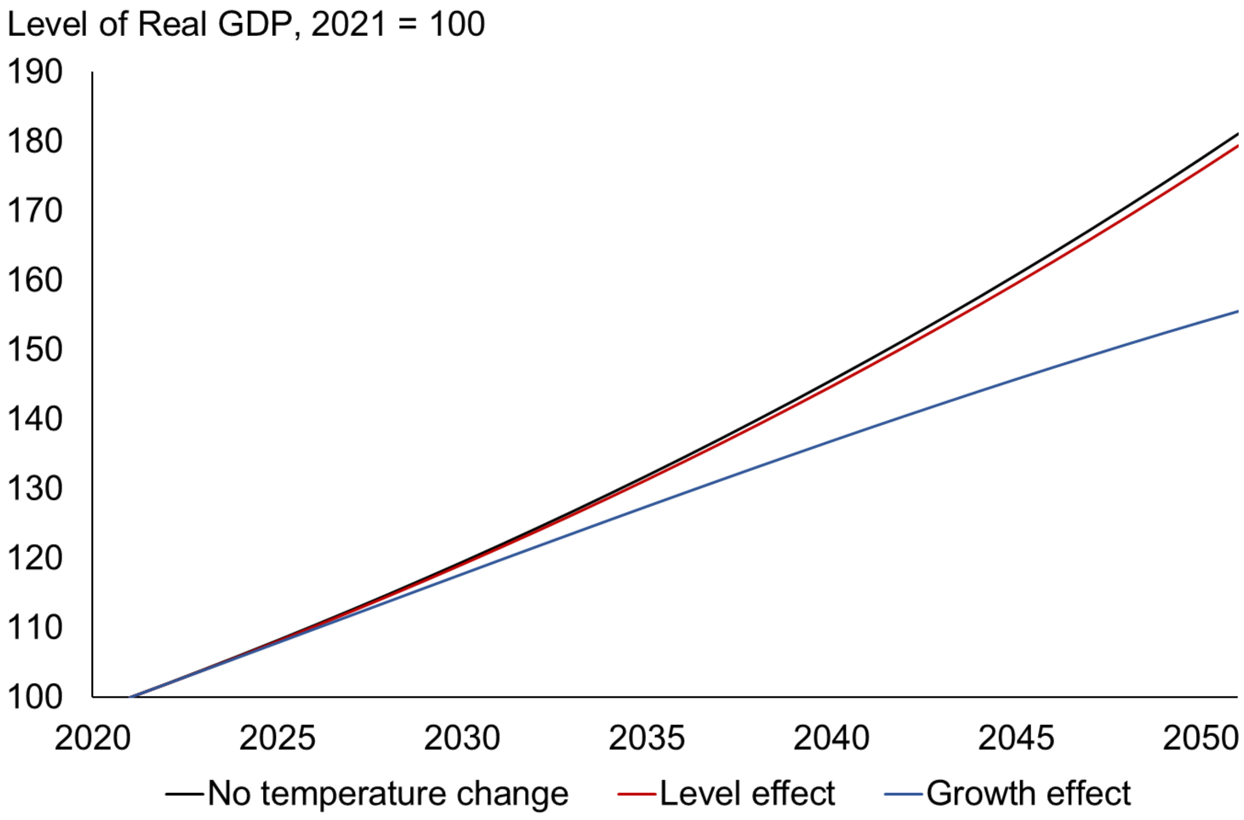
[10] For further discussion of persistence, see Carleton and Greenstone (2021) and Newell, Prest, and Sexton (2021).

Modeling the Persistence of Effects: Growth Versus Levels (Continued)

To illustrate the difference, suppose a 1 degree change in temperature is estimated to cause a 0.5 percentage-point reduction in GDP and that the United States is expected to warm by 2 degrees over 30 years.

- If that estimated reduction was a level effect, the level of real GDP would be 1 percent lower in 30 years (see the figure).
- However, if the estimated reduction was a full growth effect, the level of real GDP would be 14 percent lower in 30 years because of the compounding effects of the depressed growth rate.

Example Effect of a Gradual Temperature Increase: Level Effect Versus Growth Effect



Data source: Congressional Budget Office. GDP = gross domestic product.

How CBO Models the Persistence of Effects of Weather Patterns on Real GDP

CBO combines the econometric models with different models of persistence to compute the projections of the effect of climate change on economic output ($\hat{\theta}_s$).

For each econometric model, the agency follows the associated study as closely as possible in modeling persistence:

- Deryugina and Hsiang (2017) and Kahn and others (2019) explicitly modeled the persistence pattern over time, and CBO follows their approaches in computing the effects of changes in weather patterns over time.
- Burke and Tanutama (2019) and Colacito, Hoffmann, and Phan (2019) presented empirical evidence against a pure level effect and discussed their results as a full growth effect, meaning that the economy would forever remain on a lower growth path after a reduction in output due to a weather shock. For those studies, CBO follows the exposition and analysis by modeling a true growth effect.

How CBO Incorporates Adaptation

CBO's estimate reflects the possibility that economies will adapt to changing climatic conditions. For example, a hot summer may not have the same effect on Minnesota's economy in 2050 as it does today if the average summer has grown hotter over time.

The literature is still developing an understanding of how to model adaptation and the extent to which historical data can capture future adaptation.[11]

Deryugina and Hsiang (2017), Burke and Tanutama (2019), and Kahn and others (2019) all allowed for a measure of adaptation by allowing the incremental effect of weather to change along with the average climate.

Colacito, Hoffmann, and Phan (2019) did not do so, and CBO adjusts the associated projection to account for the effects of adaptation.[12]

[11] See Mérel and Gammans (2021), Lemoine (2021), and Auffhammer (2018) for discussions of the use of historical weather data to model climate impacts. Deryugina and Hsiang (2017) and Burke and Tanutama (2019) both allowed the marginal effect of a slightly warmer year to vary for regions with different weather. Kahn and others (2019) modeled the effect as driven by deviations from a long-term moving average of weather conditions, so that as a region's average temperature increased over time, its economy would be less affected by a very hot year.

[12] Herrnstadt and Dinan (2020) noted that CBO adjusted two of the studies' projections for adaptation. After further assessment of the recent literature examining empirical approaches to adaptation, the agency determined that Burke and Tanutama (2019) did account for adaptation for the purposes of this analysis.

Adjusting Colacito, Hoffmann, and Phan (2019) for Adaptation

CBO uses information from Deryugina and Hsiang (2017) to develop an adaptation adjustment. The agency applies that adjustment to the projection based on Colacito, Hoffmann, and Phan (2019).

Deryugina and Hsiang (2017) included a linear specification, where the effect of an additional hot day on output was the same for all counties. By contrast, the more flexible (“cubic”) specifications allowed hotter and cooler counties to experience hot days in different ways and thus allowed the experience to change as the average climate changed.

- In Deryugina and Hsiang (2017), the effect on output in 2090 was 25 percent smaller when allowing for adaptation, averaging across the two cubic specifications reported in the paper and using their median climate scenario.
- Because adaptation in 2050 would probably be more muted because of the short time horizon and fuzzier climate signal, CBO applies half of the 2090 adaptation effect (12.5 percent) to the Colacito, Hoffmann, and Phan (2019) projection.
- CBO’s central estimate is not sensitive to that adjustment.

CBO’s Modeling Assumptions Associated With Each Econometric Study

Econometric Study	Regression Specification	Persistence	Adaptation
Deryugina and Hsiang (2017)	Regressions underlying Figure 13, “full adaptation” and “full adaptation with urban-rural heterogeneity”	Econometrically estimated decay of effects over time, with associated sampling uncertainty	Econometric framework allowed incremental effects to change with average climate
Burke and Tanutama (2019)	Regression underlying Figure 3-f (U.S. only)	Statistical tests in the study rejected a level effect; CBO assumed a full growth effect	Econometric framework allowed incremental effects to change with average climate
Colacito, Hoffmann, and Phan (2019)	Table 1 (panel analysis)	Statistical tests in the study rejected a level effect; CBO assumed a full growth effect	CBO’s adjustment based on Deryugina and Hsiang (2017)
Kahn and Others (2019)	Table 10, column 4	Econometrically estimated decay of effects over time, with associated sampling uncertainty	Modeled effect of deviations from the average climate; that average could change over time in the model

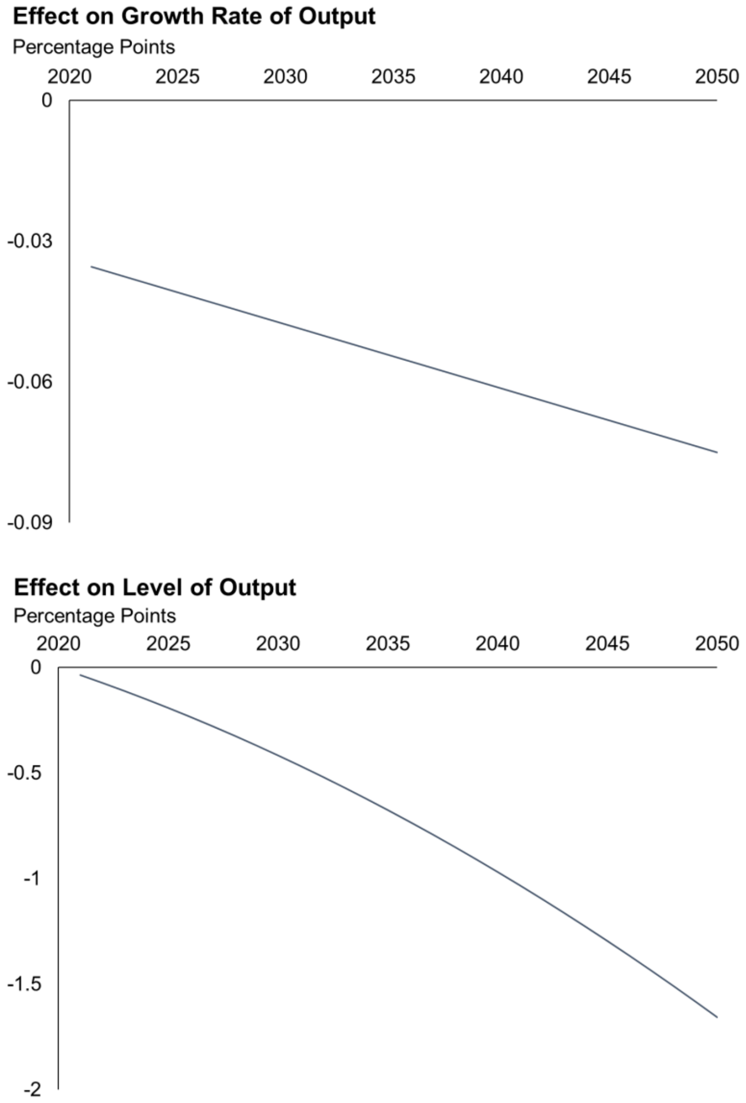
An Example Calculation of a Study-Specific Projection ($\hat{\theta}_s$)

An example illustrates how CBO computes mean effects $\hat{\theta}_s$ for an example study and climate-change projection.

Suppose that one study implied that an increase of 1 degree Celsius in average temperature has a full growth effect and reduces the growth rate of output in a region by 0.05 percentage points.

If a region's average temperature was projected to rise from the 1981–2010 average by 1.5 degrees Celsius by 2050, then the projection would have lower output growth each year from 2021 to 2050 (relative to the benchmark climate) and a level of output in 2050 that was 1.7 percentage points lower.

CBO would average such effects across all regions, weighted by the regions' relative levels of output, to obtain a mean projection $\hat{\theta}_s$ for this study and climate scenario.



Data source: Congressional Budget Office.

Computing the Variance of the Study-Specific Projections

For each projection ($\hat{\theta}_s$), the meta-analysis also requires an associated variance parameter ($\hat{\sigma}_s^2$) that measures the precision of the projection.

CBO’s estimate of that variance parameter summarizes three sources of uncertainty:

- Statistical uncertainty,
- Persistence uncertainty, and
- Model uncertainty.

Monte Carlo Approach Used to Incorporate Statistical and Persistence Uncertainty

CBO uses a Monte Carlo approach to compute the variance associated with statistical and persistence uncertainty, denoted $\tilde{\sigma}_s^2$. For all studies, CBO draws parameters many times, computes the projected effect on the level of GDP in 2050 for each draw, and calculates the variance across the draws.

For Deryugina and Hsiang (2017) and Kahn and others (2019):

- CBO draws parameters from the econometrically estimated variance-covariance matrix 1,000 times.
- The draws capture both statistical uncertainty and persistence uncertainty because the persistence structure was econometrically estimated in the studies.

Monte Carlo Approach Used to Incorporate Statistical and Persistence Uncertainty (Continued)

For Burke and Tanutama (2019) and Colacito, Hoffmann, and Phan (2019):

- CBO draws parameters from the econometrically estimated covariance matrix 1,000 times.
- The persistence structure was not embedded in those estimates, so those draws capture only statistical uncertainty.
- To incorporate persistence uncertainty, CBO allows some fraction (x) of the effect of a year's weather on output to persist forever.[13] For example, when computing $\hat{\theta}_s$ for these studies, CBO modeled a full growth effect ($x = 1$).
- For each draw of the econometric parameters, CBO also draws x 500 times from a triangular distribution between 0.5 and 1.5 (centered at 1), meaning that the effect of a year's weather on the level of GDP could decrease or increase by up to 50 percent in subsequent years.
- That full set of draws reflects both statistical and persistence uncertainty.

[13] The persistence framework is similar to that proposed in Estrada, Tol, and Gay-García (2015).

Incorporating Model Uncertainty

CBO's estimate of the overall variance of a projection ($\hat{\sigma}_S^2$) also includes model uncertainty.

Model uncertainty reflects the fact that the true empirical model is not known with certainty by researchers.[14] CBO assumes that model uncertainty is of the same magnitude as the combined statistical and persistence uncertainty averaged across the econometric models.

For a given climate-change scenario, CBO estimates the combined statistical and persistence variance for each study-specific projection ($\tilde{\sigma}_S^2$) and computes the geometric mean across those study-specific variances to obtain its estimate of model uncertainty $\bar{\sigma}_M^2$. That model uncertainty is assumed to be common across all study-specific projections.

For a given study-specific projection, the overall variance is:

$$\hat{\sigma}_S^2 = \tilde{\sigma}_S^2 + \bar{\sigma}_M^2$$

$\hat{\sigma}_S^2$	$\tilde{\sigma}_S^2$	$\bar{\sigma}_M^2$
Study-specific variance	Study-specific statistical and persistence variance	Common model uncertainty adjustment

[14] Newell, Prest, and Sexton (2021) explored model uncertainty in the context of similar panel regressions that use cross-national data. There are formal approaches to estimating and addressing model uncertainty; however, they have drawbacks such as opacity and resource intensity, and analysts still must make many assumptions.

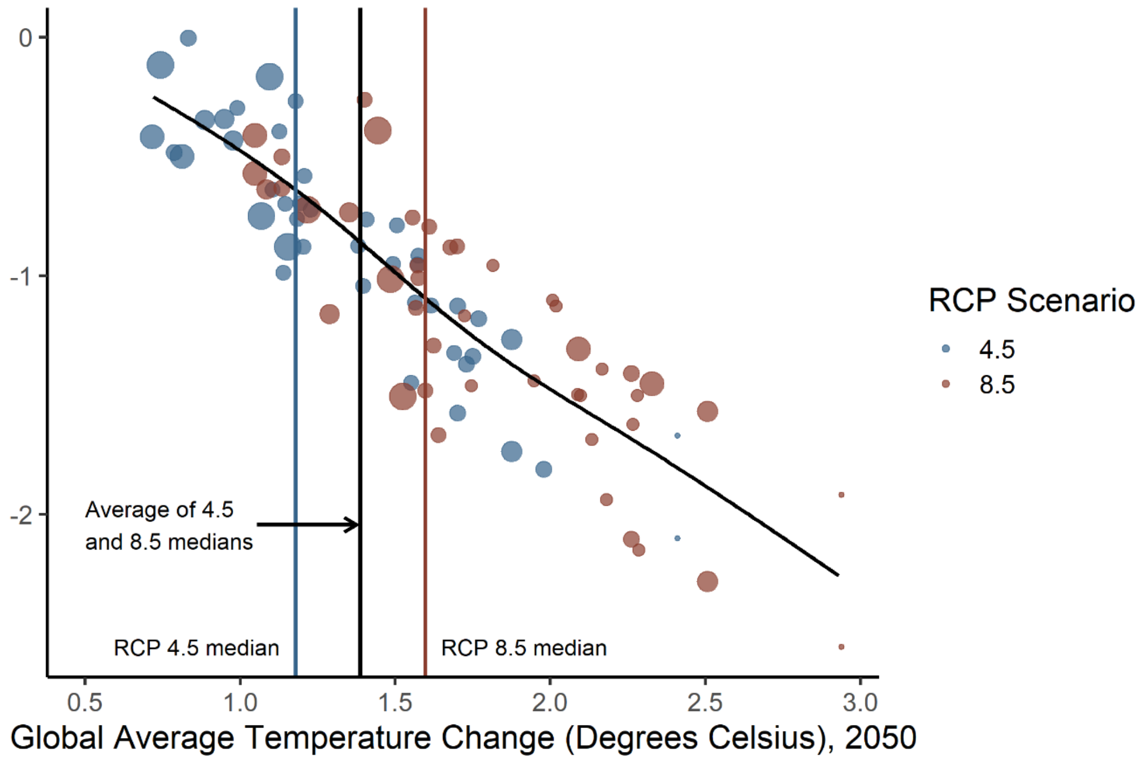
Constructing a Central Estimate From the Meta-analyses

CBO uses its study-specific projections of $\hat{\theta}_s$ and $\hat{\sigma}_s^2$ in a meta-analysis to project the effect of changing weather patterns on real GDP in 2050 ($\hat{\mu}$) for each future climate scenario.

Each climate scenario projects how much the global average temperature will change by 2050. That statistic is a commonly used summary of the severity of climate change.

CBO plots its estimates of $\hat{\mu}$ against the associated global average temperature change and fits a curve through those points.

Difference in Level of Real GDP in 2050, Relative to the Benchmark Climate
Percentage of GDP



Data source: Congressional Budget Office. GDP = gross domestic product; RCP = representative concentration pathway. The size of each dot in the plot reflects the probability weight for the corresponding climate scenario as reported by Rasmussen, Meinshausen, and Kopp (2016).

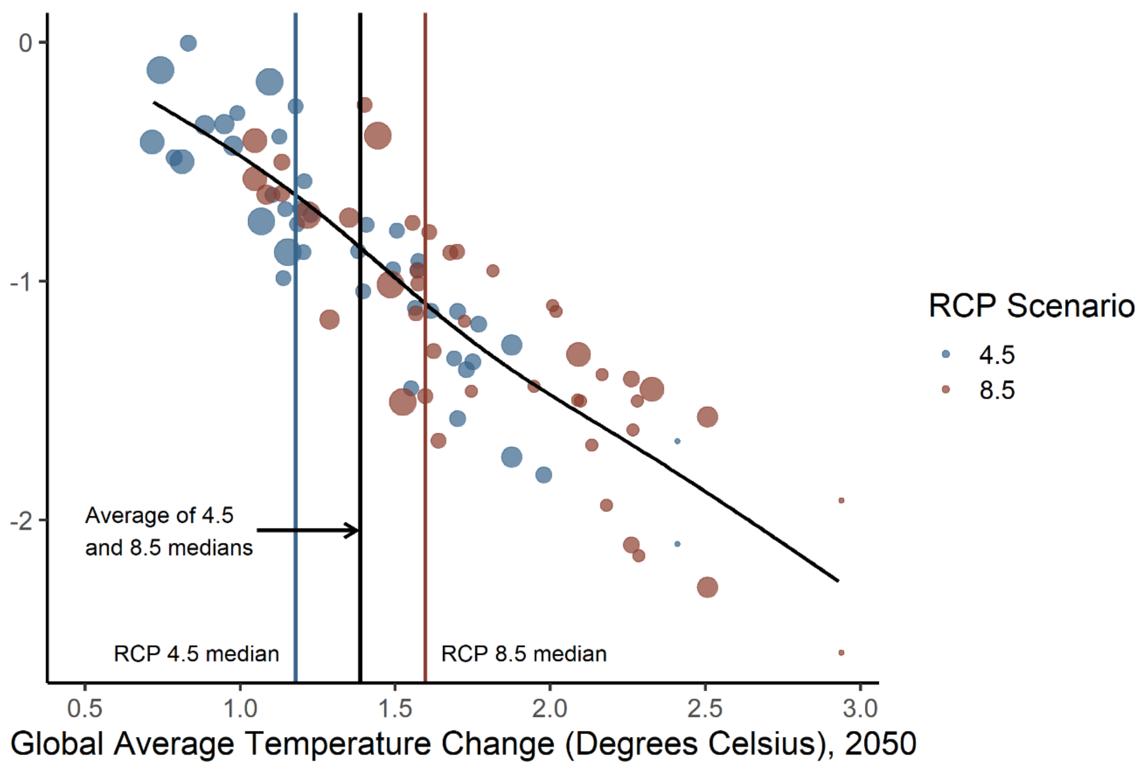
Constructing a Central Estimate From the Meta-analyses (Continued)

Different climate models project different geographic patterns of climatic change across the United States for similar global average temperature changes. By fitting a curve through those models, CBO averages over those differences.

The agency's central estimate is the curve evaluated at the average of the median temperature changes under RCPs 4.5 and 8.5 (1.4 degrees Celsius), which corresponds to a 0.86 percent reduction in the level of real GDP in 2050.

The curve does not represent CBO's estimate of the effect on GDP of extreme global average temperature changes, such as 2.5 degrees Celsius or 3 degrees Celsius. In CBO's judgment, such scenarios are too far out of sample for the model to provide guidance.

Difference in Level of Real GDP in 2050, Relative to the Benchmark Climate
Percentage of GDP



Data source: Congressional Budget Office. GDP = gross domestic product; RCP = representative concentration pathway. The size of each dot in the plot reflects the probability weight for the corresponding climate scenario as reported by Rasmussen, Meinshausen, and Kopp (2016).

How CBO Estimates the Effect of Changes in Expected Hurricane Damage on Economic Output

Estimating Changes in Hurricane Damage Due to Climate Change

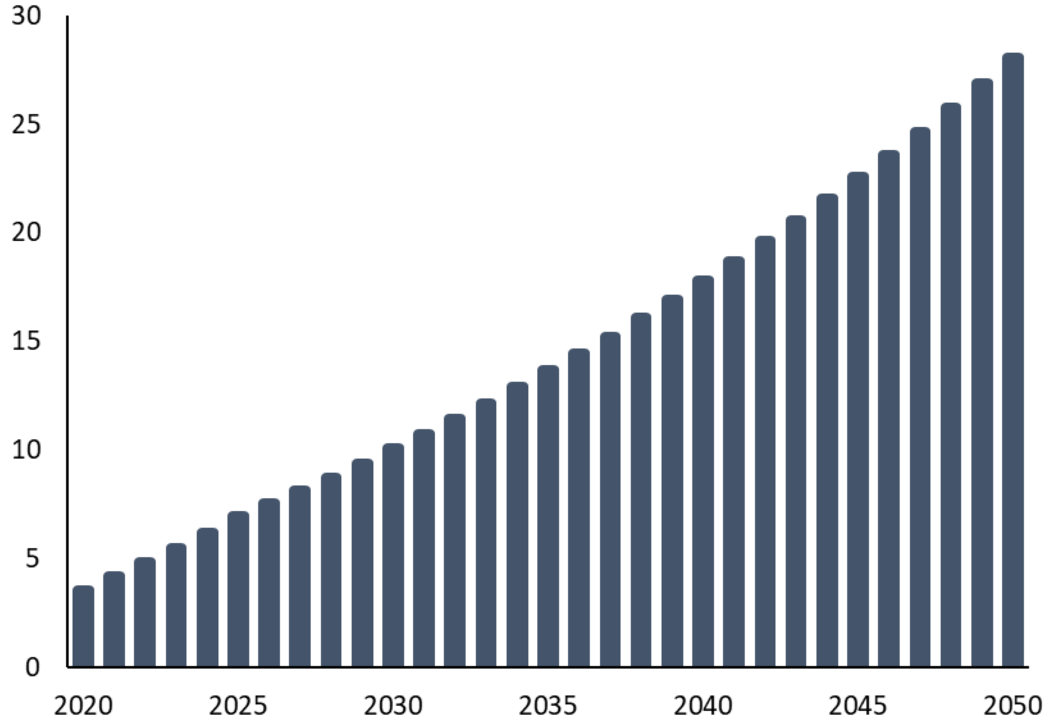
CBO's 2016 report on future increases in hurricane damage projected the effects of climate change on expected hurricane damage in 2050.

The estimate combined a risk management industry model of damage for a given hurricane category and sea level with projections of sea-level rise and changes in hurricane intensity from climate science.

In CBO's central estimate, based on the mean damage projection from the 2016 report, climate change increases annual average hurricane damage by about $28 billion in 2050 relative to damage under the benchmark climate at the end of the 20th century. Under the benchmark climate, annual average damage was about $30 billion.[15]

Change in Expected Hurricane Damage Due to Climate Change, Relative to Benchmark Climate

Billions of 2019 Dollars



Data source: Congressional Budget Office.

[15] Dollar amounts are expressed in 2019 dollars. See CBO (2016) and Dinan (2016) for more details on CBO's estimate of changes in hurricane damage due to climate change.

Converting Hurricane Damage to Effects on Real GDP

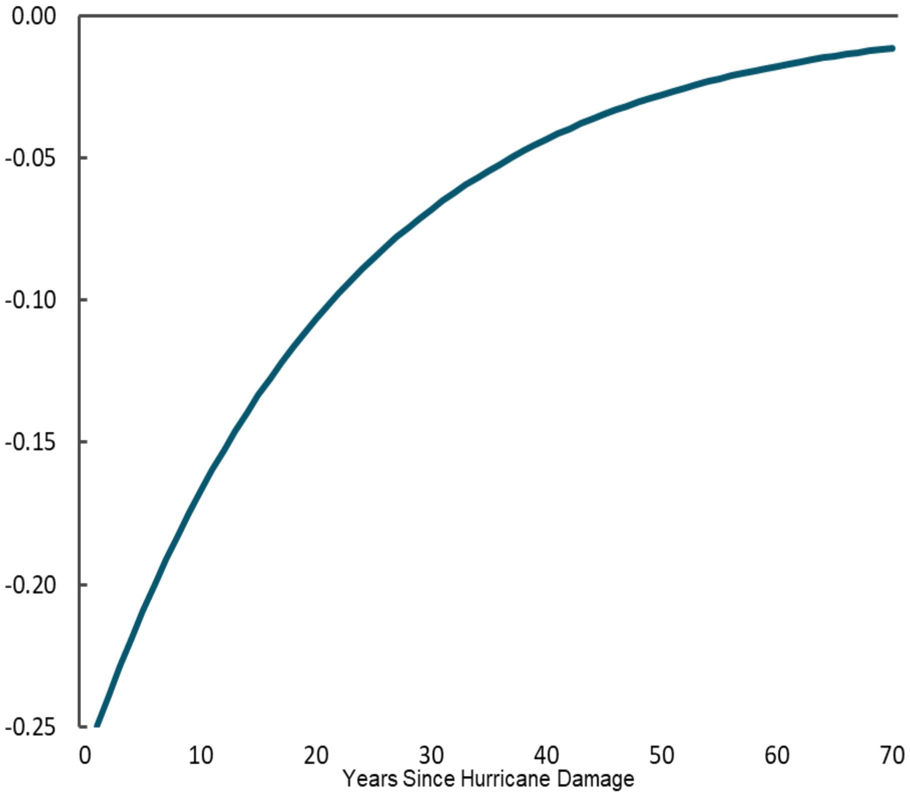
CBO combines those damage projections with an impulse response function from a computable general equilibrium model, which translates direct hurricane damage in a given year into effects on GDP in subsequent years.

For example, $1 in additional damage is associated with a $0.25 reduction in GDP the following year. That effect decays over time (see the figure).

In CBO's estimates, the projected increase in damage from 2020 to 2050 results in a 0.19 percentage-point reduction of the level of real GDP in 2050, relative to the benchmark climate that prevailed at the end of the 20th century.

Change in Real GDP per Dollar of Hurricane Damage in Year Zero

Dollars



Data source: Congressional Budget Office, using analysis from Hsiang and others (2017b).

Estimating the Effects Previously Incorporated in CBO's Baseline Projections

CBO's Previous Approach Relative to the Approach CBO Adopted in 2020

The estimates described so far compute the full projected effect of climate change relative to the benchmark climate that prevailed at the end of the 20th century. In CBO's estimates, the effects of changes in average weather patterns and hurricane damage on economic growth, relative to that benchmark climate, accumulate to create a 1.06 percent reduction in the level of real GDP in 2050.

However, CBO's economic projections involve, in part, the extrapolation of recent productivity trends into the future.[16]

In CBO's assessment, those recent trends have been influenced by climate change. Therefore, CBO's projections would already capture part of the future expected economic effect of climate change that is embodied in the agency's estimate of a 1.06 percent reduction in output.

To avoid double-counting some of the effect of climate change, CBO estimates the extent to which its projections already account for historic trends in the effect of climate change on economic growth by applying its models to climate and weather from recent years.

[16] For a description of CBO's long-run output projections, see Shackleton (2018).

CBO’s Baseline Adjustments

Weather Patterns

CBO follows the same meta-analysis-based approach to estimate how the agency’s previous growth projections would have differed if, from 1995 to 2019, the United States had experienced the average weather implied by the benchmark climate rather than the realized weather patterns.

Hurricane Damage

CBO uses its 2016 analysis of hurricane damages to model how expected hurricane damages grew over the past 25 years, computes a weighted average of the growth rate of that 25-year period, and assumes that damages would continue to grow at that rate from 2020 to 2050.

That hypothetical time path of damage captures the continuation of recent climate trends and can be compared with damage under the benchmark climate. CBO uses the impulse response function described previously to translate that difference in damage to an effect on real GDP.

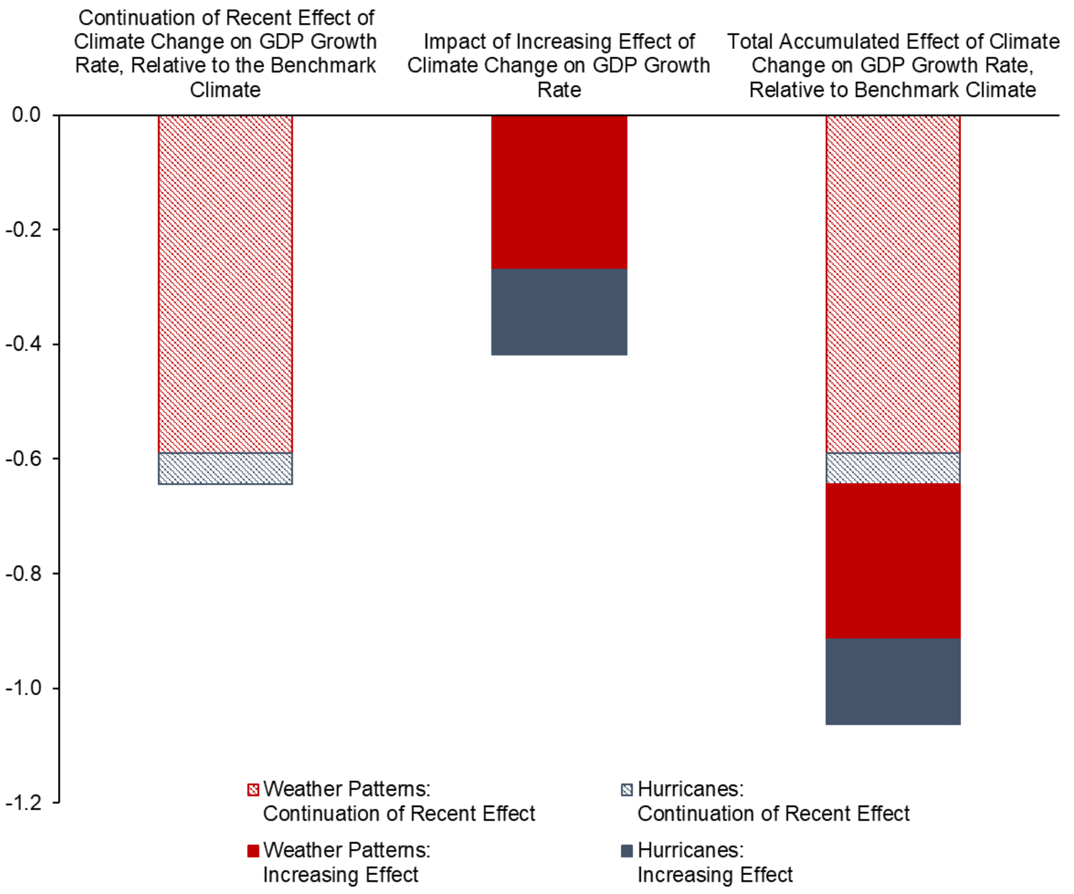
CBO’s Adjustment to Its Projections of Long-Run Real GDP Growth

In CBO’s estimates, if the recent effect of climate change on the growth rate of real GDP simply persisted through 2050, it would reduce the level of real GDP in 2050 by 0.64 percent. That reduction is captured by CBO’s previous methodology.

Of that 0.64 percent reduction, changes in weather patterns account for 0.59 percentage points, and increased hurricane damage accounts for 0.05 percentage points.

How Climate Change Is Expected to Change the Level of Real GDP in 2050

Percentage of Real GDP



Data source: Congressional Budget Office. GDP = gross domestic product.

CBO’s Adjustment to Its Projections of Long-Run Real GDP Growth (Continued)

In CBO’s estimation, however, the effect of climate change on the growth rate of real GDP is larger in the future. Because of that increasing effect, the projected level of real GDP in 2050 is an additional 0.42 percent lower than it would have been using CBO’s previous methodology.

Of that 0.42 percent reduction, changes in weather patterns account for 0.27 percentage points, and increased hurricane damage accounts for 0.15 percentage points.

CBO incorporates the increasing effect of climate change on the growth rate of real GDP through 2050 into its long-run projections by adjusting the growth rate of total factor productivity in the nonfarm business sector.

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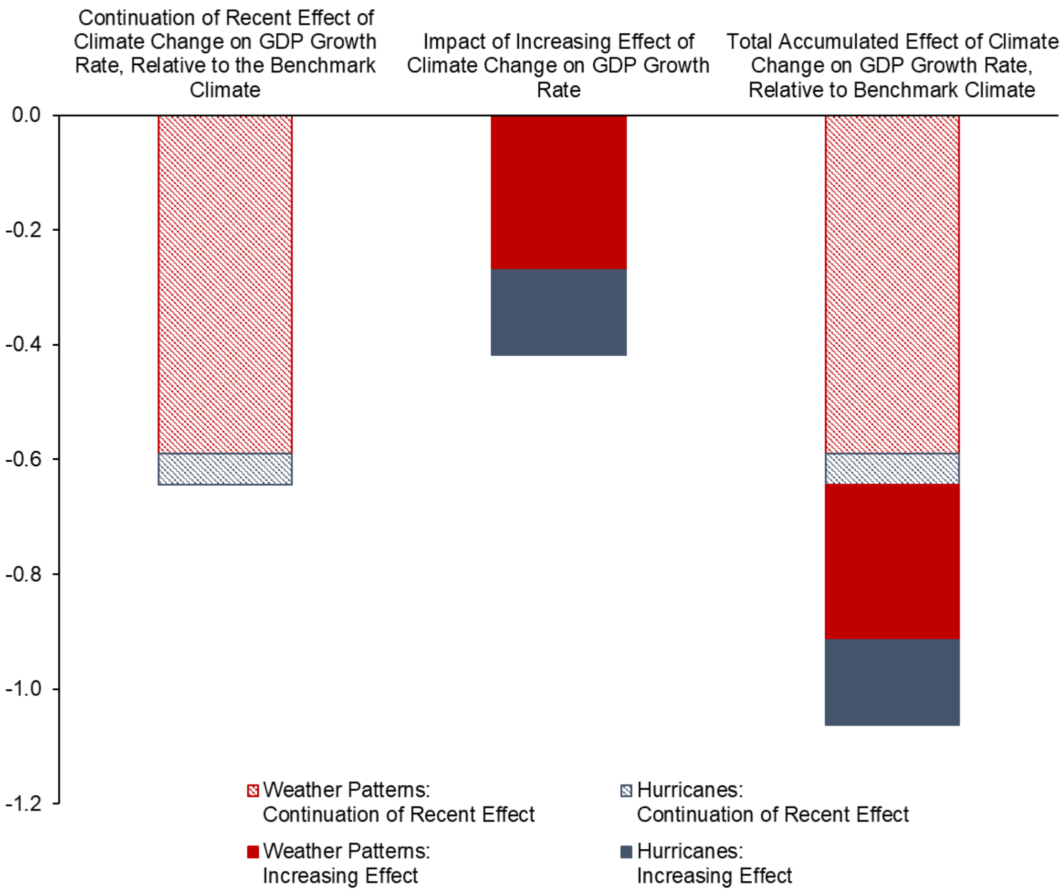

Data source: Congressional Budget Office. GDP = gross domestic product.

Limitations and Uncertainty

CBO's central projection reflects the middle of a range of widely varying potential outcomes.[17]

Although CBO's projection draws on the most recent literature and models:

- It does not fully capture all aspects of climate change that could affect GDP;
- It only measures effects on GDP, not effects on overall well-being; and
- It is subject to uncertainty about future conditions and the underlying modeling approach.

[17] See Herrnstadt and Dinan (2020) for a detailed description of the estimate's limitations and sources of uncertainty.

Citations by Topic

Econometric Studies of the Effects of Temperature and Precipitation on Output

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

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan. 2019. "Temperature and Growth: A Panel Analysis of the United States," *Journal of Money, Credit, and Banking*, vol. 51, nos. 2-3 (March-April), pp. 313–368, https://doi.org/10.1111/jmcb.12574.

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

Kahn, Matthew E., and others. 2019. *Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis*, Working Paper 26167 (National Bureau of Economic Research, August), www.nber.org/papers/w26167.

Modeling the Economic Effects of Climate Change With Weather Data

Auffhammer, Maximilian. 2018. *Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption Using Big Data*, Working Paper 24397 (National Bureau of Economic Research, March), www.nber.org/papers/w24397.

Carleton, Tamma, and Michael Greenstone. 2021. *Updating the United States Government's Social Cost of Carbon*, Working Paper 2021-04, (University of Chicago Becker Friedman Institute for Economics, January) https://ssrn.com/abstract=3764255.

Estrada, Francisco, Richard S. J. Tol, and Carlos Gay-García. 2015. "The Persistence of Shocks in GDP and the Estimation of the Potential Economic Costs of Climate Change," *Environmental Modelling and Software*, vol. 69 (July), pp. 155–165, https://doi.org/10.1016/j.envsoft.2015.03.010.

Lemoine, Derek. 2021. *Estimating the Consequences of Climate Change From Variation in Weather*, Working Paper 25008 (National Bureau of Economic Research, May), www.nber.org/papers/w25008.

Modeling the Economic Effects of Climate Change With Weather Data (Continued)

Mérel, Pierre, and Matthew Gammans. 2021. “Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation?” *American Journal of Agricultural Economics*, vol. 103, no. 4 (August), pp.1207–1238, https://doi.org/10.1111/ajae.12200.

Newell, Richard, Brian Prest, and Steven Sexton. 2021. “The GDP-Temperature Relationship: Implications for Climate Change Damages,” *Journal of Environmental Economics and Management*, vol. 108 (July), https://doi.org/10.1016/j.jeem.2021.102445.

Meta-analysis

Gelman, Andrew. 2006. “Prior Distributions for Variance Parameters in Hierarchical Models,” *Bayesian Analysis*, vol. 1, no. 3, pp. 515–533, https://doi.org/10.1214/06-BA117A.

Hsiang, Solomon, Marshall Burke, and Edward Miguel. 2013. “Quantifying the Influence of Climate on Human Conflict,” *Science*, vol. 341, no. 6151, pp. 1–12, https://doi.org/10.1126/science.1235367.

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

Veroniki, Areti Angeliki, and others. 2016. “Methods to Estimate the Between-Study Variance and Its Uncertainty in Meta-analysis,” *Research Synthesis Methods*, vol. 7, pp. 55–79, https://doi.org/10.1002/jrsm.1164.

Meta-analysis (Continued)

Viechtbauer, Wolfgang. 2010. "Conducting Meta-analyses in R With the Metafor Package," *Journal of Statistical Software*, vol. 36, no. 3 (August), http://dx.doi.org/10.18637/jss.v036.i03.

Hurricane Damage

Congressional Budget Office. 2016. *Potential Increases in Hurricane Damage in the United States: Implications for the Federal Budget* (June), www.cbo.gov/publication/51518.

Dinan, Terry. 2016. *CBO's Approach to Estimating Hurricane Damage*, Working Paper 2016-02 (Congressional Budget Office, June), www.cbo.gov/publication/51610.

Hsiang, Solomon, and others. 2017b. "Supplementary Materials for Estimating Economic Damage From Climate Change in the United States," *Science*, vol. 356, no. 1362, www.sciencemag.org/content/356/6345/1362/suppl/DC1.

Climate-Change Projections

Intergovernmental Panel on Climate Change. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (IPCC), www.ipcc.ch/report/ar5/syr.

Intergovernmental Panel on Climate Change. 2021a. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (IPCC), www.ipcc.ch/report/ar6/wg1.

Intergovernmental Panel on Climate Change. 2021b. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Frequently Asked Questions* (IPCC), www.ipcc.ch/report/ar6/wg1/#FAQ.

Climate-Change Projections (Continued)

Landry, Erik, and others. 2019. *MIT Scenarios for Assessing Climate-Related Financial Risk,* Report 339 (MIT Joint Program on the Science and Policy of Global Change, December), https://globalchange.mit.edu/publication/17392.

Rasmussen, D. J., Malte Meinshausen, and Robert E. Kopp. 2016. "Probability-Weighted Ensembles of U.S. County-Level Climate Projections for Climate Risk Analysis," *Journal of Applied Meteorology and Climatology*, vol. 55, no. 10 (October), pp. 2301–2322, https://doi.org/10.1175/JAMC-D-15-0302.1.

van Vuuren, Detlef P., and others. 2011. "The Representative Concentration Pathways: An Overview," *Climatic Change*, vol. 109, pp. 5–31, https://doi.org/10.1007/s10584-011-0148-z.

Other Citations

Congressional Budget Office. 2020. *The 2020 Long-Term Budget Outlook* (September), www.cbo.gov/publication/56516.

Environmental Protection Agency. 2017. *Multi-model Framework for Quantitative Sectoral Impacts Analysis: A Technical Report for the Fourth National Climate Assessment*, EPA 430-R-17-001 (EPA, May), https://go.usa.gov/xGTs5.

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

Shackleton, Robert. 2018. *Estimating and Projecting Potential Output Using CBO's Forecasting Growth Model*, Working Paper 2018-03 (Congressional Budget Office, February), www.cbo.gov/publication/53558.

About This Document

This document was prepared to enhance the transparency of the work of the Congressional Budget Office and to encourage external review of that work. In keeping with CBO's mandate to provide objective, impartial analysis, the document makes no recommendations.

Evan Herrnstadt prepared the document with guidance from Nicholas Chase and Joseph Kile. Terry Dinan contributed to the underlying analysis and provided helpful comments. Jeffrey Perry and Robert Shackleton also provided helpful comments.

Marshall Burke of Stanford University, Tatyana Deryugina of the University of Illinois, and Kamiar Mohaddes of the University of Cambridge provided replication code and data. CBO also received helpful input from Trevor Houser of the Rhodium Group; Solomon Hsiang of the University of California, Berkeley; Derek Lemoine of the University of Arizona; Pierre Mérel of the University of California, Davis; John Reilly of the Massachusetts Institute of Technology; James Rising of the University of Delaware; James Stock of Harvard University; Paul Waidelich of ETH Zurich; and David Wilcox of the Peterson Institute for International Economics. Their contributions were valuable, but they bear no responsibility for the subsequent analysis, which rests solely with CBO.

Mark Doms and Jeffrey Kling reviewed the document. Rebecca Lanning was the editor. The document is available on CBO's website at www.cbo.gov/publication/57421.