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What Do We Learn from the Weather? The New Climate–Economy Literature†

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A rapidly growing body of research applies panel methods to examine how temperature, precipitation, and windstorms influence economic outcomes. These studies focus on changes in weather realizations over time within a given spatial area and demonstrate impacts on agricultural output, industrial output, labor productivity, energy demand, health, conflict, and economic growth, among other outcomes. By harnessing exogenous variation over time within a given spatial unit, these studies help credibly identify (i) the breadth of channels linking weather and the economy, (ii) heterogeneous treatment effects across different types of locations, and (iii) nonlinear effects of weather variables. This paper reviews the new literature with two purposes. First, we summarize recent work, providing a guide to its methodologies, datasets, and findings. Second, we consider applications of the new literature, including insights for the "damage function" within models that seek to assess the potential economic effects of future climate change. (*JEL* C51, D72, O13, Q51, Q54)

1. *Introduction*

The idea that climate may substantially influence economic performance is an old one, featuring prominently in the writings of the Ancient Greeks, in Ibn Khaldun's fourteenth-century *Muqaddimah* (Gates 1967), and during the Enlightenment, when Montesquieu argued in *The Spirit of Laws* (1748) that an "excess of heat" made men "slothful and dispirited." To the extent that climatic factors affect economically relevant outcomes, whether agricultural output, economic growth, health, or conflict, a careful understanding of such effects may be essential to the effective design of contemporary economic policies and institutions. Moreover, with global temperatures expected to rise substantially over the next century, understanding these relationships is increasingly important for assessing the "damage function" that is central to estimating the potential economic implications of future climate change.

A basic challenge in deciphering the relationship between climatic variables and economic activity is that the spatial variation in climate is largely fixed. Canada is colder

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on average than Cameroon, and it always has been. As such, while there can be large cross-sectional correlations between a country's climate and its economic outcomes, it is difficult to distinguish the effects of the current climate from the many other characteristics potentially correlated with it. The difficulty in identifying causative effects from cross-sectional evidence has posed substantial and long-standing challenges for understanding the historical, contemporary, and future economic consequences of climate and climate change.

In the last few years, there has been a wave of new empirical research that takes a different approach. These new studies use panel methodologies, exploiting high-frequency (e.g., year-to-year) changes in temperature, precipitation, and other climatic variables to identify these variables' economic effects. As nomenclature, this new literature uses "weather variation" to describe shorter-run temporal variation. The word climate is reserved for the distribution of outcomes, which may be summarized by averages over several decades, while weather describes a particular realization from that distribution and can provide substantial variability.

The primary advantage of the new literature is identification. By exploiting exogenous variation in weather outcomes over time within a given spatial area, these methods can causatively identify effects of temperature, precipitation, and windstorm variation on numerous outcomes, including agricultural output, energy demand, labor productivity, mortality, industrial output, exports, conflict, migration, and economic growth. This literature has thus provided a host of new results about the ways in which the realizations of temperature, precipitation, storms, and other aspects of the weather affect the economy.

In light of these developments, this paper has two related goals. The first goal is to take stock of this new literature, providing a guide to its methodologies, datasets, and findings. The second goal is to clarify the interpretation of this literature. The new approach speaks directly to contemporary effects of weather on economic activity, and in this sense, provides an unusually well-identified understanding of channels affecting contemporary economic issues, including economic development, public health, energy demand, and conflict.

At the same time, this literature has important implications for the "damage function" in climate change models, which consider how future changes in climate—i.e., future changes in the stochastic distribution of weather—will affect economic activity. The opportunity here is to bring causative identification to the damage functions, elucidating the set of important climate–economy channels and their functional forms. The challenge lies in bridging from the evidentiary basis of short-run weather effects to thinking about longer-run effects of changes in the distribution of weather, which may be either larger (e.g., due to intensification effects) or smaller (e.g., due to adaptation) than the short-run impacts. While certain climate change aspects are difficult to assess, we examine a number of empirical methodologies that can help bridge toward longer-run effects while maintaining careful identification. Examples include comparing how the impact of a given weather shock differs depending on the locations' usual climate, examining whether the impact of weather shocks depends on a region's previous experience with similar shocks, and examining the impact of changes over longer time scales. We further reexamine the climate damage functions used in current climate–economy models in light of the evidence reviewed here.

This paper proceeds as follows. In section 2, we review the panel methods used in this literature and discuss the methodological choices involved in implementing them.

We further review standard climate datasets, providing guidance on how to effectively use these resources. Section 3 reviews the findings of the new literature, organized by the outcome variable of interest. This section covers the effects of temperature, precipitation, and windstorms on economic growth, agriculture, labor productivity, industrial output, health, energy, political stability, conflict, aggression, and other outcomes. Section 4 considers applications of the new literature to understanding the potential economic effects of climate change. This section first considers methodological opportunities for panel methods to inform our understanding of longer-run climate change processes. It then examines the economic damage function within Integrated Assessment Models (IAMs), which are used to estimate the social cost of carbon and guide climate change policy, and discusses how these damage functions can be informed by the new findings. Section 5 offers concluding observations and suggests promising directions forward for this literature. This paper also has two online appendices. Online Appendix I summarizes the panel data methodologies used in the papers reviewed. Online Appendix II indicates the primary data sources used in the papers reviewed.

2. *Methods and Data*

2.1 *What is the New Approach?*

To understand the impact of climate on the economy, we would ideally like to determine the following unknown functional relationship:

$$\mathbf{y} = f(\mathbf{C}, \mathbf{X}) \tag{1}$$

which links vectors of climatic variables ($\mathbf{C}$) and other variables ($\mathbf{X}$) to outcomes, $\mathbf{y}$. $\mathbf{C}$ may include temperature, precipitation, and extreme weather events like windstorms, among other climatic phenomena. Outcomes of interest include national income, agricultural output, industrial output, labor productivity, political stability, energy use, health, and migration, among others. $\mathbf{X}$ includes any characteristics that are correlated with $\mathbf{C}$ and also affect the outcomes of interest, possibly by conditioning the climate response. This section discusses several different approaches that have been used to estimate the relationship given by equation (1).

2.1.1 *Estimation using the Cross Section*

A classic approach to estimating (1) emphasizes spatial variation at a point in time. A linearized version of the above model is

$$y_i = \alpha + \beta \mathbf{C}_i + \gamma \mathbf{X}_i + \varepsilon_i, \tag{2}$$

where i indexes different geographic areas, e.g., countries or subnational entities like counties, as dictated by the question of interest and sources of data. The outcome variable and explanatory variables are typically measured either in levels or logs. The error process is typically modeled using robust standard errors, possibly allowing for spatial correlation in the covariance matrix by clustering at a larger spatial resolution or allowing correlation to decay smoothly with distance (Conley 1999).

The vector $\mathbf{X}$ typically includes several controls. For example, one may want to include other variables that are correlated with $\mathbf{C}$ and impact $\mathbf{y}$. The vector $\mathbf{X}$ could also include other exogenous geographic controls, such as elevation and ruggedness, to the extent those are correlated with the variables of interest in $\mathbf{C}$.[1]

[1] Related, it can be important to include a rich set of climatic variables in $\mathbf{C}$. Auffhammer et al. (forthcoming), for example, show that temperature and precipitation tend to be correlated, with a sign that varies by region. Thus, failing to include both could lead to omitted variables bias when interpreting a particular climatic variable estimated in isolation.

To the extent that climatic variables, like other geographic variables, are exogenously determined, reverse causation is unlikely to be a major concern.[2] The more pressing econometric challenge for estimating β from the cross-sectional equation in (2) is the potential omitted variable bias; i.e., the correlation between the climate variables of interest and other features that may influence the outcome. To the extent that these other variables are not adequately captured in the control variables $\mathbf{X}_i$, or the functional form through which they are controlled for is not exactly correct, the estimates of β will be biased.

Importantly, however, adding more controls will not necessarily produce an estimate $\hat{\beta}$ that is closer to the true β. If the **X**s are themselves an outcome of **C**, which may well be the case for controls such as GDP, institutional measures, and population, including them will induce an "over-controlling problem." In the language of the model, if **X** is in fact **X**(**C**), then equation (1) would instead be written as $y = f(\mathbf{C}, \mathbf{X}(\mathbf{C}))$ and estimating an equation that included both **X** and **C** would not capture the true net effect of **C** on y. For example, consider the fact that poorer countries tend to be both hot and have low-quality institutions. If hot climates were to cause low-quality institutions, which in turn cause low income, then controlling for institutions in (2) can have the effect of partially eliminating the explanatory power of climate, even if climate is the underlying fundamental cause.[3]

Beyond these identification challenges lies a more substantive question of what underlying structural equation the econometric equation in (2) estimates. To continue the previous example, suppose that temperature and income are correlated in the cross section today largely because climate affected the path of agricultural development, technological exchange, and/or subsequent colonialism (Diamond 1997; Rodrik, Subramanian, and Trebbi 2004). If the structural equation of interest is to estimate the very long-run historical effect of, for example, temperature on economic outcomes, one might prefer to estimate (2) without controlling for potentially intervening mechanisms, such as institutions. However, climate studies often seek to estimate the contemporaneous effect of temperature on economic activity for the purpose of assessing the potential impacts of forecasted temperature changes over the next several decades. The cross-sectional relationship, which represents a very long-run equilibrium, may incorporate processes that are too slow to accurately inform the time scale of interest, or it may include historical processes (such as colonialism) that will not repeat themselves in modern times.

2.1.2 *Estimation using Weather Shocks*

To the extent that one is interested in isolating the impact of climatic variables such as temperature—apart from the many other factors that they are correlated with and have influenced over the very long run—a

[2] Nevertheless, reverse causation may need to be considered in some settings. In the cross section, urban areas are known to be hotter than rural areas due to the heat-sink effects from asphalt, black roofs, etc. (Houghton et al. 2001), though this can be corrected for using measurements of temperatures in rural areas (Nakicenovic et al. 2000). In the panel, economic shocks in very poor countries can lead to changes in the quality of temperature measurement and potentially change the urban/mix of measurements, so even if actual $\mathbf{C}_i$ is unaffected, observed $\mathbf{C}_i$ may be. We discuss these issues in more detail in section 2.2.

[3] The fact that geographic characteristics, e.g., tropical climate, and institutional quality are highly correlated in the cross section has led to a vigorous, but ultimately hard-to-resolve debate over their relative importance for long-run economic development, where the inclusion of institutional variables in cross-sectional specifications like (2) diminishes otherwise strong relationships between geographic variables and income. See, for example, Acemoglu, Johnson, and Robinson (2001); Sachs (2003); and Rodrik, Subramanian, and Trebbi (2004).

different approach is to use longitudinal data to investigate the effects of weather *shocks*. This approach, which is the focus of this review, has emerged in recent years and emphasizes variation over time within a given spatial entity.

Using standard panel methods, the regression models in this literature typically take variations of the form

$$(3) \quad y_{it} = \beta \mathbf{C}_{it} + \gamma \mathbf{Z}_{it} + \mu_i + \theta_{rt} + \varepsilon_{it},$$

where t indexes time (e.g., years, days, months, seasons, decades). The literature uses a nomenclature of "weather variation" for shorter-run temporal variation, as opposed to "climate variation," where the word climate is used to describe the distribution of outcomes (e.g., the range of temperature experienced in Mexico), while weather refers to a particular realization from that distribution.

Noting that temperature, precipitation, windstorms, and other weather events vary plausibly randomly over time, as random draws from the distribution in a given spatial area (i.e., "weather" draws from the "climate" distribution), the weather-shock approach has strong identification properties. The fixed effects for the spatial areas, μ_i, absorb fixed spatial characteristics, whether observed or unobserved, disentangling the shock from many possible sources of omitted variable bias. Time-fixed effects, θ_{rt}, further neutralize any common trends and thus help ensure that the relationships of interest are identified from idiosyncratic local shocks. In practice, the time-fixed effects may enter separately by subgroups of the spatial areas (hence the subscript r) to allow for differential trends in subsamples of the data. An alternative (and potentially complimentary) approach to capturing spatially specific trends is to include a spatially specific time trend.

The approach in (3) is explicitly reduced form, focusing on the effect of weather variation on the outcome variable per se. Other studies use weather variation as an instrument to study nonclimatic relationships, such as the link between poverty and civil conflict (e.g., Miguel, Satyanath, and Sergenti 2004, which uses rainfall as an instrument for GDP growth; see section 3.7 below). While such instrumental variable studies rely on various exclusion restrictions to make causative inference about such relationships, the simple reduced-form analysis in (3) does not. It simply identifies the net effect of the weather shock on an outcome of interest (e.g., the effect of rainfall on conflict). Thus, the reduced-form panel approach makes relatively few identification assumptions and allows unusually strong causative interpretation.

There are a number of methodological decisions that arise in implementing panel models. One methodological choice concerns the inclusion of other time-varying observables, $\mathbf{Z}_{it}$. Including the $\mathbf{Z}_{it}$ may absorb residual variation, hence producing more precise estimates. However, to the extent that the $\mathbf{Z}_{it}$ are endogenous to the weather variation, the "over-controlling" problem that complicates cross-sectional estimation appears in the panel context as well. For example, if national income is the outcome of interest, then controlling for investment rates would be problematic if the climatic variables influence investment, directly or indirectly.

As will be reviewed in section 3 below, effects of weather shocks appear across a very wide range of economic and political outcomes, which suggests substantial caution when including explanatory variables or when asserting one particular mechanism as the unique causal path through which weather affects another one of these outcomes. Best practices suggest including only credibly exogenous regressors as control variables $\mathbf{Z}_{it}$, such as terms of trade shocks

for a small economy and other weather variables that are not the main focus of the analysis. Potentially endogenous regressors should typically only be included if there is a strong argument that these variables are not affected by climate or can otherwise be modeled appropriately in a credible structural context.

A related issue is the inclusion of lags of the dependent variable, y_{it}. Including these lags biases coefficient estimates in short panel models,[4] yet excluding the lagged dependent variable may also bias the estimates if it is an important part of the data-generating process. While what comprises a "short" panel will depend on the data-generating process, Monte Carlo experiments suggest that the bias can be nonnegligible with panel lengths of $T = 10$ or even $T = 15$.[5] The median panel length of studies cited in this review is 38, whereas the twenty-fifth percentile is $T = 18$ and the seventy-fifth percentile is $T = 57$. So in many cases, the panel is long enough that these biases can probably be safely considered second-order. When the panels are short, however, estimating models with lagged dependent variables is an active area of research, and it can be helpful to show robustness to different estimation methods. For example, further lags of levels or differences of the dependent variable can be used as instruments for $Y_{i,t-1}$ (Arellano and Bond 1991), external variables can also be used as instruments when available, and $y_{i,\,t-1}$ can be instrumented with long differences of y (Hahn, Hausman, and Kuersteiner 2007), though these methods only work if the data-generating process is correctly specified.[6]

A further implementation question involves the appropriate functional form for the weather variables. One common approach measures $\mathbf{C}_{it}$ in "levels" (e.g., degrees Celsius for temperature or millimeters for precipitation). In the panel set up, the identification thus comes from deviations in levels from the mean.[7] Another common approach, aimed at revealing nonlinear effects, considers the frequencies at which the weather realizations fall into different bins. For example, temperature may be accounted for via several regressors, each counting the number of days in the year with temperatures within prespecified degree ranges (e.g., 0–5°C, 5–10°C, etc.). Deschênes and Greenstone (2011) is an early example of this approach. The key advantage lies in avoiding functional form specifications, since this method is relatively nonparametric. Note that this approach demands high-resolution data: if one aggregates across either space or time before constructing the bins, extreme days could be averaged away, and if nonlinearities are important, this smoothing of the data may produce misleading estimates.

[4] This bias declines at rate $1/T$, where T is the number of observations within a group (Nickell 1981). To see this more intuitively, suppose that the data-generating process is $y_t = \gamma y_{t-1} + \beta w_t + \epsilon_t$. Consider the within estimator from the following regression:

$$y_t - \overline{y} = \gamma(y_{t-1} - \overline{y}) + \beta(w_t - \overline{w}) + (\epsilon_t - \overline{\epsilon}),$$

where y is the outcome of interest, w is a weather variable, ϵ is the error term, $\overline{y}$ denotes the mean of the outcome, and so forth. By definition, y_{t-1} is correlated with ϵ_{t-1}, and hence with $\overline{\epsilon}$. Therefore, $(y_{t-1} - \overline{y})$ is correlated with the error term, and all the coefficients, including the estimated weather effect β, will be biased. However, as panel length approaches infinity, the contribution of ϵ_{t-1} to $\overline{\epsilon}$ approaches zero and this problem disappears.

[5] Bond (2013), see also Arellano and Bond (1991) and Bond (2002).

[6] Another possible check is to include y_0 interacted with time dummies, in place of the lagged dependent variable(s).

[7] Logs might also be used, with identification thus coming from percentage deviations. The disadvantage of this approach for temperature data is that it requires strictly positive support and that different temperature units have different 0s (i.e., 0°F is equal to −17.8°C). Thus, log temperature may truncate the data and further raises an issue where changing units from Fahrenheit to Celsius can substantively change the coefficient estimates. Using a Kelvin temperature scale (0° Kelvin is −273.2° Celsius) eliminates negative values, although this change is not innocuous, in the sense that it alters the functional form.

A different approach emphasizes "anomalies," where the weather variable is calculated as its level difference from the within-spatial-area mean and divided by the within-spatial-area standard deviation. The first part—the difference in mean—is already captured in a broad sense by the panel model. The second part—scaling by the standard deviation—takes a particular view of the underlying climate–economy model where level changes matter not in an absolute sense but in proportion to an area's usual variation.[8]

Alternatively, outcome-specific approaches may be preferred where existing research provides guidance. For example, knowledge of biological processes in agriculture suggest refined temperature measures such as "degree-days" for crop growth, possibly with crop-specific thresholds (e.g., Schlenker and Roberts 2009). Another example comes from labor productivity studies, where laboratory evidence finds temperature effects only beyond specific thresholds (Seppanen, Fisk, and Faulkner 2003).

As a general rule, imposing specific functional forms on the data, such as crop degree-days, is useful to the extent that one has confidence in the specific model of the process that translates weather to economic outcomes. The more agnostic about the model, the more general the researcher would like to be about the functional form.

Panel studies also often examine heterogeneous effects of climatic variables. Heterogeneity may exist with regard to the climatic variables themselves. For example, positive temperature shocks may have worse effects conditional on high average temperature. Heterogeneity may also exist with regard to nonclimate variables. For example, poor institutions or poor market integration could increase the sensitivity to climate shocks, and certain groups—such as the elderly, small children, and pregnant women—may also be more sensitive to weather shocks. In practice, panel models can incorporate such heterogeneity by interacting the vector of climate variables, $\mathbf{C}_{it}$, with a variable that captures the heterogeneity of interest or by running regressions separately for subsamples of the data.

There are two notable interpretative issues with the panel models that, while not calling into question the experimental validity of the regression design, do raise questions about their external validity for processes such as global warming. One interpretive challenge is whether and how the effects of medium- or long-run changes in climatic variables will differ from the effects of short-run fluctuations. A second issue is that panel models, in focusing on idiosyncratic local variation, also neutralize broader variation that may be of potential interest, including general equilibrium effects that spill across spatial borders or are global in nature, like effects on commodity prices. These issues will be discussed extensively in section 4.1.

While this review will briefly consider cross-sectional econometric analyses as in (2), its primary purpose is to discuss the recent climate–economy literature that uses panel methodologies, as in (3). With this focus in mind, appendix table 1 categorizes the panel studies cited in this review. In addition to summarizing which weather variables and outcome variables are investigated, the table indicates each panel study's design according to (i) functional forms for the weather variables, (ii) temporal resolution, (iii) spatial resolution, (iv) nonweather

[8] It should be noted that precisely estimating a long-run standard deviation requires more data than precisely estimating a mean—and, moreover, may be particularly sensitive to data problems like weather stations entering and exiting the record (see section 2.2.1). Thus, anomalies measures in contexts with limited data may be relatively noisy, leading to attenuation bias that becomes exacerbated in the panel context.

regressors, (v) heterogeneity, and (vi) error structure.

2.2 *What Data are used to Identify Weather Shocks?*

This section outlines sources of weather data that have been used in econometric analyses. It highlights the relative advantages and disadvantages of different types of weather data and then discusses aggregation approaches—i.e., how one can aggregate underlying weather measurements into variables that can be used for economic analysis.

There are currently four principal types of weather data: ground station data, gridded data, satellite data, and reanalysis data. The most basic type of data are from *ground stations*, which typically directly observe temperature, precipitation, and other weather variables such as wind speed and direction, humidity, and barometric pressure. *Gridded data* provide more complete coverage by interpolating station information over a grid. *Satellite data* use satellite-based readings to infer various weather variables. Finally, *reanalysis data* combine information from ground stations, satellites, weather balloons, and other inputs with a climate model to estimate weather variables across a grid. The following review will focus on temperature and precipitation data.[9] Interested readers should also consult Auffhammer et al. (forthcoming) for a related review and more in-depth coverage of these issues. Appendix table 2 lists the weather datasets used by each of the panel studies discussed in this review.

2.2.1 *Ground Stations*

When a weather station is present on the ground in a given location, it will typically provide a highly accurate measurement of that exact location's climate.[10] One repository for station data is the Global Historical Climatology Network (GHCN).[11] For regions of the world with extensive ground station networks and good historical coverage, such as the United States, Canada, and Europe, as well as some developing countries, ground station data can be used even at a fairly disaggregated level of analysis. In contexts where ground station coverage is sparse, these data may still offer important advantages for locations near the station.

While ground station data in general provides highly reliable weather measures for the areas where stations are located, there are some issues researchers should be aware of. Most importantly, entry and exit of weather stations is common, especially in poorer countries, which face more severe constraints to their weather monitoring budgets.[12] Figure 1 shows how the number of stations in the Terrestrial Air Temperature database, which incorporates the GHCN and a variety of other sources, changes over time (Willmott, Matsuura, and Legates 2010). The decline in stations around 1990 resulted from the collapse of the Soviet Union, which

[9] Other weather events—such as windstorms—involve measurement methods that are too complex to be discussed in this data overview. The interested reader is referred to Hsiang (2010).

[10] There could still be measurement error, for example if strong winds prevent rainfall or snow from entering the mouth of a gauge (Goodison, Louie, and Yang 1998).

[11] Note that, while the GHCN tries to include as much ground station data as possible, it is not necessarily an exhaustive collection. Some countries consider their weather data to be proprietary, and there are extensive collections of historical data available for some regions that have yet to be digitized. The National Climatic Data Center (NCDC) is a useful online resource for downloading station data: http://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets. Station data can also be found through other organizations, such as NASA's GISS.

[12] An excellent animation of station entry and exit can be found on the Web page "Visualizations of Monthly Average Air Temperature Time Series (1900–2008)" (University of Delaware). http://climate.geog.udel.edu/~climate/html_pages/Global2_Ts_2009/Global_t_ts_2009.html.

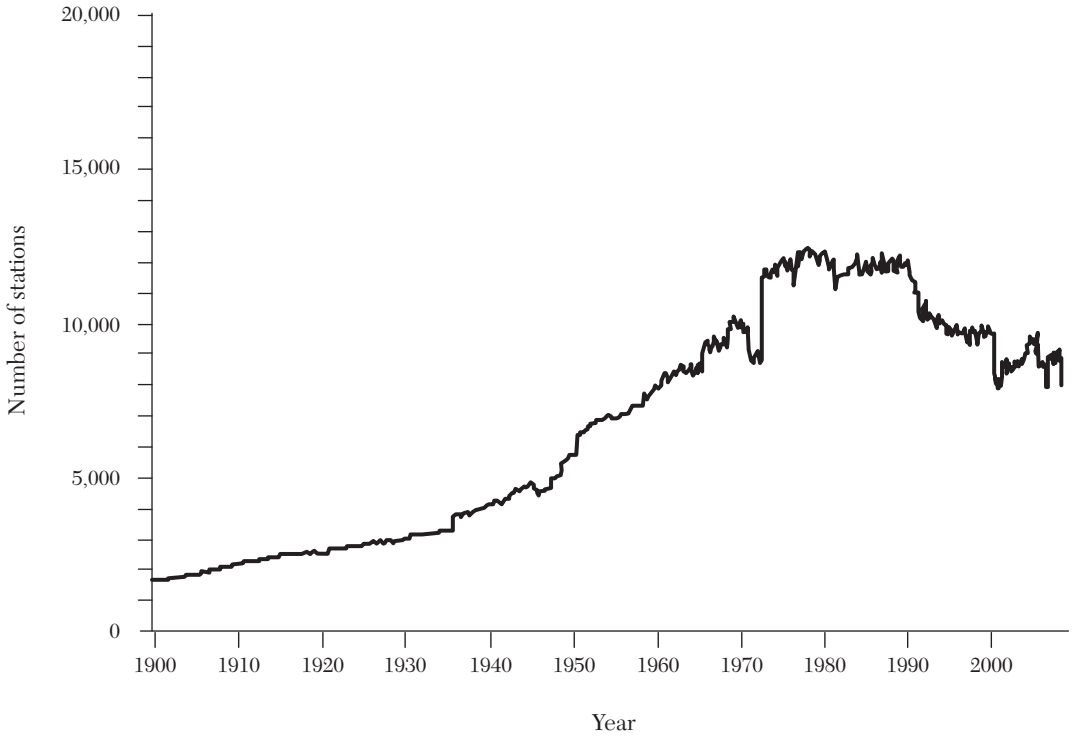

Figure 1. Changes Over Time in the Number of Ground Stations included in the Global Historical Climatology Network

Note: This figure plots the number of ground stations included each year in the GHCN dataset.

Source: Figure reproduced from http://climate.geog.udel.edu/~climate/html_pages/Global2_Ts_2009/air_temp_stat_num.pdf.

funded many weather stations in Eastern Europe, Africa, and elsewhere.[13]

While the exit and entry of stations in the GHCN data does not appear to substantially affect aggregate conclusions about overall global increases in temperature (Rohde et al. 2013), changes in ground stations can potentially matter for estimations of (3), to the extent that they substantially increase measurement error.[14] For example, if a weather station exits from a warmer part of a county, temperature in that county may erroneously

[13] More subtle changes can occur simply due to replacement of the weather sensors or slight movements in the physical location of the weather station. The current (version 3) GHCN monthly weather dataset incorporates an automatic procedure for detecting and correcting these changes by comparing a time series with its nearest neighbors (see Menne and Williams 2009), although no such correction is made for daily data.

[14] To address concerns about observable station entry and exit, Auffhammer and Kellogg (2011) and Schlenker and Roberts (2009) develop an approach that addresses station entry and attrition by estimating missing values in the station record, then using a balanced panel constructed from the "patched" station data.

appear to decrease. If the error is uncorrelated with the dependent variable, this will be essentially classical measurement error, and there will be attenuation bias reducing the estimate of β in equation (3); if exit and entry of stations is correlated with the dependent variable of interest, then biases of unknown sign could result. In any case, correlations between ground station entry and exit and dependent variables are testable, hence, may be assessed.[15] If such correlations do appear, the researcher can explicitly address the concern raised, for example by using satellite data as a robustness check.

2.2.2 *Gridded Data*

One important challenge posed by ground station data is their incomplete coverage, particularly in poor countries or areas with sparse population density. As a result, climate scientists have developed a variety of gridded data products, which interpolate among the ground stations. The result is a balanced panel of weather data for every point on a grid. Since gridded data offer a balanced panel, they are frequently used by economists in constructing weather data.

The most frequently used gridded datasets in the studies reviewed here are the global temperature and precipitation data produced by the Climatic Research Unit (CRU) at the University of East Anglia and by Willmott, Matsuura, and Legates (2010) at the University of Delaware (UDEL). Both have a spatial resolution of 0.5×0.5 degrees, but the station records and extrapolation algorithms used differ somewhat. CRU contains data on monthly minimum and maximum temperature, while the Delaware data provides the monthly average temperature. A more recently created gridded dataset for temperature is the NOAA GHCN_CAMS Land Temperature Analysis, and the Global Precipitation Climatology Center provides gridded precipitation data. There are also gridded monthly datasets for specific regions, such as the Parameter–Elevation Regressions on Independent Slopes Model (PRISM) dataset for the United States (Daly, Neilson, and Phillips 1994).[16]

In general, gridded datasets are a good source of temperature data for economic analysis in that they provide a balanced panel that potentially adjusts for issues like missing station data, elevation, and the urban heat island bias in a reasonable way. Nevertheless, there are several issues that one should be aware of when using gridded data. First, different interpolation schemes can produce different estimates, particularly in short time periods and particularly for precipitation. Precipitation has a far greater spatial variation than temperature, especially in rugged areas, and thus is more difficult to interpolate.[17] This issue is important for middle-income and developing countries, where underlying ground station data are sparse.[18] When using gridded data products in these contexts, it is useful to check

[15] See, for example, Dell, Jones, and Olken (2012), appendix table 15, which examines ground station coverage.

[16] Schlenker, Hanemann, and Fisher (2006) used PRISM and daily station data to develop an innovative dataset of daily gridded weather data for the United States, which has subsequently been used in a variety of applications.

[17] Interested readers are referred to Rudolf and Schneider (2005), Rudolf et al. (1994), and World Meterological Organization (1985) for a more detailed discussion.

[18] Auffhammer et al. (forthcoming) document how country average measures of temperature and precipitation compare across these datasets. For average long-run temperature and precipitation between 1960 and 1999, the correlation for temperature is 0.998 and for precipitation it is 0.985. When considering annual deviations from mean, these correlations fall to 0.92 for temperature and 0.70 for precipitation. The correlation for precipitation is lower because precipitation is less smooth across space, which makes the extrapolation algorithm more critical. Auffhammer et al. note that there are significant regional differences—the precipitation deviation correlation is 0.96 for the United States and thus presumably much lower for many middle-income and developing countries.

for robustness across datasets, particularly if precipitation is the main variable of interest.

A second challenge concerns cases where there are more grid cells than underlying stations. This issue would not necessarily compromise the analysis if the gridded data are aggregated to large enough units (e.g., countries), but it can pose challenges for inference regarding smaller geographic units, particularly in areas with sparse coverage, such as Africa. Users of the data in areas with sparse coverage should be aware of these issues, particularly when using fine geographic units and particularly for precipitation, which is much harder to measure accurately and much more variable than temperature. In addition to attenuation bias, it is also important to account for the underlying spatial correlation resulting from both the weather and the extrapolation algorithms.

2.2.3 *Satellite Measurements*

The third source for weather data is satellite measurements. Satellite datasets, beginning in 1979, include those produced by the University of Alabama Huntsville (UAH) and Remote Sensing Systems (RSS). These data products are available at a 2.5 × 2.5 degree resolution, and hence are considerably more aggregated than the datasets discussed above. If data are only required since the early 2000s, newer satellite sensors allow significantly higher resolution to be achieved.[19]

While satellite data can provide important weather information for areas with a limited ground network, satellite data are not necessarily a panacea. Satellites were launched relatively recently, so their data does not extend back nearly as far historically as other datasets. Furthermore, an individual ground station is more accurate than the satellite data for that particular location, in part because satellites do not directly measure temperature or precipitation, but rather make inferences from electromagnetic reflectivity in various wavelength bands. Lastly, a satellite-based series is not drawn from a single satellite, but rather from a series of satellites. Sensors have changed subtly over the years and, within a particular satellite, corrections are needed due to subtle changes in the satellite's orbit over time and other factors.[20]

2.2.4 *Reanalysis Data*

The final type of data, reanalysis data, combines information from ground stations, satellites, and other sources with a climate model to create gridded weather data products. The key difference between reanalysis and gridded data is that, rather than use a statistical procedure to interpolate between observations, a climate model is used. Prominent examples of reanalysis products used in the panel literature are those produced by the National Center for Environmental Prediction (NCEP) (Kistler et al. 2001), the European Center for Medium-Range Weather Forecasting, and Ngo-Duc, Polcher, and Laval (2005). While reanalysis may offer some improvements in regions with sparse data, it is not obviously better than interpolated gridded data, since the climate models it uses (like any model) are considerable simplifications of the climate reality.

Auffhammer et al. (forthcoming) provide correlations between CRU and UDEL gridded data and NCEP reanalysis data. Correlations are generally high for temperature. Correlations for precipitation, however,

[19] For example, NASA's TRMM Multi-satellite Precipitation Analysis (TMPA), available at 0.25 degree resolution, GPCP 1DD precipitation analysis available at 1 degree daily resolution, NOAA's CMORPH data at 0.072 degree resolution for thirty-minute time steps, and MODIS data on land surface temperature and emissivity available at 1000m resolution.

[20] For more information on these datasets, see the Third Assessment Report of the IPCC (Houghton et al. 2001) and Karl et al. (2006).

fall dramatically when examining deviations from mean, especially in poor countries where the underlying ground station data is sparse. Readers should consult Auffhammer et al. (forthcoming) for a more detailed discussion. For analysis at high spatial resolutions, particularly when underlying weather stations are sparse, the terrain is rugged, or precipitation is the main variable of interest, consulting multiple datasets that have been constructed using different approaches provides a useful robustness check. Alternatively, when interested in precipitation in areas with sparse ground station coverage, a more promising approach may be to focus on geographic areas near ground stations, rather than trying to interpolate.

2.2.5 *Aggregating Weather Data into Variables for Analysis*

Once one has an underlying source of weather data, the data typically need to be aggregated to an economically meaningful level. Aggregation may be motivated by the substantive question, such as an interest in country-level effects, or because economic data is not available at the same resolution as the weather data. Note that aggregating to larger spatial areas may also be advantageous in areas with sparse ground stations, where gridded data may otherwise give a false sense of precision or spatial independence.

One approach is to aggregate spatially; that is, to overlay administrative or other boundaries with the gridded weather dataset and take a simple area-weighted average of weather variables within the administrative unit, which can be done easily using GIS software. However, this approach will lead large areas with little economic activity and sparse populations (such as deserts, rain forests, or the Arctic) to dominate the weather averages of large spatial units such as the United States, Russia, and Brazil. A second approach is, therefore, to aggregate using a fixed set of population weights, so that the relevant concept is the average weather experienced by a person in the administrative area, not the average weather experienced by a place. The difference can matter, particularly for large and diverse geographies: in the year 2000, the average area-weighted mean temperature for the United States was 8.3ºC, whereas the average population-weighted mean temperature for the United States was 13.1ºC, the difference being driven by the many cold, sparsely populated areas in Alaska and the north central United States. Which method to use depends on the context: for analyzing agriculture, area weights may be preferable; for analyzing the impact on labor force productivity, a fixed set of population weights may be preferable.[21]

2.2.6 *Climate Projection Data*

Finally, in order to assess the potential impacts of future climate change, some studies have combined weather impacts estimated from historical data with data that predict future climate change. Estimates of future climate change rely on two major components: a time path of GHG emissions and a General Circulation Model (GCM), which is a mathematical model simulating the Earth's climate system. There are many such estimates; more detailed information about these models can be found in the IPCC Special Report on Emissions Scenarios (Nakicenovic et al. 2000) and more information about their use in economics can be found in Auffhammer et al. (forthcoming) and Burke et al. (2011).

3. *The New Weather–Economy Literature*

This section provides an overview of the relationship between weather fluctuations

[21] Note that aggregation can also create tension with the capacity to estimate nonlinear effects, since aggregation can smooth out nonlinearities across space or over time (see further discussion in section 2.1.2).

and various outcomes, including aggregate output, agriculture, labor productivity, industrial output, health, energy, political stability, and conflict. It focuses on studies employing the panel methodology outlined in section 2. We also briefly summarize some studies using alternative methodologies in order to provide insight into how the panel estimates relate to the broader climate–economy literature.

Overall, the studies discussed in this section document that temperature, precipitation, and extreme weather events exert economically meaningful and statistically significant influences on a variety of economic outcomes. These impacts illustrate the multifaceted nature of the weather–economy relationship, with numerous applications for understanding historical, present, and future economic outcomes and possible policy responses. For example, the effects of weather variables on mortality rates, labor productivity, energy demand, and agricultural output can inform investments and policy design around public health, air-conditioning, energy infrastructure, and agricultural technologies. Moreover, these studies can help inform classic issues of economic development, especially the role of geographic features in influencing development paths. Finally, these analyses may inform estimates of the economic costs of future climatic change. The possibility of future climatic change has been a primary motive for the recent, rapid growth of this literature; these applications are discussed in detail in section 4.

3.1 *Aggregate Output*

3.1.1 *Prior Literature*

Although this review focuses on panel estimates based on weather variation, it is important to have a basic understanding of the previous literature and debates that inspired these more recent studies. A negative correlation between temperature and per capita income has been noted at least since Ibn Khaldun's fourteenth-century *Muqaddimah* (Gates 1967). Claims that high temperatures cause low income appear there and continue as centerpieces of prominent subsequent works, including Montesquieu's *The Spirit of Laws* (1748) and Huntington's *Civilization and Climate* (1915), both of which hinge on the idea that high temperatures reduce labor productivity. Numerous contemporary historical analyses relate economic success to temperate climates through advantageous agricultural technologies (e.g., Jones 1981; Crosby 1986; Diamond 1997). Modern empirical work has tested the temperature–income relationship, initially using cross-sectional evidence, and more recently using the panel models featured in this review.

Cross-country empirical analyses show a strong negative relationship between hot climates and income per capita. For example, Gallup, Sachs, and Mellinger (1999) show that countries located in the tropics (i.e., between the Tropic of Cancer and the Tropic of Capricorn) are 50 percent poorer per capita in 1950 and grow 0.9 percentage points more slowly per year between 1965 and 1990. These findings have been further associated empirically with malarial prevalence and unproductive agricultural technologies (Sachs 2001; Sachs 2003), as well as the frequency of frost days that may have beneficial agricultural and/or health effects (Masters and McMillan 2001). Using temperature directly, Dell, Jones, and Olken (2009) show in the world sample in the year 2000 that countries are, on average, 8.5 percent poorer per capita per 1°C warmer.

Other cross-sectional studies examine climate variation *within countries*, harnessing climatic differences that are not entangled with cross-country differences and exist within more consistent environments, institutionally or otherwise. Nordhaus (2006)

uses a global database of economic activity with a resolution of 1° latitude by 1° longitude. Controlling for country fixed effects, this study finds that 20 percent of the income differences between Africa and the world's rich industrial regions can be explained by geographic variables, which include temperature and precipitation as well as elevation, soil quality, and distance from the coast. Dell, Jones, and Olken (2009) use municipal-level data for twelve countries in the Americas and find that a statistically significant negative relationship between average temperature and income persists within countries—and even within states (provinces) within countries. The drop in per capita income per 1°C falls from 8.5 percent (across countries) to 1–2 percent (within countries or within states), and they find little or no impact of average precipitation levels either across or within countries. Overall, geographic variation (temperature, precipitation, elevation, slope and distance to coast) explains a remarkable 61 percent of the variation in incomes at the municipal level across the 7,684 municipalities studied in these 12 countries.

In general, the cross-sectional evidence finds a strong, negative relationship between temperature and economic activity, with less clear evidence on precipitation. Of course, as discussed in section 2.1.1, cross-sectional estimates may conflate climate with other long-run characteristics of an economy, such as its institutions. To more directly isolate contemporaneous impacts of temperature, we turn to panel estimates.

3.1.2 *Panel-Based Estimates*

Panel studies exploit the exogeneity of cross-time weather variation, allowing for causative identification. We begin by examining those studies that focus on average weather across a year (e.g., temperature and precipitation), and then consider those studies that examine more extreme weather events, such as droughts and windstorms.

Studies on Temperature and Precipitation

In a world sample from 1950 to 2003, Dell, Jones, and Olken (2012) examine how annual variation in temperature and precipitation affects per capita income. They show that being 1°C warmer in a given year reduces per capita income by 1.4 percent, but only in poor countries. Moreover, estimating a model with lags of temperature, they find that this large effect is not reversed once the temperature shock is over, suggesting that temperature is affecting growth rates, not just income levels.[22] Growth effects, which compound over time, have potentially first-order consequences for the scale of economic damages over the longer run, greatly exceeding level effects on income, and are thus an important area for further modeling and research (see section 4.2). Estimating long-difference models (see section 4.1.2), Dell et al. further find that over 10–15 year time scales, temperature shocks have similar effects to annual shocks, although statistical precision decreases. Variation in mean precipitation levels is not found to affect the path of per capita income. Temperature shocks appear to have little effect in rich countries, although estimates for rich countries are not statistically precise.

Hsiang (2010) shows similar findings using annual variation in a sample of twenty-eight Caribbean-basin countries over the 1970–2006 period. National output falls 2.5 percent per 1°C warming. This study further examines output effects by time of year and shows that positive temperature shocks have

[22] Bansal and Ochoa (2011) examine the empirical relationship between a country's economic growth and worldwide average temperature shocks, as opposed to a country's particular temperature shock. They find that, on average, a 1°C global temperature increase reduces growth by about 0.9 percentage points, with effects largest for countries located near the equator. The global time variation in temperature thus appears to produce broadly similar results to Dell, Jones, and Olken (2012).

negative effects on income only when they occur during the hottest season. Mean rainfall variation is controlled for in this study, but results are not reported.

Barrios, Bertinelli, and Strobl (2010) focus on sub-Saharan Africa over the 1960–1990 period, using a subsample of twenty-two African and thirty-eight non-African countries and weather variation occurring across five-year periods. The authors find that higher rainfall is associated with faster growth in these sub-Saharan African countries but not elsewhere. They estimate that worsening rainfall conditions in Africa since the 1960s can explain 15–40 percent of the per capita income gap between sub-Saharan Africa and the rest of the developing world by the year 2000. Unlike the majority of studies, which consider the effect of precipitation and temperature levels, this study uses weather anomalies (changes from country means, normalized by country standard deviations). Other studies, like Miguel, Satyanath, and Sergenti (2004) and Dell, Jones, and Olken (2012) find that anomalies-based analyses tend to provide broadly similar results to levels-based analyses when predicting national income growth, but with weaker statistical precision.

In addition to studies focused on income effects per se, other studies use weather variation as instruments for national income, harnessing this source of income variation to test theories about how income affects other outcomes, such as conflict or political change. Leaving the ultimate objective of these studies aside for the moment (we will return to them below), the first-stage regressions provide additional information on the income effects of weather variation. Miguel, Satyanath, and Sergenti (2004), seeking to explain civil conflict, study forty-one African countries from 1981–1999 and show that annual per capita income growth is positively predicted by current and lagged rainfall growth, while not controlling for temperature.[23] However, this relationship appears weaker after 2000 (Miguel and Satyanath 2011). Bruckner and Ciccone (2011), in their study of democratization, also find that negative rainfall shocks lower income in sub-Saharan Africa. Finally, Burke and Leigh (2010) use precipitation and temperature as instruments for per capita income growth to explain democratization, studying a large sample with 121 countries over the 1963–2001 period. In their analyses, temperature is a strong predictor of income, while precipitation is weak.

Studies of Extreme Weather Events

In addition to studies of average annual precipitation, a number of studies examine extreme weather events, such as storms and severe droughts.

Several studies examine windstorms by constructing meteorological databases that track storm paths. For example, Hsiang and Narita (2012) use a detailed global windstorm dataset and investigate the effect of windstorms across 233 countries from 1950–2008. They find that higher wind speeds present substantially higher economic losses. Hsiang's (2010) study of twenty-eight Caribbean nations shows no average effect on income from cyclones, though there are significant negative impacts in some sectors (such as agriculture, tourism, retail, and mining), but positive impacts in construction (presumably due to its role in reconstruction).

Hsiang and Jina (2013) also find evidence for growth effects from windstorms, rather than level effects. Using annual fluctuations in windstorms, they find that the effects of cyclones reduce growth rates, with effects that cumulate over time. On net, they estimate that the annual growth rate of world

[23] Miguel and Satyanath (2011) further show in the same sample that current and lagged rainfall levels (as opposed to growth) predict income growth.

GDP declined by 1.3 percentage points due to cyclones during the period 1970–2008.

Looking within countries, Deryugina (2011) examines U.S. counties and finds no effect on county earnings ten years after a hurricane, a result supported by large government transfers into the affected counties after these events (suggesting that there may be a substantial loss in locally produced income, with consumption effects dampened by the transfer). Anttila-Hughes and Hsiang (2011) study a panel of provinces in the Philippines and show that local exposure to a typhoon reduces household incomes in the province on average by 6.7 percent.

Additional studies examine "economic losses" as the dependent variable, rather than looking at the income path itself. To measure such losses in cross-country studies, authors use the Emergency Events Database (EM-DAT), which includes fatalities and direct economic loss estimates that countries self-report. Yang (2008) finds that stronger storms, as measured from meteorological data from 1970–2002, lead to higher economic losses (damage from the EM-DAT database as a fraction of GDP) and greater deaths and injuries, as well as larger international aid flows in response.[24] Although not panel studies in the sense of equation (3), studies focused on the United States also find substantially increased economic losses with increasing storm severity (Nordhaus 2010b; Mendelsohn, Emanuel, and Chonabayashi 2011). For example, Nordhaus (2010b) estimates the relationship between wind speed and damages, finding that annual hurricane costs in the United States from 1950–2008 averaged 0.07 percent of GDP, but with high variability; Hurricane Katrina made 2005 an outlier, with damages nearing 1 percent of GDP.

Integrating across the weather studies above, it appears that an unusually hot year is associated with substantially lower income growth in poor countries. This finding is consistent with the strong negative cross-sectional relationship between temperature and per capita income. The studies also show that unusually low precipitation has had negative impacts on income per capita in Africa, with less clear effects elsewhere. Studies find large effects of windstorms on local income but generally smaller effects on national income, although damages from windstorms are highly convex in wind speed.

3.2 *Agriculture*

Given the natural relationship between the environment and agricultural productivity—temperature and water are direct inputs into the biological processes of plant growth—agriculture has been the focus of much of the existing research on climate impacts. It is also the area where many of the core methodological contributions occurred.

3.2.1 *Experimental and Cross-Sectional Estimates*

The early debate over the likely impacts of climate on agriculture was characterized by two approaches. One approach, frequently denoted the production function approach, specifies a relationship between climate and agricultural output, and uses this estimate to simulate the impacts of changing climate (Adams 1989; Kaiser et al. 1993; Adams et al.

[24] A number of studies also use the EM-DAT dataset to construct the weather events and then use this data to study the impacts of droughts and windstorms on national income (Raddatz 2009; Loayza et al. 2012; Fomby, Ikeda, and Loayza 2013). Given that the inclusion criteria for the events dataset is that ten or more people were killed, one hundred or more people were affected, an official state of emergency was declared, or a call for international assistance was made, a challenge with this approach is that it selects, to some extent, on events that have notable economic impact. This approach may then create a bias in the direction of finding larger effects and thus these results may not generalize to the average windstorm, drought, etc. For windstorms, meteorological-based methods can help deal with this concern. A promising direction for future research on droughts would construct a drought definition based solely on exogenous environmental variables such as precipitation, temperature, evapotranspiration, and other exogenous measures of soil moisture balance.

1995).[25] While the production function is often calibrated through the use of experimental data, it has been criticized for not realistically modeling real farmer behavior in real settings. For example, many studies do not allow farmers to adopt new crops when the temperature input into the production function changes, nor do they allow farmers to switch their cultivated land to livestock or nonfarm use.

To address these concerns, Mendelsohn, Nordhaus, and Shaw (1994) developed a second approach, which they called the Ricardian approach, that instead used cross-sectional regressions with land values to recover the net impacts of climate on agricultural productivity. By analyzing farm land prices as a function of climate and a host of other characteristics, they estimated that the impacts of climate change would be much smaller than those estimated by the production function approach and might even be positive.

While Mendelsohn, Nordhaus, and Shaw (1994) remains a major methodological contribution, it has been subject to critiques by Schlenker, Hanemann, and Fisher (2005) and others. Schlenker, Hanemann, and Fisher, for example, show that it is critical in the hedonic approach to account for irrigation. In particular, in estimating a cross-sectional relationship like equation (2) for irrigated areas, which transport water from other locations, the localized climate is not the key determinant of production. Instead, water supply is a more complicated function of precipitation in the overall supply area for the irrigation system, and since this is not measured, it biases the coefficients in (2).[26] When Schlenker, Hanemann, and Fisher estimate the hedonic model for dryland counties alone, they find robustly negative estimates, similar to those from earlier estimates.

3.2.2 *Panel Estimates*

Deschênes and Greenstone (2007), in an important methodological contribution, argue that the cross-sectional hedonic approach could be biased by unobserved determinants of agricultural productivity that are correlated with climate. Instead, Deschênes and Greenstone argued that one could exploit year-to-year within-county variation in temperature and precipitation to estimate whether agricultural profits are affected when the year is hotter or wetter than normal, as in equation (3). They find no statistically significant relationship between weather and U.S. agricultural profits, corn yields, or soybean yields, and further argue that if short-run fluctuations have no impact, then in the long run when adaptation is possible, climate change will plausibly have little impact or could even be beneficial. These findings have subsequently been questioned by Fisher et al. (2012), who point to data errors and argue that, when these are corrected, the fluctuations approach indeed finds a negative impact of climate change on U.S. agriculture, which is further consistent with studies examining nonlinear effects of extremely high temperatures on U.S. agriculture (see below). Nevertheless, the methodological contribution remains extremely important.[27]

Impacts on developing countries estimated using panel models such as (3) typically find

[25] See Adams et al. (1995); Adams et al. (1998); Kaiser et al. (1993); and Liverman and O'Brien (1991). Rosenzweig and Iglesias (1994) provides a compilation of various other studies, and the *IPCC Second Assessment Report* (Bruce, Lee, and Haites 1996) provides a discussion.

[26] In areas that depend on snowmelt, the extent of snow and timing of snowmelt may create further complexities when attempting to link local water availability to local climate.

[27] Deschênes and Greenstone (2012), in their reply to Fisher et al. (2012), summarize the implied estimates once the errors are corrected.

consistently negative impacts of bad weather shocks on agricultural output. Schlenker and Lobell (2010) use weather fluctuations to estimate a model of yield response in sub-Saharan Africa, finding that higher temperatures tend to reduce yields. Similarly, Guiteras (2009) estimates that higher temperatures in a given year reduce agricultural output in India, and Feng, Krueger, and Oppenheimer (2010) document that high temperatures reduce agricultural output at the state level in Mexico. Using a panel dataset that provides detailed data on rice farms in a variety of Asian countries, Welch et al. (2010) estimate that higher minimum temperature reduces yields, whereas higher maximum temperature increases yields. On net, their estimates suggest that Asian rice yields will decline under a moderate warming scenario. Levine and Yang (2006) show, using a panel of Indonesian districts, that more rainfall leads to more rice production.

A number of additional studies have established negative effects of low rainfall on agricultural output or rural income in developing countries as a precursor to testing other hypotheses. Examples include Paxson (1992), which uses negative rainfall shocks to test for the permanent income hypothesis and shows impacts of rainfall on rural incomes; Jayachandran (2006), which focuses on the determinants of labor supply elasticities and shows that more rainfall in Indian districts leads to higher crop yields and higher agricultural wages; Yang and Choi (2007), which uses rainfall shocks to test for international remittances as insurance and shows impacts of rainfall on rural incomes in the Philippines; and Hidalgo et al. (2010), who, in their study of land invasions, estimate that rainfall deviations in Brazil lower agricultural incomes, with a one standard deviation change in rainfall reducing income by around 4 percent.

The recent literature has also highlighted several issues that are useful for evaluating potential future impacts of global climate change, a topic we return to in much more detail in section 4. One issue is the importance of accounting flexibly for nonlinearities. For example, Schlenker and Roberts (2009) examine a panel model of U.S. agricultural yields using daily temperature data. Their approach allows flexible estimation of nonlinear relationships between yields and temperature, using very fine (1 or 3ºC) temperature bins, polynomials, or piecewise splines. They find a threshold in output effects starting between 29–32ºC, depending on the crop, with temperature being moderately beneficial at temperatures lower than the threshold and sharply harmful above the threshold. Understanding nonlinearities becomes important when considering the impact of global climate change because a right-shift in the distribution of average temperature causes a disproportionate increase in the number of very hot days (see section 4.1.2 below for more discussion of this issue). Globally, Lobell, Schlenker, and Costa-Roberts (2011) use a fixed-effects model as in (3), augmented with quadratic terms to account for nonlinearities in weather and find similar nonlinear effects of higher temperatures.

Another key issue in using estimates from short-run weather fluctuations to shed light on the long-run impacts of climate change is assessing how much adaptation is likely to occur. (We discuss these issues in more detail in section 4.1.2.) On the one hand, economic historians have pointed to the ability of agricultural producers to successfully adapt to new climates in the past. For example, as North American settlement advanced northwards and westwards in the nineteenth century, wheat started to be farmed in areas once thought too dry or too cold to farm, with the innovation of new grain varieties (Olmstead and Rhode 2011). The possibility of adaptation was a major argument for the approach of Mendelsohn, Nordhaus, and Shaw (1994), since presumably, changes

in land values would incorporate future adaptation effects. However, in the context of the American Dust Bowl, Hornbeck (2012) finds limited evidence for adaptation through changes in land use. More recently, Burke and Emerick (2013) also find limited evidence for adaptation in U.S. agriculture: long-difference estimates of changes in output on changes in temperature (as in equation (8) below), estimated for the period between 1980 and 2000, appear statistically similar to the impact of annual temperature fluctuations.

Fishman (2011) examines the potential of irrigation as a mitigating mechanism for climate change in the Indian context. To do so, he runs a panel specification interacting highly detailed weather variables with measures of access to irrigation, which change over time in his sample. Overall, he finds that the distribution of rainfall matters as well as the total amount of rainfall—i.e., conditional on the total amount of rain, the number of rainless days reduces yields. Irrigation substantially mutes this effect, though it mitigates little of the impact of higher temperatures.

Agricultural producers may also respond to a negative weather shock by moving elsewhere. Munshi (2003) documents that when rainfall is lower in a given Mexican community, it sends more migrants to the United States over the coming years. Feng, Krueger, and Oppenheimer (2010) use temperature and precipitation variation in panel data for Mexican states as instruments for crop yields, and then look at the implied relationship between crop yields and emigration to the United States. They find that lower crop yields (predicted from temperature and precipitation shocks) increase emigration, with the reduced-form effects suggesting that the effects are predominantly driven by temperature shocks. Gray and Mueller (2012) study internal migration in Bangladesh from 1994–2010. They show modest migration responses to flooding, but large migration due to rain-related crop failure. Examining internal migration in the United States, Hornbeck (2012) finds substantial migration out of areas affected by the Dust Bowl in the 1930s. More recently, Feng, Oppenheimer, and Schlenker (2012) examine the 1970–2009 period and find outmigration from corn and soybean producing areas where yields have fallen due to changes in weather patterns, particularly for young adults.[28]

The scientific literature has examined forestry changes, which may be particularly important, to the extent that forests play an important role in the global carbon balance and preserve biodiversity. These studies often use longitudinal data, but do not always exploit panel regressions to estimate the effects of temperature or precipitation shocks within spatial areas. For example, longitudinal data has established substantial increases in tree mortality throughout the western United States, with suggested links to warming and precipitation declines (van Mantgem et al. 2009). Longitudinal data has also shown that tree deaths are strongly related to low rainfall levels on the Iberian Peninsula region (Carnicer et al. 2011), although the variation used for estimation is across both space and time. Related work has shown experimentally that warming weakens trees' drought resistance (Adams et al. 2009).[29] Westerling et al. (2006) use panel

[28] While migration appears to be an important adaptation channel, it can potentially pose a complication for interpreting panel-based estimates. In many datasets, we know where people are at the time of the survey, but not necessarily where they were previously, so endogenous migration may have influenced the measured economic outcomes (such as average health or GDP). To the extent that one is interested in effects allowing for such migration, the measured response will still be appropriate. Otherwise, the use of data that incorporates place of birth, such as census data, can be helpful since one can analyze the data at the place of birth level, which removes the problems of endogenous migration.

[29] Research relating forest loss to drought and warming is reviewed by Allen et al. (2010).

data for the western United States to show that wildfire increases within subregions are closely related to shifts in local temperature and precipitation, particularly as they relate to earlier springs, hence longer and drier summer seasons.

In summary, panel estimates tend to predict economically and statistically significant negative impacts of hotter temperatures on agricultural output. These impacts are pronounced when temperatures increase beyond a crop-specific threshold. They appear in rich countries such as the United States—particularly in the rain-fed eastern part of the country—and are also important in poor countries, where agriculture is a large share of aggregate output. Evidence also suggests that rainfall and droughts impact agricultural output, although these effects can be complicated to disentangle and may be mitigated in the presence of large-scale irrigation systems. The negative effects of low rainfall on agriculture in developing counties appear consistently in those countries, perhaps due to lower levels of irrigation. Outmigration appears to be a common response to declines in local agricultural productivity.

3.3 *Labor Productivity*

The idea that temperature affects labor productivity and cognitive functioning dates back at least to the Ancient Greeks.[30] Montesquieu placed labor-productivity effects of temperature at the center of his reasoning about development in *The Spirit of Laws* (1748), and the geographer Ellsworth Huntington in *Civilization and Climate* (1915) not only argued that climate was central to culture, but also presented early empirical evidence showing a link between labor productivity and temperature in micro data. Specifically, he documented daily worker productivity for a number of types of workers (e.g., "operatives in cotton factories" in South Carolina, and "cigar makers" in Florida), and showed that productivity was highest in spring and fall, when temperatures are moderate, and lowest in summer and winter, when temperatures are more extreme.

Modern lab experiments have investigated the impact of temperature on productivity. Subjects are typically randomly assigned to rooms of varying temperatures and asked to perform cognitive and physical tasks. Examples of tasks shown to respond adversely to hot temperatures in laboratory settings include estimation of time, vigilance, and higher cognitive functions, such as mental arithmetic and simulated flight (Grether 1973; Seppanen, Fisk, and Faulkner 2003). Surveying multiple experimental studies, for example, Seppanen, Fisk and Faulkner (2003) conclude that there is a productivity loss in various cognitive tasks of about 2 percent per 1ºC for temperatures over 25ºC.

Observational and experimental studies also show a strong relationship between temperature and the productivity of factory, call center, and office workers, as well as students. Niemelä et al. (2002) examine the productivity of call center workers in different ambient temperatures, which vary both due to external weather and due to changes in cooling technology. The authors find that, within the range of temperatures from 22–29ºC, each additional ºC is associated with a reduction of about 1.8 percent in labor productivity. Other studies of call center workers also find a link between indoor climate and performance, with high temperatures (e.g., above 24–25ºC) generally associated with worse performance. They also note that the relationship is complex and find that other aspects (e.g., humidity, amount of outdoor air, carbon dioxide levels) have complex interactions with temperature within the normal

[30] The Greeks and subsequent societies believed that the body was composed of four elements (humors) and that temperature was a frequent reason for an imbalance in the humors.

temperature zone (see, e.g., Federspiel et al. 2004; Tham 2004). A meta-analysis of these studies concludes that increasing temperature from 23 to 30ºC reduces productivity by about 9 percent (Seppanen, Fisk, and Lei 2006). For students, Wargocki and Wyon (2007) run an experiment with children between ten and twelve years old in classroom settings. Classroom temperatures were randomly varied each week between warm (around 25ºC) and normal (around 20–21ºC) using a crossover design, and the authors found improvements on a variety of numerical tasks in the cooler temperatures. Lee, Gino, and Staats (2012) show using bank workers in Japan that productivity appears highest in days where outside weather is less attractive for leisure activities, arguing that nice outside weather is a distraction.

For the economy at large, Graff Zivin and Neidell (forthcoming) show, using a panel, that weather fluctuations lead to substantial changes in labor supply. Looking across the United States, Graff Zivin and Neidell use a panel-data specification similar to equation (3), examining the link between shocks to temperature and labor supply as measured by time-use surveys. They find that hot days reduce labor supply in industries exposed to outdoor temperature, such as agriculture, forestry, mining, construction, and utilities, particularly at extremes of temperature. For example, at temperatures over 100ºF, labor supply in outdoor industries drops by as much as one hour per day, compared to temperatures in the 76–80ºF range. They find no statistically detectable effects in other industries that are less exposed to climate (e.g., nonmanufacturing indoor activities). These findings suggest a potentially important role for air-conditioning in unlinking temperature and productivity; we discuss air-conditioning further in section 3.6. Connolly (2008) examines the impact of rainfall on the labor/leisure choice in the United States using time-use data. She finds that men substitute about thirty minutes per day, on average, from leisure to work when it is raining.

3.4 *Industrial and Services Output*

Given the negative effects of high temperature on labor productivity in factories, call centers, and outdoor industries such as mining, forestry, and utilities discussed above, a natural next question is whether these impacts affect aggregate output in other sectors, such as industry and services. While high temperatures per se appear to affect labor productivity, indoor air temperature is not necessarily the same as outdoor air temperature (e.g., given heating and air-conditioning), and other aspects of industrial production (assembly lines, mechanization), may further dampen any labor productivity effects. Effects of precipitation and storms are also not a priori obvious.

Recent work suggests that there are important effects of weather shocks on industrial and services output. Hsiang (2010); Jones and Olken (2010); and Dell, Jones, and Olken (2012) all examine the effect of weather fluctuations on aggregate industrial output for large samples of countries, using panel specifications as in equation (3). Hsiang (2010) measures the effects of temperature and cyclones in twenty-eight Caribbean countries over the 1970–2006 period, while also controlling for precipitation. He finds that periods of unusually high heat have large negative effects for three of six nonagricultural sectors, where nonagricultural output declines 2.4 percent per 1°C. Output losses are driven by heat shocks during the hottest season. Two of the three affected sectors are service-oriented and provide the majority of output in these Caribbean economies, while the other affected sector is industrial (mining and utilities). Hsiang does not find a statistically significant impact of temperature on manufacturing output. Cyclones, measured as years with unusually high cyclone energy dissipation, have negative output effects on

mining and utilities, among other sectors in the economy, while having offsetting positive output effects for construction, leading to no net effects on economywide output flows.

Dell, Jones, and Olken (2012) study annual industrial value-added output within a global sample of 125 countries over the 1950–2003 period. They find that industrial losses are 2 percent per 1°C, but only in poor countries. The magnitudes of these estimated temperature effects are similar to Hsiang (2010). Further, like Hsiang (2010), this study controls for mean rainfall; no effect of mean precipitation levels is found.

Jones and Olken (2010) reconsider industrial output losses in the global sample using trade data. This data, collected in rich countries, helps avoid possible data quality issues in national accounts while also allowing examination of narrower product classes. Using two-digit product codes, this analysis finds an average 2.4 percent decline in exports from a poor country per 1°C warming there. No robust effect of average precipitation appears across specifications. Analyzed by sector, twenty of the sixty-six two-digit export categories show statistically significant negative impacts of temperature. In addition to agriculture exports, negative temperature effects appear for many manufactured goods (covering fourteen different product codes such as wood, metal, and rubber manufactures; electrical machinery; office machines; plumbing, heating, and light fixtures; and footwear).

The above studies all examine sector-level aggregates. Cachon, Gallino, and Olivares (2012) examine the effects of weather at the plant level for one particular industrial sector—automobiles—in the United States, focusing on the 1994–2004 period. They find that hot days reduce output significantly: a week with six or more days above 90°F reduces that week's production by about 8 percent. The temperature effect on automobile production may be surprising because the work is indoors and presumably occurs in the presence of air-conditioning; the authors hypothesize that air-conditioning may be imperfect at extreme heat or that the temperature effects come from operational disruptions outside the plant interior. Worker absenteeism could also play a role. This study also finds large output losses from extreme windstorms, which occur on average 2.5 times per year, per plant and are associated with weekly output declines of 26 percent per windstorm day. Snow on at least two days of the week and rains on at least six days of the week are also found to have statistically significant but more modest negative output effects.

While few in number, a notable consistency emerges among the studies of industrial output using aggregated data. These estimates center approximately on a 2 percent output loss per 1°C. The findings are also remarkably consistent with micro-level studies of labor productivity (see section 3.3), which estimate labor productivity losses that center around 2 percent per additional 1°C when baseline temperatures exceed 25°C. The two studies that consider heavy winds both find large effects of windstorms on industrial production. Effects of precipitation on industrial output appear slight, although only one study looks at extremely heavy precipitation and in that case finds modest negative effects.

3.5 *Health and Mortality*

The epidemiology and economics literatures emphasize the detrimental effects of high temperatures on mortality, prenatal health, and human health more generally, across contexts ranging from seventeenth-century England to sub-Saharan Africa, and the United States in recent years.[31] Numerous

[31] The review in this section is highly complementary with Deschênes (2012), which is focused exclusively on the relationship between temperature and health.

recent papers have examined the impact on mortality, both in developed and in developing countries, using the panel approach.

In the United States, Deschênes, and Greenstone (2011) examine death records and find that each additional day of extreme heat (exceeding 32ºC), relative to a moderate day (10 to 15ºC) raises the annual age-adjusted mortality rate by about 0.11 percent. They also find that extreme cold increases mortality. The elderly and infants are at particularly high risk. Barreca (2012) reports a similar analysis using bimonthly (moving average) weather data controlling for humidity, with each additional day of extreme heat (exceeding 90ºF) increasing mortality by about 0.2 deaths per thousand, or about 0.2 percent. He also finds that extreme cold effects appear to be driven in part by low humidity, not cold per se. Curriero et al. (2002), in a study of eleven eastern cities in the United States using daily data, find higher mortality on very cold days and very hot days, with the negative impacts of hot days primarily occurring in northern cities.

Although the magnitudes estimated by these papers are substantial, they may be even larger in developing countries. When Burgess et al. (2011) repeat the same exercise as Deschênes and Greenstone (2011) for India, they find that an additional day with mean temperatures exceeding 36ºC, relative to a day in the 22–24ºC range, increases the annual mortality rate by 0.75 percent, about seven times larger than in the United States.[32] Interestingly, the mortality impacts of temperature in the United States in the 1920s and 1930s were also six times larger than the estimated impacts in the United States during more recent periods, as shown by (Barreca et al. 2013), who further find that the adoption of residential air-conditioning may explain this decline. These findings suggest that, should countries like India develop and gain widespread access to adaptation technologies (in particular, air-conditioning), the impacts of temperature on mortality may decline and more closely resemble those observed in developed countries today.

By focusing on total deaths over a period of several months or a year, many of the papers discussed here seek to address the impact of "harvesting," i.e., the idea that a particularly hot day may cause the death of someone who would have died shortly thereafter even in the absence of high temperatures. Evidence substantiates that such time shifting may be substantial: Deschênes and Moretti (2009), for example, use U.S. daily data on deaths matched with daily weather data to document that, for extreme heat events, much of the immediate mortality effect is offset by fewer deaths in the subsequent weeks. The same, however, does not apply in their sample for extremely cold periods. Similarly, Braga, Zanobetti, and Schwartz (2001) find persistent mortality effects from cold shocks in their time series study of twelve U.S. cities but, as above, substantial harvesting effects of heat shocks. Finally, Hajat et al. (2005) suggests that the harvesting effect of extreme heat may vary with income (and perhaps access to climate-control technology): they find only partial harvesting offset of heat in Delhi, somewhat more offset in Sao Paolo, and full offset in London.

The literature has identified a number of potential channels through which temperatures can have health effects. One is direct: extreme temperatures can directly affect health, particularly for those with preexisting respiratory or cardiovascular diseases. In addition, temperatures can also affect pollution levels, the rate of food spoilage—particularly in environments with low refrigeration—and potentially vector-borne

[32] While the temperature bins and empirical specifications in these two papers are somewhat different, Burgess et al. (2011) reestimate the U.S. results using the same empirical specification as they use for India and find qualitatively similar magnitudes for the United States to those reported in Deschênes and Greenstone (2011).

disease.[33] Each of these channels could have corresponding health effects. Temperatures can also affect incomes, e.g., through the channels outlined above (agriculture, labor productivity), which can in turn affect health.

Several papers examine these issues in the particular context of infant health. In U.S. data, Deschênes, Greenstone, and Guryan (2009) find that birth weight declines between 0.003 and 0.009 percent for each day above 30°C during pregnancy. Currie and Rossin-Slater (2013) find that exposure to hurricanes in Texas during pregnancy increase the probability of newborns being born with abnormal conditions or complications, though they find no impacts on birth weight or gestational age. In the developing world, Anttila-Hughes and Hsiang (2011) find that typhoons in the Philippines lead to substantial increases in infant mortality. Kudamatsu, Persson, and Strömberg (2012) pool Demographic and Health Survey data from twenty-eight African countries to examine the impact of prenatal weather on subsequent outcomes. They find impacts through two channels. First, they find that weather associated with the flourishing of malaria—sufficient rainfall, no very cold temperatures, and generally warm temperatures—during pregnancy is associated with higher infant mortality, particularly in areas where malaria is sometimes prevalent but not endemic. While they do not observe malaria directly in their data, three months higher predicted malaria exposure during pregnancy raises infant mortality risk by about three per thousand. Second, they find drought, which is likely to predict poor or delayed harvests and hence maternal malnutrition, leads to higher infant mortality, particularly in arid areas.

[33] We do not explicitly review the literature on the impacts of pollution on health; the interested reader should consult Graff Zivin and Neidell (forthcoming) for a review of that literature.

Looking in the long run, Maccini and Yang (2009) examine the implications of poor rainfall in the year of birth of Indonesian adults born between 1953 and 1974 on health outcomes in the year 2000. They find that women who experienced higher rainfall as infant girls (and likely therefore had better maternal and infant nutrition) are, as adults, taller, better educated, wealthier, and have higher self-reported health. This finding suggests that weather-induced poor nutrition as neonates and infants can have long-lasting effects.

While the focus here has been on those papers that use a panel empirical specification such as equation (3), there is also a large literature examining the impact of temperature and health (especially mortality) using other econometric approaches, such as focusing on heat waves or estimating distributed lag time series models within a set of cities, states, or countries. This literature primarily focuses on developed countries such as the United States, and each study typically considers a single or small group of cities or regions (See Basu and Samet 2002 for an extensive review). Consistent with the results discussed here, these studies generally find evidence for negative mortality effects of both extremely hot and extremely cold temperatures.

3.6 *Energy*

The literature has looked extensively at how climatic variables, in particular temperature, influence energy consumption. This relationship, which has received renewed attention in light of potential climate change, has long been important for the design of electricity systems, where demand varies with climate and weather. Understanding temperature effects matters for the energy consequences per se and for potential feedback loops, incorporated into some climatic models (see section 4.2 below), where energy demand influences greenhouse

gas emissions, which in turn affects future energy demand.

Most literature focuses on residential energy demand, where the relationship between energy consumption and temperature is naturally heterogeneous; namely, consumers demand heat when temperatures are cold and air-conditioning when temperatures are hot, so that the effect of an "unusually warm day" can either reduce or increase energy demand depending on the season or location. Separately, the energy–temperature relationship may naturally depend on the stock of heating and cooling equipment. Auffhammer and Mansur (2012) review the broad empirical literature; we focus here on panel model approaches.

Deschênes and Greenstone (2011) study residential energy consumption across the United States. Their panel model uses state–year observations from 1968–2002 and considers the number of days each state spends in nine different temperature bins. The regressions further control for precipitation and use time-fixed effects for each of eight census divisions. They find a clear U-shape relationship between energy demand and temperature, with an extra day below 10ºF or above 90ºF raising annual energy demand by 0.3–0.4 percent. The study further examines these relationships for different subregions of the United States and finds noisy distinctions between them.

Auffhammer and Aroonruengsawat (2011) examine household-level electricity consumption data in California from 2003–2006, using a similar panel design that examines temperature effects flexibly in different temperature bins. While the panel is limited to one state, the underlying dataset covers over 300 million monthly household observations. This large sample allows estimation of how the temperature–electricity demand relationship varies across different climate zones within California. This study broadly confirms the U-shape seen in Deschênes and Greenstone (2011), with similar magnitudes for increased energy demand from one additional day over 90ºF, although the shape changes across climate zones.

These panel-data papers, in using temperature bins, depart from a prior practice of using "heating degree days" (HDD) and "cooling degree days" (CDD), which count the number of days below and above a threshold temperature, with each day weighted by its temperature difference from the threshold. This degree-days approach misses the convexity found in the nonparametric approach, where extreme temperatures provoke much stronger energy demand increases. The convexity of the U-shape appears important both in getting the energy demand estimation correct and in light of climate change models, which show an increasing number of very hot days. Partly for this reason, Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011) find that the net effect of warming over the twenty-first century is likely to increase energy demand substantially, ceteris paribus, with these studies estimating 11 percent and 3 percent demand increases respectively.

Bhattacharya et al. (2003) show that there can be consequences of increased energy costs for other aspects of household budgets. Using the consumer expenditure survey, they find that low temperatures lead to higher fuel expenditures. For poor households, this in turn leads to a decline in food consumption. Richer households face even larger increases in energy costs than poor households in response to colder weather, but they do not report declines in food, presumably since they have a less tight budget constraint. The effects are stronger outside of the southern United States.

Similar panel studies have also been conducted outside the United States. In the United Kingdom, Henley and Peirson (1997) study space heating with a household panel in 1989–1990 and find that, netting out

household averages, demand for space heating declines with temperature and especially over the 10–20ºC range. Across Europe, Eskeland, and Mideksa (2010) study residential electricity consumption in thirty-one countries over ten years, with approximately 250 country–year observations. Using the "degree days" measure of temperature, they find that a one unit increase in CDD increases electricity consumption by about four times as much as a one unit increase in HDD.

Collectively, the aforementioned panel studies find some agreement in how residential energy demand responds to temperature in relatively rich countries over the short run. Several opportunities for further study are clear. One large opening in the literature concerns panel studies outside relatively rich countries.[34] Such studies appear important for understanding global energy demand responses, especially given that the penetration of heating and cooling technologies in poor countries is low.

Related, longer-run warming may lead to more installation of cooling technologies. Panel studies that isolate air-conditioning adoption, and the heterogeneity of adoption by income, will be important for understanding energy demand and, separately, adaptive mechanisms. To the extent that cooling appliances attenuate other climatic effects, including effects on labor productivity, industrial output, and health as reviewed above, the biggest question here may be less about the costs of increased energy demand and more about the adaptive benefits such energy appliances may provide. Integrating across the studies above, one (speculative) description of mechanisms may note that in rich countries, high heat raises energy demand but does not reduce GDP, while in poor countries, GDP and sectoral losses appear large. To the extent that cooling technologies decouple heat from productivity in many sectors, energy demand increases may signal important adaptive responses—but ones that are largely unavailable in much of the world. Increased energy demand may, meanwhile, further exacerbate climate change.[35] These issues appear first-order for future research in this area.

3.7 *Conflict and Political Stability*

The relationship between weather and conflict/political stability has generated an explosion of research over the past decade, providing extensive panel evidence for a weather–instability link.[36] In an early panel-data contribution, Miguel, Satyanath, and Sergenti (2004) examined

[34] Two recent studies use panel data that encompasses poorer countries, but analyze it using time-series techniques rather than fixed effect models. In China, Asadoorian, Eckaus, and Schlosser (2008) study a panel of Chinese provinces from 1995–2000, looking at residential energy use and appliance adoption in addition to nonresidential energy use. Dividing their sample into urban and rural areas, the panel includes approximately 150 urban province–year observations and approximately sixty rural province–year observations. This study works to identify price and income effects, in addition to temperature effects, and the temperature findings prove noisy. Finally, De Cian, Lanzi, and Roson (2013) study a panel of thirty-one countries worldwide from 1978–2000 at the country–year level, although the analysis uses an error correction model rather than a panel model with country and time fixed effects.

[35] Wolfram, Shelef, and Gertler (2012) examine the Oportunidades cash transfer scheme in Mexico and document large increases in purchases of electric appliances (e.g., refrigerators) with income. They suggest that many developing countries are near the point in income space where many households will soon acquire these cooling products, which would lead to an increase in electricity consumption and presumably a much larger electricity–temperature response gradient.

[36] Conflict can be defined in a variety of ways. For example, conflict is often defined for empirical research as occurring when total battle deaths in a country fall above a given threshold. However, it can also be defined using more disaggregated measures, such as the number of battles, violence against civilians, riots, and rebel recruitment (all recorded in the ACLED conflict database), or using other measures specific to a given context.

the relationship between changes in rainfall and civil conflict in forty-one sub-Saharan African countries between 1981 and 1999. This study finds that lower rainfall growth led to more conflict and also documents that economic growth is lower when rainfall growth is lower. It posits a mechanism through which low rainfall leads to a negative economic shock, which in turn spurs conflict. Subsequent panel work by Burke et al. (2009) finds that higher temperatures also lead to higher conflict incidence in Africa, with 1ºC higher temperatures increasing civil conflicts by 4.5 percentage points (49 percent of the mean).

Moreover, weather shocks also plausibly impact political stability. For example, Burke and Leigh (2010) and Bruckner and Ciccone (2011) document that weather shocks appear to lead to democratization. Dell, Jones, and Olken (2012) show that adverse temperature shocks increase the probability of irregular leader transitions (i.e., coups).

The relationship between weather and conflict/political stability documented in cross-country analysis has been supported by several studies exploiting subnational variation in weather. Hidalgo et al. (2010) document that low rainfall shocks in Brazilian municipalities between 1988 and 2004 led the rural poor to invade and occupy large landholdings. Bohlken and Sergenti (2010), using an approach similar to Miguel, Satyanath, and Sergenti (2004), find that negative rainfall shocks increase Muslim–Hindu riots in Indian states. Both of these studies posit reduced incomes as a mechanism. Using a panel specification, Fjelde and von Uexkull (2012) find that negative rainfall shocks increase communal conflict in subnational regions in Africa, particularly in areas dominated by groups outside the political mainstream. Similarly, in Somalia between 1997 and 2009, Maystadt, Ecker, and Mabiso (2013) document that droughts increased local conflict.

Evidence for a weather–conflict nexus exists across many centuries.[37] Both Kung and Ma (2012) and Jia (forthcoming) show, using panel analysis, that across four centuries, suboptimal rainfall triggered peasant rebellions in China. Nevertheless, Confucianism appears to have partially mitigated these effects (Kung and Ma 2012), and technological innovation—in the form of the introduction of drought-resistant sweet potatoes—weakened them further.[38] Similarly, Dell (2012) finds that municipalities in Mexico that experienced more severe drought in the early twentieth century were more likely to have insurgency during the Mexican Revolution than nearby municipalities with less severe drought.

Despite the large number of panel studies that find important weather effects on conflict and political stability, panel results have not been fully unambiguous, particularly for precipitation. For example, Couttenier and Soubeyran (forthcoming) find, using a standard panel specification, that the Palmer Drought Severity Index is positively related to conflict at the country level in sub-Saharan Africa between 1957 and 2005 when they control for linear weather variables, whereas the linear weather variables alone are not significantly correlated with conflict. Ciccone (2011) argues that the relationship between rainfall and conflict in sub-Saharan Africa appears weaker when the data is extended to 2009, though Miguel and Satyanath (2011) note in reply that the first stage between rainfall and economic growth also does not appear to hold in the 2000–2009 period. A

[37] Anderson, Johnson, and Koyama (2013) show, using a decadal level panel from 1100–1800, that colder growing seasons led to greater expulsion of the Jewish population from European cities during the sixteenth century.

[38] There also exist a number of studies of specific civilizations over centuries or millennia that suggest that adverse shifts in weather can lead to the collapse of civilizations. Because these are not panel studies, they fall beyond the scope of this paper, but the interested reader is referred to Hsiang, Burke, and Miguel (2013) for a review.

number of studies that are not fully identified from within-location deviations from means have also found conflicting results.[39]

The reasons for differences in this literature have been difficult to isolate for several reasons: conflict and weather shocks can be parameterized in many different ways; some studies have omitted fixed effects and included potentially endogenous controls; inference does not always account for spatial correlation; and weather measures in different datasets—for rainfall in particular—may only be weakly correlated in regions with few weather stations (Auffhammer et al. forthcoming).[40] Beyond differences in specification and data, heterogeneity is also likely to be at play. Weather shocks typically do not lead to civil conflicts in wealthy, stable countries, and in the world as a whole, weather shocks are not strongly related to civil conflict (Dell, Jones, and Olken 2012). Moreover, many of the estimates in this literature are quite noisy, making it difficult to assess whether a statistically insignificant effect is a noisily measured zero or a noisily measured large effect.[41]

To examine this issue systematically, Hsiang, Burke, and Miguel (2013) conduct a reanalysis of all empirical studies of weather and intergroup conflict whose empirical analysis can be specified as fixed-effect panel regressions of the form in equation (3). All twenty-one estimates of temperature in the reanalysis are positive. While not all estimates are statistically significant, they argue that these coefficients would be very unlikely to arise by chance if the true impact of temperature on conflict were zero or negative. Rainfall is more difficult to assess, since in some studies the focus is on negative deviations (low rainfall), in others it is on positive deviations (high rainfall), and yet others use absolute deviations or more complicated drought indices. Nevertheless, sixteen of eighteen studies reviewed predict that anomalous precipitation events increase conflict (although again, not all produce statistically significant estimates). Overall, the study calculates that on average, a one standard deviation change in weather variables generates a 14 percent change in the risk of group conflict ($p < 0.001$).

The studies discussed here and the meta-analysis by Hsiang, Burke, and Miguel (2013) in particular provide compelling evidence that weather affects conflict across a variety of different contexts. These results underline the importance of further examination of open questions in the literature relating to mechanisms, heterogeneity, harvesting, and which types of weather shocks matter most. Further subnational studies, which can employ detailed disaggregated data, may be particularly useful in improving our understanding of these open questions.

[39] For example, consider the following studies using variation across 1, 0.5, or 0.25 degree grid cells in Africa. Harari and La Ferrara (2013) document that between 1997 and 2011, droughts during the growing season increase conflict. In contrast, O'Loughlin et al. (2012) find that in East Africa, droughts have no impact on conflict, wetter precipitation deviations reduce conflict, and higher temperatures increase conflict. Using a gridded analysis for Kenya, Theisen (2012) finds, in contrast to other papers, that low rainfall seems to reduce conflict in the following year, with no clear impacts of temperature. Finally, Theisen, Holtermann, and Buhaug (2011) find no relationship between precipitation and conflict. None of these studies include grid cell fixed effects, allowing potentially confounding correlates with weather across geographic areas to influence the regression findings. Moreover, three of these four studies do not account for high spatial correlation across grid cells and they use different sources of rainfall data (interpolated versus reanalysis) that may be only weakly correlated. When Hsiang, Burke, and Miguel (2013) rerun these analyses using cell fixed effects, excluding endogenous controls and adjusting the inference for spatial correlation, they find strong evidence that temperature affects conflict, as well as evidence for drought impacts, whereas evidence for linear precipitation effects is weak (see their supplementary appendix for more details).

[40] Note that the exclusion of fixed effects and inclusion of endogenous controls is often intentional in these studies because the coefficients on the controls are themselves of interest.

[41] For example, Theisen, Holtermann, and Buhaug (2011) do not find statistically significant weather effects, but due to large confidence intervals, large effects cannot be ruled out.

First consider mechanisms: because extreme weather events lead output to decline, they potentially lower the opportunity cost of engaging in violence or in protest against the government. Moreover, a decline in economic output could decrease government revenues, in turn reducing state capacity to maintain security. Increased food prices may lead to widespread food riots that spill over into broader political instability, and weather-induced migration could potentially lead to conflict as well. Weather shocks could also directly impact conflict through changing the environment—i.e., making roads more or less passable (Fearon and Laitin 2003)—or through altering the bioneurological regulation of aggression (see below). Related to the mechanisms issue is heterogeneity: the broader political and economic circumstances that lead extreme weather to trigger instability in some places but not others remain poorly understood.[42] Finally, our understanding remains limited concerning the extent to which weather events create conflicts that would not otherwise occur, as opposed to impacting the timing at which latent conflicts surface. This issue, which is akin to the questions about harvesting discussed in the health section, is important for assessing the likely conflict impacts of climate change.[43]

3.8 *Crime and Aggression*

The idea that temperature affects the proclivity for aggression directly is an old one, also dating back to at least the Ancient Greeks.[44] During the 1960s, U.S. government officials noted that riots were more likely to occur in warmer weather, and subsequent analysis confirmed this relationship (U.S. Riot Commission 1968; Carlsmith and Anderson 1979). In analysis of detailed data from the Dallas police department, Rotton and Cohn (2004) find that the relationship between outdoor temperature and aggravated assault is substantially weaker in locations that are likely to be air conditioned. Experimental evidence has linked temperature to horn honking (Kenrick and MacFarlane 1986) and aggression by police officers (Vrij, Van der Steen, and Koppelaar 1994). By contrast, a link between precipitation and crime has been less evident in the criminology literature (see Wright and Miller 2005), although this link may be stronger in locations where precipitation exerts important impacts on income, as discussed below.

A small number of rigorous panel studies relate weather fluctuations to crime. Using a fixed effects panel specification, Jacob, Lefgren, and Moretti (2007) find that higher temperatures in a given week increase both violent and property crime in the United States during that week, whereas higher precipitation reduces violent crime but has no impact on property crime. Using a fifty-year panel of monthly crime and weather data for nearly 3,000 U.S. counties, Ranson (2012) also finds that increased temperatures lead to increased criminal activity. He finds roughly linear positive effects of temperature on violent crimes. For property crimes, he finds that very cold days (below 40°F) reduce property crimes, but very hot days do not increase them. Together, these studies and the evidence discussed above suggest that weather has an immediate effect upon criminal activity, particularly for violent crime. Some researchers have argued for a biological pathway through which temperature affects serotonin neurotransmission in the brain, influencing impulsivity and aggression (see for example Tiihonen, Räsänen, and Hakko 1997), but

[42] See Tutino (1989) for an excellent discussion of the reasons for heterogeneous responses of conflict to weather shocks in Mexico historically.

[43] Hsiang, Meng, and Cane (2011) find suggestive but statistically insignificant evidence that around 40 percent of the conflict episodes associated with El Nino are displaced in time.

[44] See p. 25 in Andaya (1993).

this hypothesis remains controversial (see, for example, Maes et al. 1993). Whether the temperature–aggression nexus occurs via neurological or social-psychological channels remains an important area of research in criminology, and studying potential linkages between aggression mechanisms and broader social conflict (section 3.7) is an interesting subject for further research.

Weather might also impact crime and aggression through its effects on income. Miguel (2005) documents that extreme rainfall events increase the murder of "witches" (typically elderly women) in Tanzania, hypothesizing that negative income shocks induced by rainfall lead households to seek to remove or kill relatively unproductive family members. Oster (2004) finds that cold weather increased witch trials in sixteenth–eighteenth century Europe. Using time series analysis, Mehlum, Miguel, and Torvik (2006) find that low rainfall in nineteenth-century Bavaria increased crime via increasing the grain price (hence reducing real wages for consumers). Sekhri and Storeygard (2011) document that dowry killing—the murder of a woman for failing to bring sufficient dowry—has been higher in India in recent years during periods of low rainfall.

3.9 *Other Channels*

This section reviews two other channels in the climate–economy interface that are potentially important but, to this point, have been the subject of comparatively few studies exploiting weather shocks. We first consider international trade. We then briefly discuss effects on innovation.[45]

Market integration has the potential to influence weather-shock sensitivity. Trade can, in principle, dampen or exacerbate local effects of productivity losses. By muting the price effects of local productivity shocks, access to foreign markets could help local consumers (who can still access products at low prices) but hurt local producers (who cannot raise prices). At the same time, foreign consumers and producers may experience more diffuse but opposing effects. Several studies discussed above shed some preliminary light on these issues. Burgess and Donaldson (2010), using annual data for 125 Indian districts, show that, while famine intensity historically in India is strongly associated with low rainfall, this famine–rainfall link is essentially eliminated in Indian districts that had access to railroads. Thus, for mortality, market integration may have substantially reduced the negative local effects of local weather shocks. Jones and Olken (2010) show that temperature shocks in poor countries reduce their exports to rich countries across a wide variety of agricultural and industrial goods. This finding is consistent with local producer losses due to the weather shocks. It also indicates that losses can be exported to consumers in other countries, although the effects for the individual foreign consumer may be small if there are many substitute providers.

Another potentially first-order adaptation mechanism is innovation. Miao and Popp (2013) study patenting in response to natural disasters using a panel of thirty countries over twenty-five years. They study earthquakes, floods, and droughts, and count patents in relevant technologies. They find, for example, that an additional $1 billion in economic losses from drought in the past five years increases current patent applications regarding drought-resistant crops by approximately 20 percent. Similarly large effects on patenting are found for earthquakes and floods. While the effectiveness of these patents is not clear, this study suggests that innovative activity does respond causatively to weather shocks, an important area for ongoing study.

[45] Note that the subject of migration is discussed elsewhere; we discuss this topic in section 3.2 when reviewing the agriculture literature and return to it again in section 4.1.2 when discussing labor reallocation as a possible adaptation mechanism.

3.10 *Summary: Weather and the Economy*

The previous sections have documented many ways in which weather fluctuations affect economic activity, from agriculture, to labor productivity, to health and conflict. These estimates provide rigorous econometric evidence that weather—temperature, precipitation, and events such as windstorms and droughts—has manifold effects on economic activity. Poor economies appear particularly vulnerable to detrimental weather effects, while certain demographic groups, such as children and the elderly, appear especially sensitive on health-related dimensions.

The unusual identification opportunity provided by weather shocks has allowed a rigorous analysis of weather–economy linkages, and implications for breadth, heterogeneity, and functional forms. While much work remains in developing a detailed understanding of the underlying mechanisms, especially for macroeconomic and political economy outcomes, the new literature shows that weather variation has substantive effects in contemporary periods. This begins to suggest policy targets, whether the goal is preventing substantial economic damages or protecting public health and security.

4. *What Does All This Mean for Thinking about Global Climate Change?*

The recent explosion of literature concerning climate–economy relationships has largely been sparked by a desire to inform the potential consequences of global climate change. According to the fourth assessment report from the Intergovernmental Panel on Climate Change (Solomon et al. 2007), which takes a mean estimate across many climate models, global temperatures are expected to rise from 1.8 to 3.1ºC over the twenty-first century, depending on the emissions scenario. At the same time, the same climate models predict a wide range of potential outcomes, even for a given emissions scenario, with a substantial upper tail globally and substantial regional uncertainties, so the range of potential outcomes is substantially higher. Some countries will naturally experience larger changes than the global mean. Moreover, these climate changes will not be limited to increased temperatures: climate change is expected to alter precipitation patterns and lead to changes in the frequency and location of intense storms, as well as other changes such as rising sea levels.

Given the substantial changes in climate that are forecast in many climate models and the intense global policy discussion about what policies can be undertaken in response, there has been substantial interest in understanding the economic consequences of potential climate changes. In section 4.1, we explore ways in which the estimates we have reviewed above—i.e., those estimates based on short-run fluctuations in weather—can and cannot be used to inform thinking about global climate change. In particular, we discuss methodological innovations for creating tighter linkages between panel estimates, which are typically estimated based on short-run weather shocks and changes over longer periods. In section 4.2, we then review the current economic approaches used to forecast economic consequences of climate change—primarily Integrated Assessment Models (IAMs). We discuss how such models could potentially be modified to incorporate the recent advances in econometric estimation of weather impacts reviewed here.

4.1 *From the Short to the Long Run: The Econometrics of Adaptation, Intensification, and Other Issues*

4.1.1 *Conceptual Issues in Moving from Short to Long Run*

To begin, return to the econometric framework in section 2.1. Suppose now that

the structural equation of interest—i.e., the analogue of equation (1), is

$$\mathbf{y}_{it} = f(\mathbf{C}_{it}, \mathbf{X}_{it}, t), \tag{4}$$

where $\mathbf{C}_{it}$ represents the distribution of climate variables in country or region i, and t indexes time, say from today until the year 2100. The key change from equation (1) is that we no longer require the climate (defined as the distribution of weather outcomes) for place i to be stationary; instead, the distribution of outcomes (i.e., the climate) changes over time. We are interested in how alternative realizations of the climate variables $\mathbf{C}_{it}$ will result in different economic outcomes.

Conceptual Issues with Estimates Based on Cross-Sectional Models

How does the structural equation of interest in (4) compare to various econometric equations that we could estimate? For example, suppose we estimate the cross-sectional equation

$$y_i = \alpha + \beta \mathbf{C}_i + \gamma \mathbf{X}_i + \epsilon_i . \tag{5}$$

Even abstracting from the identification issues discussed in section 2 (i.e., the fact that there may be omitted variables such that $\mathbf{C}_i$ is correlated with ϵ_i), the estimated β from equation (5) is not directly applicable to the climate change structural equation in 4.1.1. Why? Because even to the extent that (5) identifies the causal impact of climate on the cross-sectional outcome, y, the cross section may incorporate very long-run mechanisms that are unlikely to come into play over the next one hundred years.

For example, Acemoglu, Johnson, and Robinson (2001) argue that the patterns of colonialism and subsequent economic development were influenced by the mortality rates experienced by colonial settlers when they first arrived in new territories during the sixteenth through nineteenth centuries. These mortality rates were influenced by the local disease environment, which in turn was influenced by local climate. Therefore, some of the impact of climate that one would estimate in the cross-sectional equation in (5) might include this settler mortality channel. Yet, if climate changes over the next one hundred years, that particular channel will not be part of the impact—the era of colonialism is over, and a country's colonial origins are fixed, so institutions will not be affected by climate today in the same way they were in the era when settlers arrived. The same is likely true for a variety of other "deep historical" mechanisms that determine the cross-sectional relationship between climate and income, such as the date of adoption of agriculture. Thus, even in the absence of omitted variables that are correlated with climate purely by chance, cross-sectional estimates from (5) are unlikely to provide an adequate estimate of how climate change over the next 35, 75, or even 150 years will affect economic outcomes. Within-country cross-sectional analysis (such as Dell, Jones, and Olken 2009) suffers from the same critique, where the historical equilibrium they represent may depend on mechanisms that no longer act in the same way.

Conceptual Issues with Estimates Based on Panel Models

By contrast, panel models, as in equation (3), precisely estimate the impact of a weather shock on economic outcomes. Moreover, panel models typically estimate the impact of a weather shock in contemporary data. The panel approach thus emphasizes weather's current—as opposed to long-run—impacts, in addition to its broader identification advantages.

However, short-run changes over annual or other relatively brief periods are not necessarily analogous to the long-run changes in average weather patterns that may occur

with climate change. That is, the effect of 1ºC higher temperature in a given country in a given year, as estimated by equation (3), may have different effects than raising the average temperature of that country by 1ºC as in equation (4). Indeed, there are several reasons why the panel estimates may not be directly applicable to estimating the economic impacts of climate change over the medium or long run. We briefly lay out the potential issues in this section; section 4.1.2 then considers how these issues can be addressed within the context of panel-type estimates discussed in this paper.

Adaptation. A key issue is adaptation. If the climate changes, agents may ultimately adapt economic production processes to the new environment. Given enough time, adaptation may occur not only by adjusting among a set of existing technological opportunities, but also through technological change. Government institutions and policy, including policies around public goods, innovation, and market integration, may also play important roles in the degree and nature of adaptive responses. Examples abound: snowfalls that occasionally paralyze southern U.S. states are minimally disruptive in New England, where such events are experienced regularly and where (costly) investments in snow removal processes have been made. In that sense, the estimated coefficient β on a snowfall shock may not estimate the long-run effect of a shift in climate to more snowfall. As another example, regarding innovation, the Canadian Experimental Farms, under Canadian government auspices, successfully developed wheat varieties in the late nineteenth century that were more suitable to Canadian farming conditions (Ward 1994). See also Miao and Popp (2013) regarding innovation around natural disasters. Adaptation suggests that the short-run panel estimate of a weather shock β from equation (3) may not be the long-run impact of a permanent change in climate of the same magnitude.

Intensification of climate effects. A second, countervailing force is intensification. Climatic changes may cause damages that are not revealed by small or fleeting weather changes. Consider, for example, agriculture. A drought in a single year may have little effect if there are ample stores of water available in a reservoir. On the other hand, if the amount of rainfall permanently decreases and the reservoir eventually runs dry, then the supply of water to agriculture will fall substantially, with concomitant impacts on economic activity.[46]

General equilibrium effects. The previous two issues—adaptation and intensification—could be relevant for an isolated production process; a single farmer, for example. A third class of issues involves macroeconomic effects, including general equilibrium adjustments of prices and factor reallocations. For example, labor and capital will likely move in response to long-run climate damages. If both labor and capital are mobile, then this type of macroeconomic readjustment could reduce the long-run impacts of climate change relative to a short-run panel estimate (although any such tempering of the impacts would depend on moving costs, the extent to which the marginal product of capital is location specific, and potentially a host of other factors). If, by contrast, capital is mobile but labor is not (e.g., due to restrictions on international migration), then the effects could be reversed: in the long run, capital outflows from areas that experience negative productivity shocks would further reduce the marginal product of labor there.

Extrapolation beyond historical experience. A final issue is the degree to which the observable weather variation incorporates the range of changes that may occur

[46] Desertification would be an example of potentially substantial economic damages through an intensification process.

in the future. Average annual temperatures in a country are almost never more than 2ºC from their long-run historical mean (Dell, Jones, and Olken 2012). While temperature changes over the next thirty years will plausibly be within this range (recall the IPCC middle estimates were between 1.8–3.1ºC by 2100), the ninety-fifth percentile estimate is warming of 7ºC by 2100. If the impacts of climatic variables are linear throughout this range, then extrapolation is not an issue per se. However, if there are nonlinearities that are different from those operating within historical experience, one cannot directly extrapolate from equation (3) to climate scenarios far outside this range. This issue suggests a limited capacity for panel models to provide quantitative estimates of damages from extreme warming. In the plausible scenario in which extreme warming introduces additional costs (i.e., the costs are convex in warming), linear extrapolation from panel model evidence, suitably adjusted to confront the other issues discussed above, would provide a lower bound on future damages.

These issues highlight that, even though panel models of the form of equation (3) correctly identify the causal effect of weather shocks on contemporaneous economic outcomes, they may not estimate the structural equation of interest for understanding the likely effects of future global climate change. Moreover, even leaving aside the potential of catastrophic climate scenarios, such as rapid sea-level rise or the release of methane from melting permafrost that could greatly increase global temperature, the panel estimates are neither obviously an upper bound nor a lower bound for the effect of climate change. If the adaptation force dominates, then the effects of weather shocks will tend to be larger than the effects of climate change; if the intensification force dominates, then the effects of weather shocks will tend to be smaller than the effects of climate change.

4.1.2 *Empirical Approaches for Moving from Short to Long Run*

Delving more deeply into panel-based estimates, one can make progress on a number of the important issues outlined above. This section outlines the variety of empirical techniques through which panel approaches can still be used to say something sensible (if not definitive) about likely effects of climate change, and then reviews the attempts thus far to do so.

We examine several empirical approaches. First, different geographic areas have different baseline climates. An unusual weather shock in one area is often well within normal experience in another area, where adaptation has had the opportunity to occur. Comparing these areas by interacting weather shocks with the existing distribution of weather events can help assess the magnitude of adaptation. Second, one can examine long differences; i.e., instead of looking at annual shocks, one can examine average impacts over longer time horizons, such as decades. Third, one can focus on particular permanent shocks and trace out their impacts over many years. Fourth, combining the previous two methods with short-run panel estimation, one can explicitly compare the same event at different time scales to assess the degree of adaptation. Fifth, one can extend panel models to explicitly examine spillovers of weather shocks. We examine each of these mechanisms in turn.

Interactions with the Existing Distribution of Weather Events

One way to learn about adaptation is to examine the range of climate distributions available today, which vary greatly. In fact, the range of experience is substantial even within a given location. For example, consider New York City. Figure 2 plots the distribution of maximum daily temperatures for New York's Central Park between

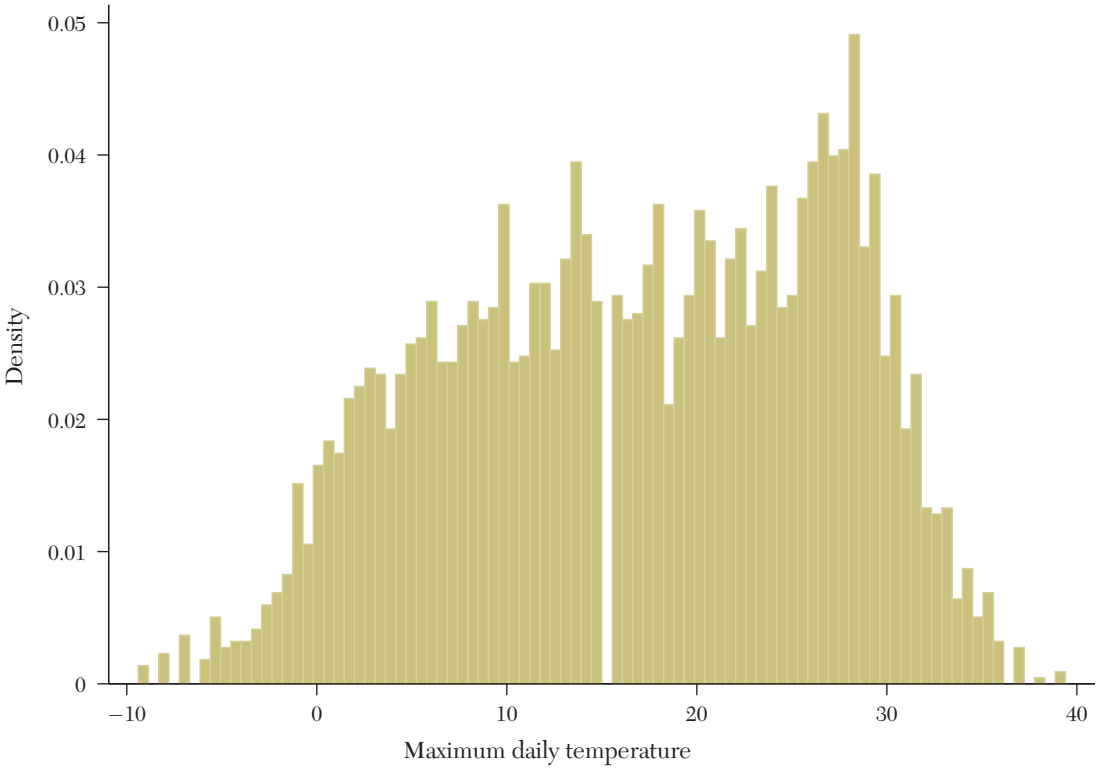

Figure 2. Maximum Daily Temperatures in New York's Central Park

Note: Data is from 2000–2010.

Source: Authors' calculations based on data from GHCN daily summaries.

2000–2010 and shows that, like many places, New York City experiences a wide range of average daily temperatures across seasons and years. The 1st percentile day in New York has a maximum temperature of –4.5ºC (that is, about thirty-five days per decade are colder than –4.5ºC). The 99th percentile day in New York has a maximum temperature of 35ºC—and New York has experienced days up to 40ºC, even though such days are rare.

A first observation is that future climate change represents a shift in the stochastic distribution of degrees that may sit largely within the support experienced historically. This distributional overlap is expected to be particularly strong when looking at temperate climates that already experience a range of temperatures during a year and when examining shorter horizons—i.e., 2050 instead of 2150. While some temperatures expected under global climate change would be novel (e.g., days with maximum temperatures exceeding 42ºC, which did not occur in the decade shown in figure 2) much of the expected shift from moderate climate change in temperate zones within a given year will occur at temperatures that are within the historical range.

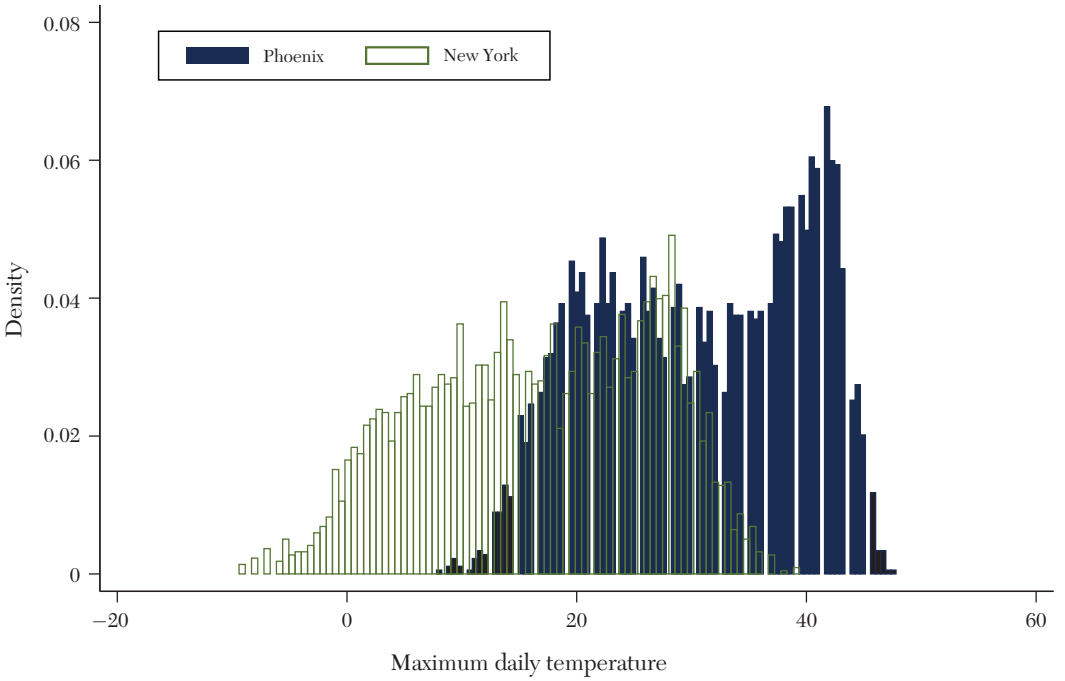

Figure 3. Maximum Daily Temperatures in Phoenix, Arizona, compared to New York's Central Park

Note: Data is from 2000–2010.

Source: Authors' calculations based on data from GHCN daily summaries.

This observation is important because, with sufficiently fine data, econometric models can estimate the impact within precise weather bins. Depending on the locus of impacts, one may then make some inference about adaptation. For example, when weather-based models find effects within existing ranges and one is interested in climate change effects within these ranges, one could argue that the scope for adaptation may be somewhat limited. As shown in the figure, New York has had much opportunity to adapt to a wide range of temperatures. Therefore, should there be weather effects within this historical range, say at 28ºC, which New York experiences quite frequently already, one might expect those effects to continue. Conversely, if one found effects in the weather bins that are rare (e.g., in the New York example, temperatures over 39ºC), one may suspect that the impacts might change as such rare events became more frequent and agents adapted.

In this stylized example, we considered a single location: New York City. Suppose we see substantive effects in New York when temperatures exceed 39ºC, which is currently rare. For a single place, one cannot know for sure if the effects of such rare events will persist when they become more

common, or whether they will attenuate substantially through adaptation. However, with multiple locations, one can begin to make progress on understanding the possibility of adaptation to such events. For example, figure 3 shows the temperature distribution of New York City overlaid with that of Phoenix, Arizona.

As is evident from the figure, the extreme 39ºC day in New York (which occurs just a few days each decade) is well within the normal range for Phoenix (where it occurs forty days per year). This variation allows one to test for adaptation econometrically. Specifically, one can modify the standard panel specification in equation (3) to estimate a model of the form

$$(6)\quad y_{it} = \beta \mathbf{C}_{it} + \gamma \mathbf{Z}_{it} + \nu \mathbf{C}_{it} \times \mathbf{C}_{i0} + \mu_i + \theta_{rt} + \varepsilon_{it},$$

where the $\mathbf{C}_{it}$ variables are weather shocks specified in narrow ranges and the $\mathbf{C}_{i0}$ variable captures the average initial conditions; in the example above, the long-run historical frequency with which a given temperature tends to occur. In taking this approach, it is important to recognize that $\mathbf{C}_{i0}$ is a fixed characteristic of place i. To the extent that $\mathbf{C}_{i0}$ is correlated with other characteristics of place i—which creates an interpretative issue for the cross section, as discussed above—one may also want to control for the interactions of those other characteristics with the climate shocks.

Several studies pursue versions of this approach. For example, Deschênes and Greenstone (2011) estimate the impact of temperature on mortality throughout the United States. They begin by estimating the weather panel model, as in equation (3), but broken up into temperature bins. They find evidence of nonlinearities—each day above 90ºF is associated with about one more death per 100,000 population, but find no impacts of days in the 80–90ºF range relative to cooler days. While they find heterogeneity across the nine U.S. census regions in the responsiveness to hot days, this heterogeneity is not systematically related to average temperatures in each of those nine regions, suggesting that adaptation to higher average temperatures does not substantially affect the mortality response.[47]

Dell, Jones, and Olken (2012) take a similar approach when studying the impact of temperature on economic growth. Rather than break temperature up into fine bins, the paper estimates a coarser version of (6) in which annual temperature shocks are interacted with a country's average temperature level. They find no evidence that hot countries experience systematically different impacts of temperature shocks on economic growth, once one controls for a country's average income level, though they note that temperature and income are correlated in the cross section, so this relationship is hard to tease out empirically.

A related approach is taken by Schlenker and Roberts (2009), who use fine temperature bins to estimate nonlinear effects of temperature on crop yields in the United States. They find a sharp nonlinearity, with negative impacts of temperature above 29ºC for corn, 30ºC for soybeans, and 32ºC for cotton. If farmers can adapt to permanently higher temperatures by growing different varieties, one would expect yields in the South to be less sensitive to extreme

[47] This paper regresses the estimated coefficient β from equation (3) in each of the nine census regions on the average number of days above 90ºF in that region. In principle, one could obtain more power by estimating the regression using much finer gradations in average temperatures across the United States.

heat. In general, however, they find similar results in northern and southern states.[48]

Similar analyses can be used for the other types of weather-related events (e.g., precipitation and windstorms). One example is found in Hsiang and Narita (2012), which examines the impact of tropical cyclones. They estimate equation (6), where the key weather variable ($\mathbf{C}_{it}$) is the intensity of a given tropical cyclone, the key climate variable is the average intensity of tropical cyclones experienced by a country ($\mathbf{C}_{i0}$), and the dependent variables are economic damages (normalized by GDP) and deaths (normalized by population). In both cases, they find statistically significant evidence of adaptation—that is, the coefficient ν in (6) indicates that the marginal effect of higher windspeed in a cyclone is lower in those places that more frequently experience higher windspeeds. However, this adaptive magnitude is small—they estimate that only 3 percent of the estimated impact of increased tropical cyclones will be "adapted away" in the long run.

While there is no theorem that the effect of adaptation in one context will apply to another context—e.g., there is no a priori reason that farmers' inability to adapt by using different corn seed technologies necessarily tells us anything about adaptation to prevent mortality from heat waves or adaptation from tropical cyclones—a notable similarity among the papers reviewed in this section is that the effects of extreme weather events do not appear to be limited to those areas that experience them only rarely. This approach seems generally useful, and more research is needed along these lines.

Interactions with Lags of Weather Events

A related econometric approach can be used to shed light on the question of intensification. Specifically, if the effects build over time, then the structure of the weather shocks can be used to examine this possibility; for example, one can examine whether the effect of a drought in year t will be different if years $t-1$ through $t-5$ were also droughts than if years $t-1$ through $t-5$ had normal climate. This possibility can also be estimated as an interaction, but instead of interacting the weather variables with the long-run averages (in equation (6)), the weather variables are interacted with their own lags, i.e.,

$$(7)\quad y_{it} = \rho y_{it-1} + \beta \mathbf{C}_{it} + \sum_{j=t-K}^{t-1} \beta_j \mathbf{C}_{ij} + \gamma \mathbf{Z}_{it} + \sum_{j=t-K}^{t-1} \omega_j \mathbf{C}_{it} \times \mathbf{C}_{ij} + \mu_i + \theta_{rt} + \varepsilon_{it}.$$

The key coefficients for estimating intensification are the ω_j, which examine whether the impact of a given shock depends on the pattern of previous shocks.

While we are not aware of existing panel analyses along these specific lines, this approach provides an opportunity to let the data speak to intensification concerns. An alternative approach is to assert a functional form for intensification; for example, drought indices that seek to capture the soil moisture balance—such as the commonly used Palmer Drought and Palmer Hydrological Drought indices—take cumulative events into account, so that the measured intensity of drought during the current month

[48] This does not imply that no adaptation is possible. Olmstead and Rhode (2011) show that North American wheat producers have made substantial adaptations between 1839 and 2009, shifting where they grew their wheat. The median annual precipitation in areas growing wheat in the United States and Canada in 2007 was one-half that of the areas growing wheat in the 1839 distribution, and the median annual temperature in wheat-growing areas in 2007 was 3.7°C lower than in wheat-growing areas in 1839. This shift, which occurred mostly before 1929, required new biological technologies, as well as human capital (immigrants from Eurasia) skilled in growing wheat in cold, arid climates.

depends on current weather patterns, plus the cumulative patterns of previous months.

Long Differences

Another econometric approach to estimating adaptation or intensification effects is to estimate the same basic panel specification, but over a longer period. To see this, start with equation (3) and take, for example, decade-long averages.

This yields the exact same econometric specification as (3) but expressed in decades (d) rather than years (t):

$$(8) \quad y_{id} = \beta \mathbf{C}_{id} + \gamma \mathbf{Z}_{id} + \mu_i + \theta_{id} + \varepsilon_{id}.$$

One could also take longer or shorter averages.

Although the econometric equation in (8) is similar to equation (3), substantively they are different; by averaging the weather variables, **C**, one is now moving closer to identifying medium-run impacts. To the extent that these averages represent longer-run changes (e.g., those induced by climate change), longer differences may begin to incorporate the adaptation or intensification effects discussed above.

For example, Dell, Jones, and Olken (2012) consider a fifteen-year average specification in studying the effect of temperature on economic growth. That paper estimates (8) with two time periods, 1970–1985 and 1985–2000, and exploits medium-run variation, where many countries' temperatures increased only slightly (e.g., Laos, Kenya, and Nigeria), whereas many others experienced increases in average temperatures of around 1ºC (e.g., Tunisia, Zambia, and Botswana). While the results are not as statistically precise as the results based on annual variation, this study finds larger negative impacts of temperature increases on economic growth in poor countries in the longer-difference specification (around 2 percentage points lower economic growth per ºC in poor countries; compared with around 1 percentage point lower economic growth per ºC in the baseline annual specification), suggesting that, if anything, intensification outweighs adaptation among poor countries.[49]

Burke and Emerick (2013) pursue an analogous econometric approach in studying U.S. agriculture. They estimate a version of equation (8), comparing the 1978–1982 average with the 1998–2002 average, exploiting substantial heterogeneity in temperature changes over this period, with some counties cooling by 0.5ºC and others warming by 1.5ºC. Comparing annual panel estimates with longer differences, they estimate the degree to which adaptation has offset the negative effects of heat. For corn productivity, their point estimate suggests that adaptation has offset 23 percent of the negative effect of increased temperatures. Given the confidence intervals, at most half of the negative short-run impacts were offset, and the authors cannot reject the null hypothesis of no adaptation.

These longer-difference estimates are perhaps the closest empirical analogue to the structural equation of interest for climate change in (4), particularly if we are interested in climate change impacts in the medium term (e.g., by 2050). However, two issues should be kept in mind when interpreting these medium-run estimates. First, even though (8) estimates the impact of a change in the average temperature variables, it is not obvious how agents perceived this change or how their beliefs conditioned their response. To the extent that adaptation requires forward-looking investments, adaptation choices will depend not only on the underlying damage functions and adaptation

[49] Among richer countries (those in the upper half of the sample by initial income per capita), the longer differences show no statistically significant effect of temperature on economic growth, similar to what was found in the short-run panel estimates for these countries.

possibilities, but also on agents' expectations. Responses will depend on whether agents both were aware of the change in average temperature, and whether they perceived it to be a permanent change or just an accumulation of idiosyncratic shocks. Burke and Emerick (2013) discuss this issue and note that their results are similar in places with lower baseline variance in temperatures (where, from a Bayesian perspective, farmers should more easily recognize a change in climate) and with higher baseline variance. Their results are also unaffected by a county's political affiliation, which they argue may be correlated with beliefs about global warming. Thus, Burke and Emerick (2013) provide interesting initial analysis of the expectations issue and suggest some methods to grapple with it. More generally, the issue of expectation formation is a rich and important avenue for ongoing research in linking historical responses to warming with forecasts of future effects.

A second issue is that these papers examine average effects on the order of fifteen to twenty years, while adaptation and intensification may take place over longer periods. In the limit, if one took sufficiently long averages (say, one hundred years), then one could plausibly begin to estimate directly the types of effects in the structural equation in (4). Such very long differences are an exciting opportunity for new research, but they also amplify an interpretative challenge. The challenge is that economies are changing and the longer the time difference taken in (8), the further back in time the analysis goes (by necessity), and the further removed from present-day economic conditions the analysis becomes. To the extent that different economies presented very different standards of living, technologies, and institutions through the twentieth century, one may still make headway by examining historical heterogeneous treatment effects along various dimensions of economic development. On the other hand, the future presumably promises new technologies and other features that may pull economies outside the range of historical experiences, calling for caution in drawing sharp conclusions from increasingly historical studies.

Long-Run Impacts of Shocks

A third empirical approach traces out the long-run effects of a given, permanent shock. Although finding geographically isolated, permanent climate shocks that one can follow empirically is challenging, there are several existing studies that illuminate this empirical design. For example, Hornbeck (2012) studies the 1930s "Dust Bowl," during which a series of large dust storms stripped topsoil from farmland in the American Great Plains, substantially degrading the agricultural productivity in some areas. Hornbeck shows that by 1940, the value of farmland fell by 30 percent in high-erosion areas relative to low-erosion areas and by 1992, no more than 25 percent of the initially lost value was recovered. While farmers did adapt by growing hay instead of wheat, these adaptation mechanisms appear to have mitigated only a small share of the lost value of the land.

These long-run studies can be especially informative when the data can further trace people over time, allowing one to estimate the role of migration in influencing long-run aggregate outcomes.[50] Several studies using similar empirical techniques suggest that migration may be an important channel of adjustment to weather shocks. In the same study, Hornbeck shows that by 1992, the population of high-erosion areas was 23 percent lower than low-erosion areas.

[50] Should migration select on people with certain characteristics (such as age, health, or education), care is needed in interpreting whether long-run changes in outcomes are due to a direct effect on the permanent portion of the population or reflect a compositional effect caused by the migration channel.

Boustan, Kahn and Rhode (2012) find similar outmigration in their study of the long-run impact of tornadoes in the United States during the 1920s and 1930s. Feng, Oppenheimer, and Schlenker (2012) document qualitatively similar patterns in a more recent period (1970–2009), suggesting that outmigration from areas experiencing negative agricultural productivity shocks still occurs today, particularly for young adults.

The degree of labor migration in response to these shocks may provoke capital adjustments and may also be muted through government programs. Hornbeck and Naidu (forthcoming) find that large floods along the Mississippi River in 1927 led many farmhands to migrate north permanently, which in turn led the farm owners to substantially mechanize their agriculture. Boustan, Kahn, and Rhode (2012), by contrast, find in-migration associated with floods, which they speculate may be related to efforts by the United States government to rebuild the affected areas and make them more flood resistant. Examining a more recent period (1980–1996), Deryugina (2011) finds no change in population, earnings, or employment in the ten years following a hurricane landfall in the United States, but does find a substantial increase in government transfer payments.[51] A common theme between the last two papers is that government assistance to disaster-prone areas may counteract the natural tendencies for out-migration from these areas, which suggests that institutions may sharply influence adaptation. More broadly, these long-run studies illustrate that factor reallocation may be an important mechanism.

[51] Yang (2008), in the international context, also finds that international financial flows may substantially mitigate the negative impact of hurricanes on economic activity.

Comparing Estimates at Different Time Scales to Model Adaptation

Implicit in several of these approaches is the idea that one can compare the short-run panel estimates from an equation like (3) with other estimates that incorporate some amount of adaptation, such as long differences or the cross section, to gauge the degree of adaptation. Burke and Emerick (2013) and Dell, Jones, and Olken (2012), for example, compare annual panel estimates from equation (3) with long differences from equation (8), and note that the similarity of the estimates suggest relatively little adaptation in their respective contexts. Similarly, as discussed above, Hornbeck (2012) compares the estimates from 1940 (right after the Dust Bowl) to estimates from 1992 (more than fifty years later) to quantify the amount of adaptation over that period.

Several papers also compare panel estimates to the cross section. Schlenker and Roberts (2009), in their study of nonlinear effects of temperature on agriculture, note that the cross-sectional and time-series estimates show similar effects. Dell, Jones, and Olken (2009) perform a similar exercise in their study of temperature in economic growth, but use an economic model to help quantify adaptation effects. Employing the current world cross section (i.e., equation (2)) to inform the very long-run impact of temperature on per capita income and coupling this data with panel estimates for the short-run effect of temperature shocks on income, this paper writes down a model with two features—neoclassical convergence, so that poor countries grow faster than rich countries, other things equal, and adaptation. Using consensus estimates on convergence rates (e.g., Barro and Sala-i-Martin 1992; Caselli, Esquivel, and Lefort 1996), one can back out an estimated adaptation parameter. The analysis implies that, at the global macro level, adaptation could offset about half of

the short-run negative effect of higher temperatures estimated from panel models.

Spatial Spillovers

Additional questions about climatic change concern global-level effects and cross-border effects that extend beyond isolated spatial responses. Assessing these issues with panel data requires adjustments to the empirical strategies. Panel models, by employing time fixed effects, eliminate common global responses. Thus, for example, the average effect of a common commodity price shock will not be revealed. Moreover, to the extent that the effects of climatic shocks in one location propagate to other locations (e.g., through trade or migration), the effect on the other region will not be captured in the typical panel setup, which narrowly examines the relationship between local shocks and local outcomes. In fact, omitting substantive spillovers in the estimation could create bias in an equation such as (3).

Localized spillovers can be examined in panel models with the appropriate setup (e.g., Munshi 2003) by including weather shocks to one's neighbors, trade partners, or aid providers, for example, as explanatory variables for local outcomes. In practice, this means extending the vector $\mathbf{C}_{it}$ in (3) to contain information about other locations that are relevant to outcomes in location i. Such empirical studies, which appear currently rare, are important because the relationships between cross-border interactions and climatic changes are potentially first order, but also subtle. For example, local weather shocks can affect exports to trading partners (Jones and Olken 2010), but consequences for the importing country do not appear to have been studied. From the perspective of the source country, market integration should soften price variation from local shocks, helping consumers but harming local producers, who are less able to raise prices as their output quantities fall (Burgess and Donaldson 2010).

Common Global Shocks

Finally, beyond local cross-border effects, one may also want to consider common global shocks, the estimation of which suggests alternative approaches. To the extent that responses are heterogeneous (e.g., a commodity price shock will have different effects on consumer countries and producer countries), one may exploit this variation via interaction terms to identify differential effects from global shocks.

To examine the average effect of global shocks, one might drop time-fixed effects from the panel altogether and attempt identification directly from the global, rather than local shock. While this approach raises the risk that the analysis is biased by time-varying omitted variables, this method may still be compelling if the global weather shocks appear randomly and over a long enough time series to see these events repeatedly. Hsiang, Meng, and Cane (2011) exploit both strategies to study the El Niño–Southern Oscillation (ENSO), a global climatic event that is frequently repeated. The analysis, comparing variation within countries over time, shows that ENSO strongly predicts civil conflict. Moreover, these effects are heterogeneous; in countries where ENSO has strong weather effects, El Niño years are associated with twice the rate of civil conflict compared to La Niña years, yet no observable effects appear in countries where ENSO is weakly felt.

Bansal and Ochoa (2011) pursue a related strategy. They seek to examine in which countries economic growth is most responsive to a global temperature shock. They therefore estimate a version of equation (3) with global temperature innovations as the key climate variable, and without global time fixed effects. They find that a 1°C temperature innovation reduces growth by about 0.9 percentage points, with stronger impacts felt in those countries closest to the equator.

Summary

Bridging from the short-run panel estimates to the potential longer-term effects of climate change requires methods to confront sector-specific adaptation possibilities, intensification effects, and macroeconomic adjustment mechanisms. While long-run predictions are innately difficult, the papers reviewed in this section present a variety of econometric approaches to confronting these potential issues, provide an informative, if still small, set of pertinent facts, and suggest that much progress may still be made in tackling these challenges.

In considering longer-run responses, it is also important to note that models of future climatic change suggest an ongoing process, rather than a permanent shock. Adaptation will thus be an uncertain progression of steps, with new uncertainties around each corner. Given that the world has been warming, with noted increases in the last several decades and at a rate broadly similar to what may occur over the remainder of the twenty-first century according to the median climate models, the last thirty to forty years provide an empirical environment that appears to closely model the climate change process—a stochastic series of annual shocks along an upward trend. The capacity to draw causal inference about short- and medium-run effects from this recent historical record is a key opportunity for understanding the trajectory the world is running along. We regard this as a critically important direction for future work.

As they stand, the panel estimates reviewed in the preceding sections already raise important questions about current practices in assessing potential climatic impacts, while also suggesting modeling innovations. For example, panel estimates suggest a remarkable breadth of effects, including agriculture, labor productivity, health, conflict, and more. The panel estimates also speak to important questions about functional forms of impacts, including level versus growth effects on national income and a host of nonlinear relationships. The next section reviews mainstream integrated assessment models, the standard tools for making climate-economy predictions, in light of these recent developments and suggests avenues through which these models could be adapted, given the recent findings.

4.2 *How the New Climate–Economy Literature Contributes to Climate Change Models and Policy Prescriptions*

In assessing possible policy responses to global climate change, the main analytical tools are integrated assessment models (IAMs). These models are the main source of well-known estimates for proposed carbon tax levels and other policy prescriptions. IAMs have been used, for example, by the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (Parry et al. 2007), the Stern Report (Stern 2007), and the U.S. Interagency Working Group on Social Cost of Carbon (Greenstone, Kopits, and Wolverton forthcoming), which plays a central role in defining current U.S. government policies around carbon emissions.

Section 4.2.1 provides a brief overview of these models. IAMs consist of multiple components, all of which are important in determining a carbon tax rate and other policies. Our focus is on the damage function, the component of IAMs that specifies how increased temperatures affect economic activity, as this is the area to which the literature discussed in this review can most contribute. We examine standard IAM damage functions in light of the evidence reviewed above and suggest ways in which these damage functions could be modified to better match recent econometric evidence.

4.2.1 *Integrated Assessment Models*

Integrated assessment models combine information about human behavior and

climate systems to make predictions about future climatic change and its consequences. IAMs used for economic policy analysis typically include four broad components: 1) a model projecting the path for greenhouse gas (GHG) emissions; 2) a model mapping GHG emissions into climatic change; 3) a damage function that calculates the economic costs of climatic change, and; 4) a social welfare function for aggregating damages over time and potentially across space. These components can be combined to estimate the external cost of burning carbon, referred to as the social cost of carbon (SCC).[52] 7/18/2014

The IAM approach was pioneered with the development of the DICE model (Nordhaus 1991; Nordhaus 1993). Current examples include the DICE/RICE models (Nordhaus and Yang 1996; Nordhaus and Boyer 2000; Nordhaus 2010a; Nordhaus 2013), the PAGE model (Hope, Anderson, and Wenman 1993; Hope 2006), and the FUND model (Tol 1999; Tol 2013), among others.[53] All IAMs must make a wide variety of modeling choices, with large uncertainties remaining across each component. In practice, each component of an IAM can be updated as the climate sciences and social sciences improve our understanding of the underlying mechanisms.

Uncertainties in the first component, the future GHG emissions path, follow from uncertainty about future economic growth and technology developments. The second, climate-science component wrestles with several central issues that are not yet well understood by climatologists, including the relationship between GHG emissions (flows) and resulting atmospheric GHG concentrations (stocks), the rate of heat transfer into the deep ocean, and the feedback loops between warming and atmospheric GHG concentrations (Allen and Frame 2007). The possibility of positive feedback loops implies that modeled climate change predictions are right-skewed; in other words, there are "fat tail" probabilities for massive climatic change in the next century (Hegerl et al. 2006; Weitzman 2009; Burke et al. 2011), which are an important subject of ongoing climate research.

The final two components, which together constitute the economic model, also face considerable uncertainty. One component is the choice of the social welfare function, which is the subject of substantial debate, especially around the discount rate.[54] Because most of the impacts of climate change will be realized in the future, IAMs must specify a social welfare function that discounts the future path of consumption. Since climate abatement policies incur costs today in order to prevent damages long into the future, the choice of discount rate leads to substantial variation in the implied SCC and the optimal level of abatement chosen.[55]

[52] Note that, in the climate science literature, the term IAM is often used more broadly to denote any model that integrates existing economic and geophysical information to assess climate change. There are a number of such models. For example, the Global Change Assessment Model (GCAM) contains only the first two components. It can be used to simulate the impacts of different emission scenarios and to assess whether a given carbon tax rate is likely to meet a target to limit warming, but it lacks a damage function and thus cannot be used to solve for the optimal carbon tax. The MIT ITSM model is another well-known example of this type of model (Prinn 2013).

[53] The DICE/RICE, PAGE, and FUND models were discussed in detail in the IPCC 4th assessment report and in the U.S. government review of social cost of carbon estimates (Greenstone, Kopits, and Wolverton forthcoming).

[54] See Litterman (2013); Weitzman (2013); Heal (2009); Newbold and Daigneault (2009); Mendelsohn et al. (2008); Nordhaus (2007); Stern (2007); Weitzman (2007) and Weitzman (1998), among others.

[55] For example, using the IAM specifications of the U.S. Working Group (2010) and Johnson and Hope (2012) but varying the discount rate, Weitzman (2013) calculates that the SCC would be $1 at a discount rate of 7 percent, $21 at a discount rate of 3 percent, and $266 at a discount rate of 1 percent. Similarly, differences in the discount rate largely drive the well-known disparity in the social cost of carbon between the Stern Report (Stern 2007), which uses a discount rate of 1.4 percent and argues for an SCC of over $200, and calculations by Nordhaus (2008), who uses a discount rate of ≈5.5 percent and finds an SCC of around $20 or less.

Another important aspect of the social welfare function is the concavity of the utility function. This property influences not only how one weighs future versus current generations, but also how one weighs rich versus poor economies at a single point in time. In order to separate climate policy issues from redistributive issues more broadly, most IAMs impose the Negishi (1972) principle, which constrains IAMs so that the existing distribution of world income remains unchanged over time.

While empirical evidence potentially provides some guidance for writing down the social welfare function, including estimates of market discount rates and the diminishing marginal utility of consumption, some have argued that the choice of the discount rate and welfare weights is a normative question that policymakers and societies more generally must decide using ethical and not positive reasoning (Stern 2007; Heal 2009). Even amongst those who agree that the social welfare function should be calibrated using empirical evidence, there is considerable controversy over which market discount rate to use (Litterman 2013; Weitzman 2013). Nonetheless, choices around social welfare functions can, in principle, be treated transparently as policy parameters in IAMs, with a given IAM model optimized repeatedly with different social welfare functions and the motivations behind different parameters explained, so that policymakers can make informed decisions given heterogeneous views of these parameters and their political constraints.[56]

The second and foundational component of the economic model of IAMs is the climate "damage function," which specifies how temperatures or other aspects of climate affect economic activity. It is this modeling component to which empirical research on climate-economy relationships can most directly speak. It is therefore instructive to understand how current IAMs typically model the economic damage from climate change, to assess whether the loss functions are, or are not, consistent with the findings of the recent empirical literature reviewed in this paper, and to consider ways in which damage functions can be designed to incorporate recent findings.

While we focus below on the damage function, it is important to remember that the various components of IAMs are all related. For example, the larger climate change is, the greater the role that nonlinear damages could play, and the more caution is needed in extrapolating from one particular part of the temperature-damage function. In general, empirical estimates are likely to tell us more about modest temperature changes—for example, those that will likely occur by 2050—than about massive changes, such as those that could possibly occur by 2150.

The Climate-Damage Function

Different IAMs model the climate-damage function in somewhat different ways. For example, the DICE/RICE models use a Cobb–Douglas production function with capital and labor as inputs, multiplied by TFP, which grows at a constant, exogenously specified rate. Output is then reduced by the climate-damage function. For example, in the DICE model, the damage function is

$$D(T) = \frac{1}{1 + \pi_1 T + \pi_2 T^2}, \tag{9}$$

[56] For example, the U.S. Interagency Working Group on the Social Cost of Carbon provided some transparency around the discount rate issue by taking a median discount rate of 3 percent, while also examining discount rates of 2.5 percent and 5 percent.

where T is this period's temperature anomaly and π's are parameters. Output is modeled as[57]

$$Y_t = D(T_t)A_tF(K_t, L_t), \tag{10}$$

where $F_t = A_tF(K_t, L_t)$ denotes output in period t in the absence of warming (e.g., a Cobb–Douglas aggregate of capital and labor, augmented by TFP). The parameters of the loss function are calibrated in different ways, but to the best of our knowledge, generally do not incorporate the type of panel-based evidence reviewed here. For example, DICE calibrates the π parameters to match cross-sectional estimates of climate damages reviewed in Tol (2009) (see Nordhaus 2013) and then adjusts damages up by 25 percent to incorporate nonmonetized damages, such as impacts on biodiversity, and to account for potentially catastrophic scenarios, such as sea level rise, changes in ocean circulation, and accelerated climate change. The DICE/RICE models use this common proportional damage function for the entire world. The PAGE model similarly specifies an aggregate, nonlinear climate-damage function that multiplies GDP in the absence of climate change, but PAGE calibrates separate loss functions by region. PAGE also separately calculates regional-specific damages for sea level impacts and extreme climatic changes (Hope 2006).

In the FUND model, rather than specify an aggregate damage function directly, climate damages are calculated at the region-by-sector level and aggregated up; that is, FUND posits separate models for agriculture, forestry, energy consumption, and health (deaths from infectious, cardiovascular, and respiratory disease), while also considering water resources, extreme storm damage, sea level rise, and the value for ecosystems, with potentially separate regional parameters for each of these models (Tol 2002; Anthoff, Hepburn, and Tol 2009).

An important challenge with the current damage functions is that, for the most part, they do not incorporate the type of rigorous empirical evidence on climate damages reviewed here.[58] In a recent review of IAMs, when discussing the calibration of the $D(T)$ function, Pindyck (2013) writes "the choice of values for these parameters is essentially guesswork. The usual approach is to select values such that $[D(T)]$ for T in the range of 2°C to 4°C is consistent with common wisdom regarding the damages that are likely to occur for small to moderate increases in temperature. . . . The bottom line here is that the damage functions used in most IAMs are completely made up, with no theoretical or empirical foundation."

Given these critiques, there is a clear opportunity for the damage functions to be improved to better match the new wave of rigorous, panel-based evidence. The implications of the econometric evidence discussed here can be thought of in two respects: how we model and calibrate the climate-damage function at a point in time, and how the climate-damage function evolves over time. Short-run panel evidence of the type reviewed in section 3 can help inform the damage function at a point in time; the evidence reviewed in section 4.1 can help inform how climate damages evolve over time due to adaptation, intensification, and other effects. We examine each of these issues in turn.

[57] Output in DICE/RICE models is also reduced proportionally by abatement costs, which we suppress here for ease of exposition.

[58] Stern (2013) also notes a second issue, where damage functions do not yet incorporate many types of damages that could occur at very large temperature increases.

4.2.2 *The Climate-Damage Function at a Point in Time*

Calibrating Magnitudes

The first and most obvious place in which the weather literature can help is in calibrating the magnitudes of the effects. That is, for models that specify an aggregate damage function such as $D(T_t)$ in equation (10), the estimates reviewed here can be useful to help calibrate $D(T_t)$. While extrapolating to the long run is challenging (as we discuss in section 4.1), the empirical estimates we have reviewed in section 3 and shown in table 3 can be a useful input for calibrating IAM models.[59] At minimum, the weather-based estimates reviewed here provide a set of short-run moments in the data for contemporaneous impacts that models should match.

For models that seek to construct aggregate damages by aggregating up sectoral effects, such as the FUND model, a second, related issue is which sectors to include. The panel studies reviewed in this paper suggest several channels that are not currently incorporated in these IAMs. Among the potentially most important are the direct impacts of temperature on labor productivity (see section 3.3) and industrial output (see section 3.4). These channels can, in principle, be added into IAMs in a straightforward manner. Conflict mechanisms, which are also omitted and can have first-order economic effects, may also be incorporated, although incorporating rare but important events may suggest using a stochastic damage function approach, and quantifying the economic impacts is more challenging than with direct economic variables.

Modeling Nonlinear Effects

A second issue is how to handle nonlinearities. Most existing IAMs incorporate nonlinearities by postulating quadratic or another similar nonlinear functional form of average temperature. Several recent studies are able to much more finely disaggregate the effect of temperatures, examining the whole temperature distribution (e.g., Schlenker and Roberts 2009 on agriculture, Deschênes and Greenstone 2011 on mortality, and Auffhammer and Aroonruengsawat 2011 on energy demand). This approach allows one to more carefully and precisely estimate nonlinearities, and these studies generally find that it is very hot days, in particular, that have a strong effect. The impact of a given, say, 2ºC increase in mean temperatures on the number of very hot days depends on the general climate distribution (mean and variance) of each place. For some outcomes (such as GDP or conflict) that are inherently more aggregated, this approach may not be possible, but incorporating this type of heterogeneity could be a useful direction in modeling these nonlinearities more accurately.

Heterogeneous Treatment Effects

The recent panel-based literature also points to substantial heterogeneity in the impacts of climatic variables. Most IAMs currently incorporate some degree of regional heterogeneity in climate damage impacts. One emerging possibility, however, is that the heterogeneity in climate damage may depend not just regionally, but rather explicitly on the level of income. For example, Barreca et al. (2013) show that the impact of hot temperatures on mortality in the United States in the 1920s and 1930s was six times larger than the impact today, which implies that the impact of temperatures on mortality

[59] Currently, DICE, for example, calibrates the climate-damage function by fitting equation (9) to the range of studies shown in table 1 of Tol (2009), which are largely a combination of estimates from other IAMs, enumerative approaches (starting from scientific studies of certain sectors and adding up) and cross-sectional regressions.

in the United States in the 1920s and 1930s is closer to the impact in India today than in the United States today. Similarly, Dell, Jones, and Olken (2012) find that the main factor distinguishing large from small temperature impacts on economic growth is a country's level of income, rather than its region or whether it is hot or cold. While violence responds to temperature in all locations, the most economically costly conflicts, civil wars, appear to respond to higher temperatures only in poorer countries (Hsiang, Meng, and Cane 2011), and more generally conflict effects appear stronger in poorer locations (Hsiang and Burke forthcoming). Modeling heterogeneity as a function of income implies that economic growth in poor countries may reduce climate damages. Incorporating this type of heterogeneity seems an important future direction for IAMs.

4.2.3 *The Dynamics of Climate Damage*

Given the long time horizons of IAMs, one needs to project climate damages not just in one year, but also over a long time period, which requires modeling assumptions about dynamic effects. Dynamic features of the damage function concern both how one characterizes the relationship between climate and economic output (and hence how climate variables affect long-run economic growth) and how the damage function itself evolves endogenously through adaptation. Over the long run, choices about how to model dynamics can have very large impacts on the results of IAMs.

The Level of Output or the Growth Rate of Output

A key modeling choice for the damage function is whether climate affects the level of output or the growth path of output (Pindyck 2011; Dell, Jones, and Olken 2012; Pindyck 2012). The main IAMs assume that the impact of climate is on the level of output only, as in equation (10) above, with the growth of total-factor productivity (A) continuing exogenously. In some models, such as DICE, a contemporaneous temperature shock can affect future output by affecting the growth rate of the capital stock, which evolves endogenously, but effects of climate on the evolution of A, which here incorporates human capital, technology, and institutions, is not allowed. Because growth effects, even small ones, will ultimately dominate even large-level effects, ruling out growth effects substantially limits the possible economic damages these models allow.

An alternative way of specifying the damage function is to allow climate to affect the long-run growth rate (i.e., the growth of A) directly. That is, the evolution of productivity can be written

$$\log A_t = \log A_{t-1} + \Delta(T), \tag{11}$$

where $\Delta(T)$ is a damage function of temperature. While in any given year there is no econometric difference between equations (10) and (11) (that is, equation (10) can be represented by a version of equation (11) with an appropriate choice of $\Delta(T)$), over many years the data-generating processes evolve quite differently.

For example, consider the impact of a permanent increase in temperature that has a contemporaneous effect of lowering economic output by 1 percent in a given year. If the growth of technology A is exogenous and the loss function is a level effect, as in equation (10), then extrapolated out over 100 years, the impact of that increase in temperature would be to lower GDP by about 1 percent.[60] Alternatively, if the impact was modeled through equation (11), so that the growth rate of technology A was 1 percentage point lower per year, then after 100 years GDP would be lower by about 63 percent.

[60] This is approximate, since capital accumulation will also respond.

This simple example suggests that understanding the functional form through which climate affects economic output is critical. Using distributed lag models, the weather-based evidence from Dell, Jones, and Olken (2012) suggests that, for poor countries, temperature shocks appear to have long-lasting effects; i.e., the damage function is consistent with (11). Hsiang and Jina (2013) find similar long-lasting effects for windstorms. Long-difference estimates, as discussed in section 4.1.2, show similar patterns; that is, the effects of high temperatures in poor countries appear to reduce the rate of economic growth as in (11), rather than a one-time output level effect as in (10). Many of the channels discussed in this review, such as civil conflict or labor productivity, could plausibly affect productivity growth. While it is hard to know definitively the correct functional form for the loss function, even small impacts on productivity growth could, over time, swamp effects on the level of output (Pindyck 2013).[61]

Adaptation

Different IAMs currently treat adaptation differently. The loss function in equation (9) does not model the adaptation process specifically. Other models incorporate adaptation explicitly and in different ways. For example, the PAGE model allows the economy to buy units of adaptation separately for sea-level rise, economic, and noneconomic costs (that is, one can pay a given economic cost to purchase an adaptation policy that reduces the climate impact up to a certain number of degrees). FUND includes adaptation in its sector-specific contexts. For example, FUND posits that the agricultural damage function depends on the rate of change in temperature (more rapid changes cause larger damage) and that adaptation causes climate damages to decay by a constant factor each year, with the adaptation parameters chosen by the modeler. The challenge is that many of the adaptation assumptions currently used in these models are not based on rigorous empirical evidence. For example, the FUND documentation describes the source of these adaptation parameters as expert guesses (Anthoff and Tol 2012).

Understanding adaptation is of first-order importance for writing down a plausible damage function. It also remains an area of substantial uncertainty. Although panel-based evidence on adaptation is currently limited and somewhat mixed, and it is hard to forecast long into the future; the evidence reviewed in section 4.1.2 does not provide substantial evidence in favor of the idea that large-scale climate damages will be mostly undone by adaptation over the sorts of horizons that have been measured thus far.

Several pieces of evidence point in this direction. First, the evidence based on medium-term fluctuations (i.e., long differences) suggests that, whether looking at the impacts on agriculture in the United States (Burke and Emerick 2013) or GDP growth in poor countries (Dell, Jones, and Olken 2012), the estimated impacts are more or less similar when looking at changes over one or two decades or more, as compared to annual temperature fluctuations.[62] Second, several studies have examined whether the marginal impacts of temperature are smaller in areas that frequently experience that range of temperature (e.g., Schlenker and Roberts 2009

[61] Recent innovations in the IAM literature, such as work in progress by Krusell and Smith (2013), have tried to incorporate this possibility, calibrating damages to allow for both long-run growth effects (impacts on A) as well as level effects.

[62] A notable exception is Olmstead and Rhode (2011), in their study of agriculture in the United States and Canada historically, who do find evidence of adaptation in agriculture to substantially colder temperatures—i.e., wheat seeds were developed that could grow in Canada.

for agriculture) and not found substantial differences. For longer periods, technological innovations, government policy innovations, or other adaptive mechanisms may play stronger roles, creating lower damages globally (Acemoglu et al. 2012; Miao and Popp 2013). Heat-related mortality is one dimension where such adaptations, in this case through air-conditioning, appear to have substantially altered the effect of heat (Barreca et al. 2013). Over the very long run, in aggregate, Dell, Jones, and Olken (2009) present a calibration exercise comparing panel and cross-sectional results, estimating that approximately half of the large short-run GDP effects of temperature increases are adapted away. We regard further empirical research on the extent of adaptation using the various empirical approaches outlined in section 4.1.2 as a key area for future work.[63]

Reallocation

A final long-run issue concerns factor reallocation, including migration. In general, IAMs treat the population distribution as exogenous. Yet, as discussed above, over the longer run, migration may be an important macroeconomic channel through which people respond, and there are several studies that document out-migration from areas that were negatively affected by climate shocks (see section 3.2.2). A key issue for IAMs is the degree to which migration is allowed to occur only within countries or cross-nationally. In a calibrated model, Desmet and Rossi-Hansberg (2012), for example, argue that economic damages of climate change would be limited if full international migration was available, but substantial if migration was restricted so people could not move from southern to northern areas. Migration may also create security issues (U.S. Department of Defense 2010). Incorporating migration is an important area for future work.

4.2.4 *Concluding Comments*

There is no doubt that building IAMs is a challenging exercise with enormous uncertainty. One may thus be pessimistic about the opportunity to pinpoint estimates of the social cost of carbon to guide policy making today. Nonetheless, if global climate change poses potentially first-order consequences for economic systems, then it demands attempts to inform the costs. We are optimistic that the damage function can be substantially informed by the recent wave of new empirical research, which has begun to provide key insights. As discussed in section 4.1.2, there are numerous opportunities to continue to make progress on functional forms, including heterogeneous and nonlinear effects, as well as to make progress on more difficult issues, including adaptation, through panel approaches. While the estimates will never be perfect, the damage functions in IAMs can be substantially improved, and decision making under the remaining uncertainty is a subject that economic methods are well suited to consider.

5. *Conclusions and Future Directions*

This paper has considered recent panel studies that examine the effect of temperature, precipitation, and windstorms on economic outcomes. We have provided an overview of this rapidly growing literature's methodologies, datasets, and findings. Core implications, limitations, and opportunities of the weather-fluctuation approach have also been discussed. Overall, this literature is providing many new insights about

[63] The importance of more research on adaptation appears throughout the climate literature. For example, while the IPCC fourth assessment report (Metz et al. 2007) acknowledges a large number of examples of adaptation, they note that they have largely been focused on sea-level rise, rather than other channels, and that considerable more work is needed in this area.

climate–economy linkages, while important open directions remain.

Integrating across the many studies reviewed, several broad themes emerge. First, there is a wide range of channels through which weather shocks affect economic outcomes. Shocks, especially temperature, affect agricultural output, industrial output, energy demand, labor productivity, health, conflict, political stability, and economic growth. Labor productivity effects alone may suggest potentially economywide mechanisms. Moreover, the magnitudes of the effects are often substantive. An interesting linkage appears across studies of labor productivity, industrial output, and economic growth, where estimates converge around a 1–2 percent loss per 1°C in poor countries.

Second, the panel studies provide an emerging set of key insights about functional forms. While the specific dimensions depend on the economic outcome of interest, a general theme emerges where effects are often not simple linear functions independent of context. Heterogeneous treatment effects are common features. One repeated form of heterogeneity—whether for economic growth or mortality—is that poor countries appear much more sensitive to temperature shocks for many outcomes. Nonlinearities also appear in the weather variables themselves, where extreme weather is often the primary source of effects. For example, studies of agricultural output, energy demand, and outdoor labor productivity in rich countries show high sensitivity to extreme temperatures, but little or no sensitivity to temperature changes within moderate temperature ranges. A final functional-form insight, which suggests compounding effects over time with large implications for the overall scope of damages, is the appearance of potential growth effects, rather than level effects, on income per capita in poor countries.

This emerging body of work also has ample room for additional progress, and on numerous dimensions. We close by considering opportunities along three broad trajectories. First, despite the broad range of outcomes already studied, there are plausibly important channels that have, to date, received comparatively little study. One dimension is cross-border effects. For example, additional analysis of cross-border labor migration would speak to both the capacity for factor reallocations and the potential for political economy problems and conflict. International and internal trade effects, including studies of how integrated markets both mute and transmit shocks, and for whom, are also a rich potential area for further study.

Second, where reduced-form effects have been established, open questions often remain about specific mechanisms. Especially in cases where there are substantial heterogeneities—i.e., where effects in some places are effectively "turned off"—carefully understanding the specific mechanism would help target potential interventions. The more we grow to understand mechanisms, the more accurately responses can be devised. Narrowly identifying mechanisms is thus an important area for future research.

Third, and perhaps most importantly, bridging from the well-identified results from short-run shocks to longer-run outcomes is an important dimension for future work. Recent empirical advances outlined in section 4 have begun to show how the same types of panel techniques used to identify short-run impacts of weather shocks can be used to credibly provide evidence about likely impacts in the medium term as well. Since different locations in the world experience extremely different climates, to which they have had time to adapt, the capacity to study shocks in very different climate contexts provides important inroads. Panel methodologies can also study medium-run and longer-run changes directly. Keeping in

mind that countries have warmed substantially on average in the last several decades, with substantial variance within and across countries, there is ample capacity to study medium-run changes. The recent warming rate is also very similar to that predicted by many climate models through at least the middle of the current century. Noting that climate change is not about a permanent climate shock, but rather about a stochastic warming process along an upward trend, recent historical experience, which has occurred on such a stochastic warming trajectory, provides a highly relevant setting to understand warming effects. Thus, while attention and beliefs about warming may change, causing changes in responses, and while nonlinear global effects (like sea-level rise) continue to sit outside recent historical experience, recent "long differences" provide an important opportunity to maintain the strength of identification from panel methodologies while studying time scales that bear more directly on longer-run responses. So far, research using longer time scales does not suggest substantial adaptation compared to shorter-run estimates over this type of time scale, but these analyses are still relatively few and much work remains ahead.

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