Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits

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Abstract

Using subnational data from 41 countries, we develop an empirical model of the mortality-temperature relationship that allows us to estimate effects where no mortality data exist and to account for the benefits of adaptation to climate. Importantly, we develop a revealed preference approach that bounds adaptation costs, even though they cannot be directly observed. Using future climate simulations, we compute a median willingness-to-pay of $20 (moderate emissions scenario) to $39 (high emissions scenario) to avoid the excess mortality risk caused by a 1t increase in CO₂ emissions (2015 USD, 3% discount rate). Allocating these costs to 24,378 political units, we find substantial heterogeneity.
1 Introduction

Understanding the likely global economic impacts of climate change is of tremendous practical value to both policymakers and researchers. Some observers claim that the climate change risk is existential, while others argue that it is a relatively small risk among the many faced by the planet. These differences in perspective are reflected in global climate policy, which is at once both lax and wildly inconsistent; for example, carbon pricing covers just 15% of global emissions and does so at a broad range of prices. At the same time, the economics literature has struggled to guide carbon pricing, and what guidance does exist tends to be highly aggregated, providing little insight into what climate change will mean at the local level for diverse populations.

Decades of study have accumulated numerous insights and important findings regarding the economics of climate change, both theoretically and empirically, but a fundamental gulf persists between the two main types of analyses pursued. On the one hand, there are models able to capture the global nature of problem, such as stylized integrated assessment models (IAMs) (e.g. Nordhaus, 1992; Tol, 1997; Stern, 2006), whose great appeal is that they provide an answer to the question of what the global costs of climate change will be. However, the many necessary assumptions of IAMs weakens the authority of these answers. On the other hand, there has been an explosion of highly resolved empirical analyses whose credibility lie in their observation of real world data and careful econometric measurement (e.g. Schlenker and Roberts, 2009; Deschénes and Greenstone, 2007) but whose analyses tend to be limited in scope and rely on short-run variation in climate that may not fully account for adaptation to gradual climate change. At its core, this dichotomy persists because researchers must trade off between being complete in scale and scope or investing heavily in data collection and analysis. The result is that no study has delivered estimated effects of climate change that are as comprehensive as those of IAMs, while simultaneously being grounded in detailed econometric analyses using globally representative data.

This paper aims to resolve the tension between these two approaches in the context of mortality risk due to climate change. Specifically, it strives to provide the scope and global scale of IAMs, but transparently built upon highly resolved econometric foundations. In so doing, it aims to account for both the benefits and costs of adaptation. The net result is that the paper produces both a global estimate of the full costs of climate change on mortality risk, which we label an excess mortality partial social cost of carbon, as well as developing separate estimates for ~25,000 regions that together account for the entire world.

There are three main features of our analysis.

First, we estimate the mortality-temperature relationship around the world, both today and into the future. This is accomplished by using the most exhaustive dataset ever collected on annual, sub-national mortality statistics. These data cover the universe of deaths from 41 countries totaling 56% of the global population at a resolution similar to that of US counties (2nd-administrative level) for each year across multiple age categories (i.e. <5, 5-64, and >64). These data allow us to estimate the mortality-temperature relationship with substantially greater resolution and coverage of the human population than previous studies; the most comprehensive econometric analyses to date have been for a single country or individual cities from several countries. We find that in our sample an additional 35°C day (-5°C day), relative to a day at 20°C, increases the annual all-age mortality rate by 0.4 (0.3)
deaths per 100,000.

These data also allow us to observe heterogeneity in the mortality-temperature response function within each age category to account for the benefits of adaptation. Specifically, we allow the effect of temperature to vary as a function of climate (Barreca et al., 2015; Auffhammer, 2018) and income per capita (Hsiang and Narita, 2012; Burgess et al., 2017). These variables were carefully chosen based on the intersection of prior evidence from the literature, economic theory, and variables that are included in standard projections of the global economy used to develop physical climate model projections (O’Neill et al., 2014). We find that there is substantial heterogeneity in the mortality-temperature relationship: moving from the poorest to richest tercile in our sample saves on average 1.1 deaths per 100,000 per day at 35°C. Similarly, moving from the coldest to hottest tercile of long-run average temperature saves on average 2.9 deaths per 100,000 at 35°C.

A critical feature of the analysis is that the explicit modeling of heterogeneity additionally allows us to project the mortality-temperature relationship to the entire world today. This exercise is possible, because there are measures of income and climate for the parts of the world where micro mortality data do not exist; we can therefore “fill in” missing information regarding sensitivity to climate for the 44% of people for whom mortality data are unavailable. A striking finding is that globally, the effect of an additional 35°C day (relative to a location-specific minimum mortality temperature) for the more vulnerable over 64 population is 9.3 deaths per 100,000, which is approximately 1.7 times larger than the effect from the regions of the world where data are currently available. An additional benefit to our explicit modeling of heterogeneity is that it allows us to predict mortality-temperature response functions individually for each of ~25,000 impact regions for which we construct location-specific estimates. In the United States, these impact regions map roughly into a county.

We then project the mortality-temperature relationship for each of these impact regions out to 2100, based on standard projections of the evolution of income, population, and climate. This is a substantial step forward from assuming that response functions are constant over time, as has been the norm in the literature to date (Deschênes and Greenstone, 2011). A key finding from this exercise is that the mortality consequences of an additional hot day decline substantially by the end of the century, due to both the protective effects of higher incomes and costly adaptations that individuals are predicted to undertake in response to warmer climates. Put plainly, adaptation has substantial benefits. The extent of these benefits is governed by observed heterogeneity in the mortality-temperature relationship in historical data from across the globe.

The second feature of our analysis is the development of a general revealed preference method capable of bounding the full adaptation costs that populations will incur to obtain the adaptation benefits that we project, even though adaptation costs cannot be directly observed. This is a critical step because a full accounting of the economic burden of warming must account for the opportunity costs of all resources used to achieve these reduced sensitivities to temperature through adaptive adjustments, in addition to the direct mortality impacts. Yet, previous research has been unable to empirically measure all of these costs directly, because the range of potential responses to warming—whether defensive investments (e.g. building cooling centers) or compensatory behaviors (e.g. exercising earlier in the morning)—is enormous, making enumeration of their costs extraordinarily challenging. Indeed, the previous literature has frequently noted that adaptation will involve costs, and occasionally produced
partial costs estimates (e.g. Deschênes and Greenstone (2011); Barreca et al. (2016)), or estimates of total impacts net of costs (e.g. Schlenker, Roberts, and Lobell (2013); Deryugina and Hsiang (2017)), but has made little progress in building a comprehensive empirical measure of the costs of adaptation.

The basis for the revealed preference approach comes from the fact that we can measure the benefits of adaptation in terms of reduced mortality sensitivities to temperature and the theoretical restriction that individuals will only make adaptation investments when their costs are less than or equal to their benefits. The examples of Seattle, WA and Houston, TX, which have similar income levels, institutions, and other factors, but have very different climates, provide some high-level intuition for our approach. On average Seattle has just 0.001 days per year where the average temperature exceeds \(\approx 32^\circ C\), while Houston experiences 0.31 of these days annually.\(^1\) Houston has adapted to this hotter climate, evidenced by the fact that a day above 32\(^\circ\)C produces \(\frac{1}{30}\) of the excess mortality in Houston than it does in Seattle (Barreca et al., 2016). If these outcomes are the result of revealed preferences, then it must be the case that the costs required to achieve Houston-like temperature sensitivity exceed the benefits that Seattle would receive from adopting them, which seems sensible since these extreme temperatures only occur \(\frac{1}{300}\) as often. Further, the costs of adopting them for Houston, compared to enduring Seattle’s temperature-sensitivity, must be less than or equal to the reduction in mortality that they provide. Indeed, the difference in air conditioning penetration rates, which were 27% in Washington state and 100% in Texas as of 2000-4, provide evidence that the observed differences in temperature sensitivities between these cities reflect cost-benefit decisions.

We leverage this intuition to build a formal theoretical framework that allows us to derive empirically implementable upper and lower bounds of the unobserved adaptation costs.\(^2\) Thus, in our projections of the future, we are able to simultaneously estimate how populations will reduce direct mortality from the climate associated with their projected patterns of adaptation, while also tracking the costs incurred in order to achieve these adaptation benefits. Importantly, our approach allows for an arbitrarily large number of unknown adaptive adjustments, and it accounts for the possibility that some adaptations generate consumption value that is independent of their mortality benefits (e.g. the consumption value of air conditioning).

Together, these two features of the analysis allow us to develop measures of the full mortality-related costs of climate change for the entire world, reflecting both the direct mortality costs (accounting for adaptation) and all adaptation costs. We find that the median estimate of the total mortality burden of climate change across 33 different climate models is projected to be worth 36 death equivalents per 100,000 at the end of the century or roughly 3.7% of global GDP when using standard assumptions about the value of a statistical life. Approximately 2/3 of the death equivalent costs are due to the costs of adaptation. Further, failing to account for income and climate adaptation as has been the norm in the literature (Deschênes and Greenstone, 2011; Hsiang et al., 2017) would overstate the mortality costs of climate change by a factor of about 3.5. Finally, we note that there is evidence of substantial heterogeneity in impacts around the globe; at the end of the century we project an increase of about 3,800 death equivalents annually in Mogadishu and a decrease of about 1,100 annually in

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\(^1\)These values are calculated using the data of Barreca et al. (2016) for the years 2000-2004.

\(^2\)We note that Schlenker, Roberts, and Lobell (2013), Guo and Costello (2013) and Deryugina and Hsiang (2017) exploit similar arguments regarding the equality of marginal adaptation costs and marginal adaptation benefits, and we describe in detail in Section 2 how our approach relates to these earlier contributions.
Oslo, Norway.

The third feature worth highlighting is the development of a transparent procedure to transform the econometrically-based results into a single number describing the full welfare cost of additional mortality risk imposed by the marginal emission of CO\textsubscript{2} today. Specifically, we estimate the full willingness-to-pay to avoid the alteration of mortality risk associated with the release of an additional metric ton of CO\textsubscript{2}, which is referred to as the excess mortality “partial” Social Cost of Carbon (A “full” SCC would encompass non-mortality impacts). Our central values suggest that with a 3\% discount rate, the excess mortality partial SCC is roughly $20 (in 2015 USD) with a low or moderate emissions scenario (i.e., RCP4.5) and $39 with a high one that resembles “business as usual” (i.e., RCP 8.5). When accounting for climate model and statistical uncertainty, the respective interquartile ranges are [$7.7$-$67.1$] for RCP4.5 and [$14.5$-$92.6$] for RCP8.5; the positive skewness of these ranges reflects the risk of outcomes substantially more costly than our central estimate. Further, we are able to trace these costs back to the \textasciitilde25,000 subnational geographic regions and find that the impacts are distributed unequally with 72\% of the global population harmed by an additional ton of CO\textsubscript{2} emissions and the remainder benefiting.

The rest of this paper is organized as follows: Section 2 outlines a conceptual framework for the problem of projecting climate damages into the future, accounting for adaptation and its cost; Section 3 describes the data used in the estimation of impacts and in the climate change projected impacts; Section 4 details the econometric approach; Section 5 describes the results of the econometric analysis; Section 6 explains how we extrapolate mortality impacts across space and project them over time while computing adaptation costs and benefits; Section 7 presents global results from projections that use high-resolution global climate models; Section 8 details the calculation of a damage function based on these results and combines it with a simple climate model to compute a partial SCC; and Section 9 concludes.

2 Accounting for costs and benefits of adaptation to climate change empirically

Climate change is projected to have a wide variety of impacts on well-being, such as altering the risk of mortality due to extreme temperatures. The ultimate effect on particular outcomes like mortality rates will be determined by the adaptations that are undertaken. Specifically, as the climate changes, individuals and societies will weigh the costs and benefits of undertaking actions that allow them to exploit new opportunities (e.g., converting land to new uses) and protect themselves against new risks (e.g., investments in air conditioning to mitigate mortality risks). The full cost of climate change will thus reflect both the realized direct impacts (e.g., changes in mortality rates), which depend on the benefits of these adaptations, and the costs of these adaptations in terms of foregone consumption. However, to date it has proven challenging to develop a theoretically founded and empirically credible approach to explicitly recover the full costs of climate change.\textsuperscript{3}

\textsuperscript{3}See Deschênes and Greenstone (2011); Hsiang and Narita (2012); Schlenker, Roberts, and Lobell (2013); Lobell et al. (2014); Guo and Costello (2013); Deschênes, Greenstone, and Shapiro (2017); Deryugina and Hsiang (2017) for different discussions of this issue and some of the empirical challenges.
This section develops an approach for empirically bounding populations’ willingness to pay (WTP) to avoid the mortality risks from climate change that reflects both the costs and benefits of adaptation. Previous work has established methods to estimate the benefits of adaptation (e.g. Auffhammer, 2018) but not its costs. Thus, our key contribution is to devise an empirical strategy to bound adaptation costs using a revealed preference approach, even when numerous individual margins of adaptation and their costs cannot be directly observed.

2.1 Definitions and intuition for the economics of adaptation

We define the climate of a location as the joint probability distribution over a vector of possible conditions that can be expected to occur at a given location over a specific interval of time. Let $C$ be a vector of parameters describing the entire joint probability distribution over all relevant climatic variables. For example, $C$ might contain the mean and variance of daily average temperature and rainfall, among other parameters. Weather realizations are a random vector $c$ drawn from this distribution. Mortality risk is a function of both $c$ and a vector of $K$ endogenous economic variables $b = \{b_1, ..., b_K\}$. The vector $b$ captures all choice variables available to individuals, except consumption of a numeraire good $x$, including possible adaptive behaviors and investments that could interact with individuals’ exposure to a warming climate, such as installation of air conditioning and time allocated to indoor activities. Mortality risk is then captured by the probability of death during a unit interval of time $f = f(b, c)$.

Climate change will influence mortality risk through two pathways. First, a change in $C$ will directly alter realized weather draws, changing $c$. Second, a change in $C$ can alter individuals’ beliefs about their likely weather realizations, shifting how they act, and ultimately changing their endogenous choice variables $b$. Endogenous adjustments to $b$ will capture all long-run adaptation to the climate (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Kelly, Kolstad, and Mitchell, 2005), since these adaptations are necessarily factor reallocations based on knowledge of the climate (Deryugina and Hsiang, 2017). Therefore, since the climate $C$ determines both $c$ and $b$, for notational simplicity we rewrite the probability of death at initial climate $C_1$ as:

$$\Pr(\text{death} | C_1) = f(b(C_1), c(C_1))$$

(1)

where we define $c(C)$ to be a random vector $c$ drawn from a distribution characterized by $C$ (Hsiang, 2016). Equation 1 describes the structure through which climate and compensatory investments, captured in $b$, will enter the health production function (Grossman, 1972).

Many previous empirical estimates of the effects of climate assume no adaptation takes place (e.g. Deschênes and Greenstone, 2007; Houser et al., 2015). Specifically, these approaches calculate changes in an outcome variable imposed by changing the distribution of $c$, assuming economic decisions embodied by $b$ do not change. Following this approach, the change in mortality risk incurred due to a change in climate from $C_1$ to $C_2$ would be calculated as:

$$\text{mortality effects of climate change without adaptation} = f(b(C_1), c(C_2)) - f(b(C_1), c(C_1))$$

(2)

$^4$See Hsiang (2016) and Deryugina and Hsiang (2017) for a more complete discussion of this approach to measuring climate with a finite vector.

$^5$Hsiang (2016) describes these two channels as a “direct effect” and a “belief effect.”
which ignores the fact that individuals will respond to the change in climate by altering $b$. Thus, Equation 2 is equivalent to a partial derivative of mortality risk with respect to climate, as individuals are not allowed to make any adjustments in response to the changing climate.

In reality, optimizing populations will update their behaviors and technologies $b$ in response to a changing climate as their beliefs about $C$ evolve. To the extent that populations may attenuate mortality damages by adjusting $b$ in response to climate change, these adaptations will generate benefits by countering the effect of climate on mortality. Thus, a more realistic estimate for the change in mortality due to a change in climate is:

$$\text{mortality effects of climate change with adaptation} = f(b(C_2), c(C_2)) - f(b(C_1), c(C_1))$$  (3)

Note that if the climate is changing such that the mortality risk from $C_2$ is higher than $C_1$ when holding $b$ fixed, then the endogenous adjustment of $b$ will generate benefits of adaptation weakly greater than zero since these damages may be partially mitigated. Stated another way, the change in Equation 3 will be weakly smaller than the change in Equation 2. Thus, Equation 3 is equivalent to a total derivative of mortality risk with respect to climate, as it reflects individuals’ compensatory responses. The costs of these responses are the costs of the $b$ adjustments, and their benefits are the resulting weakly smaller changes in mortality.

Several analyses have estimated reduced-form versions of Equation 3, confirming that accounting for endogenous changes to technology, behavior, and investment may mitigate the direct effects of climate in a variety of contexts (e.g. Barreca et al., 2016). Importantly, however, while this approach accounts for the benefits of adaptation, it does not account for its costs. If adjustments to $b$ were costless and provided protection against the climate, then we would expect universal uptake of highly adapted values for $b$ so that all comparable populations would be inoculated against the climate. But we do not observe this to be true: previous studies that demonstrate benefits of adaptation do so by demonstrating reduced sensitivity to marginal environmental changes ($\frac{\partial f}{\partial c}$) in more adverse climates (Houston) and larger sensitivity in less adverse climates (Seattle) (Deschênes and Greenstone, 2011).

Thus, observed cross-sectional heterogeneity in climate sensitivity can be reconciled if individuals who are otherwise comparable face differential unobserved costs of adaptation. We denote the costs of achieving adaptation level $b$ as $A(b)$, measured in dollars of forgone consumption.

A full measure of the economic burden of climate change must account not only for the benefits generated by adaptive reactions to these changes but also their cost. Thus, the total cost of changing climate would be:

$$\text{total cost of changing climate} = \text{mortality effects of climate change with adaptation} + \text{costs of adaptation}$$

6If the change in climate decreases mortality risk when holding $b$ fixed, then we would expect adaptation to lead to larger changes in mortality (i.e. smaller reductions) than indicated by Equation 2.

7For additional examples, see Schlenker and Roberts (2009); Burgess et al. (2017); Hsiang and Narita (2012); Hsiang and Jina (2014); Barreca et al. (2015); Heutel, Miller, and Molitor (2017); Auffhammer (2018).

8Carleton and Hsiang (2016) document that such wedges in observed sensitivities to climate—which they call “adaptation gaps”—are a pervasive and unexplained feature of the broader climate damages literature.
mortality risks that result from a climate change $C_1 \rightarrow C_2$ is

\[
\text{full value of mortality risk due to climate change} = VSL \left( f(b(C_2), c(C_2)) - f(b(C_1), c(C_1)) \right) + A(b(C_2)) - A(b(C_1)) \tag{4}
\]

where $VSL$ is the value of a statistical life. If the costs of adaptation $A(b)$ were omitted from this calculation, we might substantially underestimate the overall economic burden of warming.

A key objective of this paper is to measure the total costs of climate change’s impact on mortality risk. The next subsection develops a model of optimizing behavior that leads to an expression for adaptation costs associated with the mortality risk from climate change. Importantly, this expression is composed solely of empirically identifiable elements, despite the fact that the full range of $K$ potential adaptations is unlikely to be observable. The final subsection briefly sketches how observations of many different populations inhabiting different climates in the present allows us to empirically recover bounds for the costs of future adaptation to climate change.

### 2.2 Deriving an expression for adaptation costs from individual optimizing behavior

Taking account of the temperature-dependent mortality risk $f(b, c)$, a representative agent will maximize expected utility based on the climatological distribution of $c$ that he or she expects. We assume agents have rational expectations and can integrate over the distribution of realizations of $c$ for each climate to compute the expected probability of death $\hat{f}$ conditional on the climate and their actions: $\hat{f}(b(C), C) = \mathbb{E}_c[f(b(C), c(C)) | C]$. Thus $1 - \hat{f}(b, C)$ is the expected probability of survival, analogous to a health production function in other settings (Grossman, 1972). Let agents derive utility $u(x, b)$ both from consumption of a numeraire good $x$ and also possibly from the choice variables in $b$ (for example, air conditioning might increase utility directly, regardless of its effect on mortality risk).\(^9\)

Agents jointly solve for all $K$ margins of adaptation described in the choice vector $b$ such that $b^* = \text{arg max } u(x, b)[1 - \hat{f}(b, C)]$, subject to a budget constraint $h(b) + x = Y$, where $h(b)$ is the pecuniary cost of adaptation expended by households and $Y$ is income. Summing across $K + 1$ first order conditions and substituting for the value of the statistical life ($VSL$), $b^*$ satisfies:\(^{10}\)

\[
-VSL \sum_k \frac{\partial}{\partial b_k} \hat{f}(b^*, C) = \sum_k \frac{\partial}{\partial b_k} \left[ h(b^*) - \frac{u(x^*, b^*)}{\partial u(x^*, b^*)/\partial x} \right] = \sum_k \frac{\partial A(b^*)}{\partial b_k} \tag{5}
\]

Thus, Equation 5 governs expenditures on adaptation. Its left-hand side is the product of the sum of marginal changes to expected mortality risk due to any adjustments to $b$ and the negative of the

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\(^9\)For simplicity, we assume that agents do not receive utility directly from the climate; however, in Appendix A we allow $u(\cdot)$ to be a function of the climate.

\(^{10}\)See Appendix A for derivation.
VSL, so it represents the total marginal benefit of adjusting \( b \) through its effect on mortality risk. The righthand side of Equation 5 has two parts. The first term inside the brackets, \( h(b^*) \), represents all pecuniary expenditures required to achieve \( b^* \), such as spending on air conditioning. The second term in the brackets represents \([-\text{minus}]\) the dollar value of all utility benefits and costs derived from \( b^* \), such as the utility of enjoying air conditioning or the disutility of exercising at midnight to avoid the daytime heat (expressed in dollars of WTP). The sum of these two terms can thus be interpreted as the net cost of achieving \( b^* \) in order to reduce climate-caused mortality, since all non-mortality benefits and costs are differenced out.

We denote these net costs as \( A(b) \), just as in the previous subsection.\(^{11}\) For our purposes, it is neither important nor empirically feasible to separately identify these two components of net cost, and throughout our remaining analysis adaptation costs should be interpreted as net of any direct non-pecuniary benefits. Equation 5 is therefore further simplified by substituting \( A(b) \), showing that in equilibrium the total marginal benefits of adaptation (left-hand side of Equation 5), in terms of mortality risk, equal the total marginal net costs (far-right-hand side). So, agents will adjust every dimension of \( b^* \) in response to their climate \( C \) until their total marginal costs equal their marginal benefit as adaptive strategies.

The marginal costs and benefits of adaptation described in Equation 5 are not directly observable. In particular, there may exist an enormous number of adaptive margins \( K \). One strategy in the literature has been to construct partial cost estimates \( A_k \) that account for specific observable margins of adaptation \( b_k \) that can be easily priced. For example, Deschênes and Greenstone (2011) estimate the cost of increasing US residential energy consumption used for cooling as an adaptation strategy to reduce heat-related mortality in homes. In principle, a large number of such studies that each measure the costs of specific margins of adaptation could be assembled to construct the total cost of all margins of adaptation \( A(b) = A_1(b_1) + ... + A_K(b_K) \). However, in practice it seems unlikely to be feasible to enumerate and identify the cost of all possible margins of adaptation, especially when numerous possible margins may not even be known. Thus, the “enumerative” approach to determining the total costs, or the benefits, of adaptation seems infeasible.

However, it is possible to make the expression in Equation 5 of greater practical value if we eliminate \( b \) by noting that it is an implicit function of climate and income \(^{12}\) \( b^* = b^*(C, Y) \). This allows us to collapse all the information encoded in the large unobserved vector \( b \) into these observable terms. Thus, we take the total derivative of \( \tilde{f}(\cdot) \) with respect to the climate \( C \), applying the Chain Rule to each element \( b_k \), and obtain:

\[
\frac{d\tilde{f}(b^*, C)}{dC} = \sum_k \frac{\partial \tilde{f}(b^*, C)}{\partial b_k} \frac{\partial b_k^*}{\partial C} + \frac{\partial \tilde{f}(b^*, C)}{\partial C} \tag{6}
\]

which says that the total derivative, or the effect of climate on mortality once individuals have adapted to a change in climate, is the sum of two terms. The first term represents the impacts on mortality of all changes in adaptive investments induced by the change in climate; as discussed, this is of limited

\(^{11}\)Noting that \( x \) is fully determined by \( b \) and income through the budget constraint

\(^{12}\)Substituting \( x^* = Y - h(b^*) \) in Equation 5.
practical value because of data and estimation limitations.\(^{13}\) The second term is the effect that the climate would have if individuals were prevented from adapting, known in the climate change literature as the “direct effect” of the climate (Deryugina and Hsiang, 2017). In the case of climate change that produces an increase in the frequency of extreme heat events that threaten human health, it would be natural to expect the first term to be negative, as people make adjustments that save lives, and the second term to be positive, reflecting the impacts of additional heat on fatalities without adjustment.

It is straightforward and useful to rearrange Equation 6 to yield an expression for the impossible to observe mortality benefits of adaptation. Specifically, we can write:

\[
\sum_k \frac{\partial \tilde{f}(b^*, C)}{\partial b_k} \frac{\partial b_k}{\partial C} = \frac{\partial \tilde{f}(b^*, C)}{\partial C} - \frac{\partial \tilde{f}(b^*, C)}{\partial C}
\]

expressing the unobservable term as the difference between the total and partial derivatives of the probability of death with respect to climate. This is powerful, because we have now written the mortality benefits of adaptation as a function of two terms that can in principle be estimated.

We use this insight in combination with Equation 5 to develop an expression for the additional adaptation costs incurred as the climate changes gradually from \(C_1\) to \(C_2\). As the climate changes by an incremental \(dC\) (e.g. the warming that occurs during a single year) agents will respond by adjusting \(K\) dimensions of \(b^*\) incrementally such that the sum of all \(K\) marginal costs continuously equal the sum of the \(K\) marginal benefits (Equation 5). We wish to integrate the sum of these marginal costs to compute total costs, but they cannot be observed. However, combining Equations 5 and 7, it is apparent that we can infer them by differencing the total and partial derivatives of mortality risk with respect to the climate, both of which are in principle observable. Thus, the change in total adaptation costs along the climate change trajectory \(C_1 \rightarrow C_2\) is:\(^{14}\)

\[
A(b^*(C_2, Y)) - A(b^*(C_1, Y)) = \int_{C_1}^{C_2} \frac{\partial A(b^*)}{\partial b^*} \frac{\partial b^*}{\partial C} dC = -VSL \int_{C_1}^{C_2} \left[ \frac{d\tilde{f}(b^*, C)}{dC} - \frac{\partial \tilde{f}(b^*, C)}{\partial C} \right] dC
\]

Estimates of the total and partial derivative will thus allow us to infer net adaptation costs, even though adaptation itself is not directly observable. In the following sections, we develop an empirical panel model exploiting both short-run and long-run variation in which the total derivative \(\frac{d\tilde{f}}{dC}\) can be separated from the partial derivative \(\frac{\partial \tilde{f}}{\partial C}\). Using idiosyncratic year-to-year time-series variation within each location, we recover causal estimates of the partial derivative of mortality rates with respect to the entire daily temperature distribution, since these changes occur unexpectedly and thus individuals do not have the ability to make long-run adaptations. However, by interacting long-run temperatures between locations with this variation, we can plausibly identify the total derivative, which captures the overall effect of a shift in the temperature distribution after populations have fully adjusted.

\(^{13}\)This term is often known in the environmental health literature as the effect of “defensive behaviors” (Deschenes, Greenstone, and Shapiro, 2017) and in the climate change literature as “belief effects” (Deryugina and Hsiang, 2017); in our context they result from changes in individuals’ defensive behaviors undertaken because their beliefs about the climate have changed.

\(^{14}\)See Appendix A for derivation. Note that \(Y\) is treated as exogenously determined, although it can be varied period-to-period in actual calculations.
The key innovation of our approach is that we use the difference between these two derivatives to construct explicit estimates of all expenditures dedicated to unobservable adaptive behaviors, which has been previously unrecoverable. In the next subsection, we describe how distinct sets of assumptions regarding the nature of the cost function $A(b)$ lead to the construction of empirically estimable bounds for net adaptation costs, both of which rely on the separation of the total from the partial derivative.

2.3 Empirically implementable bounds for adaptation costs

As we have emphasized, it is very likely impossible to directly observe a complete measure of the costs of adaptation caused by changes in the climate. This subsection outlines two empirically implementable, revealed preference approaches that form bounds on these adaptation costs. At their core, the two bounds are based on different assumptions about the adaptation cost function $A(b)$. In contrast, in both cases we assume that all agents share identical adaptation benefits; that is, we assume that conditional on wealth and average climate, individuals are homogenous in terms of the mortality risk imposed by a given climate event, both within and across locations.

In the first case, we assume that there are a common set of adaptation technologies available at a common set of prices in all locations and at all times, but make no assumptions about the shape of the adaptation cost function. When this assumption is combined with the assumption that agents are homogeneous, it implies that the benefits of adaptation exactly equal their costs. Thus, any estimate of the benefits of adaptation also generates an estimate of its costs. Practically, this means that by observing how optimizing populations forgo benefits of marginal adaptation in their current climate, we can recover the exact structure of marginal costs they face; put another way, the observed benefits trace out the unobserved costs. As detailed throughout the paper, we can observe the behavior of many different populations that all inhabit different climates at present, each of which is presumably adapted to that climate. We can then compute marginal benefits, and in turn infer marginal adaptation costs, across many different climate regimes which, when integrated, recovers the structure of $A(b)$.

Throughout the paper, we refer to these estimates as an upper bound on net adaptation costs, as the assumption of homogeneous adaptation technologies across space and time implies that all benefits of adaptation are subsumed by our estimate of compensatory costs.

In the second case, we consider the plausible reality that the costs of adaptation technologies and behaviors vary across locations. Heterogeneity in cost functions — i.e. functions $A_i(b)$ for each location $i$ — is likely valid if for no other reason than that there are substantial differences in electricity prices across locations that affect the costs of cooling and heating technologies. Moreover, any barrier to free trade in adaptive technologies could lead to similar wedges in prices of the elements in $b$, and hence to differences in $A_i(b)$ across space and time. Under this assumption, the marginal costs exhibited by neighboring populations are not indicative of the costs a warming population would experience if employing the same adaptations. In this case, we have much less information about the adaptation costs a population would experience with warming that is out of their historical experience, since costs of neighbors are not a valid proxy. To provide empirical traction, we impose a second (standard) assumption: that the marginal costs of adaptation are non-decreasing for all elements of $b$, such that

\[15\] To ensure that there is a locational equilibrium and that utility is held constant across locations, there must be a compensating differential for the differences in electricity prices. It is natural to assume that land markets would serve this role (Roback, 1982).
Figure 1: Spatial and temporal coverage of the mortality statistics used in estimation of temperature-mortality relationships. Regression estimates of the temperature-mortality relationship rely on mortality statistics from all countries shown in blue, at the spatial resolution indicated by the black boundary lines. Temporal coverage for each country is shown under the map.

the total cost $A_i(b)$ increases at least linearly with $b$. Under this assumption, the first order condition specified in Equation 5 means that at an initial (historically observed) climate, agents will make adaptive investments until their benefits equal their costs. With linear total cost $A_i(b)$, knowledge of the marginal benefit at the current climate also reveals the constant marginal cost at that climate. These differences in $A_i(b)$ imply that adaptive investments taken by otherwise comparable individuals can generate benefits that are larger than costs; therefore, throughout the paper we refer to this second set of estimates as a lower bound on net adaptation costs. Note that its key difference with the upper bound is that it is based on the difference between the total and partial derivatives evaluated at the initial climate, rather than allowing this difference to evolve with the climate.

The details of implementing both adaptation cost bounds are discussed in Section 6.3, although we first describe our data and the procedure through which we estimate $\hat{f}(b^*, C)$ for all populations on the planet.

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16 In units of deaths per 100,000 population.
17 The mortality rate is winsorized at the 1% level at the high end of the distribution only.
18 Global population share for each country in our sample is shown for the year 2010.
19 ADM2 refers to the second level of administrative region in each country, while ADM1 refers to the first level. For example, in the USA, ADM2 refers to the county, and ADM1 to state.
20 European Union (EU) data for 33 countries were obtained from a single source. Detailed description of the countries within this region is presented in Appendix B.
21 Most countries in the EU data have records beginning in the year 1990, but start dates vary for a small subset of countries. See Appendix B and Table 6 for details.
22 We separate France from the rest of the EU, as higher resolution mortality data are publicly available for France.
23 It is widely believed that data from India understate mortality rates due to incomplete registration of deaths.
### Mortality records

<table>
<thead>
<tr>
<th>Country</th>
<th>N</th>
<th>Spatial scale</th>
<th>Years</th>
<th>Age categories</th>
<th>All-age</th>
<th>&gt;64 yr.</th>
<th>Global pop. share</th>
<th>GDP per capita</th>
<th>Avg. daily temp.</th>
<th>Annual avg. days &gt; 28°C</th>
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<tr>
<td>Brazil</td>
<td>228762</td>
<td>ADM2</td>
<td>1997-2010</td>
<td>0-4, 5-64, &gt;64</td>
<td>325</td>
<td>4096</td>
<td>.928</td>
<td>11271</td>
<td>24.1</td>
<td>43.3</td>
</tr>
<tr>
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<td>14238</td>
<td>ADM2</td>
<td>1997-2010</td>
<td>0-4, 5-64, &gt;64</td>
<td>554</td>
<td>4178</td>
<td>.002</td>
<td>14411</td>
<td>13.4</td>
<td>0</td>
</tr>
<tr>
<td>China</td>
<td>7488</td>
<td>ADM2</td>
<td>1991-2010</td>
<td>0-4, 5-64, &gt;64</td>
<td>635</td>
<td>7507</td>
<td>.193</td>
<td>5546</td>
<td>14.2</td>
<td>24.1</td>
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<tr>
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<td>NUTS2</td>
<td>1990^12-2010</td>
<td>0-4, 5-64, &gt;64</td>
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<td>India</td>
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<td>1957-2001</td>
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<td>25.3</td>
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<td>1975-2010</td>
<td>0-4, 5-64, &gt;64</td>
<td>788</td>
<td>4135</td>
<td>.018</td>
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<td>1990-2010</td>
<td>0-4, 5-64, &gt;64</td>
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<td>–</td>
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<th>Variable</th>
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<td>Berkeley Earth</td>
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<tr>
<td>UDEL</td>
<td>Matsura and Willmott (2007)</td>
<td>Interpolation</td>
<td>0.5° precip.</td>
<td>University of Delaware</td>
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</tr>
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</table>

Table 1: Historical mortality & climate data

## 3 Data

This section is divided into two parts to reflect the paper’s two primary analytical pieces. The first subsection details the data necessary to estimate the relationship between mortality and temperature, which we report on in Section 3.1. The second part outlines the data we use to predict the mortality-temperature relationship across the entire planet today and project its evolution into the future as populations adapt to climate change (Section 3.2).

### 3.1 Data to estimate the mortality-temperature relationship

**Mortality data.** Our mortality data represent 41 countries. In some cases our data represent the universe of reported deaths in those countries, while in others (e.g., China), data are representative samples, as no vital statistics registry system exists. Combined, our dataset covers mortality outcomes for 56% of the global population. Spatial coverage, resolution, and temporal coverage are shown in Figure 1, and each dataset is described in Table 1. Data are drawn from multiple, often restricted, national and international sources, with details on each given in Appendix B. All mortality datasets contain information on deaths per 100,000 population from all causes at a monthly or annual frequency and all contain age-specific mortality rates at various resolutions. India is the exception that only provides all-age and infant mortality. We harmonize these diverse sources into a single multi-country panel dataset of age-specific annual mortality rates, using three age categories: 0-4, 5-64, and over 64. Due to the differences in mortality rates across the life-cycle and the absence of information on

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^24Our main analysis uses age-specific mortality rates from 40 of these countries. We use data from India as cross-validation of our main results, owing to the fact that the India data, also used in Burgess et al. (2017), do not have information on age-specific mortality rates.
mortality rates for these age categories, India is not included in the primary analysis.

**Historical climate data.** We perform analyses with two separate groups of historical data on precipitation and temperature from independent sources. First, we use a reanalysis product, the Global Meteorological Forcing Dataset (GMFD) (Sheffield, Goteti, and Wood, 2006), which relies on a climate model in combination with observational data to create globally-comprehensive data on daily mean, maximum, and minimum temperature and precipitation (Auffhammer et al. 2013). Data are available as a grid covering the entire Earth’s surface at 0.25° spatial resolution. Second, we repeat our analysis with climate datasets that strictly interpolate observational data across space onto grids. We use the Berkeley Earth Surface Temperature dataset (BEST) (Rohde et al., 2013) in combination with the University of Delaware precipitation dataset (UDEL) (Matsuura and Willmott, 2007). BEST data and UDEL data are gridded at a 1° and 0.5° spatial resolution, respectively. A brief description of the data is provided in Table 1, with full data descriptions Appendix C.

**Aggregation of gridded data to administrative boundaries.** To match mortality data, gridded daily temperature data are aggregated to the same administrative level as the mortality data (see Table 1). Nonlinear transformations are computed at the pixel level before averaging the pixels across space using population weights and summing them over time. This procedure recovers pixel-by-day-level nonlinearities in the mortality-temperature relationship because mortality events are additive (Hsiang, 2016). For example, in the fourth-order polynomial specification, we begin with day $d$ data on mean temperatures at each pixel $z$ in the data, generating observations $T_{z,d}$. These pixel-level values must then be aggregated to the level of an administrative unit $j$ in year $t$. To do this, we first raise pixel-level temperature data to the power $p$, computing $(T_{z,d})^p$ for $p = \{1, 2, 3, 4\}$. We then take a spatial average of these values over administrative unit $j$, weighting the average by pixel-level population. We then sum the daily polynomial terms over days in the year $t$. The annual, administrative-level-by-year temperature variable for the $p$th term in the polynomial specification is thus:

$$T_{j,t}^p = \sum_{d \in t} \sum_{z \in j} w_{zj} \times (T_{z,d})^p$$

where $w_{zj}$ is the share of $j$’s population that falls into pixel $z$. This nonlinear transformation allows that this aggregated measure of temperature to capture pixel-by-day level exposure to very hot and very cold temperatures. Precipitation quadratic polynomials are similarly calculated and weighted averages are taken over administrative units. In Appendix Figure 16, we show robustness of the mortality-temperature relationship to four different nonlinear functional forms of temperature, all of which undergo an analogous pixel-level transformation before averaging and summing.

**Covariate data.** Our analysis allows for heterogeneity in the mortality-temperature relationship as a function of two long-run covariates: a measure of climate (i.e., long-run average temperature) and income per capita. The average temperature data are calculated from GMFD. Long-run averages are taken over every year in the mortality sample for a particular country. These average values are calculated at the ADM1-level (e.g., province or state) in order to match the level at which the administrative income data is available; importantly, this captures intra-national variation in this measure of climate, reflecting that Seattle is different than Houston, for example.

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25 This averaging period varies across countries to reflect the period for which we have data, as described in Table 1.
We obtain income data at the subnational level for the 41 countries in our dataset from three different sources: the Penn World Tables (PWT), Gennaioli et al. (2014), and Eurostat (2013a). The PWT provides national incomes which we then allocate to ADM1 level units in the countries where we have data using either the panel in Gennaioli et al. (2014) or Eurostat (2013a). More details of the data and this procedure are given in Appendix D. For each ADM1 unit, the income variable is time invariant and calculated as the simple average across the years where mortality data is available, identical to the treatment of our climate data, thereby capturing intra-national variation. The country-level values of income are reported in Table 1 in constant 2005 dollars PPP.

3.2 Data for projecting the mortality-temperature relationship around the world & into the future

Our projection of local climate change impacts requires some definitions and assumptions regarding plausible future scenarios. This subsection describes our definition of local regions and the scenarios we use to describe how climate, populations and incomes might change in the future.

Defining impact regions for projections. We partition the global land surface into a set of 24,378 regions onto which we extrapolate temperature-mortality sensitivities and location-specific projected damages of climate change. These regions, hereafter referred to as “impact regions”, are constructed such that they are either identical to existing administrative regions or are a union of a small number of administrative regions within the same country. They are formed from the approximately 295,000 primitive spatial units present in the Global Administrative Region dataset (Global Administrative Areas, 2012a). To reduce computational burdens, we amalgamate these primitive units into 24,378 larger impact regions that respect national borders, are roughly equal in population across regions, and have approximately homogenous mean temperature, diurnal temperature range, and mean precipitation within each region. Appendix E provides more details on the impact regions and the algorithm used to create them.

Climate projections. We use a set of 21 high-resolution (0.25° × 0.25°) bias-corrected global climate projections\(^26\) that provide daily temperature and precipitation through the year 2100. These Global Daily Downscaled Projections (GDDP) data are produced by NASA Earth Exchange (NEX) (Thrasher et al., 2012) and include a set of models typically used in national and international climate assessments.\(^27\) We obtain climate projections based on two standardized emissions scenarios: Representative Concentration Pathways 4.5 and 8.5 (RCP4.5 and RCP8.5). RCP4.5 represents an approximate “stabilization” scenario with mean global surface temperature warming approximately between 2°-3°C above pre-industrial levels by 2100 (Riahi et al., 2011). RCP8.5 simulates climate change under intensive growth in fossil fuel emissions from 2006 to the end of 21\(^{st}\) century with warming approximately between 4°-6°C by 2100.

The set of 21 climate models do not collectively represent a complete probability distributions of potential future outcomes because they systematically underestimate tail risks of future climate change (Tebaldi and Knutti, 2007; Rasmussen, Meinshausen, and Kopp, 2016). To correct for this,

\(^26\)Details of the models used are provided in Appendix C.
\(^27\)The NEX-GDDP downscales global climate model (GCM) output from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (Taylor, Stouffer, and Meehl, 2012).
we follow Hsiang et al. (2017) by assigning probabilistic weights to climate projections and use 12 surrogate models that describe local climate outcomes in the tails of the climate sensitivity distribution (Rasmussen, Meinshausen, and Kopp, 2016). The 21 models and 12 surrogate models are treated identically in our calculations and we describe them collectively as the 33 high resolution Global Climate Models (GCMs) for simplicity. The gridded output from these projections are aggregated to impact regions using the same method we applied to historical climate data. Full details on the climate projection data and this procedure are detailed in Appendix C.

**Population projections.** Projections of national populations are derived from the Organization for Economic Co-operation and Development (OECD) (Dellink et al., 2015) and International Institute for Applied Systems Analysis (IIASA) (Samir and Lutz, 2014) population projections as part of the “socioeconomic conditions” (population, demographics, education, income, and urbanization projections) of the Shared Socioeconomic Pathways (SSPs). The SSPs propose a set of plausible scenarios of socioeconomic development over the 21st century in the absence of climate impacts and policy. The IIASA SSP population projections provide estimates of population by age cohort, gender, and level of education for 193 countries from 2010 to 2100 in five-year increments (IIASA Energy Program, 2016). Each projection corresponds to one of the five SSPs (O’Neill et al., 2014) where SSPs differ by assumptions about fertility rates, economic growth, and policy factors such as trade and energy use. Below we present results using scenarios SSP2, SSP3, and SSP4, all of which are plausibly consistent with emissions trajectories between RCP4.5 and RCP8.5. National population projections are allocated to subnational impact region units based on current satellite-based within-country population distributions from Bright et al. (2012). Appendix F.1 provides additional details.

**Income projections.** Impact region income projections are derived from national per-capita income projections contained in the SSP scenarios, available through the end of the century. Similar to historical income, future national incomes from the SSPs are allocated to subnational impact region units. Because global subnational income data is not universally available, even at present, we allocate national incomes using nighttime light satellite imagery from the NOAA Defense Meteorological Satellite Program (DSMP). Using available subnational income data from Gennaioli et al. (2014) in combination with higher-resolution income data from the United States, China, Brazil, and India, we estimate a non-parametric empirical relationship between GDP per capita and nightlight intensity, based on relative intensity of night lights in the most recent (2013) DSMP images available. We then use this estimated relationship to allocate income across locations within each country, setting growth rates at each location to the national growth prescribed by each SSP. Appendix F.3 provides further details on the implementation of these income projections.

### 4 Methods: Causal estimation of the mortality-temperature relationship

#### 4.1 Estimating a global mortality-temperature response function

We begin by estimating a global mortality-temperature response function. The model exploits year-to-year variation in the distribution of daily weather to identify the response of all-cause mortality
to temperature, following, for example, Deschênes and Greenstone (2011) and Barreca et al. (2016). Specifically, we estimate the following equation on the pooled mortality sample from 41 countries,

\[ M_{aict} = g(T_{it}) + \phi_{1,c}R_{it} + \phi_{2,c}R_{it}^2 + \alpha_{ai} + \delta_{act} + \epsilon_{ait} \]  

(9)

where \( a \) indicates age category with \( a \in A = \{0-4, 5-64, > 64\} \), \( i \) denotes 2\textsuperscript{nd}-level administrative division (ADM2), \( c \) denotes country, and \( t \) indicates years. \( M_{aict} \) is the age-specific all cause mortality rate in ADM2 region \( i \) in year \( t \). \( R_{it} \) is cumulative annual precipitation, and it is modeled via a country-specific quadratic function. Standard errors are clustered at the 1\textsuperscript{st} administrative level (e.g. state). We experimented with estimating the effect of temperature \( T \) using four distinct functional forms for the nonlinear function \( g(T_{it}) \), all of which restrict the effects of temperature to be constant around the world: (i) 4\textsuperscript{th}-order polynomial of cumulative daily average temperatures; (ii) binned daily temperatures, where annual values are calculated as the number of days in region \( i \) in year \( t \) that have an average temperature that falls within a fixed set of 5°C bins; (iii) restricted cubic splines; and finally (iv) a 2-part linear spline measuring the effect of heating degree days below 0°C and cooling degree days above 25°C. In this pooled model, we weight observations by age-specific population so that the coefficients correspond to the average person in the relevant age category.\footnote{We constrain population weights to sum to one for each year in the sample. That is, our weight for an observation in region \( i \) in year \( t \) for age group \( a \) is \( w_{ait} = \text{pop}_{ait} / \sum_i \sum_a \text{pop}_{ait} \). This adjustment of weights is important in our context, as we have a very unbalanced panel, due to the merging of heterogeneous country-specific mortality datasets.}

We emphasize results from specifications that model temperature with a 4\textsuperscript{th}-order polynomial and include fixed effects for age × ADM2 and country × age × year. The age × ADM2 fixed effects \( \alpha_{ai} \) ensure that we isolate within-location year-to-year variation in temperature and rainfall exposure, which is plausibly randomly assigned (Deschênes and Greenstone, 2011; Hsiang, 2016). The country × age × year fixed effects \( \delta_{act} \) account for any time-varying trends or shocks to age-specific mortality rates which are unrelated to the climate. While the binned model is the most flexible functional form, this method is demanding of the data, a constraint that binds particularly in models that allow for heterogeneity in temperature sensitivity (see Section 4.2). The polynomial model strikes a balance between providing sufficient flexibility to capture important nonlinearities, parsimony, and limiting demands on the data. Robustness of this model to alternative fixed effects and error structures is shown in Section 5, and to alternative functional forms for temperature and climate datasets in Appendix G.1.

In Equation 9, the estimated response function \( \hat{g}(T_{it}) \) is an average treatment effect across each of our three age categories. However, there is substantial evidence from previous research and within our data that individuals of different ages respond heterogeneously to temperature variation (e.g., Deschênes and Greenstone, 2011). Because future shifts in demographics may be large, such heterogeneity may have important consequences for projected mortality rates under climate change. Therefore, the model we focus on throughout this paper is a modified version of Equation 9, in which a separate response function is identified for each age category. We execute this regression in a single pooled model where both terms in \( g(T_{it}) \) and the \( R_{it} \) variables are interacted with a set of age group dummy
variables. Denote these age-specific nonlinear relationships as \( g_{a}(T_{it}) \) and \( \phi_{1,ca} R_{it} + \phi_{2,ca} R_{it}^2 \).

### 4.2 Heterogeneity in the mortality-temperature response function based on climate and income

The average treatment effect identified through Equation 9 and its variants is likely to mask important differences in the sensitivity of mortality rates to changes in temperature across the diverse populations included in our sample. These differences in sensitivity reflect differential investments in adaptation – i.e. different levels of \( b^* \). To capture such heterogeneity, we develop a simple two-factor interaction model using average temperature (i.e. long-run climate) and average incomes to explain cross-sectional variation in the estimated mortality-temperature relationship. This approach provides estimates of adaptation and of income effects, as they are observed in the historical record.\(^{32}\)

The two factors defining this interaction model come directly from the theoretical framework in Section 2. First, a higher average temperature incentivizes investment in adaptive behaviors, as the return to any given adaptive mechanism is higher the more frequently the population experiences life-threatening high-heat days. In Section 2, this was represented by \( b^* \) being a function of climate \( C \), because the expected marginal mortality benefit of additional adaptation is dependent on expected number of dangerously hot and cold days. In our empirical specification, we use a parsimonious parameterization of the climate, interacting our nonlinear temperature response function with the location-specific long-run average temperature.\(^{33}\) Second, higher incomes loosen agents’ budget constraints and hence facilitate adaptive behavior. In Section 2, this was captured by optimal adaptation \( b^* \) being an implicit function of income \( Y \).

To see how we estimate this interaction model, note that any of our four parameterizations of \( g_{a}(T_{it}) \) can be written as 

\[
M_{aict} = \sum_{p} \left( \gamma_{p,0,a} + \gamma_{p,1,a} TMEAN_s + \gamma_{p,2,a} \log(GDP_{pc}s) \right) T_{it}^p + \phi_{1,ca} R_{it} + \phi_{2,ca} R_{it}^2 + \alpha_{ai} + \delta_{act} + \varepsilon_{ait} \tag{10}
\]

where \( s \) refers to ADM1-level (e.g., state or province), and \( p \) denotes the term in the nonlinear function of temperature. All other variables are defined as in Equation 9, \( TMEAN \) is the sample-period average of daily temperature, and \( GDP_{pc} \) is the sample-period average of annual GDP per capita.\(^{35}\) In contrast to the uninteracted models in Equation 9, we estimate Equation 10 without any regression weights since

\(^{32}\)Hsiang and Narita (2012) use the same two-factor model to estimate tropical cyclone mortality and adaptation.

\(^{33}\)In Appendix G.3, we show robustness of this parsimonious characterization of the long-run climate to a more nuanced specification. There, we interact our nonlinear temperature variables with long-run average degree days below 20\(^\circ\)C, and with long-run average degree days above 20\(^\circ\)C to capture the fact that locations with similar annual average temperature may have very different distributions of degree days, due to heterogeneous seasonality. As is detailed in the Appendix, our results are robust to this alternative specification.

\(^{34}\)For example, in the polynomial case, \( T_{it}^p \) indicates daily average temperature raised to the power \( p \), while in the binned case, \( T_{it}^p \) indicates the total number of days in year \( t \) that fall into bin \( p \).

\(^{35}\)The model does not include uninteracted terms for \( TMEAN \) and \( GDP_{pc} \) because they would be collinear with \( \alpha_{ai} \).
we are explicitly modeling heterogeneity in treatment effects rather than integrating over it (Solon, Haider, and Wooldridge, 2015).

5 Results: The mortality-temperature relationship

5.1 Pooled multi-country mortality-temperature response function

Pooling subnational mortality records across 41 countries, we estimate Equation 9, showing results for the mortality-temperature response function obtained with a 4th-order polynomial in daily average temperature. Table 2 displays our main result for an all-age mortality response, showing the marginal effects at various temperatures. These estimates can be interpreted as the change in the number of deaths per 100,000 per year resulting from one additional day at each temperature, compared to the marginal day being 20°C (68°F), and represent average treatment effects across all age categories. Columns (1)-(3) increase the saturation of temporal controls in the model specification, ranging from country-year fixed effects in column (1) to country-year-age fixed effects and state-level linear trends in column (3). The U-shaped response common in the prior literature is evident across all specifications. Choosing column (2) as our preferred specification, we find, for example, that a day at 35°C (95°F) leads to an increase in the all-age mortality rate of approximately 0.4 extra deaths per 100,000, relative to a day at 20°C. A day at -5°C (23°F) similarly increases the all-age mortality rate, relative to a moderate day, by 0.3 deaths per 100,000.

Robustness to temperature functional form. To ensure robustness of our result across specifications, we estimate Equation 9 for each of the functional forms of temperature described above. Results for these are displayed in Figure 16. The binned functional form is an important benchmark, because it is the closest to being fully non-parametric; the similarity of the binned functional form response functions with the ones from the three other functional forms is reassuring. We focus on results using the 4th-order polynomial for parsimony.

Alternate climate data. The main effect for our all-age response function is plotted in Figure 16 for the GMFD climate data (top) and the BEST climate data (bottom). These data are drawn from independent sources, as described in Section 3, and there is broad similarity in the response functions across all functional forms and both sets of data. The figure illustrates the importance of a nonlinear treatment of temperature impacts, while also showing broad agreement across various functional forms for both climate datasets.

Age group heterogeneity. It is likely that age cohorts respond differently to temperature (Deschênes and Moretti, 2009). This heterogeneity is important to account for, as there exist large differences in age distributions across countries today and we expect considerable demographic transitions in the future. We test for heterogeneity across age groups by estimating Equation 9 with the inclusion of age group interactions, which provide separate mortality-temperature response functions for each of the three age subcategories. The regression results are shown in Table 3, with estimates from column (2) plotted in Figure 17 for reference. It is apparent that there is substantial heterogeneity across age groups.

To estimate column 4 of Table 3, we calculate an ADM1-age specific weight, equal to the average value of the squared ADM2-age level residuals, and inverse-weight the regression using this weight. For some ADM2s, there are insufficient observations to identify age-specific variances; to ensure stability, we dropped the ADM2s with less than 5 observations per age group. This leads us to drop 246 (of >800,000) observations in this specification.
Table 2: Temperature-mortality response function estimated using pooled subnational data across 41 countries and 39% of the global population. This table shows coefficient estimates (standard errors) for a temperature-mortality response function estimated using pooled subnational data across 41 countries and 39% of the global population. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD temperature data with a sample that was winsorized at the 1% level. Point estimates indicate the marginal effect of increasing daily average temperature by 1°C, evaluated at each temperature value shown.

<table>
<thead>
<tr>
<th>Temperature (°C)</th>
<th>Mortality Rate</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>35°</td>
<td></td>
<td>0.356***</td>
<td>0.395**</td>
<td>0.183</td>
<td>0.610**</td>
<td>0.426***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.130)</td>
<td>(0.169)</td>
<td>(0.118)</td>
<td>(0.260)</td>
<td>(0.163)</td>
</tr>
<tr>
<td>30°</td>
<td></td>
<td>0.277***</td>
<td>0.280***</td>
<td>0.120*</td>
<td>0.310***</td>
<td>0.296***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.070)</td>
<td>(0.081)</td>
<td>(0.066)</td>
<td>(0.100)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>25°</td>
<td></td>
<td>0.137***</td>
<td>0.131***</td>
<td>0.053</td>
<td>0.111***</td>
<td>0.138***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
<td>(0.035)</td>
<td>(0.039)</td>
<td>(0.030)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>0°</td>
<td></td>
<td>0.112</td>
<td>0.105</td>
<td>0.108</td>
<td>0.139**</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.122)</td>
<td>(0.125)</td>
<td>(0.098)</td>
<td>(0.066)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>-5°</td>
<td></td>
<td>0.293**</td>
<td>0.261*</td>
<td>0.194*</td>
<td>0.237**</td>
<td>0.201</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.149)</td>
<td>(0.154)</td>
<td>(0.104)</td>
<td>(0.095)</td>
<td>(0.145)</td>
</tr>
</tbody>
</table>

Adj R-squared | 0.983 | 0.989 | 0.991 | 0.999 | 0.989 |
N | 820697 | 820237 | 820237 | 820237 | 820237 |
Adm2-Age FE | Yes | Yes | Yes | Yes | Yes |
Cntry-Yr FE | Yes | - | - | - | - |
Cntry-Yr-Age FE | - | Yes | Yes | Yes | Yes |
Adm1-Yr-Age Linear trend | - | - | Yes | - | - |
FGLS | - | - | - | Yes | - |
13-month exposure | - | - | - | - | Yes |

Standard errors clustered at the ADM1 level. All regressions are population-weighted. *** p<0.01, ** p<0.05, * p<0.1

People over the age of 64 experience approximately 4.5 extra deaths per 100,000 for a day at 35°C compared to a day at 20°C, and this is a substantially larger effect than that for the younger cohorts, which exhibit little response. This age group is also more severely affected by cold days than are the younger age cohorts; the estimates suggest that people over the age of 64 experience 3.4 extra deaths per 100,000 for a day at -5°C compared to a day at 20°C, while there is relatively little mortality response to these cold days for other age categories. Overall, these results reveal that the elderly are disproportionately harmed by additional hot days and disproportionately benefit from reductions in cold days. These findings from 41 countries are consistent with prior evidence on age heterogeneity in the mortality-temperature relationship in the United States (Deschênes and Moretti, 2009). It is important to note, however, that the oldest age group (over 64 years) accounts for a relatively small proportion of the global population today, limiting its similarity to the average treatment effect in Table 2.
Table 3: Temperature-mortality response function with demographic heterogeneity estimated using pooled subnational data. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level. Point estimates indicate the marginal effect of increasing daily average temperature by 1°C, evaluated at each temperature value shown.

<table>
<thead>
<tr>
<th></th>
<th>Mortality rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>Panel A: &lt;5 years of age</strong></td>
<td></td>
</tr>
<tr>
<td>35°</td>
<td>2.135***</td>
</tr>
<tr>
<td></td>
<td>(0.479)</td>
</tr>
<tr>
<td>30°</td>
<td>1.268***</td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
</tr>
<tr>
<td>0°</td>
<td>-2.142***</td>
</tr>
<tr>
<td></td>
<td>(0.318)</td>
</tr>
<tr>
<td>-5°</td>
<td>-2.258***</td>
</tr>
<tr>
<td></td>
<td>(0.389)</td>
</tr>
<tr>
<td><strong>Panel B: 5 - 64 years of age</strong></td>
<td></td>
</tr>
<tr>
<td>35°</td>
<td>4.533***</td>
</tr>
<tr>
<td></td>
<td>(0.654)</td>
</tr>
<tr>
<td>30°</td>
<td>2.538***</td>
</tr>
<tr>
<td></td>
<td>(0.256)</td>
</tr>
<tr>
<td>0°</td>
<td>-4.140***</td>
</tr>
<tr>
<td></td>
<td>(0.299)</td>
</tr>
<tr>
<td>-5°</td>
<td>-4.730***</td>
</tr>
<tr>
<td></td>
<td>(0.377)</td>
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<tr>
<td><strong>Panel C: &gt;64 years of age</strong></td>
<td></td>
</tr>
<tr>
<td>35°</td>
<td>-3.927**</td>
</tr>
<tr>
<td></td>
<td>(1.769)</td>
</tr>
<tr>
<td>30°</td>
<td>-1.922**</td>
</tr>
<tr>
<td></td>
<td>(0.768)</td>
</tr>
<tr>
<td>0°</td>
<td>8.140***</td>
</tr>
<tr>
<td></td>
<td>(0.744)</td>
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<tr>
<td>-5°</td>
<td>10.305***</td>
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<td>(0.892)</td>
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<tr>
<td>Adj R-squared</td>
<td>0.982</td>
</tr>
<tr>
<td>N</td>
<td>820697</td>
</tr>
<tr>
<td>Adm2-Age FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Cntry-Yr FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Cntry-Yr-Age FE</td>
<td>-</td>
</tr>
<tr>
<td>Adm1-Yr-Age Lin TR</td>
<td>-</td>
</tr>
<tr>
<td>FGLS</td>
<td>-</td>
</tr>
<tr>
<td>13-month exposure</td>
<td>-</td>
</tr>
</tbody>
</table>

Standard errors clustered at the ADM1 level. All regressions are population-weighted. *** p<0.01, ** p<0.05, * p<0.1
**Precision-weighting.** Due to the large variety of sources for the mortality data, some of our data sources are drawn from countries which may have less capacity for data collection than others in the sample. To account for the possibility that some data sources are less precise, we re-estimate our model using Feasible Generalized Least Squares (FGLS) under the assumption of constant variance within each ADM1 unit.\(^{37}\) The results for this procedure are displayed in column (4) of Tables 2 and 3. The differences between columns (2) and (4) are small, from which we conclude that the variability in data quality, after winsorizing, is not a major threat to the validity of our analysis.

**Lagged exposure.** Numerous previous papers have demonstrated that temperatures have a lagged effect on health and mortality (e.g., Deschênes and Moretti, 2009; Barreca et al., 2016; Guo et al., 2014). For example, cold temperatures can influence mortality rates for up to 30 days (Deschênes and Moretti, 2009). Our main analysis is conducted at the annual level, so that lagged effects within and across months in the same calendar year are accounted for in net annual mortality totals. However, to allow for the fact that January mortality may result from up to a four-week lag of temperature exposure (that includes the prior December), we define a “13-month exposure” window such that for a given year \(t\), exposure is calculated as January to December temperatures in year \(t\) and December temperature in year \(t - 1\). These results are shown in column (5) of Tables 2 and 3. Results using this specification are neither substantively nor statistically different from our main estimate in column (2).

### 5.2 Subnational heterogeneity in the mortality-temperature response function

The estimation of Equation 10 provides an opportunity to test for systematic heterogeneity in the mortality-temperature response function. Specifically, this model interacts the temperature variables with ADM1-level covariates of average climate and average income. The results for the interaction effects are reported in Table 4 for each of the three age groups of interest. Each coefficient represents the marginal effect of increasing the relevant covariate (e.g. \(T\text{MEAN}\)) by one unit on the temperature-sensitivity of mortality rates, evaluated at the daily temperature shown. For example, we see that higher incomes lower the sensitivity of infant mortality to both cold temperatures (coefficient of -0.87 on a -5°C day), as well as to hot temperatures (coefficient of -0.93 on a 35°C day). Although not all of the coefficients would be judged statistically significant by conventional criteria, it is noteworthy that higher incomes and warmer climates both mitigate the mortality consequences of hot days for all age categories. The effects of income and climate on the impacts of cold days are less consistent, but there are already very few days at these temperatures in most parts of the world, limiting the importance of these effects to calculation of the impacts of climate change.

As these terms are difficult to interpret, we visualize the heterogeneity by dividing the sample into terciles of income and climate (i.e. the two interaction terms), creating nine discreet categories describing the \(\log(GDP\text{pc}) \times T\text{MEAN}\) space. We plot the predicted response functions at the mean value of covariates within each of these nine categories. This results in a set of predicted response

\(^{37}\)To do this, we estimate the model in Equation 9 using population weights and our preferred specification (column (2) of Table 2). Using the residuals from this regression, we calculate an ADM1-level weight, equal to the average value of the squared residuals, where averages are taken across all ADM2-age-year level observations that fall within a given ADM1. We then inverse-weight the regression in a second stage, using this weight. All ADM2-age-year observations within a given ADM1-age category are given the same weight in the second stage, where ADM1 locations with lower residual variance are given higher weight.
### Table 4: Marginal effect of covariates on temperature sensitivity of mortality rates.

Coefficients (standard errors) represent the marginal effect of increasing each covariate by one unit on the temperature sensitivity of mortality rates, evaluated at each of the shown daily average temperatures. Regression is a fourth-order polynomial in daily average temperature, estimated using GMFD weather data with a sample that was winsorized at the 1% level. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects. Each temperature variable is interacted with each covariate.

<table>
<thead>
<tr>
<th></th>
<th>Age &lt; 5</th>
<th></th>
<th></th>
<th></th>
<th>Age &gt;64</th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>log(GDPpc)</td>
<td>TMEAN</td>
<td>log(GDPpc)</td>
<td>TMEAN</td>
<td>log(GDPpc)</td>
<td>TMEAN</td>
<td>log(GDPpc)</td>
<td>TMEAN</td>
</tr>
<tr>
<td>35°C</td>
<td>-0.928*</td>
<td>-0.102*</td>
<td>-0.236</td>
<td>-0.031*</td>
<td>-4.658*</td>
<td>-0.686**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.535)</td>
<td>(0.053)</td>
<td>(0.162)</td>
<td>(0.018)</td>
<td>(2.388)</td>
<td>(0.332)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30°C</td>
<td>-0.264</td>
<td>-0.044</td>
<td>-0.017</td>
<td>-0.014</td>
<td>-0.080</td>
<td>-0.299**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.277)</td>
<td>(0.027)</td>
<td>(0.068)</td>
<td>(0.009)</td>
<td>(0.919)</td>
<td>(0.141)</td>
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</tr>
<tr>
<td>0°C</td>
<td>-0.765</td>
<td>0.034</td>
<td>0.050</td>
<td>-0.029*</td>
<td>1.985</td>
<td>-0.718***</td>
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<tr>
<td></td>
<td>(0.528)</td>
<td>(0.030)</td>
<td>(0.169)</td>
<td>(0.018)</td>
<td>(2.144)</td>
<td>(0.153)</td>
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<td>-5°C</td>
<td>-0.873</td>
<td>0.035</td>
<td>0.206</td>
<td>-0.040**</td>
<td>6.019*</td>
<td>-0.888***</td>
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<td></td>
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<tr>
<td></td>
<td>(0.619)</td>
<td>(0.031)</td>
<td>(0.247)</td>
<td>(0.020)</td>
<td>(3.207)</td>
<td>(0.205)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adj R-squared: 0.933
Observations: 820237
Adm2-Age FE: Yes
Cntry-Yr-Age FE: Yes

Standard errors clustered at the state level
*** p<0.01, ** p<0.05, * p<0.1

---

functions that span the joint distribution of income and average temperature within our sample data, shown in Figure 2 for a pooled all-age model. Each subpanel in Figure 2 shows a temperature response function for the all-age mortality rate, evaluated at a particular level of income and average climate. Average incomes are increasing in the y-direction and average temperatures are increasing in the x-direction.

The results in Figure 2 are consistent with the predictions from our theoretical framework in Section 2. Recall that we expect increased frequency of exposure to higher temperatures to incentivize investment in adaptive behaviors or technologies, as the marginal mortality benefit of adaptation is higher in hotter locations. This would lead to lower temperature sensitivities to heat in places which are warmer. Indeed, across all three age categories, moving from the coldest to the hottest tercile saves on average 2.89 deaths per 100,000 at 35°C. Similarly, a loosening of the budget constraint, as proxied by increasing GDP per capita, should enable individuals to invest further in adaptation. Here too, the basic finding is visually apparent as the impact of hot days on mortality declines as one moves from the lowest to highest income tercile for all three temperature terciles; on average, moving from the poorest to the richest tercile in the sample saves 1.11 deaths per 100,000 at 35°C across all age categories.

Based on these results, it is apparent that the primary margins of adaptation to temperature relevant to climate change are at the extremes of the temperature distribution. There is little or no adaptation occurring in the middle part of the temperature distribution. Income is protective on the

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38 Versions of Figure 2 for each age group individually are shown in Appendix I.1.
Figure 2: Heterogeneity in the mortality-temperature relationship (all-age mortality rate). Each panel represents a predicted response function for the all-age mortality rate for a subset of the income-average temperature covariate space within our data sample. Response functions in the lower left are the predicted mortality-temperature sensitivities for poor, cold regions of our sample, while those in the upper right apply to the wealthy, hot regions of our sample. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level on the top end of the distribution only. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects, and where each temperature variable is interacted with each covariate.
hottest days for the middle and older age category, and is additionally beneficial on the coldest days for the youngest age category. As evidenced in Figure 2 and Appendix I.1, the richest regions exhibit substantial flattening of the response curve under warmer average climates. This is particularly the case on hot days, and is consistent with previous evidence from the United States – both Barreca et al. (2016) and Heutel, Miller, and Molitor (2017) show a steep decline in mortality sensitivity to heat when moving from the hottest to the coolest average climates within the United States.

6 Methods: Spatial and temporal projections of the mortality-temperature relationship

6.1 Spatial projection: Constructing a globally representative response

A key challenge to comprehensive analysis of the global mortality-temperature relationship is unavailability of data throughout much of the world. Although we have, to the best of our knowledge, compiled the most comprehensive mortality data file ever collected, our 41 countries only account for 39% of the global population (56% if India is included, although it only contains all-age mortality rates). This leaves more than 4.2 billion people unrepresented in the analysis of the previous section. Relying only on this subsample would present an incomplete picture of the global impact of climate change.

Our solution to this data sparsity is to use the results from the estimation of Equation 10 on the limited 39% global sample to estimate the sensitivity of mortality to temperature across the entire world. Specifically, the results from this model enable us to use two observable characteristics – average temperature and income – to predict the mortality-temperature response function for each of our 24,378 impact regions where satellite imagery is combined with other data sources to construct high-resolution estimates of average income and average temperature (see Section 3). We combine these two covariates with our multidimensional response surface in Equation 10 to construct a complete function characterizing temperature sensitivities for each level of daily temperature exposure.

The projected response function for each impact region \( r \) requires three ingredients. The first are the \( \hat{\gamma}'s \) from the estimation of Equation 10. Second, because data on GDP per capita are not available at the impact region level, we use the procedure described in Section 3.2 to predict high-resolution impact region-level income using national income statistics in combination with night lights imagery from the NOAA’s Defense Meteorological Satellite Program (DSMP). Third, we calculate average daily temperature (i.e. a measure of the long-run climate) for each impact region using the same temperature data that were assembled for the regressions in Equations 9 and 10.

With these impact region-level data in hand, we predict the shape of the response function for each age group for each region, up to a constant. These response functions are described by calculating coefficients for each temperature variable \( p \), age group \( a \), impact region \( r \), and year \( t \), which we denote as \( \hat{\beta}_{art} \):

\[
\hat{\beta}_{art}^p = \hat{\gamma}_{0,a}^p + \hat{\gamma}_{1,a}^p TMEAN_{rt} + \hat{\gamma}_{2,a}^p \log(GDP_{pc})_{rt}
\]

(11)

where the various fixed effects are unknown and omitted, since they are unaffected by a changing weather distribution. To describe predicted response functions for all impact regions \( r \) in the present, we evaluate the values of the covariates at the baseline period \( t = 2015 \). This results in a spatially
Figure 3: Joint sample coverage of income and long-run average temperature. Coverage in our sample evaluated over impact regions (red-orange), as compared to the global sample of impact regions (grey-black). Panel A shows in grey-black the global sample for regions in 2015. Panel B shows in grey-black the global sample for regions in 2100 under a high-emissions scenario (RCP8.5) and a median growth scenario (SSP 3). In both panels, the in-sample frequency in red-orange indicates coverage for impact regions within our data sample in 2015.

heterogeneous and globally comprehensive set of response functions, each of which is specific to an impact region. Note that this approach implies that every impact region is assigned a predicted response function. Once this step is complete, we have a unique set of age-specific predicted response functions for each location on earth.

The credibility of the predicted response functions for regions where mortality data are unavailable will be enhanced if there is overlap in the GDP-climate space between regions with and without available mortality data. Panel A of Figure 3 explores this overlap in 2015, where the grey squares reflect the joint distribution of GDP and climate in the full global partition of 24,378 impact regions and orange squares represent the analogous distribution only for the impact regions in the sample used to estimate equations 9 and 10. We note that temperatures in the global sample are generally well covered by our data, although we lack coverage for the poorer end of the income spectrum due to the scarcity of mortality data in poorer countries. However, panel B in Figure 3 shows that our sample is fairly representative of global temperatures and incomes in 2100, after locations have warmed and experienced income growth.

6.2 Temporal projection: Accounting for future adaptation benefits

To develop estimates of the mortality risks due to climate change, we allow each impact region’s mortality-temperature response function to evolve over time. Just as with the spatial extrapolation exercise described above, we model the evolution of response functions based on changes to average climate and GDP per capita, again using the estimation results from fitting Equation 10. Relying on the parameters $\hat{\gamma}$ from Equation 10, we allow the response function in region $r$ and in year $t$ to evolve over time as follows:

1. A 15-year moving average of temperatures for region $r$ is updated using the temperature from
year $t$ to generate a new level of $TMEAN_{rt}$.

2. A 13-year moving average of income per capita in region $r$ is calculated using national forecasts from the Shared Socioeconomics Pathways (SSP), combined with our procedure for allocating incomes within each country, to generate a new value of $\log(GDP_{pc})_{rt}$. The length of this time window is empirically derived. Appendix H.2 provides details.

3. The response curve is calculated according to Equation 11 with the updated values of $TMEAN_{rt}$ and $\log(GDP_{pc})_{rt}$ from Steps 1 and 2.

We then apply projected changes in the climate to these spatially and temporally heterogeneous response functions in order to generate predicted impacts of climate change on mortality through the 21st century. To reflect climate and statistical uncertainty in this calculation, we first compute the nonlinear transformations of daily average temperature that are used in the function $g(T_{rt})$ under both the RCP4.5 and RCP8.5 emissions scenarios for all 33 GCM projections (as described in Section 3.2). This weighted distribution of GCMs captures uncertainties in the climate system as projected into the 21st century. A second source of uncertainty in our projected impacts arises from the econometric estimates of response functions; i.e. uncertainty in the estimate of each of the $\gamma^p$s. In order to account for these sources of uncertainty, we draw multiple values from across the full distribution of these $\gamma^p$ terms, accounting for their covariance (although we also report projections where we hold all estimated terms at their central values). The resulting Monte Carlo calculation is highly computationally intensive and incorporates uncertainty from climate and econometric sources (Burke et al., 2015). These high-resolution projected impact estimates extend only to the year 2100, as both the 33 high-resolution GCMs that we use only simulate the climate through to 2100. Similarly, the socioeconomic scenarios we use to project income and demographic structure end in 2100. In Section 8 we detail a method for extrapolation of damage estimates through 2300, which are used to construct values for the social cost of carbon (SCC).

In generating these projected impacts, we impose two simple but important assumptions, guided by economic theory and the physiological literature. First, we impose the constraint that full adaptation is characterized by a flat response function having a slope equal to zero everywhere. That is, we define the fully adapted state as one in which variation in temperature has no effect on mortality. This assumption is important because Equation 10 parameterizes the flattening of the U-shaped response function such that, with enough warming or sufficiently high income, the mortality-response function would become an inverted-U-shape. This is guaranteed to occur mechanically simply as a result of extrapolating response functions out of the support of historically observed data. Because the marginal effect of hot and cold temperatures is declining with income growth from an initially positive value, they must eventually pass through zero and begin to be negative. To prevent this “adaptation overshoot,” we simply hold marginal effects at zero and assume they cannot become negative.

39GDP per capita is provided in the SSP projections only at 5-year increments. The values are held constant between SSP 5-yearly updates of values. The temporal pattern of income growth from the SSPs is maintained, but we scale the value by $\frac{GDP_{pc,rt}}{GDP_{pc,0}}$, the ratio of a future income per capita to the baseline value in 2015.

40We can derive a duration over which updating occurs in the case of income due to substantial time series variation of income in the data. For temperature, the historical trends have so far been small, making derivation of a comparable duration difficult.

41See Appendix H.1 for details on these assumptions and their implementation.

42To implement this assumption in projections of future impacts, we first identify the location-specific minimum
Second, we assume that rising income cannot make individuals worse off, in the sense of increasing the temperature sensitivity of mortality. Because increased income per capita strictly expands the choice set of individuals considering whether to make adaptive investments, it should not increase the effect of temperature on mortality rates. We place no restrictions on the cross-sectional effect of income on the temperature sensitivity when estimating Equation 10, but we constrain the effect of marginal effect of income on temperature sensitivity to be weakly negative in future projections. This assumption never binds for temperature sensitivity to hot days; however, it does bind for the >64 age category under realized temperatures in 16% and 14% of impact regions in 2050 and 2100, respectively.

Under these two assumptions, we estimate projected impacts separately for each impact region for each day from 2015 to 2100. We then aggregate these high resolution effects to state, country, and global levels, using population weighting. These results are detailed in Section 7.

### 6.3 Implementing empirical estimation of bounds on adaptation costs

The full cost of the mortality risk due to climate change is the sum of the observable change in mortality and adaptation costs. The latter cannot be observed directly; however, as derived in Section 2, we can recover an expression for adaptation costs that is empirically tractable. Theoretically, upper and lower bounds on these costs can be computed by taking the difference between the total and partial derivative of expected mortality risk with respect to changes in the climate. Here, we describe a practical implementation for this calculation.

The basic idea behind the upper bound approach is that with homogenous agents and no heterogeneity in costs across locations, marginal adaptation costs are exactly equal to the marginal benefits of adaptation for all agents. Thus, estimation of the marginal benefits of adaptation reveal the otherwise unobservable marginal costs of adaptation, meaning that this revealed preference strategy only requires that we observe the shape of the survival benefits function \( VSL(1 - \hat{f}) \) along the equilibrium \( \mathbf{b}^*(C) \). In practice, we use estimation results from the fitting of Equation 10 to obtain estimates of the total derivative of the mortality risk function \( \hat{f}(.) \) with respect to climate \( \left( \frac{df}{dC} \right) \) and the partial derivative \( \left( \frac{\partial \hat{f}}{\partial C} \right) \). Taking expectations of Equation 10 specifies expected mortality risk for an age group \( a \) in region \( r \) for year \( t \):

\[
\hat{f}(.)_{art} = E[\hat{f}(.)_{art}] = \sum_p \left( \hat{\gamma}_{0,a}^p + \hat{\gamma}_{1,a}^p TMEAN_{rt} + \hat{\gamma}_{2,a}^p \log(GDP_{pc})_{rt} \right) E[T^p]_{rt} + ... \tag{12}
\]

mortality temperature in each impact region during the baseline year of 2015, using our predicted mortality-temperature response functions. We constrain this response function minimization problem to select a temperature within the range of 10°C to 25°C, following extensive evidence from epidemiology and ergonomics indicating that temperatures outside this range are unlikely to be physiologically optimal (see Appendix H.1 for details). In calculating projected impacts, we then allow adaptation to occur (i.e. allow the response function to flatten) until the minimum mortality risk level is reached at each temperature. For example, at 35°C, this assumption binds for the >64 age category in 11% and 44% of impact regions in 2050 and 2100, respectively, in the CCSM4 climate model. Age groups will be affected by this assumption differentially, and both climate model and socioeconomic projections will affect the reported values. See Appendix H.3 for results in which the rate of adaptation is deterministically assumed to slow. Under this alternative scenario, Assumption #1 binds much less frequently.

The assumption that rising income cannot increase the temperature sensitivity of mortality does not bind for hot days because our estimated marginal effects of income are negative for high temperatures (see Table 4).
where we omit the various estimated terms orthogonal to temperature. The estimates \( \hat{\beta}_p \) describe the shape of the annual response function taking as inputs the summary climate parameter \( \text{TMEAN} \) and log income per capita, where the \( \hat{\gamma}_p \) coefficients are used to construct \( \hat{\beta}_p \) are recovered from the regression in Equation 10. \( \mathbb{E}[T^p|_{rt}] \) is an estimate for the expected value of \( T^p \) in region \( r \) and year \( t \). Using Equation 12, we compute \( \hat{f}_{art} \) in each year \( t \) of each simulation run during the years 2015-2100. Both \( \text{TMEAN}_{rt} \) and \( \mathbb{E}[T^p|_{rt}] \) are constructed using an average of weather realizations for the prior 15 years, with weights of historical observations linearly declining in time. Below we omit subscripts for clarity, but each calculation is conducted yearly for each age and region.

In order to differentiate expected mortality risk \( \hat{f}(\cdot) \) with respect to a small change in climate \( C \), we compute how \( \hat{f}(\cdot) \) would change if the distribution of daily temperatures shifted due to a change in climate. The climate affects the distribution of daily temperatures, which affects expected mortality directly by altering the distribution of daily weather events that populations are exposed to. Importantly, our econometric framework allows us to develop estimates of both the partial derivative, where no adaptation is allowed to take place, and the total derivative, which reflects optimal adaptations.

In our econometric framework, the partial derivative is captured through a change in expected events, described by the vector \( \mathbb{E}[T^p] \), whose elements are then multiplied by \( \hat{\beta}_p \). The partial effect of the climate on expected mortality risk is therefore:

\[
\frac{\partial \hat{f}}{\partial C} = \frac{\partial \hat{f}}{\partial \mathbb{E}[T^p]} \frac{\partial \mathbb{E}[T^p]}{\partial C} = \sum_p \hat{\beta}_p \frac{\partial \mathbb{E}[T^p]}{\partial C}
\]  

(13)

where \( \beta_p \) is evaluated at a climate and income that is “held fixed” for that moment in time, since the partial effect must exclude any compensatory behavior by populations. Here, \( \frac{\partial \mathbb{E}[T^p]}{\partial C} \) is the change in the expected value for these measures that describe the daily temperature distribution, resulting from an incremental change in climate.

In contrast, the total derivative of expected mortality risk with respect to a change in climate reflects endogenous adaptations through \( b \) that will change the shape of the response function in each region. Our econometric framework captures these effects through the \( \hat{\gamma}_p T\text{MEAN} \) terms that modify the shape of a region’s response function (by changing \( \hat{\beta}_p \)) conditional on the long run average conditions. When we compute the total derivative of \( \hat{f}(\cdot) \) with respect to the climate we consider both the effect of changes to \( \mathbb{E}[T^p] \) and the effect of adaptive adjustments parameterized here though \( \hat{\gamma}_p T\text{MEAN} \). The total effect of the climate on expected mortality risk is then:

\[
\frac{d\hat{f}}{\partial C} = \frac{\partial \hat{f}}{\partial C} + \frac{\partial \hat{f}}{\partial b} \frac{\partial b}{\partial C} = \frac{\partial \hat{f}}{\partial \mathbb{E}[T^p]} \frac{\partial \mathbb{E}[T^p]}{\partial C} + \frac{\partial \hat{f}}{\partial T\text{MEAN}} \frac{\partial T\text{MEAN}}{\partial C}
\]

(14)

\[
= \sum_p \left( \hat{\beta}_p \frac{\partial \mathbb{E}[T^p]}{\partial C} \right) + \left( \sum_p \hat{\gamma}_p \mathbb{E}[T^p] \right) \frac{\partial T\text{MEAN}}{\partial C}
\]

where the second summation captures the ways in which incremental changes in \( \text{TMEAN} \) affects the shape of the mortality response function through its effects on each coefficient in the polynomial. \( \frac{\partial \text{TMEAN}}{\partial C} \) is the amount that average temperatures change during a period of incremental climatic change over which populations adapt.
Both Equations 13 and 14 are fully computable for years in our projection using a combination of empirically estimated parameters ($\hat{\beta}, \hat{\gamma}$) and climate projections ($\hat{E}[T^p], \hat{T_{MEAN}}$). Substituting these estimates of the partial and total derivatives of $\hat{f}_t$ into Equation 8 allows us to estimate an upper bound on non-marginal changes in adaptation costs incurred as the climate of a population changes. As discussed in Section 2.3, this substitution of estimated marginal benefits for unobserved marginal costs is reasonable under the assumption of both homogeneous agents and homogeneous sets of available adaptation technologies, and generates an upper bound estimate of costs, as all marginal benefits of adaptation are completely offset by estimated marginal costs. In all high-resolution climate projections that we use, all climate changes occur gradually over time, causing climate in a region to be a function of time. Thus, in each projection, we solve for the upper bound of adaptation costs as a region’s climate evolves from $C(t_1)$ to $C(t_2)$:

\[
\left[A(b^*(C(t_2), Y)) - A(b^*(C(t_1), Y))\right]^{\text{Upper Bound}} = -VSL \int_{C(t_1)}^{C(t_2)} \left( \frac{df_t}{dC} \frac{\partial \hat{f}_t}{\partial C} \right) dC
\]

\[
= -VSL \int_{t_1}^{t_2} \left( \sum_p \hat{\gamma}_p p \hat{E}[T^p]_{t_1} \right) \frac{\partial T_{MEAN}}{\partial C} \frac{dC}{dt} dt
\]

\[
\approx -VSL \sum_{\tau = t_1}^{t_2} \left( \sum_p \hat{\gamma}_p p \hat{E}[T^p]_{\tau} \right) \left( T_{MEAN}_{\tau} - T_{MEAN}_{\tau - 1} \right)
\]

(15)

where the second equality results from substitution of Equations 13 and 14 into Equation 8 as well as changing the variable of integration from $C$ to $t$. The third equality is noted to be an approximation, because the integral is computed using discreet time-steps of one year in actual implementation. Notably, because the amount of climate change experienced in any single year is small, this approximation introduces limited error. It is also worth noting that income of a region is held constant in Equation 15, since we are only interested in computing additional adaptation expenditures incurred due to the changing climate and not expenditures resulting from rising incomes. These income effects are partialed out econometrically in the $\hat{\gamma}_2 p$ term of Equation 10. The approach for calculating a lower bound on adaptation costs is very similar in that its basis is taking the difference between the total and partial derivative of mortality risk with respect to climate and plugging in the empirically estimated parameters and climate projections. The key difference from Equation 15 is that $\hat{E}[T^p]$ is evaluated at a region’s initial climate, so it is not allowed to evolve as the climate changes. Recall that this approach generates a lower bound on adaptation costs, as it equates estimated marginal mortality benefits of adaptation at the current climate with contemporaneous marginal costs, and assumes that costs increase at least linearly in $b$ (Section 2.3). Specifically for each projection, we solve for the lower bound of adaptation costs as a region’s climate evolves from $C(t_1)$ to $C(t_2)$ as:

\[
\left[A(b^*(C(t_2), Y)) - A(b^*(C(t_1), Y))\right]^{\text{Lower Bound}} \approx -VSL \sum_{\tau = t_1}^{t_2} \left( \sum_p \hat{\gamma}_p p \hat{E}[T^p]_{\tau} \right) \left( T_{MEAN}_{\tau} - T_{MEAN}_{\tau - 1} \right)
\]

(16)

providing a second estimate of adaptation costs that must be below the true cost if adaptation costs
are convex.

Both of these bounds are calculated for each impact region, age group, and year, using $t_1 = 2015$ as the baseline year. In subsequent analysis, to simplify exposition, we use the average of the upper and lower bound estimates as our measure of adaptation costs to form estimates of the damage function and social cost of carbon.

7 Results: The global mortality consequences of future climate change

Section 5 established that mortality has a U-shaped and significant relationship with temperature in our multi-country pooled sample, consistent with previous studies that have covered a narrower geographic scope. We then demonstrated that there is substantial age-heterogeneity in this relationship, which motivates separating the data into three broad age groups for the remainder of the analysis. We find that this result is robust to a variety of specification choices, population-weighting schemes, estimation strategies that limit the potential bias introduced by variability in data collection capacity, and varying lag lengths of exposure. We further identified substantial heterogeneity within our sample due to differences in incomes and average climates. Here, we show how these results are used to extrapolate responses to the parts of the world where historical mortality data are unavailable, allowing us to create the first global average treatment effect of temperature on mortality. Further, we then project these responses into the future to calculate the full mortality cost of climate change, accounting for the costs of adaptation.

7.1 Spatial extrapolation of temperature sensitivity

Figure 4 demonstrates our extrapolation of mortality-temperature response functions to the entire globe. To execute this extrapolation, we use the estimates of $\gamma_p^a$ from Equation 10, combined with time-varying impact region level incomes and average temperatures, to predict response functions for each impact region $r$ in year $t$; we denote these predicted response function coefficients $\hat{\beta}_{art}$, as defined in Equation 11. In panel A, these $\hat{\beta}_{art}$ are plotted for each impact region for baseline (2015) values of income and climate for the oldest age category and for the impact regions that fall within the countries in our mortality dataset (“in-sample”). Despite a shared overall shape, panel A shows substantial heterogeneity across regions in this temperature response. As described above, note that we impose the constraint that response functions cannot fall below a location-specific minimum mortality occurring at an interior temperature. However, in the baseline year 2015, this constraint binds in less than 2% of impact regions at a temperature of 35°C for the >64 age category. In panel B, we show an analogous figure for the youngest age category; this result demonstrates our model’s ability to predict the substantial within-location differences in mortality risk across age groups. Geographic heterogeneity within our sample is shown for hot days in the maps in panels C and D. On each map, the colors indicate the marginal effect of a day at 35°C day, for ages >64 (panel C) and for ages < 5 (panel D); the grey areas are locations where mortality data are unavailable.

Figure 4E–H show analogous figures but now extrapolated to the entire globe. Again, we can fill
in the estimated mortality effect of a 35°C day for regions without mortality data by using location-specific information on income and climate during 2015. The predicted responses at the global scale imply that a 35°C day increases the annual global mortality rate for the oldest age category by 8.6 deaths per 100,000 relative to a day at 20°C; this value is considerably larger than the estimated effect of 4.5 deaths per 100,000 within the sample of countries for which we obtain mortality data. This difference in sensitivity is due to the large protective benefits of income and average temperature, and the differences in these variables between regions with and without historical mortality data. From panels G and H, it is apparent that while populations in hot average climates are generally better adapted, poor locations that are also relatively warm remain relatively susceptible to mortality effects of heat.

Figure 4: Using income and climate to predict response functions globally. In panels A, B, E and F, grey lines are predicted response functions for each impact region, and solid black lines are the unweighted average of the grey lines. Panels C, D, G and H show maps of each impact region’s mortality sensitivity to a day at 35°C, relative to a location-specific minimum mortality temperature. The top row shows all impact regions in the sample of locations with historical mortality data, and the bottom row shows extrapolation to all impact regions globally. All predictions shown are averages over the period 2001-2015.

7.2 Projection of future damages and adaptation

Expected mortality risk under climate change. The previous subsection demonstrated that the model of heterogeneity outlined in Equation 10 allows us to extrapolate mortality-temperature relationships to regions of the world without mortality data today. However, to calculate the full mortality costs of climate change, it is necessary to allow these response functions to change through time to capture the benefits of adaptation. Therefore, we use our model of heterogeneity and downscaled projections of income and climate to predict impact region level response functions for each age group and year, yielding response function coefficients $\hat{\beta}_{p \text{art}}$. Panels A and C of Figure 5 provide an initial look into a key ingredient into projections of future damages and adaptation. In particular, they plot
the spatial distribution of the change in the marginal damages of a 35°C day between 2050 and 2015 and between 2100 and 2015 for the >64 age category. The maps reveal that in most regions of the world, we see a clear downward trend in the sensitivity of mortality rates to high temperatures, as locations get both richer and hotter as the century unfolds. It is noteworthy that the global average effect of an additional 35°C day relative to day at 20°C declines by 6.6 per 100,000 between 2015 and 2100 such that it is just 2 per 100,000 in 2100. In 2015, similarly low sensitivities are only present in places like Houston, Texas, so it is as if the average location in the world in 2100 exhibits Houston-like levels of adaptation after locations become both richer and hotter. Increasing incomes account for 65% of the decline in marginal damages for the 64 age category with adaptation to climate explaining the remainder; income gains account for 72% and 68% for the <5 and 5-64 categories, respectively.

We now use our estimates of adaptation benefits, adaptation costs, and changes in climate exposure to develop measures of the expected costs of climate change induced mortality risk. These measures align with the different models of adaptation outlined in Equations 2, 3, and 4 in Section 2, although they include an additional metric that separates the role of income growth from that of adaptation to warming. As discussed, the most important metric is the full mortality-related costs of climate change, or the sum of the increase in deaths and adaptation costs, shown conceptually in Equation 4. The empirical estimation of each of these measures is displayed here in units of deaths per 100,000, although it is straightforward to monetize these measures using estimates of the value of a statistical life (VSL), and we will do so in the next section. Simplifying to a single response function coefficient \( \hat{\beta} \) and single temperature exposure variable \( T \), and omitting subscripts for impact regions and age groups for clarity, the specific measures of the expected costs of climate induced mortality risk that we estimate for an impact region and age group in a future year \( t \) are:

(i) Mortality effects of climate change without adaptation (recall Equation 2):

\[
\hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{2015}))T_t - \hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{2015}))T_{2015}
\]

(ii) Mortality effects of climate change with benefits of income growth:

\[
\hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{t}))T_t - \hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{t}))T_{2015}
\]

(iii) Mortality effects of climate change with adaptation (recall Equation 3):

\[
\hat{\beta}(TMEAN_{t}, \log(GDP_{pc}_{t}))T_t - \hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{t}))T_{2015}
\]

(iv) Full mortality risk due to climate change (recall Equation 4):

\[
\hat{\beta}(TMEAN_{t}, \log(GDP_{pc}_{t}))T_t - \hat{\beta}(TMEAN_{2015}, \log(GDP_{pc}_{t}))T_{2015} + \frac{1}{VSL} \left[ A(TMEAN_{t}, GDP_{pc}_{t}) - A(TMEAN_{2015}, GDP_{pc}_{t}) \right]^{\text{upper/lower bound}}
\]

44Specifically, these values are \( \hat{\beta}_{pert}(TMEAN_{ar2050}, \log(GDP_{pc}_{ar2050})) - \hat{\beta}_{pert}(TMEAN_{ar2015}, \log(GDP_{pc}_{ar2015})) \) and \( \hat{\beta}_{pert}(TMEAN_{ar2100}, \log(GDP_{pc}_{ar2100})) - \hat{\beta}_{pert}(TMEAN_{ar2015}, \log(GDP_{pc}_{ar2015})) \) for \( a > 64 \).
Year $t = 2015$ is treated as the baseline year, meaning that climate change impacts are defined to be zero. The superscript on (iv) indicates the possibility of either upper or lower bound estimates of adaptation costs, as described in Section 6.3.\(^{45}\)

These four measures are all reported below in the same units, but they differ in important ways. The “mortality effects of climate change without adaptation” metric provides an estimate of the increases in mortality rates when each impact region does not adapt, such that their response function in each year $t$ is a function of their 2015 level of income and average climate. In other words, mortality sensitivity to temperature is assumed not to change with future income or temperature. As discussed in Section 2, this is a benchmark model often employed in previous work.

The “mortality effects of climate change with benefits of income growth” metric allows the response function to change with future incomes, in both the warming and no-warming cases. This metric captures the change in mortality rates that would be expected from climate change if populations became richer, allowing them to spend more resources on adaptation, but they did not respond optimally to warming by adapting above and beyond how they would otherwise cope with their historical climate. The “mortality effects of climate change with adaptation” relaxes this restriction, allowing populations to adjust to experienced temperatures in the warming scenario. This metric is an estimate of the observable deaths that would be expected under a warming climate, accounting for the benefits of optimal adaptation.

The final measure is the most important, as it captures both the benefits and costs of adaptation. Recall that adaptation costs cannot be observed directly, but that we construct estimated bounds using the revealed preference methodology detailed in Section 2. We call this measure the “full mortality risk due to climate change.”

Note that in all expressions of climate change impacts, the first term represents the predicted mortality rate under a future warming climate. The second term represents a counterfactual predicted mortality rate that would be realized under current temperatures. In expression (i), the counterfactual mortality rate is identical to that under current temperatures and incomes. In all other scenarios, the counterfactual mortality rate is one that would be realized under current temperatures, but in a population that benefits from rising incomes over the coming century. This counterfactual thus includes the prediction, for example, that air conditioning will become much more prevalent in a country like India as the economy grows, regardless of whether climate change unfolds or not. By subtracting off this counterfactual, our predicted mortality levels isolate the role of climate change by netting out the effects of economic growth.

Panels B and D of Figure 5 show the spatial distribution of the full mortality risk due to climate change (i.e. expression (iv)) in 2050 and 2100 under the emissions scenario RCP8.5, expressed in death-equivalents (per 100,000). These units are measures of value in lives, which serves as a natural numeraire in our revealed preference framework since we estimate adaptation costs based on lives that could be saved via adaptation, but are not. Note that the use of the these units is why adaptation costs in expression (iv) are multiplied by $\frac{1}{VSL}$.

To construct these estimates, we generate impact-region specific predictions of mortality damages from climate change for all days between 1981 and 2100 (equal to expression (iii)) under a range of

\(^{45}\)Note that the adaptation cost term in expression (iv) is divided by the VSL in order to convert from the expression in dollars in Equation 15 into units of mortality risk.
climate and socioeconomic scenarios. Following the approach outlined in Section 6 and Appendix A, we simultaneously compute associated measures of adaptation costs for each location at each point in time. The figures display the spatial distribution of our main results, depicting the median value across our ensemble of climate models.\footnote{When calculating median values across estimates generated for each of the 33 climate models that form our ensemble, we use model-specific weights. These weights are constructed as described in Appendix C.3 in order to accurately reflect the full probability distribution of temperature responses to changes in GHG concentrations. See Appendix C.3 for details.}

Figure 5 makes clear that the costs of climate change induced mortality risks are distributed unevenly around the world. Despite the gains from adaptation shown in panels A and C, there are large losses in the global south. For example, in Mogadishu, Somalia we predict that climate change by end of century will cause damages equivalent to over 3,700 additional deaths annually under RCP8.5, a total that is composed of 3,000 lives lost and adaptation costs equivalent to the value of 700 deaths. In contrast, there are gains in many impact regions in the global north, including in Oslo, Norway where we predict that the equivalent of 1,100 lives are saved annually.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5.png}
\caption{Spatial and temporal heterogeneity in temperature sensitivity and the death toll of future climate change. Panels A and C indicate the change in mortality sensitivity to hot days (35°C) for the oldest age category (\textgreater 64) between 2015 and 2050 (A), and between 2015 and 2100 (B). Darker colors signify larger predicted adaptation to heat. Panels B and D indicate the full mortality risk of climate change, measured in units of total deaths. Estimates come from a model accounting for both the costs and the benefits of adaptation, and indicate a median across 33 climate models. Estimates shown refer to the RCP8.5 emissions scenario and the SSP3 socioeconomic scenario.}
\end{figure}

To summarize the overall global implications of the impacts in Figure 5, we aggregate location-specific impacts across all impact regions for all four measures of climate change impacts (i.e. expressions (i)--(iv)). The time series in Panel A of Figure 6 show median predictions across all 33 climate
models of the global increase in the mortality rate (deaths per 100,000) due to climate change. Figure 5 and other results below illustrate a single benchmark scenario (RCP8.5, SSP3, fourth-order polynomial specification), but in the following text and in Appendix K we explore the sensitivity of the results to choices about the functional form for temperature, the economic and population scenario, the emissions scenario, and assumptions regarding the rate of adaptation.

Figure 6: Time series of projected mortality costs of climate change. Panel A shows the projected mortality costs of climate change (black line), as compared to partial estimates from incomplete accounting of the costs and benefits of adaptation (other colors). All lines show predicted mortality impacts across all age categories and are represented by a median estimate across 33 climate models. Each colored line represents a partial mortality cost, while the black line shows the total mortality costs of climate change, accounting for both adaptation costs and benefits. Orange: no adaptation. Yellow: adaptation via income growth only. Green: adaptation via income growth and in response to a warming climate. Black: adaptation via income growth and in response to a warming climate, plus the average of lower and upper bound estimates of costs incurred to achieve adaptation. Panel B shows the statistical and climate model uncertainty in projections of mortality costs of climate change, accounting for both adaptation benefits and costs. The darker shaded inner region displays the interquartile range of projections, while the lighter outer region displays the 10th to 90th percentile range. The percentiles are calculated over Monte Carlo simulations that resample from both statistical uncertainty and from the distribution of climate projections from 33 climate models. Estimates shown refer only to the RCP8.5 emissions scenario and the SSP3 socioeconomic scenario.

Figure 6A illustrates that if we failed to account for adaptation or income growth, we would estimate that the mortality costs of climate change will be 125 deaths per 100,000 by 2100. It has been long understood that this estimate (i.e., expression (i)) is likely to overestimate the costs of climate change. Our estimates for the effects of income growth and adaptation to climate confirm that accounting for these future changes substantially reduces projected impacts. Higher incomes dramatically reduce the mortality effect, leading to 44 deaths per 100,000 in 2100; climate adaptation reduces this further to just 13 deaths per 100,000. Although substantially reduced from the “no adaptation” projection, even these smaller counts of direct mortality may be economically meaningful—for comparison, the current mortality rate from automobile accidents in the United States is approximately 11.6 per 100,000.

Figure 6A also demonstrates that climate adaptation is projected to be costly. We compute that the cost of climate adaptation, using the approach from Section 2, is valued similarly to 23 death-equivalents per 100,000 in 2100. The net result is that the full mortality risk due to climate change
(i.e., expression (iv)) is projected to equal in value 36 deaths per 100,000 by the end of the century under RCP8.5. Had we accounted for the benefits of adaptation but failed to account for their costs, we would have dramatically underestimated the total impact of these changes. Nonetheless, our estimate for the benefits of adaptation (31 deaths per 100,000) outweigh the costs of these adjustments (23 death-equivalents per 100,000).\textsuperscript{47,48}

The values in Figure 6A are median values aggregated across results from 33 high-resolution climate models. However, the full distribution of our estimated damages across climate models is right-skewed with a tail of potential mortality costs far higher than our central estimate. As evidence of this, the mean value of the full mortality risk of climate change under RCP8.5 at end of century is 59 deaths per 100,000, as compared to a median value of 36. We leave pricing the certainty-equivalent of this distribution of potential outcomes to future work, but we are able to summarize the distribution below, accounting for both climate model and econometric uncertainty.

**Uncertainty in the estimated full mortality risk of climate change.** There are multiple sources of variation across our projected results, arising from climate uncertainty across GCMs, statistical uncertainty in our estimated response function, and differences in scenarios of the emissions trajectory and socioeconomic changes in income and demographics. Median estimates were shown in panel A of Figure 6; but in panel B we show the 10\textsuperscript{th} to 90\textsuperscript{th} percentile range (in light grey) and the interquartile range (in dark grey) for emissions scenario RCP8.5 and socioeconomic scenario SSP3 over both climate model and statistical uncertainty. This range accounts for uncertainty in the future evolution of the climate (holding emissions fixed), uncertainty in statistically estimated parameters (i.e. $\hat{\gamma}$’s), and any interactions between the two. Details on our simulation method is given in Appendix J. While there is considerable uncertainty in our projected impacts, few projections fall below a value of zero death-equivalents, particularly in the second half of the 21\textsuperscript{st} century.

8 A partial Social Cost of Carbon due to excess mortality risk

Time-series of projected costs due to excess mortality risk, as developed in prior section, are alone insufficient to monetize the full social cost generated by the emission of a marginal ton of CO\textsubscript{2}. This section outlines how we use the paper’s results to compute what we refer to as a “partial SCC” attributable to mortality risk. The partial SCC represents the total WTP (in net present value) of society to avert the excess mortality risk imposed by a marginal ton of emissions, including both the value of lost life as well as the net cost of adaptations undertaken to protect populations. This calculation represents a component of the total Social Cost of Carbon that is mediated through excess mortality; however, it leaves out adverse impacts in other sectors of the economy, such as reduced labor productivity or changing food prices, that one would ideally include in the calculation of an efficient Pigouvian carbon tax; hence, it is a *partial* SCC.

There are three key steps to transforming projections of deaths due to climate change into a partial

\textsuperscript{47}We previously noted considerable heterogeneity across age-groups in our results. We will take this into account in our approach to valuing mortality damages monetarily in subsequent sections, and we display the underlying age group heterogeneity of these projections in Appendix K.

\textsuperscript{48}All of these projected damages depend heavily on the mitigation scenario: By end of century, the full mortality risk due to climate change falls from 36 deaths per 100,000 under RCP8.5 to approximately 6.3 per 100,000 under RCP4.5, demonstrating remarkable gains from mitigation (see Appendix K).
SCC attributable to excess mortality risk: monetizing damages, constructing a damage function, and computing marginal costs from a marginal CO₂ emission. This section describes these steps and reports results, including a decomposition showing the portion of the partial SCC that is borne by each of the ∼25,000 impact regions on the planet.

8.1 Monetizing damages

We follow the standard approach of using the value of a statistical life (VSL) to convert changes in mortality rates into dollars. Our preferred approach relies on the US EPA’s VSL estimate of $8.82 million (2015 USD), although the Appendix reports estimates based on the Ashenfelter and Greenstone (2004) estimate of $2.96 million. We transform the VSL into a value per life-year lost using a method described in Appendix N.1. This approach allows us to compute the total value of expected life-years lost due to climate change, accounting for the different mortality-temperature relationships among the three age groups documented above.

Assigning a total dollar value to global deaths also requires accounting for differences in income levels across the populations in which deaths occur. In general, the VSL might vary with income because the level of consumption affects the relative marginal utilities of a small increment of consumption and a small reduction in the probability of death. Consistent with the literature, in our preferred estimate we use an income elasticity of unity to adjust the US estimates of the VSL to different income levels across the world and over time. However, we also show an alternative estimate where the VSL is adjusted only based on global average income and the lives of contemporaries are valued equally, regardless of their relative incomes. The former approach is preferred, as it is most consistent with the revealed preference approach we use to estimate costs of adaptation, since we observe how individuals make private tradeoffs between their own VSL and their own consumption (recall Equation 5). However, the latter approach might be plausibly preferred by a global social planner who must trade off reductions in mortality risk with the allocation of a marginal dollar anywhere on the planet in year $t$.

In Appendix Table 11, we show the share of contemporaneous global GDP that is lost due to climate change induced changes in mortality risk. These values include both the value of lost life and the cost of compensatory investments, and are key ingredients in the subsequent steps toward calculating a partial SCC. Values shown are medians across our ensemble of 33 climate models. We find, using our preferred valuation assumptions and under emission scenario RCP8.5 and socioeconomic scenario SSP3, that mortality-related losses amount to 0.5% of global GDP in 2050, and 3.7% of global GDP at end of century, where both values represent median estimates across different climate models. However, as discussed previously, this distribution across climate models displays substantial skew; the mean losses across climate models amounts to 5.8% of global GDP in 2100.

49See Appendix Table 13 for a comparison of these VSL values with values from the OECD, which are higher than Ashenfelter and Greenstone (2004), but lower than the US EPA’s VSL.

50The EPA uses a VSL income elasticity of 0.7 and a review by Viscusi (2015) estimates 1.1 for the income-elasticity of the VSL.
8.2 Constructing damage functions for excess mortality risk

The first step to computing a partial SCC is combining the econometric estimates and the 33 high-resolution GCMs into a damage function describing costs of excess mortality risk in a given year as a function of the overall level of climate change. Specifically, a damage function describes economic losses to an economy as a function of the change in global mean surface temperature relative to preindustrial levels (ΔGMST), a notion articulated in theory at least as early as Nordhaus (1992). This function can be differentiated everywhere, allowing for marginal costs of a CO$_2$ impulse to be computed for any arbitrary global climate trajectory, as well as allowing us to disentangle the influence of economic uncertainty and climate science uncertainty.\(^{51}\) Due to differences in the character of climate projections pre- and post-2100, there are some important differences in the approach for calculation damage functions before and after 2100.

**Computing damage functions through 2100.** As described in previous sections, we generate estimates of the total value of mortality-related climate change damages in a given year, $D_t$, using many climate models, emissions scenarios, and by resampling from estimated statistical uncertainty. These simulations lead to an empirically-derived distribution of potential economic outcomes that are conditional on the ΔGMST value for the year and GCM used to generate that projection. To construct damage functions, we then fit a conditional expectation function through these outcomes, following the approach in Hsiang et al. (2017). However, in addition, we condition on the year $t$ because the year of a simulation result captures important economic factors, such as global income and population growth. Indexing GCMs by $m$, we interpret each GCM-based projection of $D_{mt}$ as a potential realization of costs that result from the spatial distribution of warming in $m$, conditional on the overall ΔGMST that is exhibited by that model.\(^{52}\) Differences in the spatial distributions of warming across models, and their mapping on populations around the world, remain an unresolved uncertain element of climate models that are idiosyncratic to each model. Thus, we condition on ΔGMST$_{mt}$ for each $t$ to estimate a damage function in each year

$$D(ΔGMST, t)_{mt} = ψ_0^t + ψ_1^tΔGMST_{mt} + ψ_2^tΔGMST^2_{mt} + ε_{mt}$$ (17)

using all model runs within a 5-year window of $t$, thereby allowing $D(ΔGMST, t)_{mt}$ to evolve flexibly and smoothly over the century.

Figure 7A illustrates the procedure for $t = 2100$, with $D_{mt}$ estimates shown as points\(^{53}\) located

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\(^{51}\)In principle, one could compute an SCC without first computing a damage function, for example by perturbing each GCM with a pulse of CO$_2$ and projecting mortality for each location in both the original and perturbed forecast. However, in practice, such a procedure is both prohibitively costly from a computational standpoint (it is already difficult for dozens of modeling teams to complete the full suite of unperturbed CMIP5 simulations that we use) and also conceptually deficient, since the 33 models available represent only a sparse sampling of range of climate sensitivities that the scientific community agrees represent the true range of uncertainty (IPCC, 2013). This sparseness would prevent the calculation of an SCC for any climate trajectory that did not exactly coincide with one of the 33 GCMs. In addition to misrepresenting the entire range of potential futures and thus the SCC, this limitation would prevent for any optimization of climate policy in any IAM.

\(^{52}\)Note that the ΔGMST manifest in each model is an emergent summary parameter, resulting from the complex interaction of many physical elements of the model that are collectively summarized by the climate sensitivity of the model, a number that describes how much warming is associated with a specified change in greenhouse gas emissions.

\(^{53}\)This scatterplot includes realizations under all RCP4.5 and RCP8.5 GCM scenarios for our preferred method of valuation – the EPA VSL, with an age-adjustment for expected life-years lost, and with a common global average VSL across all impact regions in the years 2095-2100. See Appendix L for results across different valuation assumptions. Due to the dependence of damages $D_t$ on GDP per capita and on demographics, we estimate separate damage functions for
along the horizontal axis based on their corresponding $\Delta GMST_{mt}$. The black line is the damage function estimated for the year 2100. We find a very small gradual increase in the slope of the damage function over time. Our central estimate under our preferred valuation for the full cost of warming in the median RCP8.5 scenario is $\sim 3.7\%$ of GDP by the end of the century ($\Delta GMST = +3.9^\circ C$).\(^{54}\)

![Figure 7: Empirically-derived mortality-only damage functions.](image)

**Figure 7: Empirically-derived mortality-only damage functions.** Both panels show damage functions relating empirically-derived total global mortality costs to anomalies in global mean surface temperature ($\Delta GMST$). In panel A, each point indicates the value of total mortality impacts of climate change in 2100 for a single simulation of a single climate model, accounting for both costs and benefits of adaptation. The black line is the quadratic damage function estimated through these points. Shorter blue lines indicate damage functions similarly estimated for each 5-year interval from 2015 to 2095. These lines extend only to the range of $\Delta GMST$ predicted to be realized in the corresponding time period by our ensemble of 33 climate models. The distribution of temperature anomalies at end of century (2080-2100) under two emissions scenarios across our 33 climate models is in the bottom panel. In panel B, additional damage functions are shown in grey which extrapolate to years beyond 2100. Our projection results generate mortality damages only through 2100, due to limited availability of climate and socioeconomic projections for years beyond that date. To capture impacts after 2100, we extrapolate observed changes in the damage function over the 21st century to generate time-varying damage functions through to 2300. In both panels, we use the U.S. EPA VSL, an income elasticity of one applied to all impact regions, and a life-years adjustment. Results for other valuation assumptions can be found in Appendix L.

**Computing post-2100 damage functions.** The 33 high-resolution GCMs that we use to construct detailed cost estimates are only run by their respective modeling teams to simulate the climate until the year 2100, as are the socioeconomic scenarios we use to project adaptation. One approach to dealing with this issue is to simply end economic cost calculations in 2100, as was done in Hsiang et al. every SSP scenario. Results across different scenarios are shown in Appendix M.\(^{54}\)This estimate applies under the socioeconomic scenario SSP3, the U.S. EPA VSL, with globally heterogeneous VSLs.
(2017), for example. However, a large fraction of costs, in NPV, are thought to occur after 2100 at 3% discount rates (Kopp and Mignone, 2012), thus neglecting post-2100 damages would be a substantial omission.

To estimate impacts in these later years, we extrapolate changes in the damage function beyond 2100 using the observed evolution of the damages through the 21st century. We pool values of $D_{mt}$ from 2050-2100 and estimate a quadratic model similar to Equation 17, but interacting each term linearly with year $t$. This allows us to estimate a damage surface as a parametric function of year after 2100, smoothly transitioning from our more flexible and GCM-based damage functions prior to 2100. In panel B of Figure 7, we show extrapolated damage functions for the years 2150, 2200, 2250, and 2300. In dollar terms, damages continue to rise post-2100 and become steeper, as they did pre-2100, albeit more slowly than global income growth. Although extrapolations analogous to this procedure are used in IAMs, we interpret costs after the year 2100 with qualitatively greater caution than prior to 2100. As these are highly uncertain extrapolations, in one robustness test we will show results for the partial SCC which fix the damage function at its 2100 shape, in addition to showing results in which the extrapolation is included.

8.3 Computing marginal damages from a carbon dioxide pulse

The partial Social Cost of Carbon at time $t_0$ is the marginal social cost from elevated mortality risk imposed by the emission of a marginal ton of CO$_2$ at $t_0$ holding everything else fixed, including the forecast trajectory of baseline greenhouse gas emissions. For a discount rate $\delta$, this is:

$$ Partial\ Social\ Cost\ of\ Carbon_{t_0} = \sum_{t_0}^{2300} \frac{\partial D(\Delta GMST, t)}{\partial \Delta GMST_t} \frac{\partial \Delta GMST_t}{\partial CO_2_{t_0}} e^{-\delta t} $$

where $\frac{\partial \Delta GMST_t}{\partial CO_2_{t_0}}$ is the estimated increase in $\Delta GMST$ that occurs at each moment in time along the baseline climate trajectory as a result from infinitesimally small pulse of CO$_2$ emissions occurring at time $t_0$. Its estimation requires a climate model capable of estimating the global temperature response in each year to a pulse of CO$_2$ emissions. Because we are interested in computing this value for a large number of scenarios, including ones in that reflect climate science uncertainty about the magnitude and timing of warming, we use a “simple climate model” to estimate $\frac{\partial \Delta GMST_t}{\partial CO_2_{t_0}}$. The values $\frac{\partial D(\Delta GMST,t)}{\partial \Delta GMST_t}$ are the marginal damages at each moment in time that occur as a result of this small change in all future global temperatures; they are computed using the damage functions described in the last subsection.

**Applying a simple climate model to the damage function.** To calculate the change in $\Delta GMST_t$ due to a marginal pulse of CO$_2$ in 2015, we use the Finite Amplitude Impulse Response (FAIR) simple climate model that has been developed especially for this type of calculation (Millar et al., 2017). We use FAIR to calculate $\Delta GMST_t$ trajectories for emissions scenarios RCP4.5 and

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55 Note that throughout our calculations, we consider a marginal metric ton of CO$_2$.

56 Hsiang and Kopp (2018) provide a description and discussion of climate model classes, written for economists.

57 FAIR is a zero-dimensional structural representation of the global climate designed to capture the temporal dynamics and equilibrium response of $\Delta GMST$ to greenhouse gas forcing. It has a very small number of parameters, such as transient climate sensitivity and equilibrium climate sensitivity, which summarize complex physical processes that are modeled explicitly in the GCMs we used in earlier sections.
Figure 8: Change in emissions, concentrations, and temperature in the FAIR simple climate model under the default configuration. Panel A shows a 1GtC pulse of CO$_2$ emitted in 2015 for emissions scenario RCP 8.5. Panel B displays the effect of this pulse on atmospheric CO$_2$ concentrations, relative to the baseline. In panel C, the impact of the pulse of CO$_2$ on temperature is shown where the levels are anomalies in global mean surface temperature (GMST) in Celsius. Finally, panel D shows the change in discounted damages over time due to the 1 GtC pulse of CO$_2$ in 2015, as estimated by our empirically-derived damage function, using three different annual discount rates.

RCP8.5, both with and without an exogenous impulse of 1GtC of CO$_2$ in the year 2015, essentially the smallest approximation of an infinitesimal emission for which the model numerics perform appropriately. In FAIR, this emissions impulse perturbs the trajectory of atmospheric CO$_2$ concentrations and GMST for 2015-2300, with dynamics that are influenced by the baseline RCP scenario. In each scenario, the trajectory of $\Delta$GMST$_t$ in the “RCP + pulse” simulation is differenced from the baseline RCP simulation to compute $\frac{d\Delta\text{GMST}_t}{d\text{CO}_2t}$.

Figure 8 shows difference between the “RCP + pulse” and baseline RCP trajectories for emissions (panel A, showing the pulse), CO$_2$ concentrations (panel B), and $\Delta$GMST (panel C) arising from the default values in FAIR’s configuration parameters. Finally, we calculate the stream of damages associated with both the baseline and perturbed trajectories, and discount their difference to compute the NPV of the excess mortality risk externality generated by this marginal emission, as illustrated in panel D of Figure 8.

Accounting for uncertainty in climate sensitivity. While we produce one set of results using the default configuration of FAIR, key parameter values that jointly determine the sensitivity of the climate to marginal emissions are uncertain. We account for these uncertainties by computing a distribution of partial SCC values. To do this, we resample from a joint distribution of four key FAIR parameters: the transient climate response, equilibrium climate sensitivity, the short thermal adjustment time, and the time scale of rapid carbon uptake by the ocean mixed layer. This joint distribution is constrained such that the distribution of transient warming responses they produce matches the corresponding distributions from the IPCC Assessment Report 5 (AR5)/CMIP5 multi-

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58 Using the trajectories in Figure 8 is consistent with the “SCC experiment” that is used in IAMs to calculate an SCC (National Academies of Sciences and Medicine, 2017). In its default configuration, the FAIR model assumes a transient climate response (TCR) of 1.6 and an equilibrium climate sensitivity (ECS) of 2.75. Our simple climate model simulation is discussed further in Appendix M.
model ensemble. We sample from this distribution and compute a partial SCC for each vector of climate parameters drawn. The resulting distribution of partial SCC values provides us with a sense of the overall uncertainty in the partial SCC that is attributable to unresolved uncertainty in climate models.

**Accounting for uncertainty in statistical estimation.** The second source of uncertainty in our projected impacts of climate change arises from the econometric estimation of Equation 10. Using simulation runs that resample from the empirical multivariate normal distribution characterized by the covariance between all estimated parameters in Equation 10, we account for statistical uncertainty by running quantile regressions to fit quantile-specific damage functions. As above, we run separate regressions in each 5-year period, to capture changes in the damage function over time. As before, extrapolation past the year 2100 was accomplished using a linear time interaction, here for each quantile. Results accounting for only statistical uncertainty use these quantile regressions and the default configuration the simple climate model FAIR, while results accounting for both climate model and statistical uncertainty use these quantile regressions in combination with all parameter combinations for FAIR, described above.

### 8.4 Estimates of the mortality risk partial Social Cost of Carbon

The global mortality risk partial SCC. Partial SCC estimates are shown in panel A of Table 5 using the three different annual discount rates used in prior estimates of the social cost of carbon (2.5%, 3%, and 5%) (Interagency Working Group on Social Cost of Carbon, 2010; National Academies of Sciences and Medicine, 2017) and valuation methods that adjust for cross sectional variation in incomes among contemporaries and global income growth. In panel B, it is assumed that there is a globally homogeneous VSL in a given year and that it evolves over time based on global income growth. Point estimates utilize the default parameterization of FAIR, and the point estimates from the econometric model described in Equation 10. The table reports interquartile ranges that reflect climate model uncertainty only, econometric uncertainty only, and both sources of uncertainty jointly. All values represent the global aggregate WTP today (2015 USD) to avoid changes to the trajectory of future mortality risk induced by warming from an additional ton of CO$_2$ emissions, including both the costs and benefits of adaptation.

In the preferred specification ($\delta = 3\%$, Panel A) we estimate a partial SCC of $20.2 per ton of CO$_2$ (interquartile range with full uncertainty = [$7.7 - 67.1$]) for the low to moderate emissions scenario (RCP 4.5) and $39.1 per ton (IQR = [$14.5 - 92.6$]) for the high emissions scenario (RCP 8.5). Utilizing the valuation that relies on a global average VSL in panel B, these central estimates increase to $34.3 and $63.5 per ton, respectively. Partial SCC estimates for RCP 4.5 are systematically lower than RCP 8.5 because the damage function is convex, so marginal damages increase in the high emissions scenario. The combination of this convexity and the skewness of the climate sensitivity distribution causes the distribution of partial SCCs to also be substantially skewed after accounting for climate model uncertainty, with a long right tail. Additional estimates, including different valuation

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59Details of this procedure are provided in Appendix M.
60We estimate a damage function for each of the following quantiles: 5, 25, 50, 75, and 95.
61RCP8.5 is often considered a “business as usual” scenario.
The mortality risk partial SCC for each individual location. The partial SCC values in Table 5 describe the aggregate net externality summed across all locations on the planet resulting from a marginal CO₂ emission. Such WTP values are a relevant welfare metric when considering global cost-benefit analyses, but they obscure important information regarding which populations benefit from warming on net and which bear the greatest costs. Thus, we decompose the global aggregate partial SCC above into contributions that originate from each of the ~25,000 impact regions. In essence, we compute the WTP of each impact region \( r \) to avoid the excess mortality risk imposed by a marginal ton of CO₂ emissions\(^63\) on itself.

To do this, we compute the NPV of marginal net damages experiences in each impact region in each year 2015-2300 from a pulse in 2015 exactly as was done above for global damages, except all calculations are implemented at the impact region level. We estimate a region-specific version of Equation 17 using damage estimates for only that region in each year and model run. We then compute a partial SCC for region \( r \) with an analog to Equation 18 that uses this region-specific damage function. Since region-level damages in each model run were organized by the global statistic \( GMST^r_t \) when the damage function is constructed, we only need to apply the same global values for \( \frac{dGMST^r_t}{dCO_2^t} \) from FAIR that were used above. Because this approach simply decomposes the global aggregate damage function in Equation 17 into additively separable elements and Equation 18 is linear in the derivatives of these terms, this procedure guarantees that that sum of regional partial SCCs equal the global aggregate partial SCC.

Figure 9 displays the partial SCC computed for each of the impact regions for RCP 8.5 using our preferred valuation (income adjusted life-years, \( \delta = 3\% \)).\(^64\) Globally, there is substantial heterogeneity in the partial SCC, with some regions harmed by the marginal emission by as much as $0.015 per ton CO₂ (e.g. Pakistan, Northern West Africa, portions of Central Asia) while other regions are estimated to benefit by as much as $0.003 per ton CO₂ (e.g. parts of Northern Europe, Singapore). Multiple factors contribute to these observed patterns. Several regions that are relatively wealthy and hot today (e.g. Australia, Saudi Arabia, Southeastern US) are currently so heavily adapted to hot climates that their response functions are already relatively shallow at the hot end, so additional warming leads to limited additional mortality or adaptation costs — these locations then end up benefiting from reductions is a relatively small number of cold days. Regions that are either poorer and/or moderately cooler today tend to suffer net losses, because their response functions are moderately sensitive to high temperatures, leading to direct mortality, and they are unadapted today, so future adaptations incur substantial additional costs. Some cold regions, such as the Andes and Alaska, benefit from reductions...
in the number of harmful cold days.

Figure 9: Spatial distribution of the marginal mortality damages due to a 1t CO$_2$ emissions increase. Values shown represent the net present value of all mortality damages incurred through 2300 as a result of an additional 1t CO$_2$ increase in emissions. Grey areas are regions where socioeconomic projections of income were unavailable. All values correspond to the RCP8.5 emissions trajectory, the SSP3 socioeconomic projection, a 3% discount rate, and a valuation of lives lost that uses the U.S. EPA VSL, applies a life-years adjustment, and uses an income elasticity of one.

8.5 Interpretation

As the paper has detailed, the mortality risk partial SCC has many ingredients. We have tried to probe the robustness of the results to each of them, but there are three issues that merit highlighting when interpreting the results. First, the estimates of heterogeneity in the mortality-temperature response function, from which the benefits of income increases and climate adaptation are derived, rely on the consistency of the estimated $\hat{\gamma}$’s from the fitting of Equation 10. On the reassuring side, these estimates come from rich statistical models that include age $\times$ ADM2 and country $\times$ age $\times$ year fixed effects; thus, any confounding factor would have to be correlated with a population’s mortality sensitivity to temperature, rather than be correlated with the overall level of local mortality rates. At the same time, the projections of climate change damages ultimately rely on two cross-sectional variables, and the identification of the estimated heterogeneity requires stronger assumptions than the estimated average treatment effect of temperature on mortality within our multi-country sample. However, making these stronger assumptions allows for a set of climate change projections that move the analysis beyond the “no adaptation” analyses that have characterized much of the previous literature.
Second, the paper’s estimates do not reflect the possibility of compensatory migration in response to climate change damages. If migration were free, it seems very likely that the mortality risk partial SCC would be smaller, possibly substantially so, as people from regions with high damages (such as sub-Saharan Africa) may move to regions with low or even negative damages (such as Scandinavia). However, recent history in the United States and around the globe underscores that borders are meaningful and that there are substantial political costs to migration, in addition to migrants’ moving costs, which likely put limits the scale of feasible migrations. Indeed, existing empirical evidence of climate-induced migration is mixed. Thus, the scope of the bias in our findings associated with the failure to allow for migration may not be as large as it seems at first.

Third, the paper’s projections incorporate advancements in technology that enhance adaptive ability, even though we have not explicitly modeled technological change. In particular, we allow the response functions to evolve in accordance with rising incomes and temperatures and do not restrict them to stay within the bounds of the current observed distribution of temperature responses. Thus, we effectively use our estimates to make out-of-sample predictions about how temperature sensitivity will diminish beyond that observed anywhere in the world today as temperatures and incomes rise outside of the existing global cross-section.

At the same time, our projections do not allow for climate-biased technical change that lowers the relative costs of goods which reduce the health risks of high temperatures. Specifically, our projections of the costs and benefits of adaptation do not account for such climate-biased technical change. Thus, while the projections allow for continued general adaptation, they may overstate the mortality risk partial SCC if climate change leads to technological innovations that lower the costs of adapting to high temperatures.

9 Conclusion

This paper has outlined a new method for empirically estimating the costs of climate change for a single sector of the economy and implemented it in the context of mortality risks associated with temperature change. There are several noteworthy methodological innovations and intermediate findings. First, the relationship between mortality rates and temperature is highly nonlinear and varies with a location’s income and climate. These findings were only possible due to the collection and analysis of highly resolved data covering half of the world’s population, which enabled us to estimate flexible empirical models relating mortality risk to temperature, climate, and income. Second, the costs of climate change induced mortality risks are distributed very unevenly around the nearly 25,000 regions that comprise the world. For example by 2100, we project that climate change will cause annual damages equivalent to approximately 3,700 additional deaths in the Mogadishu, Somalia impact region, but will also generate annual benefits equivalent to approximately 1,100 lives in the Oslo, Norway region. We find the extent of the heterogeneity surprising and note that it may be especially important when one considers that populations are likely to make judgments about climate change with utility functions that reflect risk aversion.

Third, the heterogeneous impacts appear to reflect investments that individuals and societies make based on the costs and benefits of responding to a changing climate. We outline and implement a
revealed preference method to bound the costs of these adaptation investments, even though they cannot be directly observed. The results suggest that adaptation costs account for approximately 2/3 of the total mortality equivalent costs of climate change in the year 2100, with the direct mortality impacts accounting for the remainder. Relatedly, estimated mortality impacts that do not account for adaptation overstate the mortality impacts of climate change in 2100 by more than a factor of 3.5. Fourth, there is substantial climate and statistical uncertainty around these estimates and we find that the distribution of projected losses is right skewed; for example the mean loss is about 60% larger than the median loss. Although we do not account for risk aversion, it is evident that doing so would increase the loss.

The paper’s ultimate goal is to estimate a partial SCC that reflects the consequences of climate change on mortality and investments in adaptation. Our central values suggest that with a 3% discount rate, the present value of excess mortality risk due to climate change imposed by a marginal ton of CO$_2$ emissions today is roughly $20 (in 2015USD) with a low or moderate emissions scenario (RCP4.5) and $39 with a high one (RCP8.5). When accounting for climate model and statistical uncertainty, the respective interquartile ranges are [$$7.7 - 67.1$$] for RCP4.5 and [$$14.5 - 92.6$$] for RCP8.5; the positive skewness of these ranges reflects the risk of outcomes substantially more costly than our central estimate. Further, the impacts are distributed unequally with 72% of the global population harmed by an additional ton of CO$_2$ emissions and the remainder benefiting.

As a basis of comparison, the Obama Administration’s initial central estimate for the full SCC (including all sectors and using a discount rate of 3%) is $41 (in 2015USD) per ton of CO$_2$ emitted in 2015 (Interagency Working Group on Socal Cost of Carbon, 2010). This value was derived using simulations from the DICE, FUND, and PAGE integrated assessment models. The DICE and PAGE models do not document the origin of their damages in a manner that allows calculation of a mortality risk partial SCC that is comparable to our results (Rose, Diaz, and Blanford, 2017). However, Diaz (2014) computes comparable partial SCC values for the FUND model (3% discount rate, “business as usual” emissions scenario) and reports values for three comparable health impacts (diarrhea, vector born diseases, and cardiovascular/respiratory impacts) that total less than $1.50. It is evident that this paper’s empirically grounded estimates of the costs of climate-induced mortality risks substantially exceed the available estimates from the models that underlie the existing estimates of the social costs of carbon. Indeed with RCP8.5 which is similar to the baseline assumptions underlying the Obama Administration’s SCC, this paper’s excess mortality partial SCC is essentially as large as the Obama Administration’s full SCC.

The climate change challenge is considered existential by some and a relatively small risk by others, yet much of what is known about its overall impacts, particularly the SCC, comes from integrated assessment models that do not sit on a robust empirical foundation. In particular, many models currently used to compute the SCC are either not calibrated against data, have a calibration that is not documented, or are calibrated against empirical estimates that are not derived from modern empirical techniques and unlikely to be globally representative. Advances in access to data and computing mean that this no longer needs to be the case. Indeed, we believe that this paper has highlighted a key role for systematic empirical analysis in providing a clearer picture of how, why, and where costs of

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65These partial SCC values from FUND differ for numerous reasons, including that they were calibrated to different studies published between 1995-2004. See Diaz (2014) for details.
climate change are likely to emerge in the future. Looking ahead, this paper’s general approach can be applied to other aspects of the global economy besides mortality risk, and we believe that doing so is a promising area for future research.
Table 5: Estimates of a partial Social Cost of Carbon for excess mortality risk incorporating the costs and benefits of adaptation as well as uncertainty in climate sensitivities and in statistical estimation

<table>
<thead>
<tr>
<th>Annual discount rate</th>
<th>2.5%</th>
<th>3%</th>
<th>5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCP 4.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>9.5</td>
<td>7.7</td>
<td>4.0</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>12.6</td>
<td>8.6</td>
<td>2.1</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>12.4</td>
<td>7.7</td>
<td>1.1</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>25.6</td>
<td>17.3</td>
<td>6.1</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>28.9</td>
<td>19.7</td>
<td>5.3</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>22.9</td>
<td>14.5</td>
<td>2.9</td>
</tr>
</tbody>
</table>


| RCP 4.5              | 45.4 | 34.3 | 15.3 |
| Climate uncertainty  | 17.4 | 14.3 | 7.5 |
| Statistical uncertainty | 22.4 | 15.6 | 4.6 |
| Climate + statistical uncertainty | 22.5 | 15.2 | 3.8 |
| RCP 8.5              |      | 63.5 |    |
| Climate uncertainty  | 41.9 | 29.0 | 10.7 |
| Statistical uncertainty | 42.4 | 29.8 | 9.1 |
| Climate + statistical uncertainty | 34.6 | 23.7 | 6.7 |


In both panels, an income elasticity of one is used to scale the U.S. EPA VSL value (alternative values using the VSL estimate from (Ashenfelter and Greenstone, 2004) are shown in Appendix M). All SCC values are for the year 2015, measured in PPP-adjusted 2015 USD, and are calculated from damage functions estimated from projected results under the socioeconomic scenario SSP3. In Panel A, all regions have heterogeneous valuation, based on local income. In Panel B, all regions globally are given the global median VSL, after scaling using income. All estimates use a value of life years adjustment, valuing deaths by the expected number of life-years lost. The first row of every valuation shows the estimated partial SCC using the default configuration of the simple climate model FAIR. Interquartile ranges (IQRs) are shown in brackets in the following rows, accounting for climate model uncertainty, statistical uncertainty, or both in combination (see Appendix M and J for details).
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A Construction of adaptation cost estimates using a revealed preference approach

A.1 Graphical solution to inferring one unobserved adaptation cost

In Section 2, we lay out a framework for recovering the costs of adapting to climate change that is micro-founded by a standard utility maximization problem. Figure 10 depicts this optimal adaptation problem faced by individuals and illustrates how we overcome two key empirical challenges to measuring adaptation costs: (1) the universe of adaptation adjustments and their costs are not directly observable and (2) adaptive adjustments are continuous for continuous changes in climate. The problem must be displayed in three dimensions because it involves at least three orthogonal subspaces: climate \((C)\), adaptive adjustments to climate \((b)\), and an outcome (expressed in dollars of WTP). For illustrative simplicity, here we assume income is held fixed, and we consider a simplified example with univariate climate and univariate adaptation. Further, for this example, higher \(C = C\) indicates higher temperatures and higher \(b = b\) indicates greater adaptation (i.e. greater protection) from high temperatures, where these terms are unbolded to indicate that they are scalars.

In the lower left panel of Figure 10, the green surface illustrates adaptation costs \(A(b)\) which are not directly observable to the econometrician. The height of this surface represents the costs that households would bear to obtain a level of adaptation \(b\). Because we assume markets for adaptive technologies are competitive, \(A(b)\) could represent the lower envelope of all firm cost-functions (offer curves) that would supply \(b\), as illustrated by the projection of the surface onto the \(A \times b\) plane. Because adaptation costs are a function of technology, they do not depend on the climate and so \(\partial A/\partial C = 0\) everywhere, i.e. individuals in Seattle can purchase the same adaptation technology (e.g. air conditioners) as individuals in Houston.

In the lower right panel of Figure 10, the red surface illustrates the expected benefits an individual would accrue for inhabiting some climate \(C\) and selecting adaptation \(b\). The height of this surface is a WTP for adaptation, conditional on the climate: it is equal to the VSL times the expected survival probability \(1 - \tilde{f}(b, C)\) at each position \((b, C)\). For notational simplicity, we refer to this WTP surface as \(V\). At low levels of adaptation, \(V\) declines rapidly with higher temperature \(C\) because survival probability declines quickly. At higher levels of adaptation, \(V\) declines more gradually with \(C\) because adaptation protects individuals against temperature. The solid black lines follow this WTP surface at fixed temperatures, showing how an individual in a given climate would benefit from additional adaptation (bid curves).

Agents at each climate endogenously adapt by selecting the optimal level of \(b\) such that the marginal costs equal the marginal benefits. This can be seen on the left panel at climates \(C_1\) and \(C_2\), focusing in this paragraph on the lower part of the figure, where slices of the benefits surface \(V\) are drawn overlaid in red and are tangent to \(A(b)\) at the blue circles. Corresponding slices of the adaptation cost surface \(A\) are overlaid in green on the benefits surface in the right panel. The blue line traces out the equilibrium.

\[66\text{In the algebraic section below, } A\text{ are net costs since they are net any utility benefits of } b.\]
For each climate $C$ there is an optimal level of adaptation $b^*(C)$ endogenously chosen, illustrated by the projection of the equilibrium downward onto the $C \times b$ plane in both panels. The projection of the equilibrium onto the $A \times C$ plane on the left panel illustrates how adaptation expenditures rise with temperature, and the projection onto the $V \times C$ plane on the right panel illustrates how expected survival benefits decline with temperature, or conversely, how mortality costs rise with temperature. The sum of changes to these adaptation expenditures and the value of mortality costs is the full cost of changes to the climate.

A key innovation to our analysis is fully accounting for adaptation costs $A(b)$ even though neither $A(.)$ nor $b$ is observed. Indeed, there may be a very large, even infinite, number of ways that populations adapt to climate that cannot be feasibly enumerated by the econometrician. All the econometrician can observe are the effects of adaptation on survival probability $\tilde{f}$. If a climate were gradually warmed from $C_1$ to $C_2$, individuals would continuously respond by adapting along $b^*(C)$ and traveling up the cost surface in the lower left panel, eventually incurring costs $A(b^*(C_2))$ rather than the initial costs $A(b^*(C_1))$ that they incurred prior to warming. We point out that the change in this total adaptation cost $A(b^*(C_2)) - A(b^*(C_1))$ can be inferred based only on the shape of the benefits surface along the
equilibrium, information that is recoverable by the econometrician.

To show this, at the top of Figure 10 we draw tangency planes for both the costs and benefits surfaces for a single location along the equilibrium adaptation locus between \( C_1 \) and \( C_2 \), indicated by black squares on the two surfaces in the lower part of the figure. Both tangency planes span an area \( \partial C \times \partial b \), indicating how much additional adaptation populations undertake (\( \partial b \partial C \)) for an exogenous change in climate (\( \partial C \)), changes that would cause them to traverse each of these planes from their respective left-most corner to their right-most corner. The corresponding change in survival benefits is \( \frac{dV}{dC} = \frac{\partial V}{\partial C} \partial b \partial C \), indicating how much additional adaptation populations undertake (\( \partial b \partial C \)) for an exogenous change in climate (\( \partial C \)), changes that would cause them to traverse each of these planes from their respective left-most corner to their right-most corner. The econometrician can observe by computing the change in survival probability due to climate between two adjacent locations after allowing them both to fully adapt to their respective climates. If the cooler location is heated by \( \partial C \) but not permitted to adapt, its survival benefits change by \( \frac{dV}{dC} \partial b \partial C \), a counterfactual outcome that the econometrician can compute by simulating a warmer environment without allowing for adaptation. The difference between these two changes is equal to the benefits of marginal adaptations \( \frac{dV}{dC} \partial b \partial C \) (upward green arrow, right panel). Along the equilibrium \( b^*(C) \), these marginal benefits of adaptation must equal their marginal costs, thus we know the corresponding increase in unobserved adaptation costs \( \frac{dA}{dB} \partial b \partial C \) (upward green arrow, left panel) must be equal in magnitude to \( \frac{dV}{dC} \partial b \partial C \). By continuously computing and differencing the total and partial derivatives of \( V \) with respect to an incremental change in climate \( dC \) (i.e. \( \frac{dV}{dC} \partial b \partial C \)), we recover the marginal benefits of unobserved incremental adaptions \( \frac{dV}{dC} \partial b \partial C \), which we know must also equal their marginal costs \( \frac{dA}{dB} \partial b \partial C \). Then by integrating these marginal costs with respect to the climate, we can compute the total change in adaptation costs \( A(b^*(C_2)) - A(b^*(C_1)) \) for the non-marginal change in climate from \( C_1 \) to \( C_2 \). This intuition holds for an unknown number of margins of adaptation and a climate of arbitrary dimension, which we allow for below. We also introduce changes in income, which influences \( b^*(C) \) through the budget constraint.

A.2 Mathematical details

The framework in Section 2 allows us to use observable relationships between mortality risk and changes in the climate to generate estimates of the unobserved cost of adaptation. Here, we provide details on the derivation of our final expression in Equation 8, which denotes the total adaptation costs incurred as a population experiences a change in climate from \( C_1 \) to \( C_2 \).

Recall that agents jointly choose \( K \) margins of adaptation described in the choice vector \( b \) such that \( b^* = \arg \max u(x, b)[1 - \tilde{f}(b, C)] \), subject to a budget constraint \( h(b) + x = Y \), where \( h(b) \) is the pecuniary cost of adaptation expended by households and \( Y \) is income. The first order conditions of this optimization problem take the form:

\[
[1 - \tilde{f}(b, C)] \frac{\partial u(x, b)}{\partial x} = \lambda, \quad [1 - \tilde{f}(b, C)] \frac{\partial u(x, b)}{\partial b} - \frac{\partial \tilde{f}(b, C)}{\partial b} u(x, b) = \lambda \frac{\partial h(b)}{\partial b}
\]

Note that because \( b \) is a vector, the second equation above represents \( K \) separate equations; there is
a distinct first order condition for each \( b_k \). Substitution of the first FOC into the second gives:

\[
- \frac{\partial \tilde{f}(b, C)}{\partial b} u(x, b) = [1 - \tilde{f}(b, C)] \left[ \frac{\partial u(x, b)}{\partial x} \frac{\partial h(b)}{\partial b} - \frac{\partial u(x, b)}{\partial b} \right]
\]

The right-hand side of the above expression represents the marginal cost of changing \( b \), valued in utils, net of any change in utility realized from direct utility effects of adaptation. We call this object “net marginal costs”. The left-hand side is simply the marginal mortality benefit realized from a change in \( b \). Multiplying by \( \frac{1}{1 - \tilde{f}(b, C)} \frac{\partial u(x, b)}{\partial x} \) translates this expression into dollars, using the standard Value of a Statistical Life (VSL) definition: \( VSL = \frac{u(x, b)}{1 - \tilde{f}(b, C)} \). Finally, summing across all choice variables \( k \) in the vector \( b \) gives the expression in Equation 5:

\[
-VSL \sum_k \frac{\partial \tilde{f}^*(b, C)}{\partial b_k} = \sum_k \frac{\partial}{\partial b_k} \left[ \frac{h(b^*)}{\partial b_k} - \frac{u(x^*, b^*)}{\partial u(x^*, b^*)/\partial x} \right] = \sum_k \frac{\partial A(b^*)}{\partial b_k}
\]

Note that the VSL is defined as the willingness to pay for a marginal increase in the probability of survival. This willingness to pay is held constant throughout our conceptual framework; however, in our empirical derivation, we allow the VSL to evolve with income, under a range of different choices for the income elasticity.

We use the expression in Equation 5, along with the definition of the total derivative in Equation 7, to derive our final expression in Equation 8 as follows:

\[
A(b^*(C_2, Y)) - A(b^*(C_1, Y)) = \int_{C_1}^{C_2} \frac{\partial A(b^*(C, Y))}{\partial C} dC
\]

\[
\quad = \int_{C_1}^{C_2} \sum_k \frac{\partial A(b(C, Y))}{\partial b_k^*(C, Y)} \frac{\partial b_k^*(C, Y)}{\partial C} dC
\]

\[
(substitution \ from \ Equation \ 5) \quad = -VSL \int_{C_1}^{C_2} \sum_k \frac{\partial \tilde{f}(b, C)}{\partial b_k^*(C, Y)} \frac{\partial b_k^*(C, Y)}{\partial C} dC
\]

\[
\quad = -VSL \int_{C_1}^{C_2} \left[ \frac{df(b^*(C, Y), C)}{dC} - \frac{\partial \tilde{f}^*(b^*(C, Y), C)}{\partial C} \right] dC \quad (19)
\]

The empirical implementation of Equation 19 is detailed in Section 6.3.
A.3 Climate in the utility function

In Section 2, we assume that climate enters a representative agent’s optimization problem only through the risk of death. In this Appendix, we set up a variant of this model in which climate directly enters the agent’s utility function. We show the implications of this variant on our empirical derivation of adaptation costs.

Let agents choose $x$, the numeraire good, and all other choice variables $b$ to maximize expected utility subject to a standard budget constraint:

$$\max_{x,b} \left[ 1 - \hat{f}(b, C) \right] u(x, b, C) \quad \text{s.t.} \quad h(b) + x = Y$$

where $h(b)$ is the pecuniary cost of adaptation and $Y$ is income, as in the main text. The only change here relative to the maximization in section 2 is the addition of climate $C$ to the utility function $u(x, b, C)$. As in the main text, summing across the $K + 1$ first order conditions for Equation 20 and using the definition of the value of the statistical life (VSL), we have that the optimal choice vector $b^*$ must satisfy:

$$-VSL \sum_k \frac{\partial}{\partial b_k} \left[ \hat{f}(b^*, C) \right] \text{expected mortality given } b = \sum_k \frac{\partial}{\partial b_k} \left[ h(b^*) - u(x^*, b^*, C) \frac{1}{\partial x} \right]$$

which simplifies to:

$$-VSL \sum_k \frac{\partial}{\partial b_k} \left[ \hat{f}(b^*, C) \right] = \sum_k \frac{\partial A(b^*, C)}{\partial b_k}$$

The only difference between this expression and the analogous condition in the main text (Equation 5) is that the net cost of adaptation, which we call $A(\cdot)$, is now a function of the climate $C$ directly, in addition to the choice vector $b^*(C, Y)$, which itself endogenously depends on climate (as well as income). Since we empirically estimate the left-hand side of Equation 22, the only change is in the interpretation of non-marginal costs. Intuitively, the direct effect of climate on utility allows the marginal direct utility benefits of $b_k$ to vary with climate, meaning that the unobserved component of $A(\cdot)$ may also change as the climate warms.

To see this, we now define the change in total adaptation costs incurred as the climate warms from $C_0$ to $C_1$ as:

$$A(b^*(C_1, Y), C_1) - A(b^*(C_0, Y), C_0)$$

As in the main text, to compute the total cost of adaptations between two climates that differ by a non-marginal amount, we integrate marginal costs. The Gradient Theorem, the Chain Rule, and
substitution from Equation 22 allows us to rewrite the total cost of adapting to climate changes as:

\[
A(b^*(C_1, Y), C_1) - A(b^*(C_0, Y), C_0) = \int_{C_0}^{C_1} \frac{dA(b^*(C, Y), C)}{dC} dC
\]

\[
= \int_{C_0}^{C_1} \left[ \sum_k \frac{\partial A(b(C, Y), C)}{\partial b_k(C, Y)} \frac{\partial b_k^*(C, Y)}{\partial C} + \frac{\partial A(b^*(C, Y), C)}{\partial C} \right] dC
\]

\[
(substitution \ from \ Equation \ 22) = -\int_{C_0}^{C_1} VSL \sum_k \frac{\partial \tilde{f}(b, C)}{\partial b_k(C, Y)} \frac{\partial b_k^*(C, Y)}{\partial C} dC + \int_{C_0}^{C_1} \frac{\partial A(b^*(C, Y), C)}{\partial C} dC
\]

Rearranging the last line gives:

\[
A(b^*(C_1, Y), C_1) - A(b^*(C_0, Y), C_0) - \int_{C_0}^{C_1} \frac{\partial A(b^*(C, Y), C)}{\partial C} dC = \int_{C_0}^{C_1} VSL \sum_k \frac{\partial \tilde{f}(b, C)}{\partial b_k(C, Y)} \frac{\partial b_k^*(C, Y)}{\partial C} dC
\]

\[
\text{new term (unmeasured)} \quad \text{observable, as shown in main text}
\]

Equation 25 shows us that the empirically estimated quantity on the righthand side can now be interpreted as adaptation costs net of one additional component. This new term represents the changing direct utility benefits of the adaptation good, \(b\), which now vary with the climate. To further understand how this affects the interpretation of our estimates, we decompose this term using the definition of \(A(b^*, C)\) in Equation 21 as follows:

\[
\int_{C_0}^{C_1} \frac{\partial A(b^*(C, Y), C)}{\partial C} dC = \int_{C_0}^{C_1} \left[ \frac{-\partial u(x^*, b^*, C)/\partial C}{\partial u(x^*, b^*, C)/\partial x} + u(x^*, b^*, C) \frac{\partial^2 u(x^*, b^*, C)/\partial x \partial C}{(\partial u(x^*, b^*, C)/\partial x)^2} \right] dC
\]

The first term in brackets is the marginal change in utility from a marginal change in the climate, relative to the marginal utility of a unit of consumption. The second term is a second order effect, and is equal to zero if no cross-partial effects are present (i.e. if the marginal utility of consumption of the numeraire is unaffected by the climate). This second term is unlikely to be consequential; we therefore focus on the first term. Because marginal utility of consumption is positive, the sign of the first term depends on the sign of \(\partial u(\cdot)/\partial C\). When this term is negative (e.g. warmer temperatures lower utility), the entire first term is positive, meaning that the new term in Equation 24 reduces our estimated adaptation costs from their true level. Given that our original formulation in Equation 5 already captures “net” adaptation costs rather than the full marginal cost \(\frac{\partial h}{\partial b}\), the formulation with climate directly entering the utility function effectively just adds another component to the net interpretation of our cost estimate.
B Mortality data

The mortality data in our analysis comprises information from 42 different countries representing approximately 56% of the global population. Each of the countries’ data are drawn from distinct databases, details of which are provided below.

B.1 Brazil

Brazilian mortality data at the ADM2-month level were obtained from the Mortality Information System (SIM) of the Ministry of Health in Brazil (Ministry of Health in Brazil). We use data from 1997-2010 and aggregate the monthly data to annual frequency. Data were provided on both place in which the death was recorded and place of residence. As with all subsequent datasets, we assign weather exposure to deaths in our data at the place of residence, as this is provided for all sources. Data were downloaded in 5-year age groups which where then aggregated to the age groups used in the analysis. ADM2-level populations were obtained form the same source. Administrative boundary files were downloaded from GADM (Global Administrative Areas, 2012b). Brazilian death data as downloaded contained a number of ADM2 units with missing values for deaths and no values of zero, implying that these are a mix of true zeros and missing values. To ascertain whether they are more likely to be the former, we examined the relationship between death counts and population in all ADM2 units, and then in only those ADM2 units that ever show a missing value in any year. Figure 11 shows that missing values are more likely to occur in low population places, and the low population threshold is much lower for older people. This lends credibility to the fact that these are places that recorded zero deaths. We consequently treat these missing values as zeros, but treating them as missing does not substantially change any of our results.

Figure 11: Brazilian ADM2 region-years death counts versus population. The left panel shows this relationship for all ADM2-years in the dataset, while the right panel shows only for ADM2 units in which there was at least one missing ADM2-year value. We see that the ADM2s with missing values have substantially lower populations, consistent with these being true zeros.

http://datasus.saude.gov.br/sistemas-e-aplicativos/eventos-v/sim-sistema-de-informacoes-de-mortalidade
B.2 Chile

Chilean mortality data at the ADM2 level are obtained from the vital registration system maintained by the Department of Statistics and Information (Departamento de Estadísticas e Información de Salud, DEIS) at the Ministry of Health (Ministry of Health, Chile). We use data at the ADM2 level for 1997-2012. The vital registration system contains information on individual dates of deaths (often with missing values for days but always containing years) which we aggregate within administrative units to provide the ADM2 total count of deaths in each unit. This also provides data with arbitrarily accurate age-grouping, and we aggregate in accordance with the age groups in our analysis. ADM2 population data were downloaded from the National Institute of Statistics (Instituto Nacional de Estadísticas, INE) and merged with the death counts to calculate mortality rates. Administrative boundary files were downloaded from GADM (Global Administrative Areas, 2012b).

B.3 China

Chinese mortality data are the same as those used in Chen et al. (2013), and were provided by the authors of that paper. The data come from the Chinese Disease Surveillance Points system and are not the universe of mortality as in much of the rest of our sample, but rather a representative sample of Chinese population benchmarked to the 1990 Chinese census. Locations are given as geographic coordinates relating to the centroid of the surveillance area. Data used in Chen et al. (2013) span from 1991-2000 and cover 145 points to which we assign a climate exposure at the level of the ADM2 unit containing that point. We supplement this with data on a further 161 points from 2004-2012 which were benchmarked to the 2000 census to reflect population changes. This gives us a total of 203 disease surveillance points due to overlap in some points across both periods. The data record deaths in 5 year age groups, as well as population estimates required to calculate mortality rates. Administrative boundaries for the ADM2 and ADM1 level are obtained from Chen et al. (2013) for the 2000 census boundaries, and points are assigned to an administrative unit based on being contained within those boundaries.

B.4 European Union

The E.U. maintains a centralized statistical database known as EuroStat (Eurostat, 2013b) which contains data on mortality counts and rates for all member countries at E.U.-specific administrative regions known as “Nomenclature of territorial units for statistics” (NUTS) boundaries. Data on mortality were obtained at NUTS2 level for all member states between the years 1990-2014, though individual countries start and end years vary, as described in table 6. Population for each NUTS2 unit were downloaded through the EuroStat database. We download age-specific data according to the age groups used in the main analysis. It is noted in the metadata that populations for NUTS2 regions are estimated to be applicable to the first day of each year, whereas mortality data are counted at the

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68 Data are accessible here: http://www.deis.cl/bases-de-datos-defunciones/
69 Data available here: http://www.ine.cl/estadisticas/demograficas-y-vitales
70 Available here: http://ec.europa.eu/eurostat/data/database
71 Administrative boundary files were downloaded from: http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts
end of that year. Because of this, we offset the assignment of population and mortality by one year, so that, for example, 2005 mortality is matched with 2006 population on January 1st. Administrative shapefiles are downloaded from the same source, and the 2013 version is used in the analysis. We drop the data on France from the E.U. dataset, as we obtain a higher spatial resolution source directly from the French government.

**B.5 France**

Mortality data for France are obtained at the ADM2-month level from the Institut National D’etudes Demographiques (INED) (National Institute for the Study of Demography (INED))\(^{72}\) for the years 1998-2010. Data from this source do not have a categorization of mortality for a 0-4 year old age group as used in the analysis. The youngest age group for which there is data is for ages 0-19. In the subsequent analysis, we assign the 0-19 France age group to the 0-4 age group in the sample. This is done mainly because the youngest and oldest age groups in our analysis represent most of the mortality, and so we assume that the majority of 0-19 deaths recorded will be in the 0-4 age group. As this introduces some measurement error in our data, we perform the analysis with the 0-19 group assigned to our 5-64 year old group, which leads to small or no change in the 5-64 age group, but a more substantial, though not significant change in our 0-4 age group. We aggregate monthly data to annual for the analysis, and obtain boundary files from GADM (Global Administrative Areas, 2012b).

**B.6 India**

Data on Indian mortality at the sub-district-year level are as used in Burgess et al. (2017) and were obtained from the authors of that paper. A more thorough description of the data are given in Burgess et al. (2017). We note here that the Indian data are not used in our main aggregate file due to the absence of data on age-specific mortality in a comparable manner to our other data sources. These data are used to assess the external validity of our extrapolation methods.

**B.7 Japan**

Japanese data on mortality and population at the prefecture-year\(^{73}\) level were obtained from the National Institute of Population and Social Security Research\(^{74}\) for the years 1975-2012. Data are available for all 47 prefectures of Japan, with no changes to administrative boundaries in that time. Mortality rates were downloaded as single-year age groups, which were then aggregated into the age groups used for the analysis. ADM1 boundaries were obtained from GADM (Global Administrative Areas, 2012b).

\(^{72}\)Available here: [https://www.ined.fr/en/](https://www.ined.fr/en/)

\(^{73}\)Japanese mortality data are the only data in our sample at first administrative level. Though this is equivalent to states in the U.S., the small size of the prefectures makes them comparable to large United States counties or EU NUTS2 regions.

\(^{74}\)Data are available at: [http://www.ipss.go.jp/index-e.asp](http://www.ipss.go.jp/index-e.asp)
B.8 Mexico

Mexican data on municipality-month deaths were obtained for the years 1990-2010 from the National Institute of Statistics and Geographical Information (INEGI), whose open-microdata repository contains the raw mortality files\(^{75}\). The data contain detailed information, including the municipality of occurrence and of residence, date, and age at death. We assign locations of deaths based on municipalities of residence. Data were downloaded as monthly mortality counts, then aggregated into municipality-year counts. These were merged with year-by-municipality population counts estimated from the Mexican census as maintained at Minnesota Population Center’s Integrated Public Use Microdata Series, International\(^{76}\). There were seven municipalities (less than one half of 1%) that had inharmonious borders across data sets and years due primarily to administrative splits or mergers; we assigned these municipalities into their respective unions before the splits or after the mergers.

B.9 United States

United States data on the universe of mortality and population at the county-year level were obtained from the Center for Disease Control (CDC) Compressed Mortality Files (CMF)\(^{77}\) for the years 1968-2010. CDC removes values for county-year-age totals that are fewer than 10 deaths to preserve anonymity in the data in public files, and we obtain these through a data user agreement with CDC. There is some overlap in years available in the restricted and unrestricted datasets, and where both are available we use the restricted data due to better spatial coverage. In the restricted data, zeros are coded as missing, and so we reassign all missing values to zero. Data were downloaded in 5-year age groups and then aggregated to the age groups used in the analysis. The CMF reports deaths at the county of residence. Administrative boundaries are obtained from the TIGER datasets of the U.S. Census Bureau.\(^{78}\)

B.10 Aggregate data

Data from each country were standardized as rates for the three age groups used throughout the analysis and merged into a single file. We note that in all cases, place of residence is used for the assignment to temperature exposures in the data. In cases of inharmonious borders between years, we assign exposure based on a temporally consistent set of boundaries that are chosen to be in the most aggregate form, i.e., before administrative units split or after they merge. A full list of these is available upon request.

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\(^{77}\)Partial data are freely available through the CDC Wonder database [https://www.cdc.gov/](https://www.cdc.gov/)

\(^{78}\)Available here: [https://www.census.gov/geo/maps-data/data/tiger-line.html](https://www.census.gov/geo/maps-data/data/tiger-line.html)

\(^{79}\)France is estimated using data from a different source and the EuroStat version of the France data is not used.
**Table 6: Details of E.U. mortality sample**

<table>
<thead>
<tr>
<th>Code</th>
<th>Country</th>
<th>Number of NUTS2 regions</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>Austria</td>
<td>9</td>
<td>1990-2014 (not 1995)</td>
</tr>
<tr>
<td>BE</td>
<td>Belgium</td>
<td>11</td>
<td>1990-2014</td>
</tr>
<tr>
<td>BG</td>
<td>Bulgaria</td>
<td>6</td>
<td>1990-2014</td>
</tr>
<tr>
<td>CH</td>
<td>Switzerland</td>
<td>7</td>
<td>1991-2014</td>
</tr>
<tr>
<td>CY</td>
<td>Cyprus</td>
<td>1</td>
<td>1993-2014 (before 1993 is not by age-group)</td>
</tr>
<tr>
<td>CZ</td>
<td>Czech Republic</td>
<td>8</td>
<td>1992-2014</td>
</tr>
<tr>
<td>DE</td>
<td>Germany</td>
<td>50</td>
<td>2002-2014 (of these 2 regions from 2011-2014)</td>
</tr>
<tr>
<td>DK</td>
<td>Denmark</td>
<td>5</td>
<td>2007-2014</td>
</tr>
<tr>
<td>EE</td>
<td>Estonia</td>
<td>1</td>
<td>1990-2014</td>
</tr>
<tr>
<td>EL</td>
<td>Greece</td>
<td>4</td>
<td>1990-2014 (13 for 2013)</td>
</tr>
<tr>
<td>ES</td>
<td>Spain</td>
<td>19</td>
<td>1990-2014</td>
</tr>
<tr>
<td>FI</td>
<td>Finland</td>
<td>5</td>
<td>1990-2014</td>
</tr>
<tr>
<td>FR</td>
<td>France</td>
<td>22</td>
<td>1990-2014 (additional 4 regions for 2014)</td>
</tr>
<tr>
<td>HR</td>
<td>Croatia</td>
<td>2</td>
<td>2001-2014</td>
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<tr>
<td>HU</td>
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<td>1990-2014</td>
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<td>1990-2014</td>
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</tr>
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<td>1995-2014 (under 5 only available from 1995)</td>
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<td>2001-2014</td>
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<td>1991-2014</td>
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<td>PT</td>
<td>Portugal</td>
<td>7</td>
<td>1992-2014</td>
</tr>
<tr>
<td>RO</td>
<td>Romania</td>
<td>8</td>
<td>1990-2014</td>
</tr>
<tr>
<td>SE</td>
<td>Sweden</td>
<td>8</td>
<td>1990-2014</td>
</tr>
<tr>
<td>SI</td>
<td>Slovenia</td>
<td>2</td>
<td>2014</td>
</tr>
<tr>
<td>SK</td>
<td>Slovakia</td>
<td>4</td>
<td>1997-2014</td>
</tr>
<tr>
<td>TR</td>
<td>Turkey</td>
<td>26</td>
<td>2009-2014</td>
</tr>
<tr>
<td>UK</td>
<td>United Kingdom</td>
<td>40</td>
<td>1999-2014 (of these 4 from 2000, 2 from 2002, 5 for just 2014)</td>
</tr>
</tbody>
</table>
C Climate data

This section describes the climate data that we use in this analysis as well as some of the methods that are used to make these data consistent with the scale and resolution of the mortality data. Broadly speaking, we use two classes of climate data, the first being historical data to estimate the temperature-mortality relationship, and the other being future climate data which is used to project the damages of climate change into the future under various emissions scenarios. We begin by describing the historical data, followed by the future projection data, and the methods for downscaling the latter and creating a distribution of future possible temperature changes.

C.1 Historical data

Global Meteorological Forcing Database The main dataset used in this analysis is the Global Meteorological Forcing Dataset (GMFD) (Sheffield, Goteti, and Wood, 2006). These data provide surface temperature and precipitation data using a combination of both observations and reanalysis. The latter approach takes observational weather data and uses a weather forecasting model to interpolate both spatially and temporally in order to establish a gridded dataset of meteorological variables. The particular reanalysis used is the NCEP/NCAR reanalysis (Sheffield, Goteti, and Wood, 2006) and is corrected with a number of station-based observational datasets. Data are available on a 0.25° × 0.25° resolution grid from 1948-2010. The temporal frequency is up to 3-hourly, but the daily data are used for current applications. The daily average temperature and monthly average precipitation are obtained for each gridcell.

Berkeley Earth Surface Temperature The Berkeley Earth Surface Temperature (BEST) dataset provides temperatures from 1701-2013 over land from a combination of observational records (Rohde et al., 2013), with spatially disaggregated data available for 175380. During the time periods used within this paper (varying between 1957-2014), as many as 37,000 station records, representing 14 separate databases of station data, are incorporated into the BEST data. Station data are incorporated using a kriging methodology that allows for the incorporation of more stations with shorter time series than other well-known global surface temperature interpolation data (like the UDEL temperature dataset). In particular, the spatial averaging method uses close neighbors of a station to identify discontinuities in a particular time series that may be due to instrumental change or re-positioning, and decreases the influence of these changes in the spatially averaged grid (Rohde et al., 2013). This does have the potential drawback of over-smoothing the spatial heterogeneity in temperatures (National Center for Atmospheric Research Staff (Eds), 2015). BEST data are provided at daily frequency on a 1° × 1° resolution grid, and we utilize the daily average 2m air temperature variable for each gridcell.

University of Delaware Climate Dataset The University of Delaware climate dataset (UDEL) (Matsuura and Willmott, 2007) is used for precipitation in combination with the BEST data. UDEL provides gridded, interpolated data derived from weather stations on many variables at a monthly frequency and on a 0.5° × 0.5° resolution grid. Data are available from 1900-2014. The UDEL data

80Available here: http://berkeleyearth.org/data/
are based on two underlying datasets of stations and so have fewer observations being combined to make the interpolated grid. This is noted to lead to some decrease in interpolation accuracy in areas where the spatial coverage of weather stations is low. The interpolation procedure used is based on inverse distance weighting to the central point of each gridcell, and the authors note that other data, like altitude and atmospheric characteristics, are used to improve that interpolation. The monthly average precipitation is obtained for each gridcell.

C.2 Climate projection data

Data on the future evolution of the climate is obtained from Global Climate Model (GCM) output. However, there are two primary limitations when implementing original or raw GCM outputs into the current analysis. First, the relatively coarse resolution (about several to one degrees of longitude and latitude) of GCMs has limited their ability to capture small-scale climate patterns, which render them unsuitable for local climate impact assessment. Second, the GCM outputs exhibit large local bias compared with observations.

To comprehensively capture spatial heterogeneity in climate damages, we use a high-resolution (0.25° X 0.25°) set of global, bias-corrected climate projections produced by NASA Earth Exchange (NEX): the Global Daily Downscaled Projections (GDDP) (Thrasher et al., 2012). The NEX-GDDP dataset comprises 21 climate projections, which are downscaled from the output of global climate model (GCM) runs in the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (Taylor, Stouffer, and Meehl, 2012). The list of the 21 GCMs is shown in Table 7. The statistical downscaling algorithm used to generate the NEX-GDDP dataset is the Bias-Correction Spatial Disaggregation (BCSD) method (Wood et al., 2004; Thrasher et al., 2012), which was developed to address the aforementioned two limitations. This algorithm first compares the GCM outputs with observational data in a historical period. NEX-GDDP uses a climate dataset from the Global Meteorological Forcing Dataset for this purpose (Sheffield, Goteti, and Wood, 2006). The daily maximum temperature, daily minimum temperature, and daily precipitation at 0.25 × 0.25 degree resolution during the period of 1950-2005 are used in the downscaling process. A relationship between daily GCM outputs and observations is derived from this comparison. This relationship is then used to adjust the GCM outputs in historical and in future time periods so that the systemic bias of the GCM outputs is removed. To disaggregate the bias-corrected GCM outputs to higher-resolution, this algorithm interpolates the daily changes relative to climatology in GCM outputs into the spatial resolution of GMFD, and merges the fine-resolution changes with the climatology of GMFD data.

For each GCM, there are three different sets of data that are generated. The first uses historical emissions to simulate the response of the climate to historical forcing from 1850 to 2005 (data after 1981 are used in our analysis). The second and third use projected emissions from Representative Concentration Pathways 4.5 and 8.5 (RCP 4.5 and RCP 8.5) to simulate emissions under those two emissions scenarios up to 2100. RCP 4.5 represents a “stabilization” scenario in which total radiative forcing is stabilized around 2100 (Riahi et al., 2011) RCP8.5 simulates climate change under intensive

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81Climate projections used were from the NEX-GDDP dataset, prepared by the Climate Analytics Group and NASA Ames Research Center using the NASA Earth Exchange, and distributed by the NASA Center for Climate Simulation (NCCS).
growth in fossil fuel emissions from 2006 to the end of the 21st century. We use daily averaged temperature and daily precipitation in RCP4.5 and RCP8.5 scenarios from the dataset, where the daily averaged temperature is approximated as the mean of daily maximum and daily minimum temperature. The gridded data are aggregated to impact regions, with any required nonlinear transformations taken before aggregating.

**Table 7: List of CMIP5 models included in NEX-GDDP**

<table>
<thead>
<tr>
<th>ACCESS1-0</th>
<th>CSIRO-MK3-6-0</th>
<th>MIROC-ESM</th>
</tr>
</thead>
<tbody>
<tr>
<td>bcc_csm1-1</td>
<td>GFDL-CM3</td>
<td>MIROC-ESM-CHEM</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>GFDL-ESM2G</td>
<td>MIROC5</td>
</tr>
<tr>
<td>CanESM2</td>
<td>GFDL-ESM2M</td>
<td>MPI-ESM-LR</td>
</tr>
<tr>
<td>CCSM4</td>
<td>inmcm4</td>
<td>MPI-ESM-MR</td>
</tr>
<tr>
<td>CESM1-BGC</td>
<td>IPSL-CM5A-LR</td>
<td>MRI-CGCM3</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>IPSL-CM5A-MR</td>
<td>NorESM1-M</td>
</tr>
</tbody>
</table>

### C.3 SMME and model surrogates

The ensembles of CMIP5 GCMs do not produce probability distributions of climate projections and they systematically underestimate the tail risks in future climate (Tebaldi and Knutti, 2007; Rasmussen, Meinshausen, and Kopp, 2016). To provide a probabilistic ensemble of climate projections, we use the surrogate model mixed ensemble (SMME) method (Rasmussen, Meinshausen, and Kopp, 2016) to assign probabilistic weights to climate projections produced by GCMs and improve representation of the tails of the distribution missing from the ensemble of GCMs. Generally speaking, the SMME uses (1) a weighting scheme based on a probabilistic projection of global mean surface temperature from a simple climate model (MAGICC6) (Meinshausen, Raper, and Wigley, 2011) and (2) a form of linear pattern scaling (Mitchell, 2003) that preserves high-frequency variability to construct model surrogates to fill the tails of probability distribution that are not captured by the GCM ensembles. This method provides us with an additional 12 surrogate models.

The SMME method first divides the unit interval [0,1] into a set of bins. For this analysis, the bins are centered at the 1th, 6th, 11th, 16th, 33th, 50th, 67th, 82th, 89th, 94th, and 99th percentiles. Bins are narrower in the tails to ensure samples are created for portions of the GMST PDF that are not captured by CMIP5 models. The bounds and center of each bin are assigned corresponding quantiles of GMST anomalies for 2080-2099 from simple climate model (SCM) output; in the application here and that of Rasmussen, Meinshausen, and Kopp (2016), this output came from the MAGICC6 (Meinshausen, Raper, and Wigley, 2011) model, constrained to match historical temperature observations and the conclusions of the IPCC Fifth Assessment Report regarding equilibrium climate sensitivity. The GMST of CMIP5 models are categorized into bins according to their 2080-2099 GMST anomalies.

If the number of CMIP5 models in a bin is less than 2, surrogate models are generated to raise the total number of models to 2 in that bin. The surrogate models are produced by using the projected annual GMST of the SCM that is consistent with the bin’s central quantile to scale the pattern of a selected CMIP5 model, then adding the intercept and residual from the same model. There are two cases of selecting CMIP5 models for pattern and residual. When there is only one CMIP5 model in
a bin, an additional model is selected that has a GMST projection close to GMST in the bin and a precipitation projection over the region of interest complementary to the model already in the bin (i.e., if the model in the bin is relatively dry, then a relatively wet pattern is selected, and vice versa.) When there is no CMIP5 model, two models are picked with GMST projections close to that of the bin, with one model being relatively wet and one being relatively dry. In the final probabilistic distribution, the total weight of the bin is equally divided among the CMIP5 models and surrogate models in the bin. For instance, if four models are in the bin centered at the 30th percentile, bounded by the 20th – 40th percentiles, each will be assigned a probability of $20\% \div 4 = 5\%$. 
D Income covariate data and downscaling method

We draw subnational incomes from three main sources:

- **Penn World Tables (PWT) data**\(^{82}\). This dataset provides national level income data from 1950 to 2014 for most of the countries in the world. We use Penn World Table version 9.0 to get national level income for all the countries in the sample (Brazil, Chile, China, France, India, Japan, Mexico, USA, and the 33 EU countries).

- **Eurostat (2013a)**\(^{83}\). This dataset provides national and sub-national (NUTS2) level income data for the European countries in our dataset. We use this dataset to get the subnational (NUTS2) level income data for the EU countries in our sample.

- **Gennaioli et al. (2014)**\(^{84}\). This dataset provides national and sub-national income data for 1,503 regions from 82 countries. We use this dataset to get the subnational (ADM1) level income data for Brazil, Chile, China, France, India, Japan, Mexico, and USA.

D.1 Downscaling methods

To obtain the subnational level (NUTS2 level for EU countries and ADM1 level for the other countries) income data, we use Eurostat (2013a) and Gennaioli et al. (2014) to downscale the PWT national level income. For region \(j\) in country \(c\) in year \(t\) we calculate a weight, \(W_{jct}\), that will apportion national income to subnational regions as follows:

\[
W_{jct} = \begin{cases} 
\frac{GDP_{pc}^{Eurostat}_{jct}}{GDP_{pc}^{Eurostat}_{ct}} & \text{if } c \in \text{EU} \\
\frac{GDP_{pc}^{Gennaioli}_{jct}}{GDP_{pc}^{Gennaioli}_{ct}} & \text{otherwise}
\end{cases}
\]

\[
Income_{jct} = W_{jct} \times GDP_{pc}^S_{ct}
\]

where \(GDP_{pc}^S\) corresponds to to per capita GDP drawn from any of the three sources, \(S\), of PWT, Gennaioli et al. (2014), or Eurostat (2013a). We then take the average of the income over all years and assign it to each ADM1 or NUTS2 unit within our dataset:

\[
\overline{Income}_{jc} = \frac{1}{T} \sum_{t=1}^{T} Income_{jct}
\]

Data in Eurostat (2013a) are an annual panel. However, the data collected by Gennaioli et al. (2014) are drawn from disparate sources, often using census data which are typically not annual, leading to an unbalanced panel. A summary of the available years of data before interpolation is given in table 8. We match incomes in the cross-section to observations in our sample by assigning each ADM1 region to the average GDP per capita over the sample period. In the Gennaioli et al. (2014)

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\(^{82}\)Penn World Tables (PWT) database: [https://www.rug.nl/ggdc/productivity/pwt/](https://www.rug.nl/ggdc/productivity/pwt/)

\(^{83}\)Eurostat database: [http://ec.europa.eu/eurostat/data/database](http://ec.europa.eu/eurostat/data/database)

\(^{84}\)[https://ideas.repec.org/a/kap/jecgro/v19y2014i3p259-309.html](https://ideas.repec.org/a/kap/jecgro/v19y2014i3p259-309.html)
data, we interpolate between years and take the average for a region at the ADM1 level over those interpolated data. All sub-national income data are in constant 2005 dollars PPP.

<table>
<thead>
<tr>
<th>Country</th>
<th>ISO code</th>
<th>Mortality sample</th>
<th>Income sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU</td>
<td></td>
<td>1990-2012</td>
<td>2003-2012</td>
</tr>
</tbody>
</table>

Table 8: Years covered in mortality sample and available sub-national income data.
E Spatial units for projection: “Impact Regions”

We create a set of boundaries that define the spatial units onto which we extrapolate temperature-mortality sensitivities derived from our estimation, and for which we create location-specific projected damages of climate change. To do so, we utilize politically defined regions, as they form a better scale for analysis than regular grids due to their use in collecting socioeconomic data. Moreover, these regions are generally more relevant to policy-makers. These regions, hereafter referred to as “impact regions”, are constructed such that they are identical to existing administrative regions or are a union of a small number of administrative regions. We use the Global Administrative Region dataset (Global Administrative Areas, 2012a) to delineate boundaries, but require fewer than the approximately 295,000 spatial units present in that dataset. We thus create a set of 24,378 agglomerated regions that allow for greater comparability and computational feasibility than unagglomerated regions. We establish a set of criteria to create these regions that makes them approximately comparable with respect to population, and internally consistent with respect mean temperature, diurnal temperature range, and mean precipitation. A map of these regions is shown in Figure 12.

We develop an algorithm which agglomerates administrative units from GADM2 into regions with approximately equal amounts of population and climate variability, and which are spatially compact. We first allot region targets to each country, based on population density and climatic variability. The population weighted target is $20000 \sum_i {p_i}$, for country $i$ with population $P_i$.

The climate weighted target is $20000 \frac{A_i}{\sum_i A_i} \frac{V_i}{\sum_i V_i}$ for areas $A_i$ and $V_i = \frac{\text{Var}[T_i]}{E[\text{Var}[T]]} + \frac{\text{Var}[D_i]}{E[\text{Var}[D]]} + \frac{\text{Var}[P_i]}{E[\text{Var}[P]]} + \frac{\text{Var}[Q_i]}{E[\text{Var}[Q]]}$, where $T_i$ is mean temperature, $E[T] = 8$ °C, $D_i$ is diurnal temperature range, $E[D] = 2.1$ °C, $P_i$ is precipitation in the wettest month, $E[P] = 250$ mm, $Q_i$ is precipitation in the driest month, and $E[Q] = 26$ mm (Hijmans et al., 2005). The final target region count for each country is the average of the population and climate weighted targets.

The target regions, relative to the available administrative levels, are shown in Figure 13. For most countries, there is no available administrative division for our preferred resolution, as shown in Figure 14.

Figure 12: Map of the 24,378 “impact regions” onto which location-specific predictions are projected. We use a clustering algorithm to form these regions, such that they are roughly similar in total population, and so that they are internally homogenous with respect to mean temperature, diurnal temperature range, and mean precipitation.
<table>
<thead>
<tr>
<th>Country</th>
<th>Number of Regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>10</td>
</tr>
<tr>
<td>India</td>
<td>10</td>
</tr>
<tr>
<td>United States</td>
<td>10</td>
</tr>
<tr>
<td>Brazil</td>
<td>10</td>
</tr>
<tr>
<td>Russia</td>
<td>10</td>
</tr>
<tr>
<td>Australia</td>
<td>10</td>
</tr>
<tr>
<td>Indonesia</td>
<td>10</td>
</tr>
<tr>
<td>Canada</td>
<td>10</td>
</tr>
<tr>
<td>Mexico</td>
<td>10</td>
</tr>
<tr>
<td>Pakistan</td>
<td>10</td>
</tr>
<tr>
<td>Colombia</td>
<td>10</td>
</tr>
<tr>
<td>Peru</td>
<td>10</td>
</tr>
<tr>
<td>Argentina</td>
<td>10</td>
</tr>
<tr>
<td>Madagascar</td>
<td>10</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>10</td>
</tr>
<tr>
<td>Ecuador</td>
<td>10</td>
</tr>
<tr>
<td>Bolivia</td>
<td>10</td>
</tr>
<tr>
<td>Algeria</td>
<td>10</td>
</tr>
<tr>
<td>Viet Nam</td>
<td>10</td>
</tr>
<tr>
<td>Egypt</td>
<td>10</td>
</tr>
<tr>
<td>Tunisia</td>
<td>10</td>
</tr>
<tr>
<td>Sudan</td>
<td>10</td>
</tr>
<tr>
<td>Chad</td>
<td>10</td>
</tr>
<tr>
<td>South Africa</td>
<td>10</td>
</tr>
<tr>
<td>Egypt</td>
<td>10</td>
</tr>
<tr>
<td>Turkey</td>
<td>10</td>
</tr>
<tr>
<td>Vietnam</td>
<td>10</td>
</tr>
<tr>
<td>Algeria</td>
<td>10</td>
</tr>
<tr>
<td>Bolivia</td>
<td>10</td>
</tr>
<tr>
<td>Iran</td>
<td>10</td>
</tr>
<tr>
<td>Ethiopia</td>
<td>10</td>
</tr>
<tr>
<td>Philippines</td>
<td>10</td>
</tr>
<tr>
<td>Japan</td>
<td>10</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>10</td>
</tr>
<tr>
<td>Peru</td>
<td>10</td>
</tr>
<tr>
<td>Argentina</td>
<td>10</td>
</tr>
<tr>
<td>Nigeria</td>
<td>10</td>
</tr>
<tr>
<td>Myanmar</td>
<td>10</td>
</tr>
<tr>
<td>Pakistan</td>
<td>10</td>
</tr>
<tr>
<td>Colombia</td>
<td>10</td>
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<tr>
<td>Mexico</td>
<td>10</td>
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<tr>
<td>Canada</td>
<td>10</td>
</tr>
<tr>
<td>Indonesia</td>
<td>10</td>
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<tr>
<td>Australia</td>
<td>10</td>
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<td>Russia</td>
<td>10</td>
</tr>
<tr>
<td>Brazil</td>
<td>10</td>
</tr>
<tr>
<td>United States</td>
<td>10</td>
</tr>
<tr>
<td>India</td>
<td>10</td>
</tr>
<tr>
<td>China</td>
<td>10</td>
</tr>
</tbody>
</table>

**Figure 13:** Countries with over 1000 target regions, based on their population and climatic targets. “Max regions” is the count of the smallest administrative regions in a country if the smallest administrative region is finer than ADM3. The range between administrative region counts above and below these targets are shown in black.

**Figure 14:** Let $C$ be a country’s target region count. Countries in dark blue have $C \geq \text{Max Regions}$; lightest blue have $C \leq 1$; other shades of blue have an administrative region with $C/2 \leq N \leq C$. All others (red) need agglomeration.
For those countries for which the target number of regions is between the total country region count at any administrative level and half that count, we take the closest administrative level. Otherwise, the agglomeration algorithm is applied.

For the agglomeration algorithm, we calculate a number of attributes at the highest available administrative level within a given country. As the agglomerations are performed, the attributes of the new agglomerated region are generated from its component regions. These attributes are as follows:

- Contained regions ($# = M$)
- Neighbors ($# = N$)
- Population ($P$), from Bright et al. (2012) and area ($A$)
- Socioeconomic and Climatic traits, e.g., income, urban fraction, temperatures, biomes ($\{T\}$)
- Containing region centroids ($Lat, Lon$)

The agglomeration process is a greedy algorithm, which performs the following steps:

1. A set of proposed agglomerations is generated. For a given region $R$ within a containing administrative region $S$, these consist of:
   - The combination of $R$ with each of its neighbors within $S$.
   - The next higher administrative region, $S$ (e.g., all counties within the same state).
   - If neither of the above is available (e.g., an island state), the combination of $R$ and the closest neighbor also at the first administrative level.

2. Each proposed agglomeration is scored, and this is compared to the score for the un-agglomerated region. For a region $R_i$ containing subregions indexed by $j$. The scores consist of a weighted sum of the following:

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Expression</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>$-(\sum_j A_j/a_0)^2$, where $A_0$ is the average US county area</td>
<td>0.01</td>
</tr>
<tr>
<td>Population</td>
<td>$-(\sum_j P_j/a_0)^2$, where $P_0$ is the average US county population</td>
<td>1</td>
</tr>
<tr>
<td>Dispersion</td>
<td>$\text{Var}[Lat] - \text{Var}[Lon \cos E[Lat]]$</td>
<td>10</td>
</tr>
<tr>
<td>Other traits</td>
<td>$\sum_T \text{Var}[T_i]/T_0$, where $T_0$ is 1 for population density, 100 for elevation, 8.0 for mean temperature, 2.1 for diurnal temperature range, 25.0 for wet season precipitation and 2.6 for dry season precipitation</td>
<td>100</td>
</tr>
<tr>
<td>Circumference</td>
<td>$M N/a \sqrt{M}$</td>
<td>1</td>
</tr>
</tbody>
</table>
3. The best possible agglomeration proposed by any region is identified, as determined by the smallest negative difference.

4. The regions within the agglomeration are merged, and new properties are applied to the new region.

5. This process repeats until the desired number of regions is reached.

The final result is shown in Figure 15.

![Figure 15: Regions used in the forecast analysis. Regions are colored randomly.](image)
F  Downscaled population and income future projections

F.1  Population projections

Projections of national populations are derived from the Organization for Economic Co-operation and Development (OECD) (Dellink et al., 2015) and International Institute for Applied Systems Analysis (IIASA) (Samir and Lutz, 2014) population projections as part of the “socioeconomic conditions” (population, demographics, education, income, and urbanization projections) of the Shared Socioeconomic Pathways (SSPs). The SSPs propose a set of plausible scenarios of socioeconomic development over the 21st century in the absence of climate impacts and policy for use by the Integrated Assessment Modeling (IAM) and Impacts, Adaptation, and Vulnerability (IAV) scientific communities. The population data are accessed from the SSP database (IIASA Energy Program, 2016). The IIASA SSP population projections provide estimates of population by age cohort, gender, and level of education for 193 countries from 2010 to 2100 in five-year increments. Each projection corresponds to one of the five SSPs, as defined in O’Neill et al. (2014). These populations are mapped to impact regions by country code using 3-digit country ISO-codes.

To generate local-level projections of climate change impacts, and to account for substantial heterogeneity in adaptation and exposure within countries, we need to assemble high-resolution information on population distributions. To do so, we downscale the country-level projections from the SSPs using current LandScan estimates of populations that fall within our impact regions within each country. Populations for impact regions in countries or areas not given in the SSP Database are held constant at their LandScan estimated values in 2011. Thus, for any given impact region $i$ in year $t$, population for scenario $s$ ($P_{i,t,s}$) is given by

$$P_{i,t,s} = \begin{cases} \sum_{j \in J} d_{i,j} \times \left( \hat{P}_{j,t,s} \frac{p_{\text{LandScan}}}{\sum_{k} d_{i,k} p_{k}} \right), & \text{if } i \in J \\ p_{\text{LandScan}} & \text{if } i \notin J \end{cases} \quad (27)$$

where $\hat{P}_{j,t,s}$ is the SSP population given for country $j$, $p_{\text{LandScan}}$ is the LandScan estimate for impact region $i$, $d_{i,j}$ is a dummy variable which is set to 1 when $i$ is in country $j$ and to 0 otherwise, and $J$ is the set of all countries in the SSP Database. Note that while this approaches distributes country-level projections of population heterogeneously to impact regions within a country, it fixes the relative population distribution within each country at the observed distribution today.

F.2  Income projections

Projections of national per-capita income are also taken from the socioeconomic conditions making up the SSPs. Multiple models are used to estimate SSP trajectories. These models predict different subsets of countries around the globe, and describe different pathways within each shared scenario. Across the models used to estimate SSP trajectories, populations are fairly similar, so we merge all models by averaging estimates across all models that predict each country.

Only the IIASA GDP model and OECD Env-Growth provide GDP per capita for a wide range of countries. The IIASA GDP model describes incomes that are lower than the OECD Env-Growth model, so we produce results for these two models to capture uncertainty within socioeconomic scenario.
OECD estimates of income are provided for 184 countries and IIASA’s GDP projections cover 171 countries. For the remaining countries, we apply the average GDP per capita from the available countries in the given year for the baseline period, and allow this income to grow at the globally averaged rate. We smoothly interpolate between the time series data provided in 5-year increments in the SSP Database. For each 5-year segment, we calculate the average annual growth rate, and apply to produce each year’s estimate.

F.3 Income downscaling procedure using nighttime lights imagery

As described above for population, our high-resolution analysis requires estimates of location-specific GDP within country borders. To generate such estimates, we allocate national GDP per capita across the impact regions within a country through a downscaling procedure that relies on night lights imagery from the NOAA Defense Meteorological Satellite Program (DSMP). Using available subnational income data from Gennaioli et al. (2014) in combination with higher-resolution income data from the United States, China, Brazil, and India, we empirically estimate the relationship between GDP per capita and nightlight intensity. We use this estimated relationship to allocate GDP data provided at the national level heterogeneously across impact regions within each country, based on relative intensity of night lights in the most recent DSMP images available (2013). While this approach models heterogeneity in income levels across impact regions, each region grows in the future at the same rate as the national country projection.

For our future socioeconomic projections we have national level incomes from SSPs. Our requirements of effectively apportioning a national level income to subnational regions is distinct from much of the literature on nightlights which seeks to measure economic activity directly. That is, we are interested in the ratio \( \frac{GDP_{pcrct}}{GDP_{pcct}} \) for impact region \( i \) in country \( c \). This ratio allows us to project income at the impact region level.

We use the stable nightlights data product from 1992-2012 from NASA’s DMSP program.\(^\text{85}\) We calculated a z-score of nightlights (ZNL) for each ADM1 within an ADM0 (country) unit using:

\[
ZN L_{rct} = \frac{NL_{rct} - \bar{NL}_{ct}}{\sigma(NL_{ct})}
\]

for ADM1 region \( r \) in country \( c \). We use Gennaioli et al. (2014) to calculate relative GDP per capita at ADM1 level with respect to the GDP of country, and regress the relative incomes on ZNL:

\[
\frac{GDP_{pcrct}}{GDP_{pcct}} = \alpha + \beta ZNL_{rct} + \epsilon_{rct}
\]

The merged data are an unbalanced panel, as described in section D. The estimated \( \beta \) was then used to compute income at impact regions level where average of stable nightlights for 2008-2012 was used to compute z-score of nightlights.

\(^{85}\)Image and Data processing by NOAA’s National Geophysical Data Center. DMSP data collected by the US Air Force Weather Agency.
G Robustness and heterogeneity of econometric estimates

In this section we present results that examine the robustness of our main econometric estimates to different functional forms of temperature and different data sources, heterogeneity in our pooled mortality estimates across each country in the sample, and the robustness of our interacted model to different functional forms of long-run climate interactions.

G.1 Robustness to alternative functional form specifications and alternative historical climate datasets

Figure 16 displays the results of estimating equation 9 using a set of different functional forms of temperature and using two different climate datasets to obtain those temperatures. The four functional forms estimated are 4th-order polynomials, bins of daily average temperature, restricted cubic splines, and piecewise linear splines.

![Figure 16: Robustness of the all-age temperature-mortality relationship to alternative functional forms and to different historical climate datasets. Row 1 shows the mortality-temperature response function as estimated using daily temperature and precipitation data from the Global Meteorological Forcing Dataset (GMFD). Row 2 shows the same response, using daily temperatures from Berkeley Earth Surface Temperature (BEST), and monthly precipitation from the University of Delaware. Each column displays a distinct functional form, with the fourth-order polynomial shown in column 1 overlaid in teal on each subsequent column. See Section 4 for details on each functional form.](image-url)
Figure 17: Temperature-mortality response function with demographic heterogeneity. Temperature-mortality response function estimated for population below 5 years of age (green), between 5 and 64 years of age (blue), and >64 years of age (red). Regression estimates shown are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects.

G.2 Age specific and country-level mortality-temperature response function

Figure 17 displays the temperature responses of mortality in our three age categories for the pooled 41 country estimate. These curves correspond with our benchmark model (2) in Table 3.

The regions in our sample represent substantial heterogeneity. To begin to examine this heterogeneity, we look at the variation of the temperature-mortality relationship across countries in our sample. Table 9 displays these results for the 9 countries or regions in our data. We additionally show only predictions at daily average temperatures actually experienced in each country over our sample period.

G.3 Nonlinear characterization of long-run average climate

Our main results rely on a parsimonious representation of the climate: to capture adaptation to long-run climate, we interact our nonlinear temperature variables with the long run average annual temperature for a given location. This leads to a linear relationship between the response function at any given temperature and long-run average temperature. To test the robustness of this linear interaction with long-run temperature, we instead characterize the climate using a common nonlinear transformation of temperature exposure: heating degree days (HDD) and cooling degree days (CDD). We replace our climate interaction term $TMEAN$ with two interaction terms: long-run average HDD’s, calculated relative to a 20°C threshold, and long-run average CDD’s, also calculated relative to 20°C.

Here we re-estimate our model with these separate characterizations of cold (HDD) and hot (CDD) days. Results for the marginal effect of each climate variable on the temperature sensitivity of mortality are shown in table 10. Consistent with our main results in Table 4, higher average temperatures, as we treat the EU here as a “country” for exposition purposes. A dummy variable is used to estimate the EU only response, but each of the 33 countries in the EU sample have their own set of country-year-age fixed effects.
Table 9: Heterogeneity by country in the mortality-temperature response function. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level. Point estimates indicate the effect of replacing a day at the reference temperature with a day at each temperature value shown. Country-specific coefficients are generated by interacting all climate variables and fixed effects with country dummies.

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<th>Temperature</th>
<th>BRA</th>
<th>CHL</th>
<th>CHN</th>
<th>FRA</th>
<th>JPN</th>
<th>MEX</th>
<th>USA</th>
<th>EUR</th>
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<td>35°</td>
<td>0.684</td>
<td>0.212</td>
<td>0.547**</td>
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<tr>
<td></td>
<td>(0.452)</td>
<td>(0.286)</td>
<td>(0.244)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>0</td>
<td>0.268*</td>
<td>-0.068</td>
<td>0.362***</td>
<td>0.863**</td>
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<td>(0.485)</td>
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<td>(0.117)</td>
<td>(0.106)</td>
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<td>-0.023</td>
<td>0.165***</td>
<td>0.287**</td>
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<td>(0.08)</td>
<td>(0.077)</td>
<td>(0.237)</td>
<td>(0.172)</td>
<td>(0.059)</td>
<td>(0.068)</td>
<td>(0.039)</td>
<td>(0.144)</td>
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<td>-0.204</td>
<td>1.12***</td>
<td>-0.419*</td>
<td>0.272*</td>
<td>4.526***</td>
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<td>(0.284)</td>
<td>(0.421)</td>
<td>(0.249)</td>
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<td>(0.991)</td>
<td>(0.119)</td>
<td>(1.063)</td>
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<td>-0.478</td>
<td>0.451*</td>
<td>10.829***</td>
<td>0.161</td>
<td>1.968</td>
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<tr>
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<td>-1.341*</td>
<td>0.773*</td>
<td>21.986***</td>
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<td>(1.736)</td>
<td>(0.541)</td>
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<td>(0.175)</td>
<td>(1.575)</td>
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Adj R-squared | .989
Observations | 820237
Adm2-Age FE | YES
Cntry-Year-Age FE | YES

Standard errors clustered at ADM1 level. Stacked regression is run with population weighting.

*** p<0.01, ** p<0.05, * p<0.1
captured by higher CDDs, lead to lower sensitivity of mortality rates to high-frequency temperature shocks. This is particularly true for the older age group. Moreover, for both under 5 and >65 categories, more frequent exposure to cold, as captured by higher average HDDs, lowers sensitivity to additional cold days.

The coefficients in Table 10 determine the spatial and temporal heterogeneity in response functions that we predict at the impact region level across the globe. To see how this alternative model compares to our preferred specification, we randomly selected administrative regions within our sample and used each model to predict the response function in each location. In Figure 18, we show both sets of response functions for three example regions: Paraná, Brazil; Himachal Pradesh, India; and Louisiana, USA. As is evident in the figure, this more nuanced characterization of the climate has a very minimal effect on our predicted response functions, and hence on our estimates of adaptation.

Figure 18: Predicted response functions for three example ADM1s within our sample. Each panel contains two predicted response functions relating annual mortality rates to daily temperature. Predictions come from a model in which a fourth order polynomial in temperature is interacted with either long-run average annual temperature (in blue) or long-run average heating degree days (HDDs) and cooling degree days (CDDs) (in red). Each column shows predictions for a different age category. Congruence between the two lines indicates robustness of our interaction model to alternative characterizations of the long-run climate.
Table 10: Marginal effect of covariates on temperature sensitivity of mortality rates using HDD-CDD interaction

<table>
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<tr>
<th></th>
<th>Age &lt;5</th>
<th></th>
<th>Age 5-64</th>
<th></th>
<th>Age &gt;64</th>
<th></th>
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<tr>
<td></td>
<td>logdppc</td>
<td>HDD</td>
<td>CDD</td>
<td>logdppc</td>
<td>HDD</td>
<td>CDD</td>
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<td>-1.07817**</td>
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<td>-0.00068</td>
<td>-0.28100*</td>
<td>-0.00004</td>
<td>-0.00030*</td>
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<td>(0.50360)</td>
<td>(0.00040)</td>
<td>(0.00067)</td>
<td>(0.15853)</td>
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<td>(0.00015)</td>
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<tr>
<td>30°</td>
<td>-0.33327</td>
<td>0.00037**</td>
<td>0.00051</td>
<td>-0.02308</td>
<td>-0.00001</td>
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<td></td>
<td>(0.26543)</td>
<td>(0.00018)</td>
<td>(0.00035)</td>
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<td>(0.00085)</td>
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Adj R-squared: 0.93353
N: 820237
Adm2-Age FE: Yes
Cntry-Yr-Age FE: Yes
H Adaptation assumptions, adaptation rates, and alternate adaptation scenarios

H.1 Adaptation assumptions imposed in the projection of climate change impacts

We impose two simple assumptions when applying our model of adaptation to projections of future climate change. These assumptions are guided by basic economic theory as well as the physiological literature. Graphical intuition for these two assumptions is shown in Figure 19.

![Figure 19: Two assumptions imposed in climate projections ensure that full adaptation is defined as a flat-line response function.](image)

Panel A demonstrates heuristically the importance of imposing assumptions on the shape of response functions under adaptation over the 21st century. As shown, linearly declining mortality rate sensitivity to hot days occurs over the course of the century as populations adapt. However, linear extrapolation can lead to mortality benefits on hot days, as shown with the dashed line and grey dots. Our assumptions (shown in teal) ensure that full adaptation is realized when hot days impose zero additional mortality risk. Panels B and C represent an empirical example of how the imposition of these restrictions can change the shape of the adapted response function, for a given impact region.

Assumption #1: Full adaptation is defined as a flat line. We define the fully adapted state as one in which variation in temperature has no effect on mortality. To implement this assumption
in projections of future impacts, we first identify a region of physiologically optimal temperatures at which the fully adapted state may, in theory, occur. Drawing on extensive research across epidemiology and medicine (e.g., Curriero et al., 2002; Guo et al., 2014), and ergonomics (e.g., Seppanen, Fisk, and Lei, 2006; Hancock, Ross, and Szalma, 2007), we let this range of possible minimum mortality risk cover the temperatures 10°C to 25°C. We then search, within this range, for the temperature at which the location-specific response function in each impact region \( r \) in the baseline years of 2001-2015 is minimized. Because distinct populations may differ substantially in the temperature at which mortality is minimized (e.g. Guo et al. (2014) demonstrate that mortality risk is smallest around the 75th percentile of local temperatures in 12 different countries), it is important to note that we allow these minimum mortality risk temperatures to be spatially heterogeneous. In calculating projected impacts, we then allow adaptation to occur (i.e. allow the response function to flatten) until the minimum mortality risk level, as defined in 2015, is reached. We note that while this approach allows for adaptive behaviors captured by future changes in our two factors, income and average climate, our imposition of this assumption precludes any changes in technology or adaptation investments which may alter the minimum mortality risk level itself.87

**Assumption #2:** Rising income cannot increase the temperature sensitivity of mortality. We assume that because increased income per capita strictly expands the choice set of individuals considering whether to make adaptive investments, future increases in income cannot raise the impacts of temperature on mortality rates. While we place no restrictions on the cross-sectional effect of income on the temperature sensitivity when estimating Equation 10, we do not allow any income gains through time to raise the marginal effect of temperature on mortality. We implement this restriction by bounding the marginal effect of income on mortality: that is, when \( \sum_{k \in K} \gamma_k^k (T_{rt}^k - T_{r,MMT}^k) > 0 \) for some region \( r \) in period \( t \), we set \( \sum_{k \in K} \gamma_k^k (T_{rt}^k - T_{r,MMT}^k) = 0 \), where \( T_{r,MMT} \) is the minimum mortality temperature for region \( r \), as discussed above. Note that this condition will only be binding if the marginal effect of income estimated in Equation 10 is positive for some nonempty set of temperatures. Further note that we impose this assumption first, before ensuring that adaptation does not lead to impacts that fall below the minimum mortality risk level described under assumption #1.

A visual example of the influence of these two assumptions can be seen for one example impact region in Figure 19. Under these two assumptions, we estimate projected impacts separately for each impact region, and then aggregate these high resolution effects to state, country, and global levels, using population weighting.

**H.2 Determining the temporal dynamics of adaptation**

The income covariate mediates the rate of income-based adaptation. If the income covariate is held at historical levels, no income-based adaptation is used. At the other extreme, if the contemporaneous income is applied in each year, then changes in income translate into immediate changes in sensitivity. Some benefits of income are expected to take many years to manifest, as richer governments and citizens invest in adaptive capital and enjoy greater health. We use a weighted average of recent year incomes \( z_{i,t-s} \), where \( s \) is a number of years of lags), according to a Bartlett kernel, to calculate the

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87See Appendix H.3 for results in which the rate of adaptation is deterministically assumed to slow. Under this alternative scenario, Assumption #1 binds much less frequently.
effective level of income-based adaptation ($\bar{z}_{it}$):

$$\bar{z}_{it} = \frac{\sum_{s=1}^{L}(L - s + 1)z_{i,t-s}}{\sum_{s=1}^{L}(L - s + 1)}$$

To find a plausible length for the Bartlett kernel, we study changes in the response of mortality for people over 65 to temperature in the United States. To do so, we estimate the same coefficients at each year. To remove the year fixed effect, we estimate the coefficient for the difference between each pair of years:

$$y_{it} - y_{i,t-1} = \alpha + \sum_k \beta_{kt}(T_{it}^k - T_{i,t-1}^k) + \text{controls} + \epsilon_{it}$$ (28)

Where $y_{it}$ is the death rate for region $i$ in period $t$, and $T_{it}^k$ is the pixel average of the mean temperature raised to the power $k$ for each region $i$. The controls are precipitation and precipitation squared. This produces a series of coefficients, $\beta_{kt}$, and their standard errors, $\sigma_{kt}$. The estimated coefficients are shown in Figure 20.

![Figure 20: Coefficients and 95% confidence intervals estimated for each year first-difference according to Equation 28 above. The horizontal line is the estimated mean across all years, including a year fixed effect.](image)

We use a Bayesian model to estimate the length of the Bartlett kernel that best explains these coefficients. Under the model, each coefficient is a draw from a Gaussian distribution with a mean that varies with the covariate:

$$\beta_{kt} \sim \mathcal{N}(\theta_k + \phi_k z_i, \tau_k + \sigma_{kt})$$

In this model, $\theta_k$ and $\phi_k$ correspond to the uninteracted and income interacted coefficients from our standard model, respectively. $\tau_k$ is a hyper-parameter which controls the rate of pooling of the
data, so that if it is 0, inverse-variance weighting is used across individual year estimates.

The covariate $z_t$ is calculated as a Bartlett kernel over up to 25 years of delayed income. National real income data is from the U.S. Bureau of Economic Analysis. The kernel is characterized by an unknown parameter $L$, which is also estimated by the model.

The maximum likelihood estimate for the Bartlett kernel length is 13 years, with a 95% confidence interval of 9.7 years, as shown in Figure 21. This corresponds to the maximum likelihood estimated value.

![Figure 21: Kernel weights for the estimated Bartlett kernel, and for the multi-kernel average. The multi-kernel average consists of the weights for all Bartlett kernel lengths (1 to 25) according to the estimated posterior probabilities.](image)

**H.3 Alternative assumptions on the rate of adaptation**

In our main results, we apply the estimated marginal effects used to extrapolate response functions in the present across space and over time to model future changes in those response functions as covariates change. Since these marginal effects are only identified by cross-sectional differences in the historical sensitivity to temperature, we develop here a robustness check where the marginal response of covariates for future adaptation is half of the estimated level of marginal response used for spatial extrapolation. This also reduces the extent to which our projection assumptions described in Section 6 bind, and can be used to understand how impacts change if the evolution of the response function toward zero occurs more slowly.

In the main model, income grows within each country $i$ according to $Y_{it} = g_{it} Y_{i,y-1}^\ast$, and the kernel-averaged climatic temperature for region $i$ used in the main model is $\bar{T}_{it}^\ast = \bar{T}_{i,t-1}^\ast + \Delta \bar{T}_{it}^\ast$. In this “slow adaptation” alternative approach, we replace income growth with $Y_{it} = (\frac{g_{it}}{2} + 1) Y_{i,t-1}$ after the year 2015, and we reduce linear growth in temperature by replacing it with $T_{it} = \bar{T}_{i,t-1} + \frac{\Delta T_{it}^\ast}{2}$. Note that both the normal and reduced growth analyses agree in 2015 (i.e. $Y_{i,2015} = Y_{i,2015}^\ast$), and similarly that $\bar{T}_{i,2015} = \bar{T}_{i,2015}^\ast$. 
Figure 22: Impacts of climate change on mortality are qualitatively similar with a model of slower adaptation rates. Time series of projected mortality costs of climate change (black line), as compared to partial estimates from incomplete accounting of the costs and benefits of adaptation (other colors). All lines show predicted mortality impacts of climate change across all age categories under the RCP8.5 emissions scenario, for the scenario SSP3, and using a single climate model (CCSM4). Panel A shows results for our standard model of adaptation, as described in Section 4. Panel B shows results for an alternative model of adaptation in which the rate of adaptation to both income growth and to warming climate is cut in half.

I Heterogeneity, Robustness, and Cross-validation of Globally Interpolated Results

I.1 Age-specific heterogeneity of the mortality-temperature response function by average income and average climate

Here we replicate the figure 2 from the main text for each of the age groups within our analysis.
Figure 23: Heterogeneity in the mortality-temperature relationship (ages 0-4 mortality rate). Each panel represents a predicted response function for the ages 0-4 mortality rate for a subset of the income-average temperature covariate space within our data sample. Response functions in the lower left are the predicted mortality-temperature sensitivities for poor, cold regions of our sample, while those in the upper right apply to the wealthy, hot regions of our sample. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level on the top end of the distribution only. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects, and where each temperature variable is interacted with each covariate and a dummy for each age category.
Figure 24: Heterogeneity in the mortality-temperature relationship (ages 5-64 mortality rate). Each panel represents a predicted response function for the ages 5-64 mortality rate for a subset of the income-average temperature covariate space within our data sample. Response functions in the lower left are the predicted mortality-temperature sensitivities for poor, cold regions of our sample, while those in the upper right apply to the wealthy, hot regions of our sample. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level on the top end of the distribution only. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects, and where each temperature variable is interacted with each covariate and a dummy for each age category.
Figure 25: Heterogeneity in the mortality-temperature relationship (ages 65+ mortality rate). Each panel represents a predicted response function for the ages 65+ mortality rate for a subset of the income-average temperature covariate space within our data sample. Response functions in the lower left are the predicted mortality-temperature sensitivities for poor, cold regions of our sample, while those in the upper right apply to the wealthy, hot regions of our sample. Regression estimates are from a fourth-order polynomial in daily average temperature and are estimated using GMFD weather data with a sample that was winsorized at the 1% level on the top end of the distribution only. All response functions are estimated jointly in a stacked regression model that is fully saturated with age-specific fixed effects, and where each temperature variable is interacted with each covariate and a dummy for each age category.
I.2 Out of sample cross-validation

Figure 4 makes clear the substantial degree of out of sample extrapolation that is required to take our multi-country model of heterogeneity and apply it to a global sample. To ensure that we are accurately representing response functions in new locations, we conduct a “leave-one-country-out” cross-validation test in which we systematically pull out the data from one country and re-run our interaction model in Equation 10. We then use the coefficients from this interaction model to predict response functions in all impact regions that fall within the country for which data were omitted. We compare these predicted response functions for the omitted country to the response estimated on that country’s data alone. In Figure 26, we show the result of this cross-validation exercise for all countries in our pooled sample that contain age-specific mortality rates. Our predicted responses for all impact regions in each country are shown in grey, and in black is the unweighted average of these predictions. The mortality-temperature response estimated using each country’s data alone (the benchmark) is shown in red. Our model performs remarkably well in most countries, with the average predicted response (in black) closely approximating the average treatment effect estimated using each country’s data (in red). This congruence occurs in most cases, despite the fact that our model has no information on the respective country’s mortality rates. In many cases, our model tends to be conservative at the hotter end of the response function. This finding is important, as we are forced to use our model to extrapolate to locations around the globe that tend to be much hotter than our in-sample countries.

I.3 Replication of Burgess et al. (2017) and cross validation in India

In Section I.2 of the main text, we show the results of a cross-validation exercise in which the data from each country in our sample are systematically removed, and the interaction model is re-estimated. Here, we conduct a similar exercise for India, to compare our predicted response functions (from a model with age-specific mortality rates from Brazil, Chile, China, the E.U., France, Japan, Mexico and the U.S.) to the estimated all-age temperature-mortality response function derived from Indian data alone. India represents the poorest and hottest region for which we have mortality records, and provides an important check on our extrapolation performance, as the global sample is substantially poorer and hotter than our data (see Figure 3). Here, we estimate the benchmark model for India using the functional form specification in Burgess et al. (2017) in order to compare directly to the existing literature. That is, in place of our preferred fourth order polynomial, we estimate the Indian regression with binned daily temperatures, where annual values are calculated as the number of days in region $i$ in year $t$ that have an average temperature within a bin range $k$, where the bin edges of $k$ in degrees Celsius are given by the following set: $K = \{-\infty, -15, -10, -5, 0, 5, 10, 15, 20, 25, 30, 35, +\infty\}$. We cluster our standard errors at the ADM1 level (in India, this is equivalent to the state level), as in all our specifications throughout the main text. Burgess et al. (2017) estimate a similar binned regression model using $2^\circ$C bins, with clustering at the ADM2 (i.e. district) level.

In Figure 27, we show the result of this cross-validation and replication exercise for India. Figure 27 compares our predicted responses for all impact regions in India (in grey) to the mortality-temperature response estimated using India’s data (in red). We generate the all-age average response function for...

88We generate an all-age response function from our age-specific interaction model by taking population-weighted averages of the responses from each age category, using age-specific population values for the year 2015.
Figure 26: Leave-one-country-out cross validation. In each panel, we test the ability of our interaction model (results shown in grey) to predict the actual response function for a country omitted from the sample (shown in red). Grey lines in all panels show predicted response functions for each impact region in each respective country, where predicted responses are estimated from the interaction model described in Section 4, but using a sample that omits data from the corresponding country. Each grey line is plotted over the range of temperatures experienced in that impact region. The solid black line is the unweighted average across all regions, while the red line is the estimated response function using only data from the country of interest. All responses are estimated in as age-specific response functions, and lines shown are population-weighted averages across age groups. Congruence between red and black lines indicates the ability of our interaction model to accurately capture across-country heterogeneity. Countries, from left to right, top to bottom: Brazil, Chile, China, EU (minus France), France, India, Japan, Mexico, USA.

Each impact region from our age-specific interaction model by taking a population-weighted average of the responses predicted for each age category, using age-specific population values for the year 2015. Our model performs remarkably well, despite containing no information on Indian mortality rates: for the hotter end of the response function, where much of the low-income world resides, our prediction is, if anything, conservative in extrapolating out of sample. Similarly reassuring results arise for cross-validation tests in other countries, as shown in Figure 26. Moreover, our results are very similar to the findings in Burgess et al. (2017), with an approximately linear increase in deaths for temperatures above 20°C.

J Calculation of uncertainty in the estimated full mortality risk of climate change

There are multiple sources of variation across our projected results, arising from climate uncertainty across GCMs, statistical uncertainty in our response function, and differences in scenarios of the
emissions trajectory and socioeconomic changes in income and demographics. The estimated impact of climate change on the mortality rate for a particular day and particular impact region depends on an RCP scenario of emissions, an SSP trajectory of income, population growth, and demographics, a climate realization from a GCM, and the empirical distribution of the estimated mortality-temperature response function. We construct projections for two RCP scenarios (RCP4.5 and RCP8.5), two SSP scenarios (SSP3 and SSP4), two income trajectories per SSP (OECD Env-Growth and IAASA GDP, see Section 3.2 for details), and 33 climate models (including surrogate models described in Sections 3.2 and C).

To do so, we execute a Monte Carlo resampling approach that proceeds in multiple steps. First, for each age category, we randomly construct a set parameters, corresponding to $\hat{\beta}$ and $\hat{\gamma}$ in Equation 10. These parameters are drawn from an empirical multivariate normal distribution characterized by the covariance between all of the parameters from the estimation of Equation 10. Second, using a realized draw for those parameters, we construct a predicted response function for each of our 24,378 impact regions. Following Equation 11, these responses functions are determined by the location- and time-specific values of income and average climate provided by a given RCP, SSP, income scenario, and GCM. Finally, with these response functions in hand, we use daily weather realizations for each impact region from the appropriate RCP and GCM to predict a daily mortality impact. This process
is repeated until approximately 1,000 projection estimates are complete for each impact region for each RCP-SSP combination. Impacts and adaptation are calculated for each of these estimates for each day of each year between 1981 and 2100.
Figure 28: Heterogeneity in the mortality climate impact projections by age-group. Each line represents the time series of changes to mortality rates for each of the three main age-groups used in the analysis: <5, 5-64, and >64. Results are shown for the combination of SSP3 (in the low growth variant) and RCP 8.5 only with a fourth-order polynomial functional form of temperature. Old-age mortality dominates the projections in terms of rates, which is taken into account in our valuation steps.

K Projection result sensitivity and heterogeneity

Here we present a set of alternate results to demonstrate heterogeneity and robustness in the main climate impact projection results of the paper. These include heterogeneity across each of the age groups in the projection stage (figure 28), variation of projected costs due to changing economic and population projection data (figure 29), robustness of climate impact projections to different functional forms of temperature used in the main regression estimates (figure 30), and the damage pathway due to a different emissions scenario (figure 31). As pointed out in the text, the valuations take into account heterogeneity across age groups, and the following figure illustrates the results that form the basis of these valuations.
Figure 29: Heterogeneity in mortality climate impact projections due to different scenarios of population and economic growth. Rows denote different Shared Socioeconomic Pathway (SSP) scenarios, and columns denote two separate modeling groups that produce the data. We sometimes refer to the OECD scenario as a “low growth” scenario, as it tends to be slightly lower than the IIASA economic projections. In each SSP-modeling group pair, we show impact projections for both RCPs 4.5 and 8.5.
Figure 30: Sensitivity of impact projections to alternate functional forms of temperature. Each line represents the time series of changes to the mortality rate for the combination of SSP3 (in the low growth variant) and RCP 8.5. Lines shown refer to the “no adaptation” scenario, in which response functions do not evolve over time. In orange is the projected impacts of climate change estimated using a fourth-order polynomial functional form of temperature in historical regressions. In green is the same object, but with binned daily temperatures used as a functional form in the historical regressions. While the binned regression imposes far fewer restrictions on the regression than does the polynomial, the projected impacts under these two sets of parameterizations are strikingly similar.
L Global value of mortality losses and adaptation expenditures

In the main text we emphasize results which value mortality damages of climate change using a valuation methodology that relies on the U.S. EPA VSL, accounts for heterogeneous life expectancies by age group, and uses an income elasticity of one to rescale VSLs to each impact region globally. These values are then used to calculate the partial SCC, which represents the total willingness to pay (WTP) of society to avoid the excess mortality risk imposed by a marginal ton of emissions. An informative piece of intermediate output linking estimates of lives lost due to climate change to the partial SCC are the stream of damages in each year, measured as the total dollar value of lives lost plus adaptation costs incurred due to the warming climate. Here, we provide such estimates under both the preferred valuation methodology used in the main text, as well as under alternative valuation assumptions.

Table 11 shows the percent of contemporaneous global GDP that is lost due to the impact of climate change on mortality and on adaptation expenditures. These values represent averages across all 33 GCMs, and average values of the lower and upper bound estimates of adaptation costs (see Section 2 for details on these bounds). As discussed in the text, we consider two VSL values, one from the U.S. EPA and the second from Ashenfelter and Greenstone (2004). We consider valuing deaths with spatially heterogenous VSLs based on income (with an income elasticity of one), or with the global median VSL applied to all locations. Table 11 shows mortality-related costs computed under different valuation assumptions and calculated for specific years, under a single socioeconomic
trajectory represented by SSP3.

Table 11: Mortality-related costs of climate change, as a percent of global GDP. Results are from a model with a fourth order polynomial temperature, under the socioeconomic scenario SSP3. All values shown are the median percentage of contemporaneous global GDP lost, where the median is taken across all climate models in a 33-model ensemble.

<table>
<thead>
<tr>
<th>VSL Method</th>
<th>2050</th>
<th>2098</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>EPA VLY, Scaled</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP45-SSP3</td>
<td>0.08%</td>
<td>0.66%</td>
</tr>
<tr>
<td>RCP85-SSP3</td>
<td>0.54%</td>
<td>3.67%</td>
</tr>
<tr>
<td><strong>EPA VLY, Global Average</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP45-SSP3</td>
<td>0.57%</td>
<td>1.21%</td>
</tr>
<tr>
<td>RCP85-SSP3</td>
<td>1.29%</td>
<td>6.26%</td>
</tr>
<tr>
<td><strong>A&amp;G VLY, Scaled</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP45-SSP3</td>
<td>0.02%</td>
<td>0.17%</td>
</tr>
<tr>
<td>RCP85-SSP3</td>
<td>0.14%</td>
<td>0.96%</td>
</tr>
<tr>
<td><strong>A&amp;G VLY, Global Average</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP45-SSP3</td>
<td>0.15%</td>
<td>0.32%</td>
</tr>
<tr>
<td>RCP85-SSP3</td>
<td>0.34%</td>
<td>1.64%</td>
</tr>
</tbody>
</table>
M Calculation of a mortality-only social cost of carbon

A core component of any analysis of the social cost of carbon is the climate module used to estimate both the baseline climate and the response of the climate system to a marginal change in greenhouse gas emissions. The Finite Amplitude Impulse Response (FAIR) model (Millar et al., 2017) satisfies key criteria for such a module, including those outlined by National Academies of Sciences and Medicine (2017). In particular, National Academies of Sciences and Medicine (2017) recommended that the climate module be transparent, simple, and “consistent with the current, peer-reviewed scientific understanding of the relationships over time between CO\(_2\) emissions, atmospheric CO\(_2\) concentrations, and CO\(_2\)-induced global mean surface temperature change, including their uncertainty” (National Academies of Sciences and Medicine, 2017, p. 88). For this last criterion, National Academies of Sciences and Medicine (2017) recommended that the module be “assessed on the basis of its response to long-term forcing trajectories (specifically, trajectories designed to assess equilibrium climate sensitivity, transient climate response and transient climate response to emissions, as well as historical and high- and low-emissions scenarios) and its response to a pulse of CO\(_2\) emissions.” National Academies of Sciences and Medicine (2017) specifically pointed to the FAIR model as an example of a model that is structurally capable of meeting all these criteria.

The FAIR model is defined by five equations. Temperature \(T\) is the sum of two temperature variables, \(T_0\) and \(T_1\), representing the slow and fast climate system response to forcing \(F\):

\[
\frac{dT_i}{dt} = \frac{q_i F - T_i}{d_i}, i \in \{0, 1\},
\]

(29)

where the \(q_i\) collectively define the equilibrium climate sensitivity (ECS) and the transient climate response (TCR), and the \(d_i\) are the thermal adjustment times. The CO\(_2\) concentration above the pre-industrial baseline, \(R\), is the sum of four fractions, \(R_j\), representing different uptake timescales:

\[
\frac{dR_j}{dt} = a_j E - \frac{R_j}{\alpha \tau_j}, j \in \{0, 1, 2, 3\}
\]

(30)

where \(E\) is the CO\(_2\) emissions rate, \(a_j\) are the fraction of emissions that enters each atmospheric fraction, \(\tau_j\) are the base uptake time scale for each fraction, and \(\alpha\) is a state-dependent coefficient that reflects feedbacks from temperature onto uptake timescales. The remaining three equations describe forcing \(F\) as a function of \(R\) and of exogenous non-CO\(_2\) forcing, and \(\alpha\) as a function of global mean surface temperature and atmospheric CO\(_2\) concentration. See Millar et al. (2017) for details. In our discussion, we focus on four parameters: the equilibrium climate sensitivity (ECS), the transient climate response (TCR), the short thermal adjustment time (\(d_2\)), and the time scale of rapid carbon uptake by the ocean mixed layer (\(\tau_3\)).

For this study, we obtained the latest release of the FAIR model version 1.3.1 from its online repository (https://github.com/OMS-NetZero/FAIR/tree/v1.3.1). For our control scenarios, we used the default specifications for RCP4.5 and RCP8.5 given in this repository. This means the core model parameters were left at their default values; specifically, ECS of 2.75°C per CO\(_2\) doubling, TCR of 1.66°C per CO\(_2\) doubling, \(d_2\) of 4.1 years, and \(\tau_3\) of 4.3 years. A complete study of the social cost of carbon should represent the uncertainty in key model parameters, including the joint probability...
distribution of the ECS and TCR. We discuss our approach to modeling climate uncertainty after describing the main control scenarios, below.

The two scenarios considered in this analysis, RCP4.5 and RCP8.5, represent two widely divergent emissions and climatic pathways, especially in years beyond 2050. Following the method used in previous estimates of the SCC, including in the National Academies of Sciences and Medicine (2017), we include projections starting in the current period (here defined as 2015) through the year 2300. Due to the long residence time of CO$_2$ in the atmosphere and the even longer residence time of the changes in global mean surface temperature associated with CO$_2$ emissions, SCC estimates can vary significantly depending on the definition of this window, especially when low discount rates are applied. Figure 32 shows fossil CO$_2$ emissions, CO$_2$ concentrations, total radiative forcing (the difference between incoming solar radiation and outgoing terrestrial radiation), and global mean surface temperature anomaly for the control scenarios used in this study.

![Figure 32](image)

**Figure 32: Behavior of key variables in the FAIR simple climate model under the default configuration.** Each panel shows the temporal trajectory of key variables in FAIR that are used in our calculation of the social cost of carbon. The trajectories shown arise under FAIR’s default parameter values for the equilibrium climate sensitivity and transient climate response.

In order to estimate the marginal effect of CO$_2$ emissions, we add two additional scenarios with an additional 1 GtC (3.66 Gt CO$_2$) pulse of fossil CO$_2$ emissions in 2015 added to each of the control scenarios described above. The model was then run again for these pulse scenarios, resulting in new concentration, forcing, and temperature anomaly series. The difference between the control and pulse scenarios may be seen in the main text Figure 8.

These temperature scenarios were then converted into estimates of mortality cost using the global damage functions estimated in this study, which describe valued mortality damages as a function of GMST. Figure 33 shows these functions in 5-year time steps for each combination of valuation assumptions. This Figure contains the same information as Figure 7 in the main text, while additionally
demonstrating substantial heterogeneity across distinct valuation scenarios.

Figure 33: Temporal evolution of empirically derived damage functions (billion USD) as a function of global mean surface temperature anomaly. Each panel shows estimates of quadratic damage functions estimated independently for each 5-year period from 2015 to 2100 under various valuation assumptions regarding the dollar value of each life lost.

The coefficients on these quadratic damage functions were developed for each year from 2015 to 2300, as described in the main text. Annual estimates of temperature-related mortality costs were then generated by applying the FAIR global mean temperature anomalies (relative to pre-industrial, the same period as was used in developing the damage functions) to the empirically derived damage functions. The resulting time series of damage estimates are given in Figure 34, shown for each set of valuation assumptions and for each emissions scenario.

After computing mortality costs associated with each scenario, each pulse scenario was subtracted from the corresponding control scenario and divided by the pulse amount to estimate the marginal effect of the pulse. This time series was then discounted using 2.5%, 3% and 5% discount rates, and summed through time to create a net-present value, as described in Section 8 of the main text. This final value is the social mortality cost of a marginal emission of CO$_2$. A more robust estimate would make use of Ramsey-like discounting, accounting for the relationship between consumption growth and the discount rate. We leave this for future study.

The analysis described above relied solely on the default configuration of the simple climate model FAIR. To represent climate uncertainties in FAIR, we varied TCR, ECS, $d_2$, and $\tau_3$ such that our climate uncertainties conform to those of the literature. For TCR and ECS, we drew upon constraints from the IPCC Fifth Assessment Report (AR5) (Collins, Knutti et al., 2013); for $d_2$ and $\tau_3$ we followed Millar et al. (2017), based on analysis of Joos et al. (2013) and ?. In general, we produced initial distributions of these parameters based on the literature constraints, then filtered them to ensure consistency with expectations regarding the initial pulse adjustment timescale (the time it takes the climate system to reach a warming peak following a pulse emission of CO$_2$). To preserve the expected correlation between TCR and ECS, rather than sampling ECS directly, we followed Millar et al. (2015) and instead sampled the realized warming fraction (RWF, the ratio of TCR/ECS), which is nearly independent of TCR.
Mortality damages for SSP3 by RCP and VSL measure (Billion USD 2015 from 1GtC pulse)

Figure 34: Empirically derived annual mortality damage projections (billion USD) due to a 1 GtC pulse of emissions in 2015. Each panel shows the temporal trajectory of the mortality damages caused by a single GtC pulse of emissions in the year 2015. Different colors indicate different valuation assumptions regarding the dollar value of each life lost. The two panels correspond to different emissions scenarios: RCP4.5 (left) and RCP8.5 (right).

Below we outline the sources used to construct the distributions of each parameter.

**TCR:** Collins, Knutti et al. (2013) concluded that “TCR is likely in the range 1°C to 2.5°C... is positive and extremely unlikely greater than 3°C” (p. 1112). In IPCC terminology (Mastrandrea et al., 2010), likely refers to a probability of at least 66%, very likely to a probability of at least 90%, and extremely likely to a probability of at least 95%. Thus we construct a log-normal distribution for TCR with the 17th to 83rd range of 1.0-2.5 °C.

**ECS:** Collins, Knutti et al. (2013) concluded that “ECS is positive, extremely unlikely less than 1°C (high confidence), and very unlikely greater than 6°C (medium confidence)” (p. 1111) and likely between 1.5 and 4.5°C. As noted by National Academies of Sciences and Medicine (2017), the ECS likely range is approximately consistent with a RWF likely range of 0.45 to 0.75. After investigation, we modified this likely range of RWF to 0.52–0.67 so that the resulting ECS distribution matched the AR5 likely range. To construct our sampling distribution, we randomly drew samples from the TCR and RWF distributions, and obtained ECS samples by calculating TCR/RWF. The constructed ECS samples follow a log-normal distribution with the 17th-83rd range of 1.67-4.34 °C.

**d²:** The AR5 does not assess the range of d². Following Millar et al. (2017), we constructed our distribution of d² as a log-normal distribution with a 5-95th percentile range of 1.6-8.4 years.
Joos et al. (2013) summarized \( \tau_3 \) in three comprehensive Earth System Models (HADGEM2-ES, MPI-ESM, NCARCSM1.4), seven Earth System Models of Intermediate Complexity (EMICs), and four box-type models (ACC2, Bern-SAR, MAGICC, TOTEM). Using the mean (4.03) and standard deviation (1.79) of these values, we constructed a normal distribution for \( \tau_3 \).

After defining these distributions, we generated a 100,000-member ensemble of parameter sets via Monte Carlo sampling. As \( \tau_3 \) should be larger than 0, we sample from a truncated normal distribution, and discard parameter sets in which \( \tau_3 < 0 \) and \( > 2 \times 4.03 \) to keep the mean of \( \tau_3 \) in parameter sets consistent with multi-model mean in Joos et al. (2013). About 2.49% of parameter sets are filtered by this constraint, leaving us with 97,515 parameter samples. Using these remaining parameter samples, we evaluated model performance according to several criteria.

Our criteria for evaluating model performance are described in detail below, and summarized in Table 12 and Figure 35.

**Initial pulse-adjustment timescale (IPT):** The results of Joos et al. (2013) and subsequent analysis by Ricke and Caldeira (2014) indicate that a peak in warming in response to a pulse emission should occur within about a decade after emission. In particular, Ricke and Caldeira (2014) estimated a very likely range for time to peak warming of 6.6–30.7 years, with a median of 10.1 years. To assess the IPT, we set a control run with observational CO\(_2\) concentrations to 2010 levels (389 ppm) and held constant thereafter. In the experiment, we inject a 100 GtC pulse of CO\(_2\) instantaneously in 2015. The difference in temperature between experiment and control run measures the temperature response to a CO\(_2\) pulse. We defined the IPT as the time at which the time derivative of the temperature response first becomes negative (noting that, in some simulations, feedbacks between temperature and the carbon cycle mean that the resulting decline may not be monotonic). The resulting IPT has a median of 10.0 years, with a very likely range of 3.0–25.0 years, which we regard as adequately consistent with the results of Joos et al. (2013) and Ricke and Caldeira (2014). The IPT distribution also exhibits a small secondary mode, clustered around 500 years (the full length of the run). This secondary mode is associated with runs in which temperature continues increasing throughout the experiment, and is composed of only 92 parameter samples (0.09% of the parameter samples that pass the \( \tau_3 \) constraint). We drop the parameter sets associated with this secondary mode and examine the overall parameter distribution in the remaining discussion.

**ECS:** We checked that the minimum, 5th, 17th, 83rd, and 90th percentiles of the ECS distribution were consistent with the AR5 assessment. Our ECS distribution is only slightly narrower than the corresponding AR5 distribution, with a likely range of 1.67–4.34 °C (Table 12).

**Transient climate response to emissions (TCRE):** The TCRE measures the ratio of transient warming to cumulative carbon emissions. Collins, Knutti et al. (2013) concluded that TCRE is likely between 0.8 and 2.5°C per 1000 GtC. To assess TCRE, we set up an experiment that increases CO\(_2\) concentrations at 1%/year until CO\(_2\) concentrations double in year 70. Since in FAIR concentrations are an output driven by emissions, we numerically solve the CO\(_2\) emissions pathway in FAIR to meet the CO\(_2\) concentration pathway. The resulting TCRE exhibits a likely range of 0.89–2.34°C per 1000 GtC, which is slightly narrower than the likely range assessed by AR5.

**Longevity of pulse warming:** The coupled climate-carbon cycle experiments of Joos et al. (2013) indicate that a majority (about 70% in the multimodel mean) of peak warming persists 500 years after
emissions. In our IPT experiments, it is likely that 81.4-116.4 percent of initial peak warming persists after 500 years.

**Representative Concentration Pathway (RCP) experiments:** Finally, we assess the warming in the RCP experiments relative to those in the CMIP5 multi-model ensemble, noting that – due to structural uncertainty – Collins, Knutti et al. (2013) interpreted the CMIP5 5th–95th percentile range as a likely range. We therefore compare the central 66% probability projections from our ensemble to those of the CMIP5 5th–95th percentile range (Table 12). In general, both the upper and lower bounds of the likely range of warming from our ensemble are close to those in AR5. In RCP4.5, the likely range of warming from our ensemble is slightly wider than that in AR5 at all the projected periods, and it is moderately below that in AR5 in the middle and end of the 21st century. In RCP8.5, the likely range of warming from our ensemble is wider than the AR5 assessed range in the middle and the end of the 21st century. The likely range of our ensemble is slightly above the AR5 likely range at the end of 22nd century, and becomes narrower than the AR5 likely range at the end of 23rd century.

After this assessment, noting the initial bimodal distribution of IPT, we discarded samples with IPT values longer than 100 years. The reduced sample set constituted 97,423 samples, and the diagnostic metrics were essentially unchanged from the pre-filtering distributions (see Table 12). Based on this post-filtering evaluation, we concluded that the resulting distribution was adequately consistent with our target constraints and the recommendations of National Academies of Sciences and Medicine (2017). We applied the retained parameter sets to FAIR to produce climate projections that represent climactic uncertainties and were further used in calculating the SCC uncertainty. The interquartile range of the final SCC values across the entire distribution of parameter sets are shown in Table 5 in the main text.

In the main text, SCC uncertainty is reported for climate uncertainty, economic uncertainty, and full uncertainty. Here we briefly describe how those values were generated.

**Full uncertainty:** Using our Monte Carlo projections of damages, for each year from 2015 to 2100 we pooled all Monte Carlo results for the associated 5-year window (so, e.g., year 2030 included the pooled Monte Carlo damages for years 2028–2032). We then ran quantile regressions to fit quantile-specific damage functions for each of the following quantiles: 5, 25, 50, 75, and 95. As before, extrapolation past the year 2100 was accomplished using a linear time interaction, here for each quantile. Because the early 21st century distribution of GMST anomalies in FAIR is wider than the same distribution in our GCMs and surrogate models, some extrapolation of our damage functions (over GMST) occurs when moving from the support of the damages data to the uncertainty described by FAIR. To mitigate against too much extrapolation of a quadratic damage function over GMST, all damage functions for the pre-2200 period with quadratic terms that were insignificant were replaced with linear damage function estimates instead.

Each damage function from the set of quantile damage functions was run through each of the 97,423 sets of FAIR parameters and up-weighted to reflect its probability mass in the damage function uncertainty space. In whole, this process reflects a joint sampling from the full space of economic and climate uncertainty. The relevant SCC IQR was resolved from the resulting distribution of SCCs.

**Climate uncertainty:** The central estimate of our damage function was run through each of the 97,423 sets of FAIR parameters, and the relevant SCC IQR resolved from the resulting distribution of
Table 12: Comparisons of the distributions of key FAIR parameter values. This table compares the distributions of key FAIR parameter values that pass the IPT constraint against the relevant distributions from the literature. Distributions shown are: transient climate sensitivity (TCR); realized warming fraction (RWF); equilibrium climate sensitivity (ECS); short thermal adjustment time ($d_2$); time scale of rapid carbon uptake by the ocean mixed layer ($\tau_3$); transient climate response to emissions (TCRE); and the change in global mean surface temperature (GMST) from the reference period 1986-2005 at various points in the projections. Note that RWF is only used to create our ECS distribution, and so the post-IPT distribution of RWF is not reported. Distributions reported are determined by the reference values from the literature, so that different parameters have different descriptions of their associated distributions: 5 to 95% ranges are given in ( ), 17 to 83% ranges are given in [ ], and means are given without ( ) or [ ].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Distribution from literature</th>
<th>Pre-IPT distribution</th>
<th>Post-IPT distribution</th>
<th>Distribution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCR (C)</td>
<td>[1.00, 2.50]</td>
<td>[1.00, 2.50]</td>
<td>[1.01, 2.50]</td>
<td>Lognormal</td>
<td>AR5</td>
</tr>
<tr>
<td>RWF</td>
<td>[0.45, 0.75]</td>
<td>[0.52, 0.67]</td>
<td>N/A</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>ECS (C)</td>
<td>[1.5, 4.5]</td>
<td>[1.67, 4.33]</td>
<td>[1.67, 4.34]</td>
<td>Lognormal</td>
<td>AR5</td>
</tr>
<tr>
<td>$d_2$ (years)</td>
<td>(1.6, 8.4)</td>
<td>(1.6, 8.4)</td>
<td>(1.6, 8.4)</td>
<td>Lognormal</td>
<td>(Millar et al., 2017)</td>
</tr>
<tr>
<td>$\tau_3$ (years)</td>
<td>(Joos et al., 2013) point estimates</td>
<td>4.03 (1.08, 6.97)</td>
<td>4.05 (1.21, 6.98)</td>
<td>Normal</td>
<td>(Joos et al., 2013)</td>
</tr>
</tbody>
</table>

Key metrics

| TCRE (C/TtC) | [0.8, 2.5] | N/A | [0.89, 2.34] | Normal | AR5 |
| Time to T_{max} (years) | (6.6, 30.7) | (3.0, 25.0) | (3.0, 25.0) | N/A | (Ricke and Caldeira, 2014) |

RCP 4.5 GMST

<table>
<thead>
<tr>
<th>Year 1 - Year 2</th>
<th>Range</th>
<th>N/A</th>
<th>Range</th>
<th>N/A</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>2046 - 2065</td>
<td>1.4 [0.9, 2.0]</td>
<td>N/A</td>
<td>1.18 [0.73, 1.95]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>2081 - 2100</td>
<td>1.8 [1.1, 2.6]</td>
<td>N/A</td>
<td>1.53 [0.93, 2.55]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>2181 - 2200</td>
<td>2.3 [1.4, 3.1]</td>
<td>N/A</td>
<td>1.93 [1.16, 3.30]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>2281 - 2300</td>
<td>2.5 [1.5, 3.5]</td>
<td>N/A</td>
<td>2.17 [1.30, 3.76]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
</tbody>
</table>

RCP 8.5 GMST

<table>
<thead>
<tr>
<th>Year 1 - Year 2</th>
<th>Range</th>
<th>N/A</th>
<th>Range</th>
<th>N/A</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>2046 - 2065</td>
<td>2.0 [1.4, 2.6]</td>
<td>N/A</td>
<td>1.78 [1.10, 2.91]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>2081 - 2100</td>
<td>3.7 [2.6, 4.8]</td>
<td>N/A</td>
<td>3.20 [1.97, 5.29]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
<tr>
<td>2181 - 2200</td>
<td>6.5 [3.3, 9.8]</td>
<td>N/A</td>
<td>6.28 [3.84, 10.36]</td>
<td>Normal</td>
<td>AR5</td>
</tr>
</tbody>
</table>
Figure 35: Distributions of key FAIR parameters for climate uncertainty both before (red curve) and after (blue shading) applying the constraints. Each panel indicates the distribution of a key parameter in the FAIR simple climate model, both before (in red) and after (in blue) the imposition of constraints described in the text. Distributions shown are: A transient climate response (TCR); B equilibrium climate sensitivity (ECS); C short thermal adjustment time ($d_2$); D time scale of rapid carbon uptake by the ocean mixed layer ($\tau_3$).

Economic uncertainty: The set of quantile-year damage functions described above was then run through the FAIR default parameter set. Each damage function from the set of quantile damage functions was run through the default FAIR parameter set. The SCCs associated with 25th and 75th percentile damage functions were reported as the economic uncertainty IQR of the SCC.
M.1 Spatially disaggregated social cost of carbon

Figure 36 displays the spatially disaggregated SCC divided into contributions from the pre-2100 period and the post-2100 period.

Figure 36: Spatial SCC: Contributions of nearer-term (pre-2100) and longer-term (2100-2300) warming on net present value of marginal CO$_2$ damages by impact region Values shown are the $/tonCO_2$ in each impact region in the left panel. The right panels divide up the total marginal cost of CO$_2$ into contributions due to warming n different periods.

Figure 37: Spatial SCC: Effect of varying emissions scenario and discount rates on spatial SCC calculation Values shown are the $/tonCO_2$ in each impact region.
Table 13: Value of statistical life estimates. VSL values are converted to 2015 USD using The World Bank’s US GDP Deflator.

<table>
<thead>
<tr>
<th>Source</th>
<th>VSL (Millions USD)</th>
<th>Unadjusted</th>
<th>2015 Dollars</th>
</tr>
</thead>
<tbody>
<tr>
<td>EPA ($2006)</td>
<td>$7.40</td>
<td>$8.57</td>
<td></td>
</tr>
<tr>
<td>Ashenfelter and Greenstone ($1997)</td>
<td>$1.54</td>
<td>$2.24</td>
<td></td>
</tr>
<tr>
<td>OECD (OECD Countries; $2005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base</td>
<td>$3.00</td>
<td>$3.59</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>$1.50 - $4.50</td>
<td>$1.79 - $5.38</td>
<td></td>
</tr>
<tr>
<td>OECD (EU27 Countries; $2005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Base</td>
<td>$3.60</td>
<td>$4.31</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>$1.80 - $5.40</td>
<td>$2.15 - $6.46</td>
<td></td>
</tr>
</tbody>
</table>

N The influence of alternative VSL approaches, discount rates, and emissions trajectories on estimates of a mortality-only social cost of carbon

N.1 Value of a Statistical Life

As described in Section 8, we report partial Social Cost of Carbon (SCC) calculations which value deaths according to the total value of expected life-years lost. We do so in order to accommodate the large heterogeneity in mortality-temperature relationships that we uncover across age groups. To adjust VSL values accordingly, we first calculate the value of lost life-years by dividing the U.S. EPA VSL by the remaining life expectancy of the median-aged American. This recovers an implied value per life-year. We then apply an income elasticity of one to convert this life-year valuation into a per life-year VSL for each impact region in each year. To calculate life-years lost for a given temperature-induced change in the mortality rate, we use the SSP projected population values, which are provided in 5-year age bins, to compute the implied conditional life expectancy for people in each age bin. We take the population-weighted average of remaining life expectancy across all the 5-year age bins in our broader age categories of <5, 5-64, and >64. This allows us to calculate total expected life-years lost, which we multiply by the impact-region specific VSL per life-year to calculate total damages. Note that this procedure assumes that our estimated climate change driven deaths occur with uniform probability for all people within an age category.
Table 14: The influence of damage function extrapolation in years after 2100 on estimates of a mortality-only Social Cost of Carbon (SCC). An income elasticity of one is used to scale the U.S. EPA VSL value, all SCC values are for the year 2015, measured in PPP-adjusted 2015 USD, and are calculated from damage functions estimated from projected results under the socioeconomic scenario SSP3. For the first column, damage functions continue to evolve over time in the years after 2100, according to the method described in Section 8. In the second column, the damage functions estimated for the year 2100 is used for all years after 2100.

<table>
<thead>
<tr>
<th></th>
<th>Extrapolating post-2100 damage function</th>
<th>Holding post-2100 damage function fixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-2100 damages</td>
<td>$24.71</td>
<td>$24.71</td>
</tr>
<tr>
<td>Post-2100 damages</td>
<td>$14.43</td>
<td>$10.43</td>
</tr>
<tr>
<td>Total damages</td>
<td>$39.14</td>
<td>$35.14</td>
</tr>
</tbody>
</table>

N.2 The influence of damage function extrapolation post 2100 on SCC estimates

N.3 Social Cost of Carbon under alternative valuation approaches and socioeconomic scenarios

This section shows the effect of different VSL values on the SCC, as well as showing the effect of varying the socioeconomic projections on the SCC for a single such valuation.

89 As noted in the main text, the U.S. EPA uses a VSL income elasticity of 0.7 and a review by Viscusi (2015) estimates 1.1 for the income-elasticity of the VSL.
Table 15: Estimates of a mortality-only social cost of carbon (SCC) under different valuation assumptions. In all panels, an income elasticity of one is used to scale either the U.S. EPA VSL, or the VSL estimate from (Ashenfelter and Greenstone, 2004). All SCC values are for the year 2015, measured in PPP-adjusted 2015 USD, and are calculated from damage functions estimated from results using the socioeconomic scenario SSP3. In Panel A, all regions have heterogeneous valuation, based on local income. In Panel B, all regions are given the global median VSL, after scaling using income. Value of life years estimates adjust death valuation by expected life-years lost. The first row of every valuation shows our estimated partial SCC using the default configuration of the simple climate model FAIR. The uncertainty ranges are interquartile ranges [IQRs] showing the influence of climate model and statistical uncertainty (see Appendix M and J for details).

<table>
<thead>
<tr>
<th>Valuation</th>
<th>EPA</th>
<th>A &amp; G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount rate</td>
<td>$\delta = 2.5%$</td>
<td>$\delta = 3%$</td>
</tr>
<tr>
<td>Value of life years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>27.2</td>
<td>20.2</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[9.5, 63.9]</td>
<td>[7.7, 45.6]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[12.6, 86.3]</td>
<td>[8.6, 57.1]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[12.4, 100.6]</td>
<td>[7.7, 67.1]</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>58.6</td>
<td>39.1</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[25.6, 120.8]</td>
<td>[17.3, 80.6]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[28.9, 108.4]</td>
<td>[19.7, 69.0]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[22.9, 143.4]</td>
<td>[14.5, 92.6]</td>
</tr>
<tr>
<td>Value of statistical life</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>71.2</td>
<td>52.9</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[26.6, 162.8]</td>
<td>[21.3, 116.3]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[81.3, 143.9]</td>
<td>[60.1, 104.8]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[51.1, 266.1]</td>
<td>[37.0, 147.1]</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>147.3</td>
<td>99.0</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[65.7, 300.9]</td>
<td>[44.6, 201.5]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[117.4, 227.8]</td>
<td>[85.2, 156.4]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[73.6, 321.4]</td>
<td>[52.1, 220.9]</td>
</tr>
<tr>
<td>Panel B: Global average valuation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value of life years</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>45.4</td>
<td>34.3</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[17.4, 102.7]</td>
<td>[14.3, 74.3]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[22.4, 132.4]</td>
<td>[15.6, 89.4]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[22.5, 156.5]</td>
<td>[15.2, 108.0]</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>93.1</td>
<td>63.5</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[41.9, 189.7]</td>
<td>[29.0, 128.3]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[42.4, 184.3]</td>
<td>[29.8, 117.6]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[34.6, 220.7]</td>
<td>[23.7, 147.6]</td>
</tr>
<tr>
<td>Value of statistical life</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>104.9</td>
<td>79.9</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[41.7, 233.7]</td>
<td>[34.7, 169.4]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[111.2, 195.3]</td>
<td>[84.5, 145.2]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[73.0, 297.7]</td>
<td>[55.9, 219.7]</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>213.5</td>
<td>145.8</td>
</tr>
<tr>
<td>Climate uncertainty</td>
<td>[97.5, 431.2]</td>
<td>[68.0, 291.3]</td>
</tr>
<tr>
<td>Statistical uncertainty</td>
<td>[157.6, 234.7]</td>
<td>[118.3, 235.9]</td>
</tr>
<tr>
<td>Climate + statistical uncertainty</td>
<td>[103.2, 468.1]</td>
<td>[76.7, 329.4]</td>
</tr>
</tbody>
</table>
**Table 16:** Estimates of a mortality-only social cost of carbon (SCC) under a range of valuation assumptions. In all panels, an income elasticity of one is used to scale VSL estimates from the U.S. EPA, (Ashenfelter and Greenstone, 2004), and OECD. All SCC values are for the year 2015, measured in PPP-adjusted 2015 USD, and are calculated from damage functions estimated from projected results under the socioeconomic scenario SSP3. In Panel A, all regions have heterogeneous valuation, based on local income. In Panel B, all regions globally are given the global median VSL, after scaling using income. Value of life years estimates adjust death valuation by the expected number of life-years lost. Each valuation shows our estimated SCC using the default configuration of the simple climate model FAIR.

<table>
<thead>
<tr>
<th>Valuation</th>
<th>EPA</th>
<th>A &amp; G</th>
<th>OECD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount rate</td>
<td>$\delta = 2.5%$</td>
<td>$\delta = 3%$</td>
<td>$\delta = 5%$</td>
</tr>
<tr>
<td>Value of life years</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>27.2</td>
<td>20.2</td>
<td>9.0</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>58.6</td>
<td>39.1</td>
<td>13.3</td>
</tr>
<tr>
<td>Value of statistical life</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>71.2</td>
<td>52.9</td>
<td>23.0</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>147.3</td>
<td>99.0</td>
<td>33.5</td>
</tr>
</tbody>
</table>

**Panel A:** Globally varying valuation (2015 US Dollars)

<table>
<thead>
<tr>
<th>Valuation</th>
<th>EPA</th>
<th>A &amp; G</th>
<th>OECD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of life years</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>45.4</td>
<td>34.3</td>
<td>15.3</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>93.1</td>
<td>63.5</td>
<td>22.0</td>
</tr>
<tr>
<td>Value of statistical life</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td>104.9</td>
<td>79.9</td>
<td>35.6</td>
</tr>
<tr>
<td>RCP 8.5</td>
<td>213.5</td>
<td>145.8</td>
<td>50.1</td>
</tr>
</tbody>
</table>
Table 17: Estimates of a partial Social Cost of Carbon for excess mortality risk incorporating adaptation for various socioeconomic projections

<table>
<thead>
<tr>
<th></th>
<th>Annual discount rate</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>δ = 2.5%</td>
<td>δ = 3%</td>
<td>δ = 5%</td>
<td></td>
</tr>
<tr>
<td>RCP 4.5</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>SSP2</td>
<td>32.0</td>
<td>23.2</td>
<td>9.7</td>
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</tr>
<tr>
<td>SSP3</td>
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<td>20.2</td>
<td>9.0</td>
<td></td>
</tr>
<tr>
<td>SSP4</td>
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<td></td>
</tr>
<tr>
<td>RCP 8.5</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSP2</td>
<td>37.7</td>
<td>28.1</td>
<td>12.0</td>
<td></td>
</tr>
<tr>
<td>SSP3</td>
<td>58.6</td>
<td>39.1</td>
<td>13.3</td>
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</tr>
<tr>
<td>SSP4</td>
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<td>30.4</td>
<td>12.5</td>
<td></td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSP2</td>
<td>41.7</td>
<td>31.6</td>
<td>14.3</td>
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<td>SSP3</td>
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<tr>
<td>SSP4</td>
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<td>34.4</td>
<td>16.0</td>
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</tr>
<tr>
<td>RCP 8.5</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSP2</td>
<td>51.6</td>
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<td>SSP4</td>
<td>71.5</td>
<td>52.0</td>
<td>20.9</td>
<td></td>
</tr>
</tbody>
</table>

In both panels, an income elasticity of one is used to scale the U.S. EPA VSL value. All SCC values are for the year 2015, measured in PPP-adjusted 2015 USD. In Panel A, all regions have heterogeneous valuation, based on local income. In Panel B, all regions globally are given the global median VSL, after scaling using income. All estimates use a value of life years adjustment, valuing deaths by the expected number of life-years lost. Each row shows our estimated SCC using the default configuration of the simple climate model FAIR for a different SSP scenario.