NBER WORKING PAPER SERIES

ESTIMATING THE CONSEQUENCES OF CLIMATE CHANGE FROM VARIATION IN WEATHER

Derek Lemoine

Working Paper 25008
http://www.nber.org/papers/w25008

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018, Revised November 2018

I thank Laura Bakkensen, Olivier Deschênes, Larry Karp, Ashley Langer, Emanuele Massetti, Antony Millner, Robert Pindyck, and Jeffrey Shrader for helpful comments. I also thank seminar participants at the University of Arizona, the University of California Berkeley, and the University of Massachusetts. A previous version circulated as “Sufficient Statistics for the Cost of Climate Change.” The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Estimating the Consequences of Climate Change from Variation in Weather
Derek Lemoine
NBER Working Paper No. 25008
September 2018, Revised November 2018
JEL No. D84,H43,Q54

ABSTRACT

I formally relate the consequences of climate change to time series variation in weather. First, I show that the effects of climate change on adaptation investments can be bounded from below by estimating responses to weather outcomes. The bound becomes tighter when also estimating responses to forecasts. Second, I show that the marginal effect of climate change on long-run payoffs is identical to the average effect of transient weather events. Empirical work should begin estimating the average effect of weather within each climate, which differs from previous approaches.

Derek Lemoine
Department of Economics
University of Arizona
McClelland Hall 401EE
Tucson, AZ 85721
and NBER
dlemoine@email.arizona.edu

A data appendix is available at http://www.nber.org/data-appendix/w25008

1 Introduction

A pressing empirical agenda seeks to estimate the economic costs of climate change. Ignorance of these costs has severely hampered economists' ability to give concrete policy recommendations (Pindyck, 2013). The challenge is that although variation in climate has been primarily cross-sectional, cross-sectional regressions cannot clearly identify the effects of climate.[1] Seeking credible identification, an explosively growing empirical literature has recently explored panel variation in weather.[2] The hope is that variation in transient weather identifies—or at worst bounds—the effects of a change in climate, which manifests itself through weather but differs from a transient weather shock in being repeated period after period and in affecting expectations of weather far out into the future.

I here undertake the first formal analysis that precisely delineates what and how we can learn about the climate from the weather. Linking weather to climate requires analyzing a dynamic model that can capture the distinction between transient and permanent changes in weather. I study an agent (equivalently, firm) who is exposed to stochastic weather outcomes. The agent chooses actions (equivalently, investments) that suit the weather, but adjusting actions from period to period is costly. When choosing actions, the agent knows the current weather, has access to specialized forecasts of the weather some arbitrary number of periods into the future, and relies on knowledge of the climate to generate forecasts at longer horizons. A change in the climate shifts the distribution of potential weather outcomes and alters the agent's expectations about future weather.

I show several novel results. First, I show that estimating the effects of weather on actions understates the long-run effect of climate on actions. Much empirical research has sought to estimate the consequences of climate change for decision variables or functions of decision variables, including productivity (Heal and Park, 2013; Zhang et al., 2018), health (Deschenes, 2014), crime (Ranson, 2014), and energy use (Auffhammer and Aroonruengsawat, 2011; Deschênes and Greenstone, 2011). Many economists have intuited that short-run adaptation responses to weather are likely to be smaller than long-run adaptation responses to climate (e.g., Deschênes and Greenstone, 2007). I show that the critical ingredient for this result is adjustment costs, not expectations of future weather. The actions an agent takes in response to a transient weather shock are constrained by the agent's desire to not change actions too much from period to period, but when the same weather shock is repeated period after period, even a myopic agent eventually achieves a larger change in activity through a sequence of incremental adjustments. I demonstrate that combining short-run adaptation responses to weather realizations with short-run adaptation responses to weather forecasts can better

[1] For many years, empirical analyses did rely on cross-sectional variation in climate to identify the economic consequences of climate change (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005; Nordhaus, 2006). However, cross-sectional analyses fell out of favor due to concerns about omitted variables bias. See Dell et al. (2014) and Auffhammer (2018b) for expositions and Massetti and Mendelsohn (2018) for a review.

[2] For recent reviews, see Dell et al. (2014), Carleton and Hsiang (2016), and Heal and Park (2016). Blanc and Schlenker (2017) discuss the strengths and weaknesses of relying on panel variation in weather.

approximate long-run adaptation to climate. Further, I show that agents respond to forecasts only because they face adjustment costs. Estimating responses to forecasts therefore allows for a nice test: if actions are much less sensitive to forecasts than to weather and agents are patient over the forecasts' timescales, then adjustment costs may be small and responses to weather may approximate responses to climate.

Second, I show that the marginal effect of climate on steady-state expected payoffs is equal to the average treatment effect of weather in the current climate. Much empirical research has sought to estimate the consequences of climate change for flow payoffs such as profits (e.g., Deschênes and Greenstone, 2007) and for variables such as gross output or income that are potentially related to aggregate payoffs (e.g., Dell et al., 2012; Burke et al., 2015; Deryugina and Hsiang, 2017). I show that an easily estimated function of weather is a sufficient statistic for the impact of limited climate change on such variables.[3] This is a surprising and powerful result. Changing the climate is equivalent to changing expected weather in all future periods, yet transient weather shocks identify the marginal consequences of climate. The analysis implies that empirical work should bin locations by climate (e.g., by long-run average temperature) and estimate a single coefficient on weather (e.g., realized temperature) within each bin. The estimated coefficients describe the effect of marginally changing a location's climate on steady-state payoffs, and summing coefficients across bins describes the effect of nonmarginal climate change on steady-state payoffs. Time series variation therefore identifies the consequences of marginal changes in climate and cross-sectional variation identifies the consequences of nonmarginal changes in climate.[4] Care should be taken, however, in extrapolating to very large changes in climate. Estimating the consequences of such large changes will require pushing the available cross-sectional variation beyond the limits of credible identification and may simply be beyond the reach of reduced-form methods.

Figure 1 depicts the intuition underlying the average treatment effect result. Consider estimating the effect of temperature on agricultural profits, as in Deschênes and Greenstone (2007). Each solid curve in the left panel plots profits as a function of current inputs (such as labor and irrigation), conditional on growing season temperature being either typical or hot. Agents maximize profits by choosing inputs at the points labeled a and b. The dotted

[3] I describe the average treatment effect of weather as a sufficient statistic because multiple combinations of structural parameters can yield the same welfare consequences. Estimating the average treatment effect of weather does not recover all deep primitives but does provide a credibly identified estimate of marginal climate impacts (compare Chetty, 2009).

[4] The combination of panel and cross-sectional variation is similar in spirit to, for example, Auffhammer (2018a), except that the suggested approach estimates a coefficient on weather that can vary with the climate rather than estimating a coefficient on weather that varies with both the weather and the climate. (Deryugina and Hsiang (2017) estimate nonmarginal impacts in a different fashion, by allowing the effect of a weather realization to be nonlinear in its frequency.) The use of cross-sectional variation raises the usual concerns about identification. Results in the appendix suggest a sanity test: moving between climates should not have a stronger effect than do extreme weather events within the current climate.

line connecting points a and b then gives the effect on time t profits of time t temperature. Because profits are flat in inputs around point a, small changes in temperature do not have first-order effects on profits through input choices. This is the content of the envelope theorem, as applied by Deschênes and Greenstone (2007) and subsequent literature. If climate differs from weather only through beliefs that affect input choices, then the effects of climate are identified by the effects of transient weather shocks (Hsiang, 2016; Deryugina and Hsiang, 2017).

However, envelope theorem arguments miss the dynamics that distinguish climate from weather. Now imagine that changing inputs imposes adjustment costs, so that time t profits also depend on time $t-1$ inputs. A change in climate means that previous years were hot and subsequent years are also expected to be hot. If last year was hot, then last year's input choices reflect that outcome and it becomes less costly to choose high inputs this year. The dashed curve in the left panel of Figure 1 plots profits in a current hot year conditional on having already adjusted last year's input choices in response to last year's being hot. The inputs that maximize this year's profits increase to point c because they are less constrained by last year's choices. Now consider the implications of agents expecting the subsequent year $t+1$ to once again be hot. Applying more inputs at time t carries the dynamic benefit of reducing time $t+1$ adjustment costs. As a result, the dynamically optimal input choice is point d, where the marginal effect on this year's profit is negative but the marginal effect on expected intertemporal profits is zero (equation (2) below). The dotted line connecting points a and d then gives the change in profit corresponding to permanently increasing temperature. In line with intuition in Deschênes and Greenstone (2007), long-run adjustments potentially make the effects of a permanent change in weather less severe than the effects of a transient change in weather.

But how can we estimate the dotted line connecting points a and d? The right panel of Figure 1 again plots profits as a function of current inputs, but it holds current weather fixed between curves and instead varies only the previous year's input choices. The curve labeled "ss" depicts profits when the typical temperature has occurred many years in a row, so that previous inputs reached a steady state. The other two curves depict this year's profits under the typical temperature outcome but with higher ("H") and lower ("L") choices of inputs in the previous year. The adjustment costs imposed by these past choices constrain this year's choice of inputs and thereby reduce profits.

The dotted curve gives the effect on myopically optimized profits of changing last year's input choices. This curve has a peak at the myopically optimal labor input implied by curve "ss". Around this point (labeled 1), a permanent change in weather does not have first-order effects through past input choices. So the left panel's point c converges to point b. Now imagine that the agent expects the typical temperature to also occur next year. Because this year's input choices do not have first-order effects on next year's profits around point 1, the myopically optimal input choice is also dynamically optimal. So the left panel's point d converges to point c. Combining these results, line a-b converges to line a-d around point

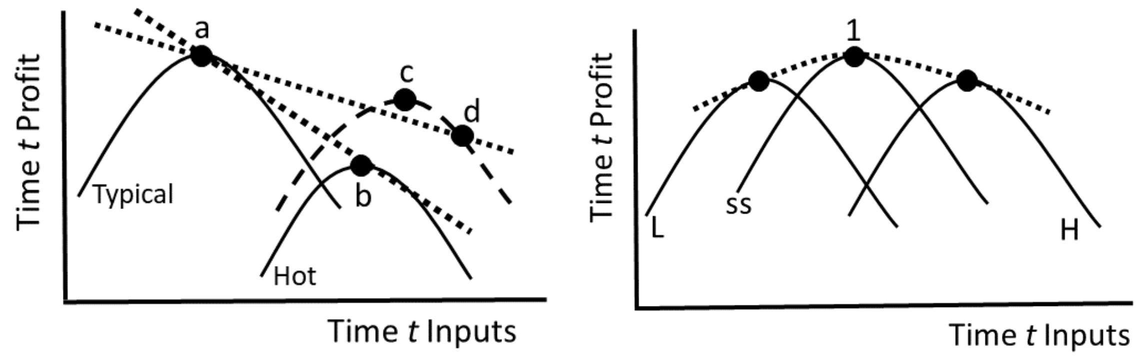

Figure 1: Left: Profits against inputs, conditional on temperature. Line a-b gives the effect on profits of increasing temperature from "typical" to "hot" in the absence of long-run adaptation. Line a-d accounts for adaptation to previous hot years and for expecting next year to again be hot. Right: Profits against inputs, conditional on past input choices. The curve labeled "ss" sets previous inputs to the steady state that would result if the current temperature were maintained forever.

1, so that the treatment effect of a transient weather shock indeed recovers the effect of permanently changing the weather. However, an econometrician may not know which observations in a data set are near a steady state. I show that averaging over potential previous input decisions and potential temperatures can center the estimated marginal effect of temperature around the steady-state inputs corresponding to a location's average temperature. Estimating the average treatment effect of temperature then recovers the effect of a marginal change in that location's climate.

Despite the importance of empirically estimating the costs of climate change and the sharpness of informal debates around the relevance of the recent empirical literature to climate change, there has been remarkably little formal analysis of the link between weather and climate. Previous formal analysis has consisted in appeals to the envelope theorem in static environments (Deschênes and Greenstone, 2007; Hsiang, 2016; Deryugina and Hsiang, 2017), but as described above, a static environment misses the distinction between transient and permanent weather shocks.[5] Envelope theorem intuition has led the literature (i) to of-

[5]A few other papers are also related. First, in an initial expositional analysis, I showed how envelope theorem arguments can fail in a three-period model (Lemoine, 2017). The present work precisely analyzes the consequences of climate change in an infinite-horizon model and constructively shows which types of empirical estimates can be informative about the climate. Second, Kelly et al. (2005) study the cost of having to learn about a change in the climate from an altered sequence of weather as opposed to knowing outright how the climate has changed. I here abstract from learning in order to focus on mechanisms more relevant to the growing empirical literature. Third, calibrated simulations have shown that dynamic responses are critical to the effects of climate on timber markets (Sohngen and Mendelsohn, 1998; Guo and Costello, 2013) and to the cost of increased cyclone risk (Bakkensen and Barrage, 2018). Finally, a few empirical papers have

ten ignore how the effects of transient weather shocks depend on a location's climate and (ii) to often treat the marginal effects of common and uncommon weather events as equally informative about climate change. Because of (i), most empirical literature pools the marginal effects of weather across units that reside in different climate zones, which conflates units for which a weather shock is rare with units for which a weather shock is common.[6] Because of (ii), some empirical literature (e.g., Deryugina and Hsiang, 2017) estimates how payoffs respond to additional days with each type of weather and then combines these estimates with scientific models' projections of how climate change will alter the frequency of each type of weather.[7] In the appendix, I show that this estimator overstates the cost of marginal climate change by capturing the nonlinear consequences of transient weather shocks, which I also show have little bearing on the effects of climate change.

The next section describes the setting. Section 3 solves the dynamic programming problem. Sections 4 and 5 analyze the effects of climate on agents' chosen actions and payoffs, respectively. The final section discusses limitations of the present analysis. The appendix contains additional results, generalizes the analysis, and provides proofs.

2 Setting

An agent is repeatedly exposed to stochastic weather outcomes. The realized weather in period t is w_t. This weather realization imposes two types of costs. A first type of cost arises independently of any actions the agent might take. These unavoidable costs are $\frac{1}{2}\psi(w_t-\bar{w})^2$, where the parameter $\bar{w}$ defines the weather outcome that minimizes unavoidable costs and the parameter $\psi \geq 0$ determines the costliness of any other weather outcome. A second type of cost depends on the agent's actions A_t. These avoidable costs are $\frac{1}{2}\gamma(A_t - w_t)^2$, where $\gamma \geq 0$. They vanish when the agent's actions are well-matched to the weather and potentially become large when the agent's actions are poorly matched to the weather.

In each period, the agent chooses her action A_t. This action may be interpreted as a level of activity (e.g., time spent outdoors, energy used for heating or cooling, irrigation applied to a field) or as a stock of capital (e.g., outdoor gear, size or efficiency of furnace, number or efficiency of irrigation lines). The agent's actions impose two types of costs. First, maintaining A_t imposes costs of $\frac{1}{2}\phi(A_t - \bar{A})^2$, where $\phi \geq 0$. When A_t represents a capital stock, these maintenance costs reflect depreciation. The parameter $\bar{A}$ defines the level of

demonstrated that actions respond to forecasts of future weather (e.g., Neidell, 2009; Rosenzweig and Udry, 2013, 2014; Wood et al., 2014; Shrader, 2017).

[6]Some empirical literature has begun estimating how the effects of weather shocks vary with a location's climate, as summarized in Auffhammer (2018b). The appendix discusses which estimates in Deschênes and Greenstone (2007) come closest to the theoretically recommended approach.

[7]This two-step strategy has also become the dominant approach to estimating the effects of climate on actions (see Carleton and Hsiang, 2016). In the appendix, I show that these estimates do indirectly use some of the information available from responses to forecasts.

activity or capital that is cheapest to sustain. Second, the agent faces a cost of adjusting actions from one period to the next. This cost is $\frac{1}{2}\alpha(A_t - A_{t-1})^2$, where $\alpha \geq 0$. When A_t represents a capital stock, these adjustment costs are investment costs. Relating to the literature on climate adaptation (e.g., Fankhauser et al., 1999; Mendelsohn, 2000), small adjustment costs allow adaptation investments to occur after weather is realized ("reactive" or "ex-post" adaptation), but large adjustment costs require adaptation to occur before weather is realized ("anticipatory" or "ex-ante" adaptation). Maintenance costs make the agent want to choose actions close to $\bar{A}$, and adjustment costs make the agent want to keep actions constant over time.[8]

The agent observes time t weather before selecting her time t action. The agent has access to specialized forecasts of future weather and knows her region's climate, indexed by C and which I will often interpret as temperature. Specialized forecasts extend up to $N \geq 0$ periods ahead. Each period's forecast is an unbiased predictor of later weather. Beyond horizon N, the agent formulates generic forecasts that rely only on knowledge of the climate, not on information germane to that particular time period. For instance, the agent may rely on the local news to predict weather one week out and on forecasts of El Niño conditions to predict weather six months out but relies on knowledge of typical weather to predict weather one year out. Horizon N is therefore the shortest forecast horizon at which the agent receives information beyond knowledge of the climate.

Formally, let f_{it} be the i-period-ahead forecast available in period t. The time t weather realization is a random deviation from the one-period-ahead forecast: $w_t = f_{1(t-1)} + \epsilon_t$, where ϵ_t has mean zero and variance σ^2. Because forecasts are unbiased predictors, any changes in forecasts must be unanticipated: for $i \in \{1, ..., N\}$, $f_{it} = f_{(i+1)(t-1)} + \nu_{it}$, where ν_{it} has mean zero and variance τ_i^2. Forecasts at horizons $i > N$ are $f_{it} = C$.[9] The ν_{it} and ϵ_t are serially uncorrelated, the covariance between ν_{it} and ν_{jt} is δ_{ij}, and the covariance between ϵ_t and ν_{it} is ρ_i.[10] Note that $E_t[w_{t+j}] = f_{jt}$. For notational convenience, collect all specialized forecasts available at time t in a vector F_t of length N.[11]

[8] The general analysis in the appendix does not require allocating either costs or weather impacts in this fashion and allows, among much else, $\bar{A}$ to vary with w_t and A_{t-1} to affect time t payoffs directly.

[9] One might be concerned about a sharp discontinuity in information at horizon N. However, I have left the variances τ_i^2 general. Defining them to decrease in i and to approach zero as i approaches N would allow for the informativeness of the signal about time t weather to increase smoothly from long horizons to short horizons.

[10] Assuming that each shock is serially uncorrelated does not imply that weather and forecasts are serially uncorrelated. For instance, for $t > N$, $Cov_0(w_t, w_{t+1}) = \rho_1 + \sum_{i=1}^{N-1} \delta_{i(i+1)}$.

[11] Climate here controls average weather. One might wonder about the dependence of higher moments of the weather distribution on climate. In fact, the effects of climate change on the variance of the weather are poorly understood and spatially heterogeneous (e.g., Huntingford et al., 2013; Lemoine and Kapnick, 2016). Further, we need to know not just how climate change affects the variance of realized weather but how it affects the forecastability of weather at each horizon: the variance of the weather more than N periods ahead is $\sigma^2 + \sum_{i=1}^{N} \tau_i^2$, so we need to apportion any change in variance between σ^2 and each τ_i^2. The appendix analyzes the consequences of a change in variance and connects these consequences to empirical strategies.

The agent maximizes the present value of payoffs over an infinite horizon. Time t payoffs are:

$$\pi(A_t, A_{t-1}, w_t) = -\frac{1}{2}\gamma(A_t - w_t)^2 - \frac{1}{2}\alpha(A_t - A_{t-1})^2 - \frac{1}{2}\phi(A_t - \bar{A})^2 - \frac{1}{2}\psi(w_t - \bar{w})^2.$$

She chooses time t actions as a function of past actions, current weather, and current forecasts. In order to study an interesting problem, assume that $\gamma + \phi > 0$. The agent solves:

$$\max_{\{A_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t E_0 \left[\pi(A_t, A_{t-1}, w_t)\right],$$

where $\beta \in [0, 1)$ is the per-period discount factor, A_{-1} is given, and E_0 denotes expectations at the time 0 information set. The solution satisfies the following Bellman equation:

$$\begin{aligned} V(Z_t, w_t, F_t) =& \max_{A_t} \left\{ \pi(A_t, Z_t, w_t) + \beta E_t \left[V(Z_{t+1}, w_{t+1}, F_{t+1})\right] \right\} \qquad (1) \\ \text{s.t.} \quad Z_{t+1} =& A_t \\ w_{t+1} =& f_{1t} + \epsilon_{t+1} \\ f_{i(t+1)} =& f_{(i+1)t} + \nu_{i(t+1)} \quad \text{for } i \in \{1, ..., N\} \\ f_{N(t+1)} =& C + \nu_{N(t+1)} \quad \text{if } N > 0. \end{aligned}$$

The state variable Z_t captures the previous period's actions. Optimal actions satisfy the first-order condition:

$$\frac{\partial \pi(A_t, Z_t, w_t)}{\partial A_t} = -\beta E_t \left[\frac{\partial V(Z_{t+1}, w_{t+1}, F_{t+1})}{\partial Z_{t+1}} \right]. \qquad (2)$$

When the right-hand side is nonzero, the myopically optimal point c differs from the dynamically optimal point d in Figure 1.

The setting is sufficiently general to describe many applications of interest. For instance, much empirical literature has studied the effects of weather on energy use. The agent could then be choosing indoor temperature in each period, where maintenance costs reflect energy use and avoidable weather costs reflect thermal comfort. Empirical literature has also studied the effect of weather on agricultural profits. The decision variable could then be irrigation, labor, fertilizer, or crop varieties, maintenance costs reflect the cost of purchasing these in each year, adjustment costs reflect the cost of changing equipment and plans from year to year, and weather costs reflect the deviation in crop yields from their maximum possible value.

The primary specialization in the setting is the assumption of quadratic payoffs. Linear-quadratic models have long been workhorses in economic research because they allow for explicit analytic solutions to the Bellman equation (1). In the appendix, I instead use perturbation methods (Judd, 1996) to generalize the analysis to an arbitrary functional form for $\pi(A_t, A_{t-1}, w_t)$, to vector-valued actions, and to multi-dimensional weather indices.

3 Solution

The following proposition describes the value function that solves equation (1):

Proposition 1. *The value function $V(Z_t, w_t, F_t)$ has the form:*

$$a_1 Z_t^2 + a_2 w_t^2 + \sum_{i=1}^{N} a_3^i f_{it}^2 + b_1 Z_t w_t + \sum_{i=1}^{N} b_2^i Z_t f_{it} + \sum_{i=1}^{N} b_3^i w_t f_{it} + \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} b_4^{ij} f_{it} f_{jt} + c_1 Z_t + c_2 w_t + \sum_{i=1}^{N} c_3^i f_{it} + d.$$

Optimal actions are:

$$A_t^* = \frac{\alpha A_{t-1} + \gamma w_t + \beta b_1 f_{1t} + \beta \sum_{i=1}^{N-1} b_2^i f_{(i+1)t} + \beta b_2^N C + \beta c_1 + \phi \bar{A}}{\gamma + \alpha + \phi - 2\beta a_1}. \tag{3}$$

The coefficients are as follows:

1. *$a_1 \leq 0$, with $a_1 < 0$ if and only if $\alpha > 0$.*

2. *$a_2 \leq 0$, with $a_2 < 0$ if and only if $\psi + \gamma(\phi + \alpha) > 0$.*

3. *$a_3^i \in [\beta^i a_2, 0]$, with $a_3^i < 0$ if and only if both $a_2 < 0$ and $\alpha\beta > 0$ and with $a_3^i > \beta^i a_2$ if and only if $\beta\alpha\gamma > 0$.*

4. *Each of the b coefficients is positive, with $b_1 > 0$ if and only if $\alpha\gamma > 0$ and $b_2^i, b_3^i, b_4^{ij} > 0$ if and only if $\beta\alpha\gamma > 0$.*

5. *$c_1 \geq (\leq)$ 0 if C is sufficiently large (small), and $c_2, c_3^i \geq (\leq)$ 0 if, in addition, $\bar{w} \geq (\leq)$ 0.*

6. *Each a and b coefficient is independent of C.*

7. *Each c coefficient weakly increases in C, and each c coefficient strictly increases in C if and only if $\beta\alpha\gamma > 0$.*

Proof. See appendix. □

The value function is concave in previous actions ($a_1 \leq 0$), in weather outcomes ($a_2 \leq 0$), and in forecasts ($a_3^i \leq 0$). If $\beta\alpha\gamma > 0$, then each a and b coefficient is nonzero. Several coefficients depend on C, reflecting how climate controls the agent's beliefs about long-run weather. I henceforth omit the asterisk on A_t^* when clear.

4 Effect of Climate on Actions

Now consider how climate change affects the agent's actions, which is of direct relevance to much empirical work and produces results that we will use to analyze the effect of climate on payoffs. Define $\hat{A}_t \triangleq E_0[A_t]$. From equation (3),

$$\hat{A}_t = \frac{\alpha \hat{A}_{t-1} + \gamma C + \beta b_1 C + \beta \sum_{i<N} b_2^i C + \beta b_2^N C + \beta c_1 + \phi \bar{A}}{\gamma + \alpha + \phi - 2\beta a_1}$$

for $t > N$. The following proposition describes long-run behavior:

Proposition 2. *As* $t \to \infty$, $\hat{A}_t \to \frac{\gamma}{\gamma+\phi} C + \frac{\phi}{\gamma+\phi} \bar{A} \triangleq A^{ss}$.

Proof. See appendix. □

Expected actions converge to a steady state, denoted A^{ss}. This steady-state expected action is a weighted average of the action that minimizes expected weather impacts and the action that minimizes maintenance costs. Steady-state policy fully offsets the avoidable portion of expected weather impacts (determined by the climate C) when there are no maintenance costs ($\phi = 0$), but steady-state policy becomes unresponsive to the climate as marginal maintenance costs become large relative to marginal avoidable weather costs (as ϕ becomes large relative to γ). Adjustment costs slow the approach to the steady-state expected action, but they do not affect its level.

From Proposition 2, an increase in the climate index affects steady-state expected actions as

$$\frac{\mathrm{d}A^{ss}}{\mathrm{d}C} = \frac{\gamma}{\gamma + \phi} \in [0, 1].$$

As $\gamma \to 0$, there are no avoidable weather impacts, and as $\phi \to \infty$, maintenance costs are too large to justify changing actions on the basis of the climate. In either case, $\mathrm{d}A^{ss}/\mathrm{d}C \to 0$. Steady-state actions otherwise strictly increase with the climate index. But this increase is less than one-for-one when $\phi > 0$: adaptation is less than perfect when maintenance costs deter the agent from fully offsetting the change in climate.

Now consider how we might estimate $\mathrm{d}A^{ss}/\mathrm{d}C$ from data. Reduced-form empirical models can estimate the derivatives $\partial A_t/\partial w_t$ and $\partial A_t/\partial f_{it}$ by regressing observed A_t on weather and forecasts.[12] Imagine that empirical researchers were to then approximate the effect of climate change as

$$\frac{\mathrm{d}A^{ss}}{\mathrm{d}C} \approx \frac{\partial A_t}{\partial w_t} + \sum_{i=1}^{j} \frac{\partial A_t}{\partial f_{it}}, \tag{4}$$

[12] Note that the estimation equation should include either A_{t-1} or time $t-1$ forecasts: time $t-1$ actions can directly affect time t actions (see equation (3)), and the dependence of time $t-1$ actions on time $t-1$ forecasts makes them correlated with time t weather and forecasts. The appendix derives a related omitted variables bias from ignoring time t forecasts.

for $j \in \{0, ..., N\}$. For $\mathrm{d}A^{ss}/\mathrm{d}C > 0$ (i.e., for $\gamma > 0$), the bias from this approximation as a fraction of the true effect is

$$Bias(j) = \frac{\frac{\partial A_t}{\partial w_t} + \sum_{i=1}^{j} \frac{\partial A_t}{\partial f_{it}}}{\frac{\mathrm{d}A^{ss}}{\mathrm{d}C}} - 1.$$

$Bias(0)$ is the bias from using only $\partial A_t/\partial w_t$, and $Bias(N)$ is the bias when also using all available forecasts. The approximation underestimates $\mathrm{d}A^{ss}/\mathrm{d}C$ if and only if $Bias(j) < 0$ and correctly estimates $\mathrm{d}A^{ss}/\mathrm{d}C$ if and only if $Bias(j) = 0$. The following proposition establishes several results about this bias:

Proposition 3. *Assume $\gamma > 0$. Then:*

1. *$Bias(j) \in (-1, 0]$, with $Bias(j) < 0$ if and only if $\alpha > 0$.*
2. *$\frac{\mathrm{d}Bias(j)}{\mathrm{d}j} \geq 0$, $\frac{\mathrm{d}Bias(j)}{\mathrm{d}N} = 0$.*
3. *$\frac{\mathrm{d}Bias(j)}{\mathrm{d}j} \to 0$ as $\beta \to 0$.*
4. *$Bias(j) \to \frac{-\alpha}{\gamma+\alpha+\phi-2\beta a_1}$ as $j, N \to \infty$.*
5. *$\partial A_t/\partial w_t \to 0$, $\partial A_t/\partial f_{it} \to 0$, and $Bias(j) \to -1$ as $\alpha \to \infty$.*
6. *$\mathrm{d}A^{ss}/\mathrm{d}C \to 1$ and $Bias(j) \to 0$ as $\gamma \to \infty$.*
7. *$\partial A_t/\partial w_t, \partial A_t/\partial f_{it}$, $\mathrm{d}A^{ss}/\mathrm{d}C \to 0$ as either $\gamma \to 0$ or $\phi \to \infty$.*

Proof. See appendix. □

The approximation in (4) never overestimates $\mathrm{d}A^{ss}/\mathrm{d}C$ ($Bias(j) \leq 0$, result 1), and it underestimates $\mathrm{d}A^{ss}/\mathrm{d}C$ whenever there are nonzero adjustment costs ($\alpha > 0$). The quality of the approximation improves when we include the effects of forecasts in addition to the effects of weather shocks ($\mathrm{d}Bias(j)/\mathrm{d}j \geq 0$, result 2), because a weather shock that also affects forecasts is less transient. However, nonzero bias remains even when estimating responses to forecasts at arbitrarily long horizons (i.e., even as $j, N \to \infty$, result 4): the response to current weather and to information about future weather cannot capture how incremental adjustments accumulate over time. The accumulation of incremental adjustments also generates nonzero bias even when agents are myopic.

The bias vanishes in a few special cases. First, as adjustment costs vanish ($\alpha \to 0$, result 1), actions adjust instantaneously to realized weather, so neither expectations nor the slow accrual of incremental adjustments matters for steady-state actions. Second, as avoidable weather impacts become infinitely costly ($\gamma \to \infty$, result 6), the agent tries to exactly match A_t to w_t in every period, regardless of adjustment costs or maintenance costs. Third, when there are no avoidable weather impacts ($\gamma \to 0$, result 7) or maintenance costs are prohibitive ($\phi \to \infty$, result 7), actions become completely insensitive to the climate and also to realized weather and forecasts. In all other cases, the bias is nonzero and becomes large as adjustment costs become large.

Finally, we also see two cases in which $Bias(j) < 0$ but including the effects of forecasts does not improve the quality of the approximation in (4): $\mathrm{d}Bias(j)/\mathrm{d}j \to 0$ as either $\beta \to 0$ (result 3) or $\alpha \to \infty$ (result 5).[13] The reason is that actions are not sensitive to forecasts in these cases.[14] First, forecasts enable the agent to take actions that improve future payoffs, but when agents are myopic, they act for the present only. Second, as adjustment costs become very large, agents barely adjust actions on the basis of forecasts. The steady state will change due to the accumulation of tiny changes over a long time horizon, but these effects will not be detectable from responses to forecasts.

5 Effect of Climate on Value

Now consider the expected effect of climate change on intertemporal value and per-period payoffs. From Proposition 1, we have:

$$\begin{aligned}
V(Z_t, w_t, F_t) =& V(A^{ss}, C, \boldsymbol{C}) \\
&+ [Z_t - A^{ss}] V_Z(A^{ss}, C, \boldsymbol{C}) + [w_t - C] V_w(A^{ss}, C, \boldsymbol{C}) + \sum_{i=1}^{N} [f_{it} - C] V_{f_i}(A^{ss}, C, \boldsymbol{C}) \\
&+ [Z_t - A^{ss}]^2 a_1 + [w_t - C]^2 a_2 + \sum_{i=1}^{N} [f_{it} - C]^2 a_3^i + [Z_t - A^{ss}][w_t - C] b_1 \\
&+ \sum_{i=1}^{N} [Z_t - A^{ss}][f_{it} - C] b_2^i + \sum_{i=1}^{N} [w_t - C][f_{it} - C] b_3^i + \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} [w_t - C][f_{it} - C] b_4^{ij},
\end{aligned}$$

where $\boldsymbol{C}$ is an $N \times 1$ vector with all entries equal to C. The envelope theorem and the fact that $\partial \pi(A_t, A_{t-1}, w_t)/\partial A_{t-1} = 0$ around a steady state imply $V_Z(A^{ss}, C, \boldsymbol{C}) = 0$. The

[13] In addition, $\mathrm{d}Bias(j)/\mathrm{d}j = 0$ if $\alpha = 0$ because, from result 1 in Proposition 3, $\alpha = 0$ implies that $Bias(j) = 0$ for all j.

[14] From Proposition 1, $\partial A_t / \partial f_{it} \to 0$ as $\beta \to 0$ and, using the solutions for a_1 and b_1 given in the proof, also as $\alpha \to \infty$.

expectation at time 0 of $V(Z_t, w_t, F_t)$ at some future time $t > N$ is:

$$E_0[V(Z_t, w_t, F_t)] = V(A^{ss}, C, \boldsymbol{C}) + E_0[(A_t - A^{ss})^2]a_1 + \sigma^2 a_2 + \sum_{i=1}^{N} \tau_i^2 a_3^i + Cov_0[Z_t, w_t]b_1 + \sum_{i=1}^{N} Cov_0[Z_t, f_{it}]b_2^i + \sum_{i=1}^{N} Cov_0[w_t, f_{it}]b_3^i + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} Cov_0[w_t, f_{it}]b_4^{ij}. \tag{5}$$

Recalling from Proposition 1 that each a and b coefficient is independent of C, and recognizing that each covariance is independent of C,[15] we have:

$$\frac{\mathrm{d}E_0[V(Z_t, w_t, F_t)]}{\mathrm{d}C} = \underbrace{\frac{\mathrm{d}V(A^{ss}, C, \boldsymbol{C})}{\mathrm{d}C}}_{\text{change in ss value}} + \underbrace{2a_1 E_0\left[(Z_t - A^{ss})\left(\frac{\mathrm{d}Z_t}{\mathrm{d}C} - \frac{\mathrm{d}A^{ss}}{\mathrm{d}C}\right)\right]}_{\text{change in transition value}}.$$

We see two components to the expected change in value due to climate change: the change in steady-state value and the change in value along the transition to the steady state.[16]

The next proposition signs the change in transition value:

Proposition 4. *If $\alpha\gamma > 0$, then $\frac{\mathrm{d}E_0[V(Z_t,w_t,F_t)]}{\mathrm{d}C} < \frac{\mathrm{d}V(A^{ss},C,\boldsymbol{C})}{\mathrm{d}C}$ if and only if $A_0 < A^{ss}$. $\frac{\mathrm{d}E_0[V(Z_t,w_t,F_t)]}{\mathrm{d}C} \to \frac{\mathrm{d}V(A^{ss},C,\boldsymbol{C})}{\mathrm{d}C}$ as $\alpha \to 0$, as $\gamma \to 0$, as $t \to \infty$, or as $A_0 \to A^{ss}$.*

Proof. See appendix. □

The transition to a warmer climate imposes costs over and above the change in steady-state value when $A_0 < A^{ss}$ but provides benefits over and above the change in steady-state value when $A_0 > A^{ss}$. When $A_0 < A^{ss}$, the agent is in the process of approaching A^{ss} from below. We already saw that A^{ss} increases in C. Increasing C moves the steady state further away from the current state and therefore requires even more adjustment from the agent. However, when the agent is approaching A^{ss} from above, raising C reduces the total adjustment that the agent will have to undertake before reaching the steady state.

It is reasonable to believe that agents in warmer climates may be approaching their steady-state investment level from below (e.g., by installing air conditioning) and that agents in colder climates may be approaching their steady-state investment level from above (e.g., by installing insulation). We should then expect the cost of adjusting to a warmer climate to be positive in regions with warmer climates and negative in regions with cooler climates. Further, we should expect transition costs (or savings) to be larger in regions that are not

[15] Observe from Proposition 1 that A_t is separable in C, w_t, and f_{it}, and observe that the stochastic terms in w_t and f_{it} are independent of C. Therefore each covariance in equation (5) is independent of C.

[16] Tol et al. (1998) informally draw a similar distinction.

as far along the process of adapting to their baseline climate, whether because these regions have lower incomes, were settled only recently, or have outdated capital stock.

Now consider how climate change affects steady-state value. Using Proposition 1, we have:

$$\begin{aligned}\frac{\mathrm{d}V(A^{ss}, C, \boldsymbol{C})}{\mathrm{d}C} =& V_w(A^{ss}, C, \boldsymbol{C}) + \sum_{i=1}^{N} V_{f_i}(A^{ss}, C, \boldsymbol{C}) \\ &+ \frac{\mathrm{d}c_1}{\mathrm{d}C} A^{ss} + \frac{\mathrm{d}c_2}{\mathrm{d}C} C + \sum_{i=1}^{N} \frac{\mathrm{d}c_3^i}{\mathrm{d}C} C + \frac{\mathrm{d}d}{\mathrm{d}C}. \end{aligned} \tag{6}$$

The first line recognizes that a change in climate alters average weather and average forecasts. The second line arises because agents anticipate that climate change is permanent: climate change therefore alters the value function itself, beyond altering realized weather and forecasts. For instance, a permanent change in climate can make past adaptation investments more valuable (Proposition 1 showed that $\mathrm{d}c_1/\mathrm{d}C \geq 0$) and can make higher weather outcomes more valuable (or less painful) because they are closer to average weather (Proposition 1 showed that $\mathrm{d}c_2/\mathrm{d}C \geq 0$).

The following proposition describes the net effects of climate change on steady-state value:

Proposition 5.

$$\frac{\mathrm{d}V(A^{ss}, C, \boldsymbol{C})}{\mathrm{d}C} = \frac{1}{1-\beta} \frac{\mathrm{d}\pi(A^{ss}, A^{ss}, C)}{\mathrm{d}C} = \frac{1}{1-\beta} \left[\frac{\gamma\phi}{\gamma+\phi}(\bar{A} - C) + \psi(\bar{w} - C) \right]. \tag{7}$$

Proof. See appendix. □

Value increases in the climate index if and only if C is sufficiently small. The change in steady-state value is equal to the change in steady-state per-period payoffs, valued as a perpetuity. The first term in brackets reflects the change in the cost of maintaining the adaptation investments chosen for this climate. When the climate is sufficiently cold, a warmer climate may justify investments that require less maintenance, but as the climate becomes sufficiently warm, eventually the chosen investments require more upkeep. This term vanishes as either maintenance costs vanish ($\phi \to 0$) or as the link between actions and weather is broken ($\gamma \to 0$). The second term in brackets reflects the changing cost of unavoidable weather impacts. This term makes a warmer climate valuable when $C < \bar{w}$ but makes a warmer climate costly when $C > \bar{w}$. This term vanishes when weather outcomes impose no unavoidable costs ($\psi \to 0$).

A rapidly growing empirical literature hopes to estimate the cost of climate change from time series variation in weather. From Proposition 1, the marginal effect of weather on value is:

$$\frac{\partial V(Z_t, w_t, F_t)}{\partial w_t} = 2a_2 w_t + b_1 Z_t + \sum_{i=1}^{N} b_3^i f_{it} + c_2.$$

If we average the marginal effect of weather over many observations in a given climate and assume that actions are, on average, close to the steady-state level A^{ss} (as when a location is well-adapted to its current climate), then we obtain the following average treatment effect of weather on value:[17]

$$ATE_w^V(C) \triangleq E_0\left[\frac{\partial V(Z_t, w_t, F_t)}{\partial w_t}\right] = 2a_2 C + b_1 A^{ss} + \sum_{i=1}^{N} b_3^i C + c_2,$$

for $t > N$. Proceeding analogously, we have the average treatment effect of weather on payoffs around a steady state as

$$ATE_w^\pi(C) \triangleq E_0\left[\frac{\mathrm{d}\pi(A_t, A_{t-1}, w_t)}{\mathrm{d}w_t}\right] = E_0\left[\frac{\partial \pi(A_t, A_{t-1}, w_t)}{\partial w_t}\right],$$

using that $E_0[\partial\pi(A_t, A_{t-1}, w_t)/\partial A_t] = E_0[\partial\pi(A_t, A_{t-1}, w_t)/\partial A_{t-1}] = 0$ around A^{ss}. The next proposition relates these average treatment effects to the marginal effect of climate:

Proposition 6.

$$\frac{\mathrm{d}\pi(A^{ss}, A^{ss}, C)}{\mathrm{d}C} = ATE_w^V(C) = ATE_w^\pi(C)$$

Proof. See appendix. □

This is a surprising result: once all adjustments are complete, the expected change in per-period steady-state payoffs due to a change in climate is identical to the average change in payoffs estimated from weather events around a steady state.[18] The appendix shows that the same result holds for general, non-quadratic payoff functions as long as (i) $\partial\pi(A_t, A_{t-1}, w_t)/\partial A_{t-1} = 0$ at $A_t = A_{t-1}$ and (ii) σ^2 and each τ_i^2 are not too large. When (i) holds (as it does in the main text and in the right panel of Figure 1), the effects of climate on past actions becomes irrelevant for steady-state payoffs and the dynamically optimal action converges to the myopically optimal action, in which case the envelope theorem concludes that the effect of climate on current actions also becomes irrelevant for steady-state payoffs. And when either (ii) holds or payoffs are quadratic, the average treatment effect of weather is approximately linear and thus equivalent to the treatment effect of average weather. The result follows from recognizing that average weather defines the climate.

[17] Relating to the Rubin causal model, the potential outcomes are the realizations of $\partial V/\partial w_t$ if A_{t-1}, w_t, and F_t took on different values.

[18] Further, the appendix shows that the average treatment effect of forecasts can identify the discount factor β and thus yield $\mathrm{d}V(A^{ss}, C, \boldsymbol{C})/\mathrm{d}C$ from Proposition 5.

6 Limitations

I have demonstrated how to estimate the effects of climate change from time series variation in weather. The setting is fairly general, and the appendix generalizes it further. Nonetheless, the results are subject to three main caveats.

First, the present setting omits constraints that could make the short-run effects of weather shocks less severe than the long-run effects of permanently changing the climate. In particular, some have argued that short-run adjustments could be greater than long-run adjustments because some actions may not be sustainable indefinitely (e.g., Fisher et al., 2012; Blanc and Schlenker, 2017; Auffhammer, 2018b), such as water withdrawals from a reservoir. Future work could explore such possibilities by imposing constraints on cumulative deviations in actions from some benchmark value.

Second, the present setting successfully captures the distinction between transient and permanent changes in weather, but global climate change also differs from most weather shocks in its spatial structure. A change in global climate affects weather in every location and thus will have general equilibrium consequences. The present setting has followed most empirical work in abstracting from such effects, but some recent empirical work has begun exploring the implications of changing the weather in many locations simultaneously (e.g., Costinot et al., 2016; Dingel et al., 2018; Gouel and Laborde, 2018).

Finally, the present analysis has held the payoff function constant over time. However, climate change should induce innovations that alter how weather affects payoffs. Some historical studies have begun exploring the interaction between climate and agricultural innovation (e.g., Olmstead and Rhode, 2011; Roberts and Schlenker, 2011). Future work should consider approaches to bounding the scope for innovation.

References

Auffhammer, Maximilian (2018a) "Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption using big data," Working Paper 24397, National Bureau of Economic Research.

——— (2018b) "Quantifying economic damages from climate change," *Journal of Economic Perspectives*, Vol. 32, No. 4, pp. 33–52.

Auffhammer, Maximilian and Anin Aroonruengsawat (2011) "Simulating the impacts of climate change, prices and population on California's residential electricity consumption," *Climatic Change*, Vol. 109, No. 1, pp. 191–210.

Bakkensen, Laura and Lint Barrage (2018) "Climate shocks, cyclones, and economic growth: Bridging the micro-macro gap," Working Paper 24893, National Bureau of Economic Research.

Blanc, Elodie and Wolfram Schlenker (2017) "The use of panel models in assessments of climate impacts on agriculture," *Review of Environmental Economics and Policy*, Vol. 11, No. 2, pp. 258–279.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel (2015) "Global non-linear effect of temperature on economic production," *Nature*, Vol. 527, pp. 235–239.

Carleton, Tamma A. and Solomon M. Hsiang (2016) "Social and economic impacts of climate," *Science*, Vol. 353, No. 6304, p. aad9837.

Chetty, Raj (2009) "Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods," *Annual Review of Economics*, Vol. 1, No. 1, pp. 451–488.

Costinot, Arnaud, Dave Donaldson, and Cory Smith (2016) "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world," *Journal of Political Economy*, Vol. 124, No. 1, pp. 205–248.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2012) "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, Vol. 4, No. 3, pp. 66–95.

——— (2014) "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, Vol. 52, No. 3, pp. 740–798.

Deryugina, Tatyana and Solomon Hsiang (2017) "The marginal product of climate," Working Paper 24072, National Bureau of Economic Research.

Deschenes, Olivier (2014) "Temperature, human health, and adaptation: A review of the empirical literature," *Energy Economics*, Vol. 46, pp. 606–619.

Deschênes, Olivier and Michael Greenstone (2007) "The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather," *American Economic Review*, Vol. 97, No. 1, pp. 354–385.

——— (2011) "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, Vol. 3, No. 4, pp. 152–185.

Dingel, Jonathan I., Kyle C. Meng, and Solomon M. Hsiang (2018) "The spatial structure of productivity, trade, and inequality: Evidence from the global climate," working paper.

Fankhauser, Samuel, Joel B. Smith, and Richard S. J. Tol (1999) "Weathering climate change: some simple rules to guide adaptation decisions," *Ecological Economics*, Vol. 30, No. 1, pp. 67–78.

Fisher, Anthony C., W. Michael Hanemann, Michael J. Roberts, and Wolfram Schlenker (2012) "The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment," *American Economic Review*, Vol. 102, No. 7, pp. 3749–3760.

Gouel, Christophe and David Laborde (2018) "The crucial role of international trade in adaptation to climate change," Working Paper 25221, National Bureau of Economic Research.

Guo, Christopher and Christopher Costello (2013) "The value of adaption: Climate change and timberland management," *Journal of Environmental Economics and Management*, Vol. 65, No. 3, pp. 452–468.

Heal, Geoffrey and Jisung Park (2013) "Feeling the heat: Temperature, physiology and the wealth of nations," Working Paper 19725, National Bureau of Economic Research.

——— (2016) "Temperature stress and the direct impact of climate change: A review of an emerging literature," *Review of Environmental Economics and Policy*, Vol. 10, No. 2, pp. 347–362.

Hsiang, Solomon M. (2016) "Climate econometrics," *Annual Review of Resource Economics*, Vol. 8, pp. 43–75.

Huntingford, Chris, Philip D. Jones, Valerie N. Livina, Timothy M. Lenton, and Peter M. Cox (2013) "No increase in global temperature variability despite changing regional patterns," *Nature*, Vol. 500, No. 7462, pp. 327–330.

Judd, Kenneth L. (1996) "Approximation, perturbation, and projection methods in economic analysis," in Hans M. Amman, David A. Kendrick, and John Rust eds. *Handbook of Computational Economics*, Vol. 1: Elsevier, pp. 509–585.

Kelly, David L., Charles D. Kolstad, and Glenn T. Mitchell (2005) "Adjustment costs from environmental change," *Journal of Environmental Economics and Management*, Vol. 50, No. 3, pp. 468–495.

Lemoine, Derek (2017) "Expect above average temperatures: Identifying the economic impacts of climate change," Working Paper 23549, National Bureau of Economic Research.

Lemoine, Derek and Sarah Kapnick (2016) "A top-down approach to projecting market impacts of climate change," *Nature Climate Change*, Vol. 6, No. 1, pp. 51–55.

Massetti, Emanuele and Robert Mendelsohn (2018) "Measuring climate adaptation: Methods and evidence," *Review of Environmental Economics and Policy*, Vol. 12, No. 2, pp. 324–341.

Mendelsohn, Robert (2000) "Efficient adaptation to climate change," *Climatic Change*, Vol. 45, No. 3-4, pp. 583–600.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw (1994) "The impact of global warming on agriculture: A Ricardian analysis," *The American Economic Review*, Vol. 84, No. 4, pp. 753–771.

Neidell, Matthew (2009) "Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations," *Journal of Human Resources*, Vol. 44, No. 2, pp. 450–478.

Nordhaus, William D. (2006) "Geography and macroeconomics: New data and new findings," *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 103, No. 10, pp. 3510–3517.

Olmstead, Alan L. and Paul W. Rhode (2011) "Responding to climatic challenges: Lessons from U.S. agricultural development," in Gary D. Libecap and Richard H. Steckel eds. *The Economics of Climate Change: Adaptations Past and Present*, pp. 169–194.

Pindyck, Robert S. (2013) "Climate change policy: What do the models tell us?" *Journal of Economic Literature*, Vol. 51, No. 3, pp. 860–872.

Ranson, Matthew (2014) "Crime, weather, and climate change," *Journal of Environmental Economics and Management*, Vol. 67, No. 3, pp. 274–302.

Roberts, Michael J. and Wolfram Schlenker (2011) "The evolution of heat tolerance of corn: Implications for climate change," in GaryD. Libecap and Richard H. Steckel eds. *The Economics of Climate Change: Adaptations Past and Present*, pp. 225–251.

Rosenzweig, Mark R. and Christopher Udry (2014) "Rainfall forecasts, weather, and wages over the agricultural production cycle," *American Economic Review: Papers and Proceedings*, Vol. 104, No. 5, pp. 278–283.

Rosenzweig, Mark and Christopher R. Udry (2013) "Forecasting profitability," Working Paper 19334, National Bureau of Economic Research.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher (2005) "Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach," *American Economic Review*, Vol. 95, No. 1, pp. 395–406.

Shrader, Jeffrey (2017) "Expectations and adaptation to environmental risks," working paper.

Sohngen, Brent and Robert Mendelsohn (1998) "Valuing the impact of large-scale ecological change in a market: The effect of climate change on U.S. timber," *The American Economic Review*, Vol. 88, No. 4, pp. 686–710.

Tol, Richard S.J., Samuel Fankhauser, and Joel B. Smith (1998) "The scope for adaptation to climate change: what can we learn from the impact literature?" *Global Environmental Change*, Vol. 8, No. 2, pp. 109–123.

Wood, Stephen A., Amir S. Jina, Meha Jain, Patti Kristjanson, and Ruth S. DeFries (2014) "Smallholder farmer cropping decisions related to climate variability across multiple regions," *Global Environmental Change*, Vol. 25, pp. 163–172.

Zhang, Peng, Olivier Deschenes, Kyle Meng, and Junjie Zhang (2018) "Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants," *Journal of Environmental Economics and Management*, Vol. 88, pp. 1–17.