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SUFFICIENT STATISTICS FOR THE COST OF CLIMATE CHANGE

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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. Instead of estimating the marginal effect of weather within distinct weather bins, empirical work should estimate the average effect of weather within each climate.

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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 who is exposed to stochastic weather outcomes. These weather outcomes impose some costs that are unavoidable and some costs that depend on the agent's actions (equivalently, investments). The agent wants to choose actions that best match the weather, but actions also impose costs: maintaining a given level of activity is costly, and 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 affects the distribution of realized weather in every period and also affects the agent's expectations of 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. 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 factor 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

[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) for an exposition and Massetti and Mendelsohn (2018) for a review.

[2] This literature has estimated the effects of climate on gross domestic product (Dell et al., 2012; Burke et al., 2015), on profits (Deschênes and Greenstone, 2007), and on behavioral 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), among many others. 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.

activity through a sequence of incremental adjustments. I also show that combining short-run adaptation responses to weather realizations with short-run adaptation responses to weather forecasts can better approximate long-run adaptation to climate.

Second, I show that the effect of climate on steady-state payoffs is equal to the average treatment effect of weather around a steady state in the current climate. An easily estimated function of weather is therefore a sufficient statistic for the impact of climate change on variables such as welfare and profits.[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 consequences of climate. This result arises for three reasons. First, the envelope theorem implies that small changes in current actions do not have first-order effects on maximized value. Second, standard representations of adjustment costs imply that small changes in past actions also do not have first-order effects on maximized value around a steady state. Together, these two observations imply that we do not need to consider how expectations of weather affect actions around a steady state. Finally, the treatment effect of weather is linear when payoffs are quadratic and is otherwise approximately linear when the weather has small variance. The average treatment effect of transient weather shocks is then equivalent to the effect of changing the average weather, which in turn is the definition of the effect of changing the climate. This result suggests that reduced-form empirical work should begin estimating the average treatment effect of weather as a function of long-run average weather.[4]

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. The most prominent defense of using panel variation to estimate the effects of climate change rests on an appeal to the envelope theorem: if climate differs from weather only via expectations and if expectations matter only via actions, then the envelope theorem suggests that expectations do not matter for the effects of climate on payoffs. This argument dates to Deschênes and Greenstone (2007) and has been most forcefully elaborated in Hsiang (2016) and Deryugina and Hsiang (2017). However, these envelope theorem arguments apply static analysis to an inherently dynamic problem. In fact, climate change can affect predetermined variables that are not subject to the envelope theorem but are themselves actions that were chosen in previous periods based on expectations of weather in the current period

[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 climate impacts. See Chetty (2009) for a general treatment of sufficient statistics for welfare analysis.

[4] In contrast, much empirical literature estimates the marginal effect of weather by weather bin (see Carleton and Hsiang, 2016), sometimes allowing the marginal effects to differ by climate zone (e.g., Barreca et al., 2015; Deryugina and Hsiang, 2017; Auffhammer, 2018). The standard practice can identify nonlinearities in the effects of weather on payoffs. In the appendix, I show that nonlinear weather impacts may not indicate anything about the consequences of changing the climate.

and beyond. I here show precisely when researchers can ignore the effects of expectations and show precisely which panel estimators can recover the effects of climate.[5]

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 implications for empirical work. The appendix analyzes a more general setting, provides results about forecasts and nonlinearities, and contains 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 $\phi \geq 0$. The parameter $\bar{A}$ defines the level of activity or capital that is cheapest to sustain. It can also be interpreted as the capital stock that would be chosen if weather imposed only unavoidable costs. 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), low adjustment costs allow adaptation investments to occur after weather is realized ("reactive" or "ex-post" adaptation), but large adjustment costs require adaptation to occur

[5]A few other papers are also related. First, in an 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 exactly 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, Shrader (2017) demonstrates the importance of distinguishing adaptation motivated by expectations of future weather in an application to fisheries.

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.

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. 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 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 $f_{it} = C$.[6] 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.[7] 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.[8]

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:

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

[6] 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.

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

[8] The system of weather and forecasts can be written as a vector autoregression. Climate here controls average weather. One might wonder about the dependence of higher moments of the weather distribution on climate. However, the effects of climate change on the variance of the weather are poorly understood and potentially heterogeneous (e.g., Huntingford et al., 2013). 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.

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:

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

The state variable Z_t summarizes the previous period's actions.

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, fertilizer inputs, 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). The appendix generalizes the analysis to arbitrary functional forms and vector-valued actions by applying perturbation methods (Judd, 1996).

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:

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

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 (2),

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

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 it.

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.[9] Imagine that empirical researchers were to then approximate the effect of climate change as

$$\frac{\mathrm{d}A^{ss}}{\mathrm{d}C} \approx \frac{\partial A_t}{\partial w_t} + \sum_{i=1}^{j} \frac{\partial A_t}{\partial f_{it}}, \tag{3}$$

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 $\beta \to 0$.*

[9] Note that the estimation equation should include A_{t-1}, because time $t-1$ actions can directly affect time t actions (see equation (2)) and the dependence of time $t-1$ actions on time $t-1$ forecasts makes them correlated with time t weather and forecasts.

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 (3) never overestimates $\mathrm{d}A^{ss}/\,\mathrm{d}C$ ($Bias(j) \leq 0$), 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 ($\mathrm{d}Bias(j)/\,\mathrm{d}j \geq 0$), although the bias with any number of forecasts is independent of the length of the longest forecast horizon ($\mathrm{d}Bias(j)/\,\mathrm{d}N = 0$).

The approximation in (3) can underestimate $\mathrm{d}A^{ss}/\,\mathrm{d}C$ for three reasons. First, the approximation misses the effect of changing expectations at horizons longer than N (i.e., it misses the βb_2^N in equation (2)). Second, the approximation misses the change in the policy rule induced by the anticipated permanence of climate change (i.e., it misses the effect of C on c_1 in equation (2)). Third, the approximation misses the accumulated effect of changing the weather period after period: even for a given policy rule, the long-run effect of repeating short-run shocks is greater than the effect of a single short-run shock because incremental adjustments accumulate over time (i.e., the approximation misses the effects on A_{t-1} in equation (2)). The first two reasons make the bias sensitive to the discount factor β and explain why estimating responses to forecasts can be helpful. The third reason is why nonzero bias can arise even when agents are myopic (i.e., even as $\beta \to 0$) and even when estimating responses to forecasts at arbitrarily long horizons (i.e., even as $j, N \to \infty$).

The bias vanishes in a few special cases. First, as adjustment costs vanish ($\alpha \to 0$), 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 ($\gamma \to \infty$), 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 ($\gamma \to 0$) or maintenance costs are prohibitive ($\phi \to \infty$), 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 (3): $\mathrm{d}Bias(j)/\,\mathrm{d}j \to 0$ as either $\beta \to 0$ or $\alpha \to \infty$.[10] The reason is that actions are not sensitive to forecasts in these cases.[11] First,

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

[11]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 $\alpha \to \infty$.

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 many tiny changes over a very 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 expectation at time 0 of $V(Z_t, w_t, F_t)$ at some future time $t > N$ is:

$$\begin{aligned}
E_0[V(Z_t, w_t, F_t)] =& V(A^{ss}, C, \boldsymbol{C}) + E_0[(A_t - A^{ss})^2]a_1 + \sigma^2 a_2 + \sum_{i=1}^{N}\tau_i^2 a_3^i + Cov_0[Z_t, w_t]b_1 \\
&+ \sum_{i=1}^{N} Cov_0[Z_t, f_{it}]b_2^i + \sum_{i=1}^{N} Cov_0[w_t, f_{it}]b_3^i + \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} Cov_0[w_t, f_{it}]b_4^{ij}.
\end{aligned} \tag{4}$$

Recalling from Proposition 1 that each a and b coefficient is independent of C, and recognizing that each covariance is independent of C,[12] we have:

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

[12] 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 (4) is independent of C.

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.[13]

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 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:

$$\begin{aligned}\frac{\mathrm{d}V(A^{ss},C,\boldsymbol{C})}{\mathrm{d}C} =& V_w(A^{ss},C,\boldsymbol{C}) + \sum_{i=1}^{N} V_{f_i}(A^{ss},C,\boldsymbol{C}) \\ &+ \frac{\mathrm{d}c_1}{\mathrm{d}C}A^{ss} + \frac{\mathrm{d}c_2}{\mathrm{d}C}C + \sum_{i=1}^{N}\frac{\mathrm{d}c_3^i}{\mathrm{d}C}C + \frac{\mathrm{d}d}{\mathrm{d}C}. \end{aligned} \tag{5}$$

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 $\mathrm{d}c_2/\mathrm{d}C \geq 0$).

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

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

Proposition 5.

$$\frac{\mathrm{d}V(A^{ss}, C, \boldsymbol{C})}{\mathrm{d}C} = \frac{1}{1-\beta}\frac{\mathrm{d}\pi(A^{ss}, A^{ss}, C)}{\mathrm{d}C} = \frac{1}{1-\beta}\left[\frac{\gamma\phi}{\gamma+\phi}(\bar{A}-C) + \psi(\bar{w}-C)\right]. \tag{6}$$

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 expected actions are, on average, close to their steady-state level, then we obtain the following average treatment effect of weather on value:

$$ATE_w^V(C) \triangleq 2a_2 C + b_1 A^{ss} + \sum_{i=1}^{N} b_3^i C + c_2.$$

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 steady state. 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.[14] The appendix shows that the same result holds for general, non-quadratic payoff functions if (i) $\partial\pi(A_t, A_{t-1}, w_t)/\partial A_{t-1} = 0$ when $A_t = A_{t-1}$ and (ii) σ^2 and τ_i^2 are not too large. The envelope theorem holds that the effect of climate on current actions does not matter for the effect of climate on value. When (i) holds (as it does in the main text), the effects of climate on past actions also vanish around a steady state, so that adjustment costs and beliefs about future weather both become irrelevant for value. Finally, 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.

6 Implications for Empirical Work

A rapidly growing empirical literature seeks to estimate the effects of climate change from panel variation in weather. I now discuss how the present paper's results should influence that research agenda.

First, 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 have recognized that long-run adjustment to a new climate regime may be more complete than the adjustment seen in response to short-run weather shocks.[15] I have formally demonstrated that this intuition relies on adjustment costs, not on forward-looking behavior, and I have shown that empirical work can better approximate the effects of a change in climate by also estimating how actions respond to forecasts of future weather. Further, the appendix shows that modeling forecasts is not optional: ignoring forecasts can act like omitted variables bias when estimating the consequences of weather. Finally, if agents are patient (i.e., if β is

[14] 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.

[15] Some have argued that short-run adjustments could be greater than long-run adjustments because some actions may not be sustainable indefinitely (e.g., Blanc and Schlenker, 2017), such as water withdrawals from a reservoir. Future work could explore such possibilities by imposing constraints on cumulative deviations in A_t from some benchmark value.

close to 1) over timescales of interest, then responses to weather and to forecasts differ only because of adjustment costs. In this case, estimating the response to forecasts allows for a nice test: if actions are much less sensitive to forecasts than to weather, then adjustment costs may be small and responses to weather may approximate responses to climate.

Second, 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 that are potentially related to aggregate payoffs (e.g., Dell et al., 2012; Burke et al., 2015; Deryugina and Hsiang, 2017). I have shown that the average effect of weather in a given climate is a sufficient statistic for the consequences of marginally perturbing the climate. This new result suggests that empirical work should estimate the average effect of weather as a function of long-run average weather, in contrast to the standard approach of estimating the marginal effect of weather within different weather bins and simulating how climate change will alter the frequency of weather in each bin.[16] The suggested approach combines panel and cross-sectional variation: panel variation will identify the average effect of weather within a region's current climate and thus the consequences of marginally changing each location's climate, and cross-sectional variation will identify how that average effect varies across climates and thus the consequences of nonmarginal changes in climate.[17]

References

Auffhammer, Maximilian (2018) "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.

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.

[16]The standard technique emphasizes the curvature of either V or π in w_t, but the appendix shows that this curvature is not necessarily informative about climate change. In particular, the appendix shows that climate impacts can be linear (or even nonexistent) even when weather impacts are arbitrarily nonlinear. Also, note that some empirical work has estimated average effects (e.g., Schlenker and Lobell, 2010; Dell et al., 2012; Wilson, 2017; Colacito et al., 2018), but this is not the dominant practice.

[17]The use of cross-sectional variation raises the usual concerns about identification: if the average effect of weather correlates with unobserved fixed factors, then the nonlinear effects of climate change will not be identified. Similar concerns about combining cross-sectional variation with panel identification apply to the recent empirical studies that estimate how the marginal effects of weather bins vary with the climate (e.g., Barreca et al., 2015; Deryugina and Hsiang, 2017; Auffhammer, 2018). 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.

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.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro (2015) "Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900-2004," *American Economic Review: Papers and Proceedings*, Vol. 105, No. 5, pp. 247–251.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro (2016) "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, Vol. 124, No. 1, pp. 105–159.

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.

Colacito, Ric, Bridget Hoffmann, and Toan Phan (2018) "Temperature and growth: A panel analysis of the United States," working paper.

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.

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.

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, doi:10.1016/S1574-0021(96)01014-3.

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.

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.

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.

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.

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.

Schlenker, Wolfram and David B. Lobell (2010) "Robust negative impacts of climate change on African agriculture," *Environmental Research Letters*, Vol. 5, No. 1, p. 014010.

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.

Wilson, Daniel J. (2017) "The impact of weather on local employment: Using big data on small places," Working Paper 2016-21, Federal Reserve Bank of San Francisco.

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.