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Quantifying Economic Damages from Climate Change

Maximilian Auffhammer

Climate scientists have spent billions of dollars and eons of supercomputer time studying how increased concentrations of greenhouse gases and changes in the reflectivity of the earth's surface affect dimensions of the climate system relevant to human society: surface temperature, precipitation, humidity, and sea levels. Recent incarnations of physical climate models have become sophisticated enough to be able to simulate intensities and frequencies of some extreme events, like tropical storms, under different warming scenarios. The current consensus estimates from what may be the most heavily peer-reviewed scientific publication in human history, the 5th Assessment Report of the Intergovernmental Panel on Climate Change, are that the average global surface temperature has increased by 0.85° Celsius (1.5° F) since the industrial revolution. Estimates of future warming by the end of the current century range from 0.9 to 5.4°C (1.6 - 9.7°F) (IPCC 2013; Hsiang and Kopp in this issue of the journal).

In a stark juxtaposition, the efforts involved in and the public resources targeted at understanding how these physical changes translate into economic impacts are disproportionately smaller, with most of the major models being developed and maintained with little to no public funding support. This is concerning, because optimal policy design in the context of addressing the biggest environmental market failure in human history requires an understanding of the external cost imposed

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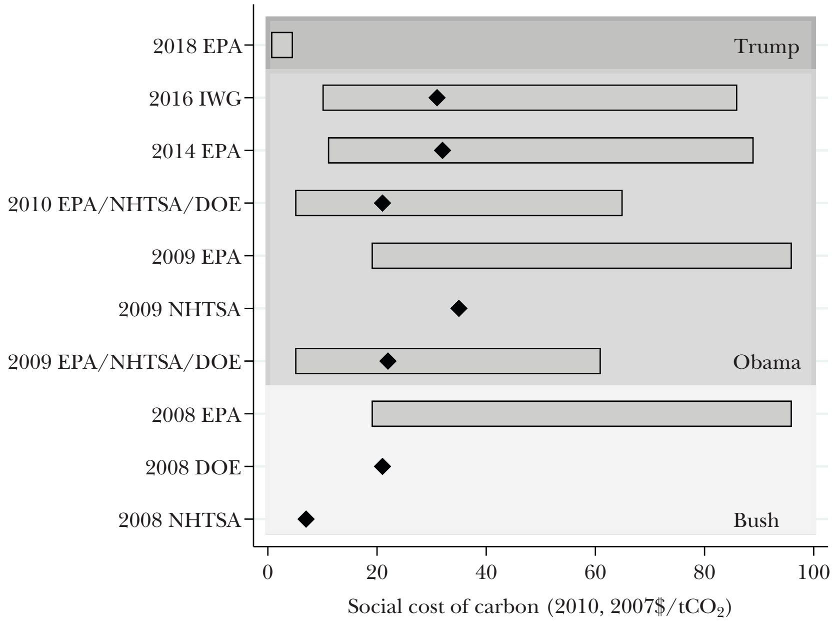
by additional emissions of greenhouse gases. Estimating this number is far from straightforward for two main reasons: First, climate change is a global phenomenon and hence local emissions result in global damages, the quantification of which is challenging as damages vary across space and time. Second, greenhouse gases are long-lived, which means that today's emissions affect generations hundreds of years from now. Hence if one would like to calculate the external cost of one more ton of CO_2 equivalent emitted—which is about what you would emit if you drove a Ford Mustang GT from San Francisco to Chicago—you would need to calculate the discounted stream of global damages from that additional ton over the next 300 years or so relative to a baseline with one less ton of CO_2.

The goal of this paper is first to shed light on how (mostly) economists have gone about calculating this "social cost of carbon" for regulatory purposes and to provide an overview of the past and currently used estimates. In the second part, I will focus on where in this literature empirical economists may have the highest value added: specifically, the calibration and estimation of economic damage functions, which map weather patterns transformed by climate change into economic benefits and damages. A broad variety of econometric methods have recently been used to parameterize the dose (climate) response (economic outcome) functions. The paper seeks to provide both an accessible and comprehensive overview of how economists think about parameterizing damage functions and quantifying the economic damages of climate change. There are a number of more technical surveys, which I invite the interested reader to consult (useful starting points include Carleton and Hsiang 2016; Dell, Jones, and Olken 2014; Diaz and Moore 2017).

The Social Cost of Carbon

The social cost of carbon is an estimate of the discounted present value of damages from one additional ton of CO_2 equivalent emitted at a certain point in time. This social cost of carbon is increasing over time, as later emissions result in larger damages due to the elevated stock of greenhouse gases in the atmosphere, and because GDP grows over time and some damage categories are modeled as proportional to GDP (EPA 2016). Calculations of the social cost of carbon are obtained through so-called Integrated Assessment Models. The most well-known of these models are DICE (Dynamic Integrated Climate–Economy model by 2018 Nobel Laureate William Nordhaus), FUND (Climate Framework for Uncertainty, Negotiation and Distribution model by David Anthoff and Richard Tol), and PAGE (Policy Analysis of the Greenhouse Effect model by Chris Hope), although there are a number of more recent and ambitious modeling efforts. These models "integrate" simple socioeconomic scenarios that produce future emissions trajectories, which are fed into a simple climate model that translates emissions paths into concentrations and produces scenarios for future temperatures, precipitation, and sea levels. These climatic outcomes are then fed into a set of damage functions, which map the climate model output into economic damages at the regional or global level. The discounted difference in damages between a baseline future and a future with one

Figure 1
Sample of Social Cost of Carbon Estimates Used in Federal Rulemakings



Sources: Rose (2012); Rose et al. (2014); IWG (2016); EPA (2018).
Note: Estimates for the social cost of carbon are for emissions of a ton of CO_2 in 2010 in 2007 dollars. NHTSA is National Highway Traffic Safety Administration; IWG is Interagency Working Group; EPA is Environmental Protection Agency; DOE is Department of Energy. The black diamond indicates the "central estimate," if one was identified. The grey bars indicate selected upper and lower bounds used in regulatory analyses.

more ton of emissions then becomes the social cost of carbon—essentially the external cost of one ton of additional CO_2 emissions at a point in time. There is a nascent literature calculating social costs of other greenhouse gases (for example, methane is a more potent greenhouse gas, but with a shorter atmospheric lifetime).

A tremendous number of modeling assumptions need to be made to calculate the social cost of carbon for use in rulemaking. The modeler needs to decide on the time horizon to be considered, the approach to discounting and the rate to be used, the reflection of uncertainties, the changes to risks, which impacts can be included, the choice of reference conditions, whether one should equity weight across countries, and what recent literature should be incorporated (Rose 2012). Among these, the three factors of possibly biggest consequence are the choice of discount rate, which sectors are omitted (for example, ecosystem services), and whether one should consider only domestic or global damages. The latter decision is really a legal question, as the externality is global and hence, from an economic point of view, the global number is the correct estimate of the externality. Figure 1 shows the evolution of the social cost of carbon for a ton emitted in 2010 (measured in 2007 US dollars) in federal rulemaking for a sample of rules.

The first official estimates of the social cost of carbon in 2008 were made under the Bush administration. The 2008 National Highway and Traffic Safety Administration (NHTSA) number was an estimate of global damages used for setting fuel economy standards. The 2008 Department of Energy (DOE) number was a global social cost of carbon used for setting air conditioner equipment and gas range standards. The 2008 Environmental Protection Agency (EPA) estimates were used in the proposed rulemaking for regulating greenhouse gas emissions under the Clean Air Act. The bar here indicates the distribution of the central number used. The actual analysis also considered an additional range from −\$7 to \$781. It is noteworthy that this first round of proposed rulemaking under the Bush administration stated that CO_2 is a global pollutant and that "economic principles suggest that the full costs to society of emissions should be considered in order to identify the policy that maximizes the net benefits to society, i.e., achieves an efficient outcome (Nordhaus, 2006)." The document further acknowledges that "domestic estimates omit potential impacts on the United States (for example, economic or national security impacts) resulting from climate change impacts in other countries" (US EPA 2008).

President Obama convened an Interagency Working Group, which was charged with calculating an official social cost of carbon to be used across the board in federal rulemaking (Greenstone, Kopits, and Wolverton 2013). Three prominent Integrated Assessment Models—Nordhaus's DICE model,[1] Anthoff and Tol's FUND model,[2] and Hope's proprietary PAGE model—were used to calculate a distribution of the social cost of carbon across time and scenarios for a set of common socioeconomic assumptions, discount rates, and uncertainty over a number of parameters. The central and often-cited estimate of the social cost of carbon, which is the mean number across 50,000 simulations for each model at a 3 percent discount rate, is \$42 (in 2007 dollars) for one ton of emissions made in the year 2020.[3] If one uses a 5 percent discount rate, this value drops to \$12; if one uses a 2.5 percent discount rate, it increases to \$62. The Interagency Working Group also ran a so-called "high-impact scenario," which is the 95th percentile number at a 3 percent discount rate and valued at \$123. The central estimate of the social cost of carbon was projected to rise to \$50/ton in 2030 and \$69 in 2050.

The Obama administration later commissioned the National Academies of Sciences to assess the Interagency Working Group modeling exercise and suggest improvements. The National Academies of Sciences (2017) recommended substantial revisions to the way the social cost of carbon is estimated. President Trump, however, disbanded the Interagency Working Group, which could have implemented these changes. Two current proposed rulemakings under the Trump administration use a social cost of carbon that only considers *domestic damages* and discount rates of *3 percent* and *7 percent*.

[1] The DICE model is at https://sites.google.com/site/williamdnordhaus/dice-rice.
[2] The FUND model is at http://www.fund-model.org.
[3] Of course, 42 is also the Answer to the Ultimate Question of Life, the Universe, and Everything, according to the *The Hitchkiker's Guide to the Galaxy*.

The top bar in Figure 1 indicates the range of the domestic social cost of carbon using the 3 percent and 7 percent discount rates currently proposed by the National Highway Traffic Safety Administration for the "revision" of the Corporate Average Fuel Economy (CAFE) standards for fuel economy of cars and light trucks, which clearly represent a drastic decrease in the estimated externality to between $1 and $7 for a ton emitted in 2020.

The estimates also do not incorporate any of the major updates suggested by the National Academies of Sciences (2017) report, which implies that the 2018 estimates do not represent best available science. For example, the National Academies of Sciences made suggestions relating to how one constructs a baseline future economy out to the year 2300, assumptions made in the climate modeling, and the discounting approach taken. Maybe most importantly for the purposes of this paper, the National Academies of Sciences report points a stern finger at the damage functions used in all three Integrated Assessment Models.

The damage functions in the Integrated Assessment Models, which are used to calculate the social cost of carbon, are outdated. Greenstone (2016) points out that the most recent studies in the FUND model stem from 2009, with the majority of the literature cited stemming from the early and mid-1990s. For example, the damage function for agriculture in the FUND model implies that warming up to roughly 5°C produces benefits for the sector (Rose et al. 2014). This is not consistent with the recent literature on agricultural impacts, which for example, points at the significant negative impact of extreme heat days. Moore, Baldos, Hertel, and Diaz (2017) updated the FUND damage function by incorporating the most recent empirical estimates for agriculture and find a doubling of the social cost of carbon by simply updating this sector alone. The literature underlying the DICE damage function also mostly comes from studies conducted in the 1990s. None of the cites for the PAGE model are from after 2010. As Greenstone (2016) shows, this ignores more than 100 studies published since 2010—which use more up-to-date econometric techniques and exploit the explosion in data availability.

Damage Functions, Weather, and Climate

In the context of climate change studies, a "damage function" refers to a mapping of climate into economic outcomes—essentially what is broadly called a "dose response function." One question arises immediately: What is "climate"? When we leave our homes in the morning, weather is what we encounter. Weather outcomes are draws from an underlying distribution. For the purposes of this paper, I consider the moments of this distribution the *climate*. This approach is consistent with the often-used definition that climate is a 30-year average of (for example) surface temperature, although thinking about climate as a set of statistical moments is broader than just an average. Climate change is hence a slow shift in some moments of the weather distribution over time. The changes could be variance-preserving mean shifts or higher-order changes to the distribution. It is important to remember that even the simple case of a variance-preserving rise in mean temperature—think of a bell-shaped curve of daily temperature outcomes shifting upward—will lead to a higher frequency of "extreme events"—the incidence of what would have been 95th or 99th percentile temperature outcomes under the old climate regime.

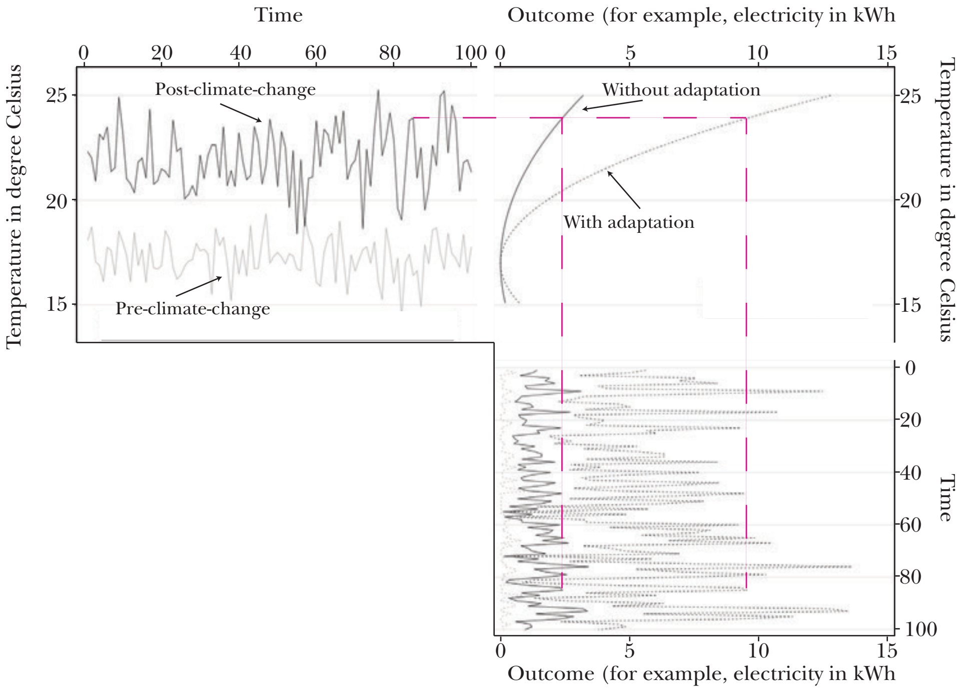
To estimate economic effects of such changes, we need to take into account how economic actors respond to weather generated by a new climate regime. For example, individuals in San Francisco have historically recognized that extreme warm-weather outcomes were rare, and so almost no one had air conditioners installed in their homes. However, if San Franciscans learn that climate is changing and their summers will resemble Fresno's much hotter summers in most future years, many will go ahead and install room air conditioners or central air units in new construction. Hence, a hotter climate will result in higher electricity consumption due to the presence of more air conditioners, which consumers incurred costs to install. In terms familiar to the economist, there is an extensive margin response in many sectors (the installation of air conditioning, irrigation equipment, sea walls) as well as an intensive margin response (the more frequent operation of air conditioners and irrigation equipment).

In order to provide estimates of damages from climate change, one needs to estimate damage functions that take both extensive and intensive margin adaptation into account—and to do this for *all* climate-sensitive sectors across the globe for a number of dimensions of climate. Some key climate-related changes would include changes in temperature, humidity, precipitation, sea level, and the occurrence of extreme events like storms.

With this perspective in mind, what are the properties that damage functions used in policy analysis of the economic impacts of climate change should posses? First, we would like to parameterize damage functions between the distribution of pre- and post-climate-change weather and economic outcomes of interest. Second, we would like these functions to identify and estimate parameters that carry a plausibly causal interpretation. Third, we would like the damage function to account for adaptation and measure the full costs of adaptation. Fourth, we would like the damage function to allow an estimation of economic welfare impacts.

This sounds as difficult as it is in practice. Figure 2 helps to explain why. The top left panel shows the weather pattern of temperature generated in two climate regimes. The light gray time series depicts a pre-climate-change world and the dark series shows a post-climate-change world, displaying higher mean and variance of the temperature series. The top right panel displays two damage functions (the parabolas) which map weather into an outcome, in this case temperature into household electricity consumption (measured in kilowatt-hours). The damage function, as has been confirmed in many empirical settings, is highly nonlinear. When it is cold outside and temperatures rise, electricity consumption falls, as people heat less. When it is hot outside and temperatures rise, electricity consumption increases as people air condition the indoor environment. In the pre-climate-change San Francisco, this response is relatively shallow, as few people have air conditioners as indicated by the solid damage function. If climate changes and produces the warmer more variable weather, we assume that people eventually will adapt by buying and operating air conditioners, which changes the damage function to the

Figure 2
Mapping Weather into Impacts—The Importance of Accounting for Adaptation



Source: Author.
Note: The top left panel shows the weather pattern of temperature generated in two climate regimes. The light gray time series depicts a pre-climate-change world and the dark series shows a post-climate-change world, with a temperature series displaying higher mean and variance. The top right panel displays two damage functions (the parabolas) which map weather into an outcome, in this case temperature into household electricity consumption (measured in kilowatt-hours). The effect can be seen in the bottom panel.

dotted parabola (labeled "With adaptation"). The response, especially at higher temperatures, is now steeper—resulting in stronger post-adaptation increases in electricity consumption on a one-degree warmer day when it is hot outside.

The effect can be seen in the bottom panel. If climate changes and we use the flatter (and wrong) pre-climate-change response function, which ignores the extensive margin adaptation, projected electricity consumption is the black solid line. This is clearly incorrect, as one is using the right weather but the wrong damage response function. The correct response function is the dotted parabola, which results in the dotted time series of electricity consumption in the bottom panel. It is much higher and much more variable compared to the no adaptation prediction. In the literature, this distinction is often referred to as the "weather versus climate response." I think it a better way to phrase this is "the impacts of weather simulated with versus without an extensive margin adaptation response." In a world changed by climate, we will still face weather when we walk out of our front door. As I will discuss below, a rapidly growing empirical literature uses weather variation to identify response functions that partially or fully allow for adaptation.

So how does one go about calibrating these damage functions and using them to project damages? The question asked of any empirical economist these days is "what would the perfect counterfactual be?" In this context, a researcher actually needs to be concerned about two counterfactuals: 1) the counterfactual future climate; and 2) the counterfactual for identifying the appropriate damage function.

The first counterfactual, the climatic one, asks the question: What level of climate change will occur? Given our metaphysical inability to experiment by randomly imposing different levels of greenhouse gases on a large sample of otherwise identical Planet Earths, researchers instead resort to computational counterfactuals of the climate system, which are referred to as "global circulation models" (GCMs). These models use different scenarios of greenhouse gas emissions and physical representations of the climate system to predict changes in the climate system (IPCC 2013; Auffhammer, Hsiang, Schlenker, and Sobel 2013). They provide projections of, for example, surface temperatures, precipitation, and sea-level rise at a reasonable level of disaggregation and make these freely available through public depositories (Climate Impact Lab 2018; NASA 2018). A companion paper in this symposium by Hsiang and Kopp discusses these models and their limitations in more detail.

For the second counterfactual, we need to identify how agents in a given location respond to weather generated from a different climate regime. As a thought experiment, what is the right counterfactual for climate change in the United States by end of century? The US average historical (1986–2005) June/July/August temperature is 74°F. By end of century (under the aggressive RCP8.5 scenario), this temperature is projected to be 84° (Climate Impact Lab 2018).

One could contemplate a number of counterfactuals that might be used. If one has a set of units that are similar on observables and unobservables, but with different weather due to different local climate regimes, one might use a cross-sectional comparison. If one has long time series over a period of time where climate has changed, one might exploit time-series variation, possibly across units, to get econometric identification. But these approaches become questionable when we are comparing places that are far apart in characteristics space. Neighboring counties in California might possibly serve as counterfactuals for each other. However, using the economies of Pakistan, India, Mali, and Thailand as "hotter counterfactuals" for the United States or Europe, on the grounds that current mean temperatures in these countries are close to 84 degrees, is a stretch.

The econometric approaches discussed below all suffer from this issue of a fundamental lack of comparability, and I am afraid that there is no perfect way to overcome it. Indeed, the problem is even more severe than thinking about counterfactuals based on geographic and time-series variation would suggest. Comparing any current day or preindustrial society to a climate-changed world 100 years from now will be an imperfect comparison.

Many of the econometric studies I will describe below, including ones I have authored, use a counterfactual where we impose end-of-century climate on today's economy, which is a suboptimal way to circumvent the challenge of characterizing an end-of-century economy as attempted by the Integrated Assessment Models used to calculate the social cost of carbon. As I will discuss below, the current state of knowledge predicts that climate change will affect economic growth, the distribution of population and wealth across space, and also significantly affect technology—both through mitigation and adaptation channels. An ideal counterfactual for several decades into the future would need to compare how these demographic and economic factors would change in the absence and presence of climate change as well.

Estimating Economic Damages from Climate Change

One of the first known reflections on an association between human/economic activity and climate goes back to Parmenides, a disciple of Pythagoras writing in the fifth century BCE, who divided the world into five zones: one torrid, two temperate, and two frigid (Sanderson 1999). The torrid zones (which we call the tropics today) he thought were too hot and the frigid zones too cold for human habitation. Aristotle later agreed with this view. He believed that the only areas on earth habitable by humans were located between the tropics and the Arctic and Antarctic circles—the area where he lived.

The emergence of climate change as field of study in the physical sciences in the late 1970s led social scientists to think about estimating the possible consequences of a *changing* climate on economic sectors such as agriculture (D'Arge 1975; Kokoski and Smith 1987; Adams, McCarl, Dudek, and Glyer 1988; Adams 1989).

Ricardian Cross-Sectional Approaches

Thousands of econometric papers control for weather in regressions, but Mendelsohn, Nordhaus, and Shaw (1994) offered the first attempt at estimating a damage function econometrically with the purpose of simulating the impacts of climate change on an important economic sector. They proposed a cross-sectional Ricardian framework, which is maybe the most widely used approach in climate impact estimation to this day. The intuition underlying this approach is that in a stationary climate, farmers optimize their production technology and crop choice according to the environment they face. This includes soil quality, slope of the land, agro-ecological zone, and of course climate, as captured by a set of statistical moments of the weather distribution over a substantial period of time. If land markets function perfectly, the land value should reflect the discounted present value of expected profits for a given parcel of land. In a regression framework, one can then decompose land values into their different components, one of which is long-run (for example, 30-year) averages of weather. In standard practice, one regresses farmer self-reported land values on polynomials of climate, which are often broken out by season. The marginal effects on the climate variables then indicate the marginal value of a one-unit change in a measure of climate.

Figure 3 helps cement the economic intuition behind this approach. Imagine a single farmer, who is currently growing crop 1 and earning profits corresponding to the *y* value at point *A*. If faced with a significantly hotter climate, the farmer becomes indifferent between growing crop 1 and crop 2 at point *B*. If climate warms further still, the farmer would be much better off at point *C*, that is, switching to crop 2, rather than at point D where the farmer continues to grow crop 1. Because the cross-sectional regression observes optimizing farmers across the climate spectrum, this approach estimates the envelope of the individual crop-specific payoff functions and allows for climate adaptation. As a result, this approach both estimates a response that allows for adaptation to climate change and relies on data that are readily available in many regions in both the developed and developing world. It uses hotter locations as a counterfactual for the response of cooler location to climate change.

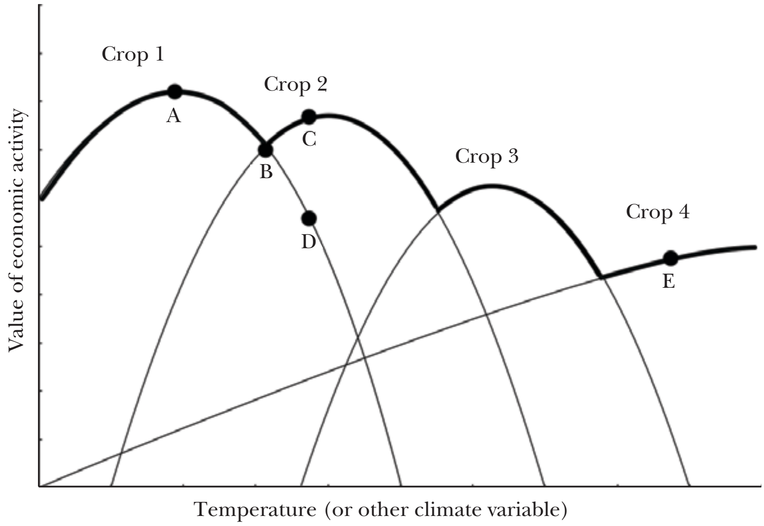
Three main criticisms of this method have been raised. First, this cross-sectional approach to damage function estimation is vulnerable to omitted variables bias, hence putting in question whether the estimates are *plausibly causal*. Any drivers of land values (or net profits) that are correlated with the climate indicators and outcome and are excluded from the model will confound the estimates of the marginal value of climate. As one vivid illustration, Schlenker, Hanemann, and Fisher (2005) reexamined the analysis of Mendelsohn, Nordhaus, and Shaw (1994), and point out that irrigation is an important driver of farm profits. This was omitted from the original regression model. When correcting for this by limiting the analysis to agricultural land east of the 100th meridian (the 100th meridian runs down through the middle of North and South Dakota and down through the middle of Texas) where agriculture is mostly non-irrigated, the marginal value of climate changed significantly. The estimated impacts of climate change went from being slightly beneficial to robustly negative.

Second, this Ricardian approach essentially assumes *costless adaptation* to climate change. But switching crops is not costless (Quiggin and Horowitz 1999). The fixed costs to switching from growing one crop to another may include investment in new harvesting equipment, irrigation infrastructure, and the acquisition of technical know-how. If these costs are big enough, it may be optimal for the farmer to delay or avoid change—in Figure 3, to continue farming crop 1 at point *D* rather than changing to crop 2 at point *C*. Hence, this method may provide biased estimates of the effect of climate change depending on how costly it is for farmers to switch from one crop to the next.

Third, this framework is applied retrospectively under the assumption that only historical climate matters. This assumption may no longer be tenable, as the climate has been changing since the 1960s. If agents know this, they should base their actions on expected rather than historical climate. Severen, Costello, and Deschenes (2016) provide an interesting extension of the Ricardian method by incorporating climate expectations. They show evidence that farmers already incorporate this information, suggesting that failing to incorporate expectations leads to a significant underestimation of projected impacts of climate change.

This cross-sectional framework has been applied in a number of other sectors. For example, Albouy, Graff, Kellogg, and Wolff (2016) back out the marginal value of climate in a cross-sectional study looking at residential home values. Mansur,

Figure 3
Crop Choice and Profits in the Long and Short Run



Source: Figure inspired by Mendelsohn, Nordhaus, and Shaw (1994).
Note: Imagine a single farmer, who is currently growing crop 1 and earning profits corresponding to the *y* value at point *A*. If faced with a significantly hotter climate, the farmer becomes indifferent between growing crop 1 and crop 2 at point *B*. If climate warms further still, the farmer would be much better off at point *C* (switching to crop 2) rather than at point *D* (continuing to grow crop 1).

Mendelsohn, and Morrison (2008) use this approach to study the effects of impacts of climate change on energy consumption, where the adaptation is not crop-switching, but rather fuel-switching.

Panel Data Approaches

Motivated by concern over the possibility of omitted variables in the Ricardian approach, Auffhammer, Ramanathan, and Vincent (2006) and Deschênes and Greenstone (2007) proposed using year-to-year variation in agricultural outcomes, temperature, and precipitation to estimate damage functions. Observing longitudinal panels of India's state-level rice output and US corn/soy and wheat yields, respectively, these papers can control for unit-specific and time-period fixed effects, which does away with some of the concerns over omitted variables bias. The regression equation in this approach regresses outcomes of interest (say, crop yields) on measures of contemporaneous weather (instead of the long-run averages of historical weather). If the right-hand-side weather variable enters the regression linearly, the estimated response has often been characterized as a short-run/weather/no-adaptation response—which is of course different from the weather response after a future persistent change in climate which accounts for adaptation. In this simplest version of the framework, econometric identification arises from within-unit year-to-year fluctuations in weather and the outcome of interest.

From the standpoint of analyzing the economic effects of climate change, an obvious concern with this approach is that it may capture short-run (intensive margin) adaptation to weather fluctuations, but not long-run (extensive margin) adaptation. For example, this approach captures farmer responses to bad weather draws in the short-run (like lower fertilizer application in a drier year) rather than in the long-run (like installation of irrigation infrastructure).

It is generally true that agents have more adaptation choices in the long run, especially along the extensive margin, and thus estimates that do not take this adaptation into account may overstate impacts. For example, farmers in the long run can switch crops, change the cropping calendar, or move their operations north, all of which would dampen the estimated impacts of climate change. However, there are also examples of adaptation options that are available in the short run and not in the long run. One example is a farmer with very limited groundwater resources and a slow refilling aquifer, who can smooth bad rainfall outcomes in the short run, yet continued water withdrawals would deplete the aquifer. As a result, this kind of adaptation would be only available in the short run, not the long run. Hence the bias may work in either direction depending on the nature of the adaptation options available to economic agents.

The critique that it is difficult to infer long-run adaptations based on short-run changes has some validity, but as I discuss later, several methods have been proposed for deriving long-run adaptation to climate change from panel data. Moreover, while the criticism of the lack of long-run adaptation in this approach may seem intuitive, it does not apply to all panel studies using weather as a right-hand-side variable. McIntosh and Schlenker (2006) consider the case in which the weather variable on the right-hand-side enters as a second-degree polynomial. Because the response function is calibrated by two parameters, the coefficient on the higher-order term uses both variation from *within units* as well as *across units*. Econometric identification arises from both within-unit time series variation as well as cross-sectional variation across units. Hence, it has been argued, that studies using this nonlinear specification allow for plausibly causal estimates that incorporate adaptation.

The papers leaning on this approach most strongly are panel studies of GDP *growth rates* across countries as a function of annual temperature fluctuations (Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015a). The most recent of these papers find impacts of climate change on global GDP around 20 percent by end of the century, which is an *order of magnitude* larger than what is found by most Integrated Assessment Models. There is broad enthusiasm for this approach, especially in the interdisciplinary climate literature. Aside from the fact that the choice of growth rate as the dependent variable implies that temperature shocks have persistent effects on economic growth, it is important to remember that this approach introduces cross-sectional variation and all that comes with it in the identification of the higher-order term.

Another critique of the panel data approach is that if weather is measured with error, then as more fixed effects are included in the regression, concerns over measurement error loom larger (Fisher, Hanemann, Roberts, and Schlenker 2012). In the vast majority of locations, weather is measured with error, and the bigger the distance between weather stations, the bigger measurement error concerns become. The United States and Europe have tens of thousands of weather stations, but many locations in in sub-Saharan Africa do not have a weather station within hundreds of miles. If the measurement error is classical, this is likely to attenuate the response towards zero.

Long Difference Estimation

Motivated by omitted variables bias issues in Ricardian models and the possible issues relating to capturing long-run adaptation in panel data models, Burke and Emerick (2016) proposed an alternate approach, which seeks to provide plausibly causal estimates of damages that fully account for observable adaptation. Climate has already changed in the United States over the previous half-century; in particular, they show that warming and precipitation trends are quite heterogeneous across US counties east of the 100th meridian. Hence, one can use differential climate trends as a source of econometric identification. The beauty of this approach is that the distribution of observed trends includes changes similar in magnitude to those expected over the next century, which creates some overlap between the temperature and precipitation variation used for identification and out-of-sample projection.

In their estimation, they use the difference between five-year moving averages of crop yields two decades apart and regress these on five-year moving averages of weather also two decades apart for all agricultural counties east of the 100th meridian. The differencing is equivalent to the inclusion of county fixed effects and the variation used to identify a climate effect incorporates adaptation. The marginal effects from this estimation show that the long-run estimates are at best half of those estimated from panel data models using short-run variation in weather. However, given the range of statistical significance, one cannot rule out that the two are equivalent. The authors interpret this finding as evidence of only limited long-run adaptation, which is one interpretation. Those working with panel data approaches might argue that the comparison here is flawed, because the baseline used for comparison incorporates some degree of adaptation.

This long difference approach is appealing because it provides plausibly causal estimates of climate impacts that account for adaptation. However, the data requirements are significant. One needs broad spatial coverage of data over long periods of time. The other application where this long difference approach has been applied is in measuring the impacts of climate change on aggregate GDP across countries (Dell, Jones, and Olken 2012). However, other than in the cross-country sense, there are no applications of this estimator in nonagricultural sectors or in the developing country context. There should be more applications of this method in settings where data are sufficient.

Ricardo Meets Panels: Climate Adaptive Response Estimation

A small but rapidly expanding literature attempts to estimate how the dose response function between weather and outcomes of interest changes *as a function of a changing climate*. There are two approaches. The first is similar to a "split sample approach," where one splits a long panel of observable outcomes and weather into two periods and estimates the response function separately. One can then use statistical tests to search for evidence of adaptation between the two periods. For example, Barreca, Clay, Dechenes, Greenstone, and Shapiro (2016) examine the mortality response to weather over time in the United States and show a massive decrease in the effect of a hot day on mortality over time, which is due to the significant rollout of air conditioning in the hot and often humid areas of the United States. One example of this approach is Roberts and Schlenker (2011).

A second approach along these lines represents a marriage of the panel data estimation approach using short-run weather fluctuations and the Ricardian approach. The concept here is that if one observes a large number of units (like counties, households, or firms) over a significant number of periods covering a spatial area with large heterogeneity in climate, one can estimate separate response functions for subgroups of the individual units using observed short-run weather fluctuations (for example, use within-household variation to identify a short-run response function by zip code). By controlling for unit- and time-fixed-effects, it is possible to obtain plausibly causal estimates of local short-run dose response functions. One can then either in a second step regress the slopes of the dose response on climate (for example, long run average summer temperature) across subgroups, or, through an interaction term in a single regression, estimate how the slope of the dose response function varies across areas with different climates, incomes, and other observables that vary across space. Sightings of this approach include Bigano, Hamilton, and Tol (2007), Auffhammer and Aroonruengsawat (2012), Hsiang and Narita (2012), Butler and Huybers (2013), Davis and Gertler (2015); Heutel, Miller, and Molitor (2017), and Carleton et al. (2018).

This approach offers two important forward steps beyond the panel studies discussed above. First, it explicitly models climate adaptation by exploiting cross-sectional differences in the slopes of dose response functions. Second, it allows us to model explicitly the effects of income and population on the damage functions.

While this approach has significant appeal, it does not overcome some of the shortfalls of the Ricardian and panel methods. The econometrician is always limited by using historical observations in order to parameterize equations. The best we can do is simulate how income, population, and climate have affected short-run dose response functions historically and to assume that this relationship remains stable. We can approximate a future San Francisco with the climate of Fresno by assigning the appropriate climate, income, and population, but none of these approaches properly address the fact that Fresno may be structurally very different from a future San Francisco—even if we assign the right income and population. We simply lack the crystal ball that lets us look to 2100 and beyond. But this issue has plagued social science broadly, because predicting what the world looks like 100 years out is, well, rather difficult.

Room for Expert Elicitation?

This literature on estimating the economic damages of climate change has been criticized on four grounds, which have been well-enunciated in Pindyck

(2013, 2016, 2017). Ultimately, these criticisms raise the possibility that for studying climate change, conventional econometric studies may need to be supplemented with a healthy dose of "expert elicitation."

Pindyck's first criticism is that in Integrated Assessment Models, the functional form of relationships and their parameterization—including those in damage functions—are "arbitrary." Second, he expresses concern that many of the studies cited above "are limited to short time periods and small fluctuations in temperature and other weather variables," which is effectively the same as pointing out that econometricians rely on observed data and technology to parameterize their dose response functions. In whichever way one phrases this concern, the bottom line is that existing studies may not account well for long-term adaptation and in particular for the possibility of very significant changes in technology. Third, the biggest impacts of climate change may result from extreme and catastrophic events, which can be thought of as low-probability events with possibly massive economic consequences. Examples would include the shutdown of the Thermohaline Circulation that gives Europe its lovely climate, the melting of the West Antarctic ice sheet, and the possible rapid release of significant amounts of methane from the tundra. We have (fortunately!) not observed these events in the measured historical record and hence econometric estimation cannot provide estimates of the economic damages from such events. A final concern is that there is little agreement over the correct approach to discounting and which discount rate to apply in placing a value on future damages from climate change.

In response to these concerns, Pindyck has strongly argued for "expert elicitation." For example, in response to estimating the risks and costs of extreme climate events, one can imagine that teams of scientists with an understanding of the physical and economic consequences might be able to provide coarse estimates of the damages resulting from such large events. There are well-established procedures for such expert elicitation, and this may be a fruitful avenue forward to make progress on this topic. However, experts in this arena have to rely on "process understanding," as there are no data here to help. Similarly, one can imagine a group of experts who might tackle the question of what discount rate is most appropriate to use, which is what Drupp, Freeman, Groom, and Nesje (forthcoming) did. The median answer for the risk-free social discount rate is 2 percent in their study, which is quite different from the 3 percent and 7 percent rates applied in the most recently used social cost of carbon in proposed US government rulemakings for automotive fuel economy (CAFE) standards.

However, expert elicitation seems less useful in coming up with better estimates of damages in order to overcome the first two of Pindyck's critiques. I would argue that the recent literature has made significant headway in estimating plausibly causal damage functions incorporating adaptive response from partially cross-sectional variation. The formulations doubtless can be critiqued and questioned, but they are not arbitrary. I question whether experts would come up with "better" estimates than the cutting-edge papers in this literature. Maybe more fundamentally, a group of experts called upon to participate in an expert elicitation exercise concerning the functional form of damage models and extrapolations to larger climate changes or time periods would begin with—of course—a review of the existing recent models in this area, which brings us back to the importance of better econometric models.

What We Know and What We Don't

Cline (1992) put forth a list of important sectors for which we require a better understanding of their climate sensitivity. Table 1 below replicates his table and I have subjectively filled in where this literature currently stands in terms of published and ongoing efforts. A glance shows that there is a lot of work to do.

Yet it is clear that the literature on the econometric estimation of damage functions of climate change is rapidly expanding—both in terms of methods as well as sectoral and spatial coverage. The previously stagnant state of affairs where most of the damage functions in Integrated Assessment Models had not been updated significantly in over a decade has changed dramatically. Economists need to push forward in improving sectoral and spatial coverage of the damage functions provided to modelers, using methods that allow us to parameterize plausibly causal damage functions, which account for adaptation and allow us to estimate welfare impacts of climate change. The current frontier is probably best described by work using the "Ricardo meets panel data" approach.

Moore et al. (2017) is one published attempt to incorporate the most recent estimates of damage functions for the agricultural sector into an Integrated Assessment Model (the FUND model) and this one-sector exercise doubles the social cost of carbon (SCC), which underlines the importance of these efforts.

Those interested in this area will want to keep an eye on two major efforts that involve ambitious ongoing collaborations between climate scientists and economists. The Climate Impacts Lab, managed jointly by researchers at the University of Chicago, UC Berkeley, Rutgers University, and the Rhodium Group, produces damage functions for mortality, migration, energy consumption, agricultural yields, and conflict which satisfy the characteristics laid out above and have global coverage. At the same time, a group at Resources for the Future has undertaken the task of implementing the changes suggested by the National Academies of Sciences in the modeling of the social cost of carbon. The governments of Mexico and Canada have pledged their support of these efforts, as all US federal government development of the modeling behind the social cost of carbon has been halted—a fact which is deeply concerning.

As these and other researchers dig deeper, three key areas require especially deep thinking. First, we need to improve how we incorporate damages from catastrophic events, which may well require abandoning the econometric toolkit and relying on cross-disciplinary expert solicitation. Second, we need to think about general equilibrium effects across space and spillover effects across sectors in our models. Collaborations between trade and climate economists (Dingel, Meng, and Hsiang 2018), as well as academics working on supply chains (for example, Seetharam 2018), will likely yield fruitful insights. Finally, it is shocking how little work has been done on the effects of climate change on nonmarket goods other than mortality. It is

Table 1
Coverage of the Damage Function Literature

Sector	*Plausibly causal estimates*	*Adaptation addressed*	*Global coverage*	*Examples*
Agriculture	Yes	Yes	Yes	Schlenker and Roberts (2009); Moore, Baldos, Hertel, and Diaz (2017)
Forestry	No	No	No	
Species loss	No	No	No	
Sea-level rise	Yes	Yes	No	Houser, Hsiang, Kopp, and Larsen (2015)
Energy	Yes	Yes	No	Auffhammer (2018)
Human amenity	Yes	~ Yes	No	Albouy, Graf, Kellogg, and Wolff (2016); Baylis (2015)
Morbidity and mortality	Yes	Yes	Yes	Deschênes and Greenstone (2011); Carleton et al. (2018)
Migration	Yes	No	No	Bohra-Mishra, Oppenheimer, Hsiang (2014); Missiran and Schlenker (2017)
Crime and conflict	Yes	No	Maybe	Burke, Hsiang, and Miguel (2015b)
Productivity	Yes	No	No	Peng, Deschênes, Meng, and Zhang (2018)
Water consumption	No	No	No	
Pollution	Yes	Maybe	No	Bento, Mookerjee, and Severenini (2017)
Storms	Yes	Yes	No	Hsiang and Narita (2012); Deryugina, Kawano, and Levitt (2018)

Source: Cline (1992) put forth a list of important sectors for which we require a better understanding of their climate sensitivity. Table 1 below replicates this list and I have subjectively filled in where this literature currently stands in terms of published and ongoing efforts.

paramount that we begin developing approaches that will allow us to quantify damages from species loss, ecosystem services—as well as effects on human morbidity—and incorporate these into the models that estimate costs of climate change.

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