Estimating the Economic Impacts of Climate Change Using Weather Observations

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Introduction

Physical changes in the climate due to greenhouse gas emissions have been well documented (e.g., Stocker et al. 2013), and future physical changes due to unmitigated greenhouse gas emissions are also generally well understood. However, it has long been recognized that quantifying the *economic* consequences of changes in temperature, rainfall, sea level, and other climate variables is extremely challenging. Nevertheless, such quantification is critical for developing effective climate mitigation and adaptation policies.

Early studies estimating the economic damages associated with climate change relied on process models that used scientific theory to specify models that simulated the effects of changes in climate variables on a particular sector (e.g., Smith and Tirpak 1989). Much of the recent work has focused instead on statistical approaches that use historical data. The benefit of such models is that they are based on observed relationships in real-world settings.[1] Early versions of these statistical models used cross-sectional variation in climate (occurring at one point in time) to estimate the marginal economic effect of long-run changes in the distribution of temperature and rainfall (e.g., Mendelsohn, Nordhaus, and Shaw 1994). However, since the early 2000s, a large literature has emerged using data that varies over *both* space and time (i.e., panel data) to estimate the effects of interannual (i.e., from one year to the next) variation in weather on economic outcomes (see Carleton and Hsiang [2016] and Dell, Jones, and Olken [2014] for reviews).

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[1]For the most part, these models do not assume any theory-based structural relationships among variables (i.e., they are reduced-form specifications).

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Panel approaches have significant advantages over cross-sectional regressions, not only because of the type of data used (varying in time and space), but also because such approaches are able to control for many more unobserved omitted variables than is possible using cross-sectional data alone (Deschênes and Greenstone 2007).

However, there have long been concerns that the effect of year-to-year weather variation on economic impacts cannot be used to identify the effect of climate changes because the response to short-run weather fluctuations may be fundamentally different from the response to a permanent change in climate. The potential difference in responses is due to adaptation; that is, people and firms may respond differently (adapt) to permanent changes in the expected distribution of weather (i.e., the climate) than to short-term and unanticipated fluctuations in weather. If adaptation is important, then the impact of weather fluctuations may not be a good proxy for the effect of a permanent change in the climate.

The issue of how best to estimate the effects of long-run changes in climate has long been contentious (Burke et al. 2016). Given the importance of this issue of weather versus climate, a major focus of recent climate economics research has been to develop and apply methods to statistically identify climate change impacts using historical panel data. A number of new approaches have been proposed that exploit the richness of many panel datasets. This article discusses different methods for estimating climate impacts with the goal of identifying the state of the art and highlighting opportunities for future advances. With this in mind, the article begins by establishing a conceptual framework for examining climate, weather, adaptation, and the overall economic costs of climate change. Then we review different approaches that have been proposed for econometrically estimating the effects of climate change, including the classic cross-sectional approach and more recent panel approaches that use interannual weather variation. This is followed by a discussion of emerging hybrid approaches that use a mix of cross-sectional and interannual variation in order to better identify climate change impacts. We conclude with a summary of our findings and some priorities for future research.

Key Concepts and a Framework for Estimating the Value of Climate Impacts

Before delving into our discussion of different approaches for estimating the economic impacts of climate change, it is useful to review some key concepts used in the empirical literature. In particular, weather and climate are both common words, but it is important to give them a precise statistical definition in order to understand differences in the statistical methods that will be discussed in the sections that follow.

Weather, Weather Statistics, and Climate

Strictly speaking, weather is the state of the atmosphere at a particular location and moment in time (see any dictionary). Weather is a complex and time-varying concept. At any given point in time it can be described not only by temperature and rainfall, but also by numerous other variables, including air pressure, wind speed and direction, relative humidity, cloud cover, and wind shear.

For most economic and policy applications, representing weather is impractical; summary statistics are generally sufficient, with the choice of statistic depending on the application and context. In agriculture, for example, annual or monthly growing and killing degree days[2] and total monthly or annual precipitation have been useful. For human health, peak wet-bulb temperature (temperature that has been adjusted for evaporative cooling) may be more relevant, while heating and cooling degree days are often used to model energy demand. In this article we will refer to the time- and space-varying summary statistic for weather as the "weather statistic" or simply "weather."[3]

Weather, by its nature, has an inherent randomness to it. This means that the weather at any given point in time can be thought of as a draw from a probability distribution. That probability distribution over weather outcomes is the climate. In the economic and policy context (and in this article), climate will be defined as the full (possibly joint) probability distribution of the relevant weather statistic(s). This means that climate change is a change in the probability distribution from which the weather statistic is drawn in each time period.[4] For further discussion of these issues see Hsiang (2016) and Lemoine (2018).

Framework for Examining Welfare Consequences of Changes in Weather and Climate

Ultimately, for the purposes of informing mitigation and adaptation policy, we are interested in the welfare consequences of climate change. To understand how weather, climate, and adaptation decisions determine the welfare impacts of climate change, begin by imagining a simple production process (e.g., Pope and Chavez 1994; Kelly, Kolstad, and Mitchell 2005; Hsiang 2016), in which output is determined by two sets of variables: the weather and production choices. Weather cannot be controlled by the economic agent and is generally unanticipated, while production choices (e.g., what to plant and when, or how much capital to invest) are decisions made by the economic agent and are based on factors such as prices and expectations about (stochastic) weather.

Natural weather variability

Even in a stationary climate (i.e., one that is not changing over time), there is variation in the weather that arises from fluctuations in the earth system, which the climate science literature calls "internal" or "natural" variability (Deser et al. 2012). Assuming that agents know the

[2]Degree days are daily temperature differences summed over a period of time. Usually the temperature differences are the difference between the average temperature on a day and some base temperature. For instance, heating degree days are defined by the US Energy Information Administration as the extent to which temperature is less than a base of 65°F. The agricultural literature often defines growing degree days as the extent to which daily temperature exceeds 8°C for the days in a growing season; similarly, killing degree days are defined with respect to a base temperature of 29°C (e.g., Butler and Huybers 2012; Schlenker and Roberts, 2009).

[3]We recognize, however, that the exact nature of this summary statistic will depend on the application, and that this is sometimes a multivariate quantity (e.g., temperature and precipitation).

[4]The World Meteorological Organization (WMO) requires member nations to compute 30-year "climate normals"—the annual or monthly mean and variance of weather variables over a defined 30-year period—and to update these every 30 years (Arguez and Vose 2011). In statistical terms, this simply means that the climate (weather distribution) is estimated using a 30-year sample, although measuring only two moments (mean and variance) may not be the best way to estimate the underlying distribution of a weather statistic.

stationary climate distribution they face, they will make investments to reduce the net losses associated with weather variability. For example, investments in irrigation capital reduce the losses from variable natural precipitation; these investments may be profitable in a dry or highly variable climate, but they may not be justified in a wetter climate.

A change in climate

If the climate changes, then the weather faced by the agent will change. If the agent knows about the change in climate, he or she can adjust management choices in order to maximize production under the changed climate. Determining optimal responses to the new climate involves trading off the costs of these management changes against the benefits in terms of expected losses or gains in production given the new distribution of weather. In the context of climate change, these actions are known as private adaptation; in economics, this is simply the natural adjustment response of an economic agent to changed technologies or prices.[5]

The total equilibrium cost (i.e., the economic damages) of the change in climate is the change in production after reoptimization of management practices under the new climate, plus any additional production costs from the change in management. For instance, if climate change consists of a decrease in annual mean precipitation, then adaptive action may involve costly investments in irrigation and water storage; here the equilibrium cost of climate change would be the change in the value of agricultural production under the new climate plus the costs of the irrigation and water storage systems. In general, the net costs of the change in climate may be positive or negative.[6]

Short-run versus long-run effect of climate change

Both expectations and fixed capital investments can adjust in response to *permanent* changes in climate, but they cannot adjust in response to short-term variation in weather. Thus we define the short-run response to a change in climate as the effect of a shift in the true climate, with expectations, beliefs, and, by extension, investments held fixed (Kelly, Kolstad, and Mitchell 2005). This means that the short-run response could be estimated by observing the effects of weather fluctuations. In contrast, the long-run response is the effect of a change in climate after both expectations and capital investments have been allowed to adjust to the new climate. As long as there are management or investment adaptations that can be taken to improve outcomes under the changed climate, the short- and long-run effects of climate change will be different.

Instantaneous versus gradual changes in climate

To further complicate the issue of estimating the effect of climate changes, the change in climate may be instantaneous or gradual, and the impacts will differ under the two cases.

[5]Some adaptation (such as investments in flood control or public infrastructure) is taken collectively rather than by individual agents. Typically, governments are involved in such public adaptation, and market failures may result in underprovision of these adaptations (Mendelsohn, 2000). We focus here on private adaptation and do not consider these inefficiencies further.

[6]The impacts of changes in *weather*, which are the focus of most panel models, do not capture the full impacts of climate change because such models do not consider adaptive actions.

Consider a change in the climate. First imagine an instantaneous shift in the climate.[7] Since the climate can only be inferred from the actual experience of weather, this sudden shift is unanticipated. In other words, the weather that is initially experienced under the changed climate (the weather distribution) may be interpreted only as an unusual (i.e., "extreme") weather event. Over time, however, the evidence (in the form of repeated weather observations) will lead an agent to update their beliefs regarding the underlying climate distribution, which will cause the agent to reoptimize their investments and management to maximize welfare under the new climate distribution.

In this simple production model, the sudden change in climate lowers welfare,[8] both because of inherently worse outcomes under the changed climate and because agents are initially not adapted to or even informed about the new climate. More specifically, the equilibrium costs of a shift in climate are defined as the residual loss in welfare, including adaptation costs, after adjusting to the new climate, while the adjustment costs are the additional costs associated with being imperfectly adjusted to a particular climate. Adjustment costs can arise from both incorrect beliefs about the state of the climate distribution ("mistakes") and the time it takes to replace obsolete factors of production (e.g., capital). Beliefs and factor investments will both adjust over the long run in response to changes in climate, but not in response to short-run fluctuations in weather.[9] The magnitude of adjustment costs will depend on the net benefits of adaptation options and the timescale over which adaptation occurs (Kelly, Kolstad, and Mitchell 2005). Thus sectors in which long-lived capital stocks are important (e.g., forestry, coastal defenses) are likely to have larger adjustment costs than other sectors.

A more realistic representation of climate change reflects the fact that consequences accumulate gradually over time rather than instantaneously.[10] The concepts of equilibrium and adjustment costs translate to this setting. In this case, imperfect adjustment to the climate at any given point in time still results in a gap between equilibrium welfare and adjustment costs (i.e., the welfare achieved by agents with imperfect information), with welfare converging to the equilibrium value over time once the climate has stabilized. If climate change is slow relative to the rate of adjustment, or if agents are able to anticipate future climate change, then adjustment costs will be smaller.

Framework for Quantifying Climate Change Damages

Given that a full accounting of the net economic costs (i.e., the damages) of climate change must include both the equilibrium costs (which include both the costs remaining—sometimes referred to as "residual damages"—after full adaptation and the costs of adaptation) and the adjustment costs (which are temporary and will depend on the rate of adaptation and the effectiveness of adaptation options), the question arises of how to empirically determine these damages. Few empirical methods are able to fully estimate all three components of climate damages (i.e., residual damages, adaptation costs, and adjustment costs). In general,

[7]See Appendix figure 1a for a graphical illustration.
[8]See Appendix figure 1b.
[9]For nonclimate adjustment cost applications, see Abel and Eberly (1994) and Cooper and Haltiwanger (2006).
[10]See Appendix figure 1c, which shows the same change in climate (as in Appendix figure 1a) occuring gradually over 25 years, and Appendix figure 1d, which shows the resulting changes in welfare.

with the exception of some special cases, considering only how economic output changes with weather shocks is generally not a good proxy for the economic impacts of a change in climate.

The no adaptation case

One such special case is when the possible adaptations and adjustments are ineffective or very limited. In this case, the short-run responses to weather changes and the long-run responses to climate change will be nearly identical. This means that knowing either response is sufficient to characterize climate change damages. With this in mind, Hsiang (2016) has shown that in cases where adaptation technologies are continuous (i.e., the adaptation technologies have continuous values, such as the amount of irrigation water to apply), adaptation is unlikely to be significant, at least for marginal changes in the climate. Guo and Costello (2013) provide a corollary, however, and show that in cases where adaptation technologies are *dis*continuous (i.e., the adaptation technologies have discrete values, such as which crop to plant), the potential benefits of adaptation are theoretically unbounded, even for marginal changes in climate. In other words, the importance of adaptation in driving differences between short- and long-run responses to climate change is likely to differ substantially across locations and sectors, depending on the types of adaptation options available.

The rapid adaptation case

A second special case is one in which adaptation is possible and the rate of adaptation is fast. In this case, equilibrium costs will account for the vast majority of climate change damages because rapid adaptation means that adjustment costs will be small. Thus, in this case, adjustment costs can safely be ignored (i.e., they are of secondary importance). To quantify climate damages in this setting, only the residual damages under equilibrium and the adaptation costs need to be known.

Some economists have argued that because climate only changes over decades or centuries, economic adjustment rates will be relatively rapid and the corresponding adjustment costs will be small (Schlenker, Hanemann, and Fisher 2005). However, with the exception of the two special cases just discussed, fully quantifying the costs of climate change requires estimating both equilibrium and adjustment costs. This in turn requires knowing both the short- and long-run response to a change in climate, as well as the timescale of adaptation.

Trade-offs for estimation

A long-standing debate in the literature concerns the trade-off between, on the one hand, improving confidence in empirical estimates by using dummy variables (i.e., fixed effects) to control for unobserved omitted variables and, on the other hand, estimating the long-run equilibrium response to climate change by using cross-sectional variation. Given the conceptual framework we have outlined here, it is clear that, depending on the setting, the short-run response, long-run response, and rate of adaptation could all be relevant to fully quantifying climate change impacts.

With these issues in mind, in the next two sections we review empirical methods that have been used to estimate the effects of weather and climate. We first review some of the most common econometric approaches and then discuss more recent "hybrid" techniques that combine the short- and long-run variation in panel data in order to improve estimates of climate change damages (see also Dell, Jones, and Olken 2014; Hsiang 2016; Blanc and Schlenker 2017). For each approach, we discuss the kind of climate or weather variation used in the model, a stylized estimating equation,[11] the relevance of the method in estimating equilibrium and/or adjustment costs, and the statistical requirements for accurately estimating the regression coefficients of the true climate or weather effect.

Cross-sectional and Linear Panel Approaches

This section describes the cross-sectional and linear panel approaches to estimating the effects of weather and climate, which are well established in the literature, and further highlights the trade-off between the benefits of the cross-sectional approach's ability to account for long-run adaptations (in order to identify the effect of long-run changes in climate) and the panel approach's ability to accurately identify the short-run impacts of weather.

Cross-sectional Models

The earliest econometric approach for estimating climate change impacts used cross-sectional variation in long-term climates to estimate the equilibrium (i.e., long-run) effects of a change in climate. Pioneered by Mendelsohn, Nordhaus, and Shaw (1994),[12] this approach compares outcomes across space, essentially using hotter places under the current climate to understand how currently cool places will change as the climate warms. Because the differences in climate observed across space are long term and assumed to be stable, it is reasonable to assume that the investments and management practices of agents will be fully adjusted so as to maximize output under the current climate. This means that the cross-sectional approach provides an estimate of the *long-run* response to climate change and can therefore be used to estimate the equilibrium costs of a change in climate.

Econometric specification

The econometric specification involves a dependent variable that is an economic outcome of interest (such as land values, output, or income) that varies over space at a moment in time, which is modeled as a function of climate, various other observable control variables (i.e., any variables potentially correlated with both climate and the dependent variable, which would bias the estimate of the climate effect if omitted from the estimating equation), and an error term.[13]

[11]Appendix table 1 presents the stylized equations for each approach.
[12]Johnson and Haigh (1970) use a very similar approach to estimate a cross-sectional model of land prices in 1964 that is determined by soil characteristics and climatic variables, as well as other exogenous parameters. As noted by Auffhammer et al. (2013), as early as 1925, researchers were examining the effect of weather on economic output. However, the Mendelsohn, Nordhaus, and Shaw (1994) analysis is more widely known and much more specifically focused on the issue of the economic impacts of a change in climate.
[13]See Appendix table 1, row 1. Note that panel data, where available, can be used to estimate pooled cross-sectional models (Schlenker, Hanemann, and Fischer 2006; Massetti and Mendelsohn 2011). Because in most settings relevant to climate change, cross-sectional variation is large relative to time-series variation, models that use panel data but do not include unit dummy variables (i.e., fixed effects) will have the same

Advantages of cross-sectional models

The main advantage of the cross-sectional approach is that it estimates the long-run equilibrium effects of climate change by incorporating the net benefits of all possible adaptation options. If adjustment costs are small, either because they occur rapidly relative to the rate of climate change or because opportunities for adjustment are limited, then an unbiased cross-sectional regression is sufficient to estimate the impacts of climate change.

However, some researchers have argued that long-lived legal, political, or economic institutions mean that adjustment costs could be substantial, despite the relatively gradual nature of climate change. It is possible that adjustment costs may even account for the vast majority of climate change damages (e.g., Quiggin and Horowitz 1999). This implies that in such cases the cross-sectional approach will substantially underestimate total impacts because it estimates only equilibrium costs (Quiggin and Horowitz 1999).

Challenges of cross-sectional models

There are a number of other potential drawbacks with the cross-sectional approach. The first issue, which has received much attention in the literature, is whether the set of observable cross-sectional variables included as controls are able to remove all confounding variables that would bias estimates of the effect of climate if omitted from the estimating equation. More specifically, if unobservable factors are correlated with the climate and also affect the outcome, then the estimated effect of climate will be biased. In agriculture, for example, soil quality often varies with climate, but it also affects productivity and therefore land values. To the extent that soil quality is observed, the analyst can include it as a control variable in the regression. However, there is always the possibility that unobservable characteristics that are unmeasured and therefore cannot be controlled for, are important. For example, Schlenker, Hanemann, and Fisher (2005) show that the estimated effect of climate on land values differs significantly for irrigated versus nonirrigated counties in the United States, suggesting that ignoring historical investments in irrigation infrastructure will lead to biased estimates of the effect of climate change. Other variables that have been shown to confound the relationship between land value and climate in the United States include the value of potential future development that is unrelated to agricultural land productivity (Ortiz-Bobea 2019).

A second challenge for the cross-sectional approach is defining the climate variables that are used as explanatory variables, because, as discussed earlier, the climate itself (as a probability distribution over weather outcomes) is not directly observable. If the climate is stationary (or the relevant agents believe that the climate is stationary), then the historical distribution of the relevant summary weather statistic (e.g., growing degree days or the heat index) can be used as an imperfect approximation of the climate. In fact, the literature commonly assumes a stationary climate, with the past 30 years of weather observations used to estimate the climate distribution (Mendelsohn and Reinsborough 2007; Mendelsohn, Nordhaus, and Shaw 1994). However, if agents recognize that the climate is changing (i.e., it is *nonstationary*), then the issue of estimating the effect of climate is more complicated, with

advantages and disadvantages regarding identification as standard cross sections, since they are primarily estimated using cross-sectional variation.

the largest effect being on forward-looking outcomes (i.e., those that capture expectations of a stream of future benefits or damages) such as land prices. For example, Severen, Costello, and Deschênes (2018) show that climate change projections are already capitalized into agricultural land markets. Therefore, using past observations of weather to estimate the climate distribution will result in a biased estimate of climate change impacts, since land values already capture expectations of future climate damages. The ideal variable to use as a measure of climate in a cross-sectional regression would be agents' beliefs about the weather distribution. However, this is not usually directly observable.

Linear Panel Models

In response to concerns about identification in cross-sectional approaches, there has been growth over the last decade in the use of panel data to estimate weather impacts (Dell, Jones, and Olken 2014; Carleton and Hsiang 2016). Because panel data include observations of many individual units (these could be countries, subnational counties, businesses, or individuals, depending on the context) over many time periods, it is possible to flexibly control for all time-invariant differences between units and all differences between time periods that are common across units, thus improving confidence that the causal effect of weather on the outcome of interest has been properly identified.

Econometric specification

In a linear panel model, an economic outcome of interest (such as output or income), which varies over time and space, is the dependent variable and is modeled as a linear function of a weather variable (which also varies over time and space), a fixed effect that varies over space, a fixed effect that varies over time, and an error term.[14] The fixed effects control for unobservable differences between units and between time periods, which increases confidence (relative to the cross-sectional approach) that the estimated relationship between the economic outcome of interest and the weather variable is not biased by omitted variables.[15]

Disadvantages of linear panel models

In the linear panel setting, the coefficient on weather is estimated by averaging the effect of time-series variation in weather in each location. Permanent differences in climate across locations (i.e., the variation used in the cross-sectional approach) are captured through the location fixed effect and do not affect estimation of the impact of weather on economic outcomes. More specifically, with linear panel models, the statistical power in estimating the effect of weather comes from using the *deviation* of the weather statistic in a particular year from its average value in each location. This means that the variation used for estimating the impact of weather tends to come from temporary, and unexpected, weather shocks (Schlenker 2010). Because we would not expect capital investments, factor use, or beliefs about the average climate to adjust in response to short-term weather shocks, estimates derived from this unexpected and temporary variation in weather provide an estimate of the *short-run* response to climate change. This approach is sufficient for estimating the long-

[14]Appendix table 1, row 2, presents a stylized estimating equation.
[15]Nonlinear panels, which represent adaptation very differently, are discussed in the next section.

run equilibrium effects of climate change only in cases where opportunities for adaptation and adjustment are small. Hsiang (2016) argues that this is the case when adaptation technologies are continuous. However, in cases where there is substantial adaptation potential, using the short-run response to infer climate change impacts will result in a biased estimate of damages because it does not account for longer-term changes (i.e., adaptations) that can be made to improve outcomes under a permanent change in climate.

Another potential problem with the linear panel approach is that although time-invariant omitted variables are not an issue (because they are addressed by the location fixed effect), time-*varying* omitted variables could still be a problem. One example concerns the effect of temperature on mortality. More specifically, temperature and relative humidity are correlated and both affect mortality rates, but with climate change they are projected to change in opposite directions (Fischer and Knutti 2013). This means that a panel regression of mortality rates and temperature that does not also control for relative humidity could provide a biased estimate of the effects of climate change on mortality.

Emerging Hybrid Approaches

There are a number of emerging hybrid approaches that use panel data in innovative ways. These approaches combine cross-sectional, interannual, and decadal variation in weather to estimate climate change effects, using panel data and controlling for unobservable confounding variables. We divide these approaches into three categories: panel models that allow for heterogeneous marginal effects, long-differences models, and models that partition the variation available in panel data.

Non-linear Panel and Multistage Methods for Estimating Heterogeneous Marginal Effects

Warmer temperatures will likely have different effects on cold versus hot places. This means that a linear response function (with a constant marginal effect) will often be inappropriate for modeling the effect of climate change. In other words, the marginal effect of warming will likely vary as a function of climate, which implies the need for a *nonlinear* response function. Panel data can be used to model this heterogeneity because it contains information on the effect of interannual weather variability across multiple locations. Two approaches have been proposed to estimate these heterogeneous marginal effects: nonlinear panel models and multistage models.

Nonlinear panel models

In contrast to linear panel models, nonlinear panel models represent economic outcomes as a nonlinear function of weather.[16] Using a nonlinear function of weather means that, by definition, the marginal effect of a change in weather (i.e., the gradient of the weather response function) is itself a function of weather.[17] Although the effect of climate on the level of the

[16]See Appendix table 1, row 3.
[17]For example, if the function is a quadratic in weather, then the marginal effect of weather is a linear function of weather, since the derivative of a quadratic is a line.

economic variable of interest is removed through the location fixed effect (as in the linear panel models discussed earlier), the *expected* marginal effect of a change in weather in a particular location depends on the distribution of the weather (i.e., on the climate) in that place. Thus the nonlinearity in weather implicitly allows the marginal effect of weather to vary with climate across locations.

Because a nonlinear panel allows the marginal effect of weather to vary cross-sectionally with climate, in these models it is the time-series variation in weather in places with hot and cold climates that is used to estimate the gradient of the hot and cold parts of the weather response function, respectively. If long-run adaptation alters the marginal response to weather variation, then these adaptations will be captured in the panel estimates. In other words, unlike a linear panel specification, nonlinear panel estimates do not reflect only the short-run response to climate change (although these estimates are still not able to fully capture the effect of a change in climate on output).

By allowing for varying marginal effects of warming, estimates of the effect of weather that are derived from nonlinear specifications are a mix of long- and short-run responses. To illustrate how such nonlinear panel specifications work, consider a hypothetical simple panel dataset that includes observations of weather and economic value from two locations, one that is hot and one that is cold.[18] The data in this panel will result from two sources of variation: cross-sectional variation in mean weather (i.e., climate) between the two locations and time-series variation from the natural fluctuation of weather within each location. Each location will choose a production technology adapted to its climate. The hot location chooses a technology that does well in hot temperatures but poorly in cold temperatures and the cold location chooses the opposite. Observations of hot temperatures in our hypothetical panel dataset come mostly from the hot location, thus most of the variation in the data used to estimate the hot part of the weather response function will come from the technology already adapted to hot climates. Because the converse is true for cold climates, the full nonlinear response function captures some long-run adaptations because the hot part of the curve is estimated from locations with hot-adapted technology and the cold part is estimated from locations with cold-adapted technology. The precise mix of long- and short-run response captured in a nonlinear panel estimate will depend on the relative importance of cross-sectional and time-series variation in the dataset, which will depend on the particular setting and dataset.

Deryugina and Hsiang (2017) provide a theoretical argument for this intuition, as well as an empirical estimate of the effect of climate on income in the United States. They suggest that the marginal effect of weather on output is the same as the marginal effect of *climate* on output. This argument—that the effects of climate can be identified exactly using the effects of weather fluctuations—relies on the envelope theorem, and therefore applies only to outcomes that are optimized (such as profits or welfare) and locations where available adaptations are continuous.[19] Although this is a relatively recent result, which has not yet been

[18]For details, see Appendix figure 2.

[19]More specifically, the envelope theorem states that if y is a maximized quantity (e.g., profits or welfare) with a value that depends on both the weather statistic (w) and a set of agents' production decisions (b), then agents will choose b conditional on their beliefs about the distribution of the weather state (i.e., the climate c), thus producing the value function $V(c)$, which equates to the optimized outcomes (i.e., value) as a function of climate. Differentiating the value function with respect to c results in an expression for the

widely embraced or confirmed in the literature, it is a potentially important breakthrough in the indirect measurement of the economic impact of climate.

Multistage models

Another emerging approach that is closely related to the nonlinear panel approach models the effect of weather and climate in two steps. First, the linear effect of weather variation is estimated for each unit in the panel dataset, which allows the linear response to weather fluctuations to vary across space. Second, the coefficient on weather (from the first step) is modeled as a function of climate and other control variables.[20] In the first example of this approach, Butler and Huybers (2012) separately estimate the effects of extreme heat on maize yields for each county in the United States. Then they model this marginal effect as a function of expected heat exposure and find evidence of adaptation to climate change in the form of lower heat sensitivity in warmer places. Schlenker, Roberts, and Lobell (2013) extend the analysis, showing the importance of accounting for both lower average yields and improved heat tolerance when estimating the long-run effects of climate change.

Heutel, Miller, and Molitor (2017) follow a similar approach in estimating the mortality effect of temperature fluctuations in the United States, allowing the impact of different temperatures to vary depending on climate. They find heterogeneity in the marginal effect of both hot and cold days, with evidence of adaptation at both ends of the temperature distribution (i.e., hot days are more damaging in cold places and cold days are more damaging in hot places); this has significant implications for the estimated impact of climate change. Carleton et al. (2018) use this two-step approach to estimate the global mortality effects of climate change, first identifying the local effect of weather variation and then modeling these coefficients as a function of average climate (and income).

Finally, using individual billing data, Auffhammer (2018) estimates the short-run relationship between daily weather and energy consumption for each zip code in California. In a second step, he models how the zip code–specific response of energy consumption to weather varies with climate. Long-run adaptations to hotter climates, such as air conditioner adoption, would be expected to change the relationship between temperature and energy use. He finds that this is indeed the case and that estimates of the effect of climate change on energy demand in California differ significantly for the short-run response using the zip code–specific linear response versus the long-run response that allows the response to change as a function of climate.

Advantages of heterogeneous marginal effect models

A major advantage of allowing for heterogeneous marginal effects of warming, either through a nonlinear panel or though the two-stage process described above, is that they can be used to estimate the long-run effect of climate change while still using fixed effects to control for time-invariant unobservable variables that might otherwise bias the estimated effect of climate change in a standard cross-sectional regression. In the two-stage approach, the short-run

marginal value of a small change in the climate. The envelope theorem tells us that the derivative of b with respect to c is zero, which simplifies the result. In their theoretical argument, Deryugina and Hsiang (2017) assume that w is deterministic, which simplifies their analysis and allows them to conclude that the value of a small change in climate is the same as the value of a small change in weather. It is not clear if this result still holds in the more realistic case of w being stochastic.

[20] See Appendix table 1, row 4.

response and the long-run response are both modeled explicitly, while in the nonlinear panel, the long-run response can (under certain assumptions) be recovered from the estimated nonlinear function (Schlenker, Roberts, and Lobell 2013).

Challenges of heterogeneous marginal effect models

Although the unit fixed effect in nonlinear panel and multistage models removes all time-invariant unobservable variables, thus improving confidence in the identification of these models relative to the cross-sectional approach, there could still be problems with omitted variables in these models. This is because the variation in the marginal effect of weather fluctuations is estimated using cross-sectional variation; that is, it is estimated by comparing the effect of weather variation in hot climates to the effect of weather variation in cold climates. This means that any time-invariant differences that affect the *marginal response to weather* can introduce omitted variable bias in this setting if these time-invariant variables are not included in the regression.

To illustrate this issue, consider the effect of temperature on gross domestic product (GDP). It is well known that, on average, hotter countries have lower per-capita income (i.e., income is negatively correlated with climate). There are also reasons why poorer countries might be more sensitive to weather variations, because, for example, agriculture accounts for a larger share of the economy in poor countries and protective technologies such as air conditioning are generally less available (i.e., income is correlated with the marginal effect of weather). This means that not accounting for income differences but allowing for heterogeneous marginal effects of warming will likely lead to a biased estimate of the true GDP response because some of the negative effects of warmer temperatures in hot places could be due to lower incomes rather than hotter climates. To explicitly control for this, per-capita income could be included as an independent variable in the second part of the two-stage approach or different response curves could be estimated for rich and poor places, as is done in Burke, Hsiang, and Miguel (2015).

Long Differences Approach

A second emerging hybrid approach for measuring the effects of climate change relies on the fact that weather varies randomly over a range of timescales (e.g., annual, decadal, multi-decadal). This means that trends in weather over the medium term have a random component that is plausibly exogenous to other variables and can be used to estimate the effect of variations over a longer time frame than interannual variations.[21] This is helpful because even a stationary climate may appear to be changing if economic agents are informed by only a short sample of weather data.

The long differences approach regresses a long difference (e.g., between 1960 and 1990) in economic value on a long difference in weather.[22] In this context, long differences usually means at least several decades. Because the estimating equation typically includes an intercept

[21] These quasi-random decadal variations in weather trends result from chaotic fluctuations in the climate system, which tend to have larger amplitudes at smaller spatial scales. For instance, variance in the 10-year temperature trends in a county will be larger than the variance in the 10-year average temperature trends over the whole United States (Deser et al. 2012; Thompson et al. 2015).

[22] See Appendix table 1, row 5.

term (and sometimes includes regional fixed effects) that removes the *average* trends in weather and outcome across the sample, the model's statistical power comes from the medium- to long-term variations in the climate system (i.e., the effect of idiosyncratic variation in weather trends around the average).

Thus the long differences approach is essentially a cross-sectional regression that uses long-term trends to remove the effect of time-invariant omitted variables that are a major drawback of the standard cross-sectional regression. However, any variables that are correlated with trends in weather and also affect trends in the outcome variable will bias identification if they are not controlled for. This is why it is important that medium-run trends in weather are random—that is, spatially random trends are very unlikely to be correlated with other variables that might also affect the dependent variable.

To illustrate how the apparent randomness of long differences in weather might vary depending on seemingly arbitrary choices such as the length of the difference, figure 1 shows the variation in the change in 30-year averages of annual temperatures across the continental United States over two different timescales. The upper panel presents changes over a longer timescale (1850–2017) and the lower panel presents changes over a shorter time period (approximately 50 years). Changes over the longer time period are both larger and less spatially random than changes over the shorter time period and could be correlated with a number of other socioeconomic or biophysical climate variables that vary latitudinally across the United States. More generally, the spatial pattern of variation in long differences will depend on the weather statistic (e.g., temperature will be different from rainfall) and the timescale under consideration.

Variability due to climate change versus variability due to sampling

One issue concerning long differences is whether the variation used for the estimation reflects an actual change in the climate distribution or simply sampling variability that would be expected in such a stochastic process. This issue has not been explicitly addressed in the literature, but it has important implications for the interpretation of long differences estimates. In particular, would one expect to observe adaptation in response to fluctuations that may be consistent with a stationary climate distribution? In practice, this concern has been addressed to some extent in the literature by either demonstrating the robustness of results to multiple start and end periods (e.g., 10-year averages versus 30-year averages) or using fitted linear trends that capture long-term nonstationarity (Moore and Lobell 2015; Burke and Emerick 2016). It is important to note that, at the time and spatial scales that have been examined using long differences regressions thus far, most of the variation would *not* be expected to result from anthropogenic climate change. Rather, the variation arises largely from low-frequency natural variability in the climate system (Deser et al. 2012; Hawkins and Sutton 2012).

If there are adaptations that are available over decadal timescales but not over interannual timescales, then the marginal effect of a gradual change in weather will be less than the effect of a sudden change in weather. Because long differences use a longer timescale of variation than the interannual variation in standard panel models, the long differences approach should capture the effect of adaptations that occur over the medium term. Moreover, because the long differences approach is estimating something in between the short- and long-run

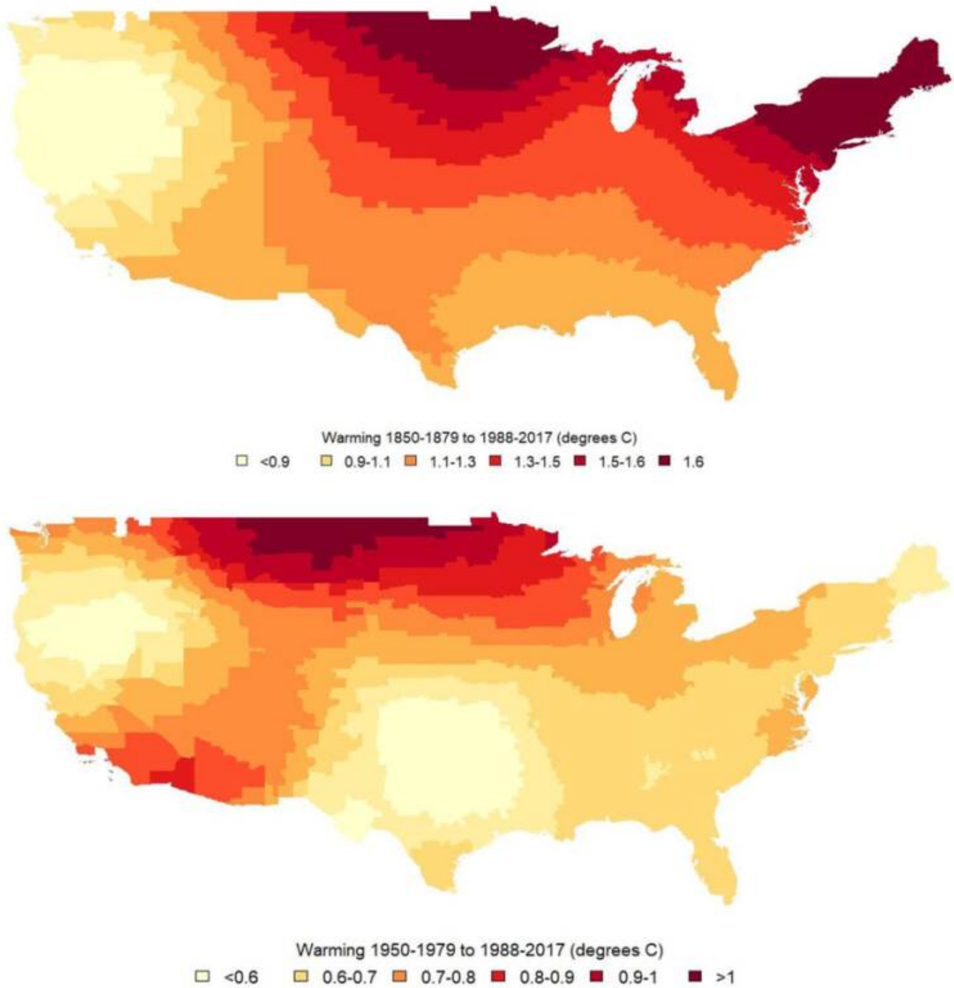


Figure 1 Long differences in 30-year averages of annual temperatures over the continental United States.
Notes: Values are spatial averages over U.S. counties of temperature data on a 1° grid interpolated from station data by Berkeley Earth.
Source: Berkeley Earth. Retrieved March 5, 2018, from http://berkeleyearth.org/data/.

climate change effects, depending on the rate of adaptation in the particular system, the estimate may be closer to one or the other.

Applications

Dell, Jones, and Olken (2012) use long differences to estimate the effect on GDP growth rates of a 1°C warming that occurs over 15 years. They find an effect that is similar to the effect of interannual variations, and argue that this provides evidence that adaptation is not particularly effective over this timeframe. Burke and Emerick (2016) use long differences to examine the effect of changes in temperature over a 20-year period on rain-fed maize yields in the United States and also find effects similar to those estimated in a panel using interannual variation. Lobell and Asner (2003) and Moore and Lobell (2015) estimate the effect of decadal trends in temperature on yields in Europe and the United States using specifications similar to long differences, and find evidence that longer-term changes in climate have affected crop yields.

With a long enough dataset, it is possible to develop a panel of long differences by observing multiple periods of medium-term change in the same location, thus improving the precision of the estimate of effects of changes at these timescales and allowing for better control of unobserved variables. For example, Taraz (2017) develops a panel of decadal changes in the Indian monsoon to test for changes in irrigation adoption and crop choice. Based on a panel of crop yield and temperature variation at various frequencies from 5 years to 33 years, Hsiang (2016) finds that the estimated response of yield to temperature change is similar on all timescales, again suggesting the limited effectiveness of adaptation.

Partitioning Variation

A final emerging approach relies on the fact that panel data contains variation in both weather and climate to jointly estimate the effects of both long- and short-run variation. We refer to this approach as "partitioning variation," because it decomposes the variation in the outcome variable into the part associated with climate and the part associated with interannual fluctuations around the climatological average, with the former indicating the long-run effect and the latter indicating the short-run impact. The estimating equation typically has economic value as the dependent variable, which is modeled as a nonlinear function of the deviation of weather from its long-run mean, a nonlinear function of climate, control variables, and an error term.[23] For example, Kelly, Kolstad, and Mitchell (2005) and Moore and Lobell (2014) use an estimating equation of this form to jointly estimate the short- and long-run effects of warming on agriculture.

Although this approach uses panel data, the long-run function of climate is estimated using cross-sectional variation. This means it is susceptible to the omitted variable problems of the standard cross section, and thus typically requires the inclusion of a large set of control variables. Some authors have proposed an alternative partitioning variation approach that relies on the fact that a location's climate varies over time to estimate both the long- and short-run effects in a panel that includes location and period fixed effects. This has the important advantage of allowing for the control of time-invariant omitted variables through the location fixed effect. However, it also changes the interpretation of the climate term—rather than indicating the long-run equilibrium effect, it captures the medium-run effect. Depending on the timescale of adaptations, this effect may be closer to the long- or short-run response. Merel and Gammans (2017) applied this approach to U.S. crop yields.

One challenge when using panel data to partition variation into long-run variation that agents expect and shorter-run, surprising variations that deviate from those expectations is knowing how to measure the long-term climate. This is particularly a problem when the climate is nonstationary and because we typically do not observe agents' expectations of weather. If the estimated climate is different from what agents are expecting or prepared for, then this will introduce measurement error into the deviation term and bias the estimation of the short-run response. In practice, this does not appear to be a significant issue. For

[23] See Appendix table 1, row 6.

example, Moore and Lobell (2014) use both a 30-year baseline climate and a 30-year rolling average to define climate and find that this approach does not affect estimates of the short-run response.

Using weather forecasts

Another approach that is based on the same theory as studies that use partitioning variation is to use both forecasted and unforecasted weather events to estimate the difference in response to weather that is surprising and weather that is expected. This approach relies on the fact that reliable forecasts change the information available to actors, thus removing the gap between the short- and long-run response that is driven by imperfect information about the weather (Allen, Graff-Zivin, and Schrader 2016; Schrader 2017). In this sense, forecasted weather is analogous (in terms of the information available to actors) to a change in climate. Only a few studies have examined weather forecasts in the context of climate change adaptation. Although not directly linked to climate change, Rosenzweig and Udry (2014) find that Indian farmers adjust fertilizer application in response to skillful forecasts of monsoon intensity, which suggests that accurate forecasts have significant value in this setting.

Rates of Adjustment and Adaptation

The previous sections have described the rich and varied literature that seeks to identify the short-, medium-, and long-run effects of climate change. However, as discussed earlier, in order to identify the total costs associated with climate change, we also need to determine the rate and cost of adaptation to a change in climate. For a given magnitude of adaptation (i.e., the difference between short- and long-run response curves), the adjustment costs will be higher if the transition time is longer. Kelly, Kolstad, and Mitchell (2005) divide the rate of adaptation into two components: the part associated with learning about a changed climate based on weather observations and the part associated with replacing long-lived capital and other quasi-fixed factors after the learning has occurred.

This suggests that the rate of adaptation is constrained if agents must infer a change in the underlying climate distribution using their own observations of weather, which provide only a noisy signal of the climate state. Several studies have examined this issue. Kelly, Kolstad, and Mitchell (2005) develop a model of learning about climate sensitivity to estimate learning-related adjustment costs in U.S. agriculture. Moore (2017) shows that adjustment costs do not appear to be particularly sensitive to learning as long as agents are able to learn from weather and update their expectations about the climate distribution. However, neither of these studies tests their learning models against data. In contrast, Kala (2017) uses data on how planting dates respond to changes in the onset of the Indian monsoon to empirically compare several learning models and finds evidence of aversion to ambiguity in decision making among farmers.

Even after accounting for learning-related adjustment costs, adaptation could be further slowed by the turnover time of long-lived capital.[24] Because climate change is relatively

[24]It may also be slowed by other factors of production that do not reequilibrate instantaneously and costlessly.

gradual, it may be that capital will adjust gradually. However, very few studies have examined this issue empirically. Hornbeck (2012) shows that equilibrium adjustment to the productivity shock from the Dust Bowl in the United States in the 1930s took decades, suggesting that at least in some cases, the rate of adjustment and adaptation could be similar to the rate of climate change. Long differences studies that show similar impacts of medium- and short-run changes in weather may suggest either that the potential for adaptation is small or that adaptation occurs only over longer timescales (Burke and Emerick 2016).

Summary and Conclusions

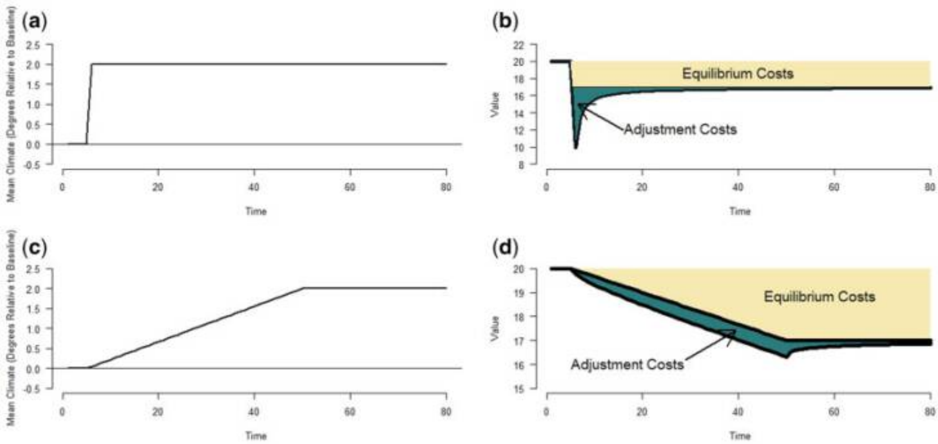
Improving the empirical basis for estimating the economic consequences of climate change is important as both an area of academic inquiry and an input into climate adaptation and mitigation policy decisions (Diaz and Moore 2017). A long-standing (and by now widely recognized) debate has developed in the literature between using cross-sectional versus panel analysis to estimate climate change impacts. On the one hand, cross-sectional analysis is able to capture the long-run equilibrium impacts of different climates, at least on agriculture. However, the problem of omitted variables makes it difficult to interpret the results. On the other hand, although panel regressions address many of the concerns about omitted variables through the use of location and time fixed effects, they risk identifying only the short-run response to weather variation, which will tend to overestimate the impacts of climate change if there is substantial adaptation.

This article has sought to inform this debate through a careful review of the literature. First, much of the debate around cross-sectional versus panel regressions has focused on identifying the equilibrium costs of climate change. We have emphasized, however, that total damages consist of both equilibrium and adjustment costs and neither cross-sectional nor standard panel models can alone identify both types of costs. Thus the relative importance of these two components will depend on the speed and predictability of climate change and the dynamics of capital adjustment in a particular sector.

Second, panel data contains rich information on the effects of short-, medium-, *and* long-term variation in weather. Our review of new "hybrid" approaches suggests that these methods are relying on this fact to estimate the response functions on multiple timescales. These approaches greatly reduce the omitted variable concerns of using a cross section while still estimating a response that includes more adaptation than would occur in response to only interannual variation in weather.

Our review of the literature has also identified a number of urgent priorities for research, including better integration of new empirical approaches with theoretical models that describe the dynamic response of agents to a changing climate and further research on the rate of adaptation in various locations and sectors. Finally, while much empirical work has focused on the United States, particularly the agriculture sector, research is needed that goes beyond these settings in order to improve researchers' and policymakers' understanding of the effects of climate change. Given the number of new and innovative papers being produced on the economic impacts of climate change, we are confident that this will continue to be an active, exciting, important, and fertile field for research.

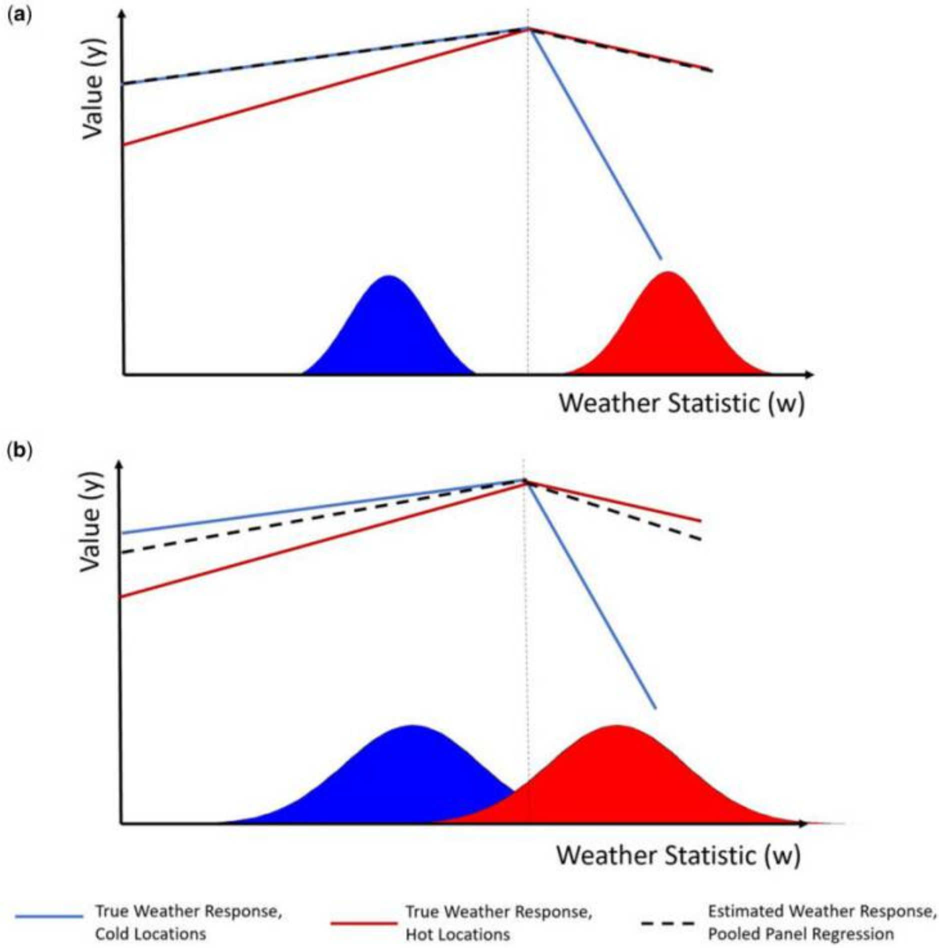
Appendix



Appendix Figure 1 Components of welfare losses under sudden and gradual climate change. (a) Mean temperature for a sudden change in climate. (b) Equilibrium and adjustment costs given a sudden change in climate. (c) Mean temperature for a gradual change in climate. (d) Equilibrium and adjustment costs given a gradual change in climate.

Notes: Temperature is in degrees Celsius and time is in years. Numeric values are illustrative only.

Source: Adapted from Kelly, Kolstad, and Mitchell (2005).



Appendix Figure 2 Examples of panel estimates with heterogeneous marginal effects of weather.
(a) Large cross-sectional variation in climate relative to time-series variation in weather. (b) Smaller cross-sectional variation in climate relative to time-series variation in weather.
Notes: There are two locations (red and blue), with unidimensional weather (e.g., temperature). Climate (weather distributions) is shown in the shaded areas, and two production technologies are shown by the solid lines. In panel a, the weather at the two locations is quite different, with no overlap between the two distributions. In panel b, the two locations are more similar. The warmer location (red) uses the production technology that is less sensitive to extreme heat while the cooler location (blue) uses the technology that performs better at cooler temperatures. The panel estimate (dashed line) will be a weighted combination of the two marginal effects, with the weighting depending on the relative importance of time-series versus cross-sectional variation. Note that the nonlinear panel estimate is only for the marginal value weather function (i.e., the slope of the dashed line in the figure).
Source: The authors.

Appendix Table 1 Overview of empirical approaches for estimating the impacts of weather and climate on economic activity

Approach	Stylized estimating equation	Typical representation of weather	Typical representation of climate	Remarks	Selected papers
Cross section	$y_i = f(c_i) + Controls_i + \varepsilon_i$	None	Direct and nonlinear	Applies at a single time point	Mendelsohn, Nordhaus, and Shaw (1994)
Linear panel	$y_{it} = \beta w_{it} + \mu_i + \theta_t + \varepsilon_{it}$	Linear	Removed through fixed effects		Deschênes and Greenstone (2007) Dell, Jones, and Olken (2012)
Heterogeneous marginal effects: nonlinear panel	$y_{it} = f(w_{it}) + \mu_i + \theta_t + \varepsilon_{it}$	Nonlinear	Removed through fixed effects. Marginal effect of weather varies with climate		Deryugina and Hsiang (2017) Burke, Hsiang, and Miguel (2015)
Heterogeneous marginal effects: two-stage panel	Stage 1: $y_{it} = \beta_i w_{it} + \mu_i + \theta_t + \varepsilon_{it}$ Stage 2: $\beta_i = f(c_i) + Controls_i + \varepsilon_i$	Linear in stage 1, a bsent in stage 2	Fixed effects in stage 1, direct nonlinear in stage 2	Coefficient on weather in first stage becomes left-hand side in stage 2	Butler and Huybers (2012), Heutel, Miller, and Molitor (2017) Auffhammer (2018)
Long differences	$y_{i,t} - y_{i,t-\Delta t} = f\left(w_{i,t} - w_{i,t-\Delta t}\right) + \varepsilon_i$	Linear	Medium-run climatic variation captured through long differences		Burke and Emerick (2016), Moore and Lobell (2015)
Partitioning variation	$y_{it} = f(w_{it} - c_i) + g(c_i) + Controls_i + \varepsilon_{it}$	Nonlinear	Nonlinear		Kelly Kolstad, and Mitchell (2005), Moore and Lobell (2014)

Notes: y represents the value of economic activity, w represents a weather statistic, c represents the climate (i.e., the distribution of the weather statistic), i is an index on spatial location, t is an index on time, μ is a fixed effect varying with time, θ is a fixed effect varying over space, ε is an error term, and "controls" refers to other relevant exogenous variables. β is a coefficient to be estimated and f() is a nonlinear function, also to be estimated.

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