NBER WORKING PAPER SERIES

# ESTIMATING THE CONSEQUENCES OF CLIMATE CHANGE FROM VARIATION IN WEATHER

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

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018, Revised November 2023

I thank numerous seminar participants for valuable comments. I thank Olivier Deschênes, Ryan Kellogg, and Wolfram Schlenker for helpful conversations and Wint Thu for assistance compiling weather data. An early 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.

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JEL No. D84,H43,Q54

## ABSTRACT

I formally demonstrate how to use the effects of short-run weather shocks to learn about the consequences of long-run climate change. I show that short-run adaptive responses to weather shocks differ from long-run responses to climate change when payoffs depend on a capital or resource stock. I derive a new indirect least squares estimator that bounds long-run climate impacts from short-run responses to weather. In an application to U.S. counties' economic output, I show that conventional methods project end-of-century losses of 8–12%, depending on the region of the country, whereas my theoretically grounded estimator projects larger losses of at least 12–20%.

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

# 1 Introduction

Ignorance of the economic costs of climate change has hampered policy. A pressing research agenda seeks to estimate these costs. Recognizing that different locations have different climates, many economists have hoped to estimate the effects of climate change from the correlation between climate and outcomes of interest over space (e.g., Mendelsohn et al., 1994; Schlenker et al., 2005; Nordhaus, 2006). However, locations differ in many ways, making it difficult to isolate the effects of being in one climate or another.[1]

Intriguingly, though, the same location does experience different weather at different times. Stimulated by Deschênes and Greenstone (2007), a rapidly growing empirical literature estimates the consequences of a location happening to experience cooler-than-average or hotter-than-average weather.[2] Researchers project the consequences of climate change by combining credibly estimated effects of weather with scientists' predictions about how climate change will alter the distribution of weather. But it has been unclear whether extrapolating estimated effects of weather is truly informative about climate change impacts.[3]

This paper formally relates the effects of climate change to the effects of weather shocks. I focus on the dynamic structures of weather shocks and climate change: weather shocks are transient, whereas climate change permanently alters the distribution of weather. I show that estimating long-run effects of climate change requires estimating the direct effects of altered average weather and the average effects of adapting to altered weather, which encompasses both ex-post adaptation (through which agents react to altered weather realizations) and ex-ante adaptation (through which agents anticipate the altered distribution of future weather).

I show that the best possible weather regressions differ from the ones that empirical researchers typically run by including lags of weather and including forecasts of weather. However, I also show that even the best possible weather regressions suffer from three biases when used to project climate change impacts. All three biases derive from the adaptation channel. These biases reflect the possibility of fixed-cost adaptation and reflect the transience of shocks to forecasts and weather.

First, agents may not pay the fixed costs of modifying long-lived infrastructure in response to a transient weather shock but would pay those costs in response to a permanent change in climate. When the envelope theorem applies (but see Guo and

[1]See Dell et al. (2014) and Auffhammer (2018) for expositions and Massetti and Mendelsohn (2018) for a review.

[2]For reviews, see Dell et al. (2014), Carleton and Hsiang (2016), Heal and Park (2016), and Carter et al. (2018). Blanc and Schlenker (2017) and Kolstad and Moore (2020) discuss the strengths and weaknesses of relying on panel variation in weather.

[3]For instance, Dell et al. (2014, 771–772) emphasize that "short-run changes over annual or other relatively brief periods are not necessarily analogous to the long-run changes in average weather patterns that may occur with climate change." And Mendelsohn (2019, 272) observes, "An important failing of current weather panel studies is that they lack a clear theoretical model."

Costello, 2013), these potential adjustments to changes in infrastructure do not matter directly. However, I show that they do bias estimates of other types of adaptation if those adjustments would affect shorter-run adaptation decisions that do vary in the data.

Second, understanding that the climate has changed is equivalent to altering average weather forecasts in every period, whereas an empirical researcher estimates responses to one-off changes in weather forecasts (if the empirical researcher observes weather forecasts at all).[4] I show that the latter variation identifies only a combination of the ex-ante adaptation relevant to climate change and preparation for transient changes in ex-post adaptation. The latter is not relevant to the effects of climate change that alters agents' expectations in every period.

Third, experiencing a changed climate is equivalent to living with altered weather period after period, whereas an empirical researcher estimates only the consequences of reactions to one-off weather shocks. Actions are intertemporal complements (substitutes) if actions in one period increase (decrease) optimal actions in later periods through a stock variable. For example, actions are intertemporal complements when they represent capital investment in the presence of adjustment costs and are intertemporal substitutes when they deplete a scarce resource stock. In the former case, estimates derived from short-run weather variation understate long-run adaptation to climate change because agents have more flexibility in the long run, but in the latter case, estimates derived from short-run weather variation overstate long-run adaptation to climate change because agents have a hard time maintaining adaptation responses.[5]

What, then, is an empirical researcher to do?[6] I develop a new indirect least squares estimator of climate impacts (Tinbergen, 1930, 1995). I show that we can

[4] I show how to adapt the estimator to capture ex-ante adaptation if agents have forecasts that the empirical researcher does not observe. However, if agents do not have forecasts of weather on the timescale of the data, then nothing in the data identifies ex-ante adaptation that would be undertaken by agents who understand that the climate has changed.

[5] Both types of stories exist in the literature (see Auffhammer, 2018). For instance, in studies of the agricultural impacts of climate change, Deschênes and Greenstone (2007) conjecture that long-run adjustments to changes in climate should be greater than short-run adjustments to weather shocks because there may be costs to adjusting crops, whereas Fisher et al. (2012) and Blanc and Schlenker (2017) conjecture that constraints on storage and groundwater pumping, respectively, could make short-run adjustments exceed long-run adjustments.

[6] Recent literature has sought to sidestep concerns about the relevance of short-run variation in weather by estimating how the effect of weather varies cross-sectionally with a location's climate (e.g., Auffhammer, 2022; Carleton et al., 2022) or by using "long difference" estimators (e.g., Dell et al., 2012; Burke and Emerick, 2016). The former approach forsakes the clean identification of panel variation; I instead explore the limit of what researchers can learn from purely panel variation in weather. Appendix A analyzes long difference estimators, showing that they inherit the biases suffered by standard weather regressions (see also footnote 34). Finally, other work uses quasi-random spatial variation in water supplies to estimate long-run adaptation (e.g., Hornbeck and Keskin, 2014; Blakeslee et al., 2020; Hagerty, 2020), but similar variation will not be available for many environmental variables affected by climate change.

in fact partially identify the long-run effects of climate change in a fairly general setting, even without observing the actions agents and firms could choose, without observing the capital or resource stocks that they interact with, and without assuming functional forms for payoffs or for the evolution of stock variables. I first express climate change impacts in terms of my setting's theoretical primitives. I then express reduced-form weather coefficients in terms of the same theoretical primitives. This system is just-identified in that there are as many unknown theoretical primitives as there are equations. So I next solve for the unknown theoretical primitives in terms of the estimable reduced-form coefficients. With these in hand, I calculate climate impacts from the analytical expression derived in the first step.

The identification is purely reduced-form, as the only point of contact with data is a fixed effects regression that relies on conventional panel variation in weather. Theory determines both the specification of the regression and the calculations that use its estimates.[7] Intuitively, variation in contemporary weather identifies a combination of direct weather effects and ex-post adaptation. Past weather affects current payoffs only through the effects of ex-post adaptation on capital or resource stocks, so variation in past weather identifies ex-post adaptation and enables us to isolate direct weather effects from variation in contemporary weather. Forecasts affect current payoffs only when agents base actions on them, so variation in forecasts identifies ex-ante adaptation.[8] And comparing the effects of weather with shorter and longer lags identifies whether actions are intertemporal substitutes or complements.

This indirect least squares estimator eliminates the bias induced by the transience of forecasts. It also signs the wedge between short-run and long-run adaptation induced by the transience of weather shocks, which enables us to bound the effects of climate change. The remaining bias is the possibility that some long-lived infrastructure could adjust on timescales not observed in the data and thereby alter the adaptation responses that are recovered from the data. Such bias would matter only if it were in a direction that would violate the estimated bound.

Every projection of climate impacts from weather regressions is valid only under particular assumptions on the economic environment. That is true both for my indirect least squares estimator and for conventional panel regressions. When empirical researchers do not specify a formal model, those assumptions remain unstated and unclear. I show that conventional methods require strict assumptions and that my

[7]Critically, this calculation does not require the specification of structural parameters or even of functional forms. This approach is in the spirit of Marschak's Maxim. Heckman (2010, 359) writes, "Marschak's Maxim suggests that economists should solve well-posed economic problems with minimal assumptions. All that is required to conduct many policy analyses or to answer many well-posed economic questions are policy invariant combinations of the structural parameters that are often much easier to identify than the individual parameters themselves and that do not require knowledge of individual structural parameters." It is also related to sufficient statistics approaches (see Chetty, 2009) and to price theory (see Weyl, 2019).

[8]Shrader (2020) also uses variation in forecasts to identify ex-ante adaptation, in an analysis not focused on climate change.

new estimator weakens these assumptions. Here theory clarifies exactly what object the calculations aim to capture (the change in long-run average payoffs) and under what conditions they do so (when long-lived infrastructure does not affect short-run adaptation responses).

I demonstrate the new method using a panel analysis of the effect of average annual temperature on U.S. counties' output from 2001–2019.[9] I find that higher temperatures reduce output, with an effect that varies by Census region. If I followed conventional methods, then I would multiply that estimated effect by climate models' projected changes in temperature to conclude that end-of-century climate change will reduce U.S. output in a business-as-usual scenario by 8–12% (depending on the Census region), which is consistent with the damage calibration in Hänsel et al. (2020). My theoretical analysis established that this calculation implicitly assumes that economic decisions are not linked over time. However, capital and resource stocks are intuitively important for economic output, and my regression estimates do in fact show that lagged temperatures matter for output. The assumption required by the conventional calculation is unlikely to hold in this application.

My new indirect least squares estimator does not require this strong assumption. Applying it, I estimate that end-of-century climate change will reduce output by 12–20% in three Census regions, with a larger but very noisy estimate in the fourth. My approach predicts losses around twice as large as suggested by the conventional approach. The reason for the larger losses is that the conventional approach relies on an estimated coefficient that entangles direct costs of temperature shocks with short-run benefits from ex-post adaptation. For optimizing agents, those short-run benefits come at the expense of long-run costs and thus should be cleaned from projected climate change consequences. By disentangling direct effects and ex-post adaptation, my indirect least squares estimator nets out the implied long-run costs of ex-post adaptation. The isolated direct effects drive my estimated total effects.

My indirect least squares estimator also shows that actions are intertemporal complements. This result is consistent with adjustment costs in capital stocks. From the theoretical analysis, ex-post adaptation to climate change will therefore be greater than ex-post adaptation to the weather shocks observed in the data. Because long-run costs of optimized ex-post adaptation dominate short-run benefits in a calculation of steady-state consequences, my estimated total costs of climate change are a lower bound on the combination of direct effects and ex-post adaptation.

I cannot recover ex-ante adaptation in this particular application. To identify ex-ante adaptation, I require agents to have forecasts of coming weather, but such forecasts are not yet important at the annual level. Therefore the correct way to interpret my estimated losses from climate change is that avoiding them will require some combination of ex-ante adaptation based on foreknowledge of climate change and

[9]Colacito et al. (2019) estimate negative effects of summer temperature on output growth in U.S. states. Barker (2022) critique their methods and interpretation. Deryugina and Hsiang (2017) estimate effects on county income over 1969–2011.

emission reductions that limit climate change. This result highlights the importance of producing and disseminating high-quality, localized climate projections that can facilitate ex-ante adaptation.

Despite the importance of empirically estimating the costs of climate change and the sharpness of informal debates around the relevance of the burgeoning weather regression literature to climate change, there has been remarkably little prior formal analysis of the economic distinction between weather shocks and climate change.[10] The primary exceptions are Hsiang (2016) and Deryugina and Hsiang (2017). They argue that the simplest weather regression exactly identifies the effect of climate on payoffs. Their setting assumes that there are no dynamic linkages and that outcomes and actions depend only on the distribution of weather (i.e., only on the climate), not on the weather realized from this distribution. Their setting is a special case of the present setting (see Section 3). I show that their optimistic result does not survive generalizing payoffs to depend on a stock variable, such as capital or natural resources. The envelope theorem implies that changes in actions have no effects on payoffs in the static environment of Hsiang (2016) and Deryugina and Hsiang (2017), but in a dynamic environment, the envelope theorem applies to the intertemporal value function, not to the flow payoffs that empirical researchers typically observe.

The challenge of attempting to estimate long-run effects from short-run variation is a common one in empirical economics. The present analysis and methods could inform approaches in other fields. For instance, labor economists desire the long-run consequences of changing the minimum wage, but inflation converts observed minimum wage increases into short-run shocks (Sorkin, 2015).[11] And macroeconomists formerly hoped to learn about long-run output-inflation tradeoffs by estimating distributed lag models, but Lucas (1972) argued that, when agents have rational expectations, the response to a transient inflation shock is not informative about the long-run effects of permanently changing inflation policy. Here we desire the long-run effect of changing the "policy rule" used by nature to generate weather.

The next section describes the setting. Section 3 analyzes a special case without dynamic linkages, as in prior literature. Section 4 analyzes the full model and delineates what we can learn from reduced-form regressions. Section 5 derives the

[10] Mérel and Gammans (2021) explore the conditions under which actions chosen under the full distribution of weather identify actions chosen for average weather, assuming that the envelope theorem prevents actions from having first-order consequences for the cost of climate change. Carter et al. (2018) discuss several econometric issues in the estimation of panel models of weather.

[11] Three other papers are related to both Sorkin (2015) and the present paper's project. First, I here formalize analogues to arguments in Hamermesh (1995) about why the pre- and post-periods around a minimum wage increase are not true pre- and post-periods. Second, in a model of dynamic stock accumulation, Hennessy and Strebulaev (2020) show that estimated responses to transient shocks can differ substantially from the theory-implied causal effects that empirical researchers seek to test. The present paper is similar in deriving sufficient conditions for estimated effects to match theory-implied effects. Third, Keane and Wolpin (2002) describe tradeoffs between cross-sectional and panel variation when estimating the effects of welfare benefits. These tradeoffs are similar to those that motivate the present paper.

indirect least squares estimator. Section 6 applies the new estimator to U.S. counties' economic output. The final section describes potential extensions. The appendix contains additional analysis and proofs.

# 2 Setting

In each period $t$, agents receive payoffs $\pi(w_t, A_t, S_t; K)$, with $\pi$ bounded.[12] After observing weather $w_t$, agents choose actions $A_t$ as a form of adaptation, where $\pi_{AA} < 0$ (subscripts indicate partial derivatives). Agents can also affect a stock variable $S_t$, where $\pi_S = 0$ in Section 3 and $\pi_{SS} < 0$ everywhere else. The stock evolves as $S_{t+1} = g\, S_t + h(A_t)$, with $h$ monotonic.[13] The parameter $g \in [0, 1)$ controls the persistence of actions. If $g = 0$, the time $t + 1$ stock depends only on time $t$ actions, as with acreage planted versus fallowed. If $g > 0$, the time $t + 1$ stock depends on all past actions, as with a capital stock that depends on past investments and overdrafts from a groundwater reservoir that recharges towards its steady state.

The stock can affect an agent's payoffs from pursuing different actions. When $h'\, \pi_{AS} < 0$, actions are ***intertemporal substitutes***, so that choosing a higher action in one period reduces the marginal benefit of actions in the subsequent period. I describe this case as a resource scarcity story. For instance, pumping groundwater today raises the cost of pumping groundwater tomorrow. When $h'\, \pi_{AS} > 0$, actions are ***intertemporal complements***, so that choosing a higher action in one period increases the marginal benefit of actions in the subsequent period. I describe this case as an adjustment cost story because it favors approaching a high action via a sequence of smaller steps. For instance, small changes to capital stocks may be easier to implement than large changes. The magnitude of $h'\, \pi_{AS}$ affects how agents prepare in advance of a weather event that they know will change their preferred actions. When $|h'\, \pi_{AS}|$ is large, agents prefer to begin adapting actions before a weather event arrives, but when $|h'\, \pi_{AS}|$ is small, agents may wait to undertake most adaptation only once a weather event has arrived.

Agents understand the climate $C$, which controls the distribution of weather. I interpret weather as realized temperature and climate as a location's long-run average temperature. At all times before $t - 2$, an agent's only information about time $t$ weather consists in knowledge of the climate. However, at time $t - 2$ specialized information about time $t$ weather becomes available in the form of a random variable $\epsilon_{2,t-2}$. The agent uses this information to form a forecast $f_{2,t-2}$ of time $t$ weather:

[12] I refer to "agents" and "actions", but one can also think of firms choosing quantities, with weather affecting profits through prices and/or the production function. The assumption of boundedness is a technical condition that ensures optimal policy is single-valued (used in Appendix E.3).

[13] I abstract from externalities in use of the stock and from the possibility that the stock is directly vulnerable to weather shocks. Future work could consider common pool resources and weather-exposed stocks.

$f_{2,t-2} = C + \zeta\epsilon_{2,t-2}$.[14] The parameter $\zeta \geq 0$ is a perturbation parameter that will be useful for analysis (see Judd, 1996). At time $t-1$, the agent receives additional news about time $t$ weather in the form of a random variable $\epsilon_{1,t-1}$. The agent refines her forecast of time $t$ weather to $f_{1,t-1} = f_{2,t-2} + \zeta\epsilon_{1,t-1}$. Finally, the agent may be surprised by a random component $\epsilon_{0,t}$ of time $t$ weather, where $w_t = f_{1,t-1} + \zeta\epsilon_{0,t}$. Reflecting rationality of beliefs, the random variables are mean-zero and serially uncorrelated. Ordering the $\epsilon_{i,t}$ by $i$, they have covariance matrix $\Sigma$ at any time $t$. Even though the news represented by $\epsilon_{i,t}$ is serially uncorrelated, the weather realizations $w_t$ are serially correlated if $\Sigma$ is not diagonal.[15]

Each agent chooses actions to maximize the expected present value of payoffs over an infinite horizon:

$$\max_{\{A_t(S_t,w_t,f_{1,t},f_{2,t})\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t E_0 \left[\pi(w_t, A_t, S_t; K)\right],$$

where $\beta \in (0,1)$ is the per-period discount factor, $E_0$ denotes expectations at the time 0 information set, and $S_0$, $w_0$, $f_{1,0}$, and $f_{2,0}$ are given. The solution satisfies the following Bellman equation:

$$V(S_t, w_t, f_{1,t}, f_{2,t}; \zeta, K) = \max_{A_t} \left\{ \pi(w_t, A_t, S_t; K) + \beta E_t \left[V(S_{t+1}, w_{t+1}, f_{1,t+1}, f_{2,t+1}; \zeta, K)\right] \right\}.$$

Agents also choose long-lived infrastructure $K$. This represents capital-intensive adaptation that takes years to construct, such as irrigation canals or sea walls (see Aldy and Zeckhauser, 2020). This infrastructure is fixed over the period of analysis; agents cannot adapt it to short-run weather outcomes or forecasts. This is the only kind of action analyzed in previous work that formally relates climate change to weather variation (Hsiang, 2016; Deryugina and Hsiang, 2017). In order to facilitate comparison to prior literature that has assumed actions that depend on climate but not on weather realizations, let the agent choose $K$ to maximize long-run payoffs

[14] Implicitly, $f_{k,t} = C$ for $k > 2$. Results generalize straightforwardly when extending the analysis to allow for specialized forecasts of weather more than two periods away. Because doing so generates little new insight but imposes additional notation, I restrict attention to the case with specialized forecasts beginning only two periods ahead of a weather event.

[15] Consistent with much previous literature, 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 likely to be spatially heterogeneous (e.g., Huntingford et al., 2013; Lemoine and Kapnick, 2016). Further, for economic analysis, we need to know not just how climate change affects the variance of realized weather but how it affects the forecastability of weather: the variance of the weather more than two periods ahead is $\zeta^2 trace(\Sigma)$, so we need to apportion any change in variance between the diagonal elements of $\Sigma$ (i.e., between each of the $\epsilon_{i,t}$). I leave such an extension to future work.

under expected outcomes:[16]

$$\max_K \left\{ \lim_{t\to\infty} \pi(E_0[w_t], E_0[A_t], E_0[S_t]; K) \right\}.$$

Together, the decision variables $A_t$ and $K$ bracket the many types of actions actual agents may take, which fall on a spectrum between the immediate consequences of changing $A_t$ and the purely long-run consequences of changing $K$.

The setting is meant to be fairly general. To fix ideas, consider a few examples pertinent to previous empirical research. In an agricultural application, weather could affect yields or crop prices, actions could be irrigation or planting decisions, the stock could be water supplies or machinery, and long-lived infrastructure could be irrigation canals or available crop varietals.[17] In a flooding application, weather could affect rental value, actions could be investments in the property, the stock could be the quality of the property, and long-lived infrastructure could be sea walls. In a migration application, weather could affect wages, actions could be the choice of future location, and the "stock" (i.e., the inherited state) could be one's current location.[18] In a health application, weather could affect mortality, individuals could organize their outdoor activities around weather forecasts in order to maximize utility net of mortality risks, and they could find their flexibility restricted as more days go by and the stock of postponed activities accumulates (as in Graff Zivin and Neidell, 2009). In an innovation application, weather could affect the value of patents, the action could be investing in research, and the stock could be existing patents on adaptation technologies. In a labor or energy application, weather could affect labor productivity or residential comfort, the action could be using air conditioning, and the stock could be air conditioning equipment. And in a macro application (e.g., Section 6), weather could affect profits via prices or input availability, actions could be factor use, and the stock could be capital.

I assume the following technical conditions in settings with $\pi_S \neq 0$. The first ensures that the payoff function is strictly concave in $S_t$ and $S_{t+1}$, which in turn ensures that there is a uniquely optimal action (Appendix E.3):

$$[h'(A_t)\pi_{AS}]^2 < [h'(A_t)]^2 \pi_{SS} \left[ \pi_{AA} - \frac{h''(A_t)}{h'(A_t)} \pi_A \right]. \tag{1}$$

[16]This form of the infrastructure decision problem simplifies exposition without sacrificing the qualitative insight of maximizing expected payoffs. The problem of choosing $K$ to maximize the present discounted value of expected payoffs reduces to the present form if all third derivatives of $\pi$ involving $K$ are zero.

[17]Recent literature reports that actions such as irrigation choices and crop substitution (Cui, 2020), acreage planted (Aragón et al., 2021), and pesticide use and weeding effort (Jagnani et al., 2021) respond to weather.

[18]The choice of future location fits the formal framework if it depends on the current location's present and forecasted weather and on the alternate location's average weather.

Observe that inequality (1) and $\pi_{SS} < 0$ imply

$$\pi_{AA} - \frac{h''(A_t)}{h'(A_t)}\pi_A < 0. \tag{2}$$

The next two conditions ensure that a steady state exists in a deterministic system with $\zeta = 0$ (Appendix E.4):

$$\lim_{A_t \to -\infty} \Big[ -(1-\beta g)\pi_A(C, A_t, \cdot; K) - \beta h'(\bar{A})\pi_S(C, A_t, \cdot; K) \Big] < 0, \tag{3}$$

$$\lim_{A_t \to \infty} \Big[ -(1-\beta g)\pi_A(C, A_t, \cdot; K) - \beta h'(\bar{A})\pi_S(C, A_t, \cdot; K) \Big] > 0. \tag{4}$$

The final condition ensures that the expression for expected optimal actions converges (Lemma 2 in Appendix E.6):

$$h'(A_t)\pi_{AS} \in \Bigg( -\frac{[1+2g(1+\beta)+3\beta g^2]\left[-\pi_{AA} + \frac{h''(A_t)}{h'(A_t)}\pi_A\right] - \beta[h'(A_t)]^2\pi_{SS}}{1+\beta+2\beta g}, \\ \frac{[1-2g(1+\beta)+3\beta g^2]\left[-\pi_{AA} + \frac{h''(A_t)}{h'(A_t)}\pi_A\right] - \beta[h'(A_t)]^2\pi_{SS}}{1+\beta-2\beta g}\Bigg). \tag{5}$$

The interval includes zero. This condition therefore permits both intertemporal complementarity and intertemporal substitutability but limits the degree of either.

The analysis approximates the solution to the full, stochastic model around the steady state of the deterministic model, which has $\zeta = 0$ (Judd, 1996). In order to ensure an adequate approximation, I will often impose at least one of the following assumptions:

**Assumption 1.** *$\zeta^2$ is small.*

**Assumption 2.** *$\pi$ is quadratic.*

**Assumption 3.** *The $\epsilon_{i,t}$ are jointly normally distributed.*

Either of the first two assumptions will limit the consequences of stochasticity for optimal policy, whether by limiting the variance of weather outcomes (Assumption 1) or by making the policy function independent of that variance (Assumption 2).[19] And using either the first or the third assumption will eliminate covariances of certain higher-order terms.

I am interested in empirical researchers' ability to estimate the consequences of altering $C$ from observable responses to panel variation in $w_t$ and, where available, panel variation in $f_{1,t}$ and $f_{2,t}$. I assume that empirical researchers observe $J$ agents

[19]When applying Assumption 2, the *chosen policy* is affected by the variance of weather (through realized weather) even though the *policy rule* is independent of that variance.

(equivalently, firms) in each of $T$ periods. Index these agents by $j$. To highlight the issue at hand, they are in the same climate $C$ with the same payoff function $\pi$ but their own stocks $S$.[20]

It is important to be clear about the treatment effect of interest. I study the average effects (over time, and thus over weather shocks) of moving agents from one climate to another once agents have had time to adapt to the new climate. This adaptation is based both on experiencing weather drawn from the new distribution of weather and on understanding the distribution of future weather. This climate change treatment is consistent with the dominant exercise in the empirical literature to date, which calculates the effect of replacing today's distribution of weather with a distribution projected to hold by the end of the century. Following this literature, I will not study how the transition from one climate to another interacts with agents' decisions,[21] or how expectations of a future change in climate affect agents today.[22] These are both important questions but are beyond the scope of the present analysis—and thus far largely beyond the empirical literature that this analysis seeks to inform.

# 3 Estimating Climate Impacts When There Are No Dynamic Linkages

Begin by considering a setting in which payoffs are independent of the stock $S_t$: $\pi_S = 0$. Each period's decision problem simplifies to a static problem, with optimal actions $A_t^*(w_t; K)$ satisfying the first-order condition $\pi_A(w_t, A_t^*, S_t; K) = 0$ and independent of all other periods' actions.[23]

Define $\bar{A} \triangleq A_t^*(C; K)$ and $\bar{\pi} \triangleq \pi(C, \bar{A}, S_t; K)$. Appendix E.1 shows that, under

[20] Omitted variables bias affects the analysis below when regressions do not control for variables (such as forecasts and actions) that are defined within the theoretical model. I do not explicitly model the further unobservable characteristics that motivate fixed effects specifications: I am here interested not in whether regression coefficients consistently estimate weather impacts but in whether climate change impacts are in principle recoverable from weather data.

[21] Kelly et al. (2005) frame the cost of learning as an adjustment cost. Quiggin and Horowitz (1999, 2003) discuss broader costs of adjusting to a change in climate. These papers' adjustment costs are conceptually distinct from the adjustment costs studied here. The present use of "adjustment costs" follows much other economics literature in referring to the cost of changing decisions from their previous levels. I study how these adjustment costs hinder estimation of the consequences of climate change from weather impacts, not how they affect the cost of transitioning from one climate to another.

[22] Severen et al. (2018) show that land markets capitalize expectations of future climate change and correct cross-sectional analyses in the tradition of Mendelsohn et al. (1994) for this effect. I here study responses to widely available, shorter-run forecasts in a longitudinal context and show how to use them to improve panel analyses in the tradition of Deschênes and Greenstone (2007).

[23] Using terminology defined below, ex-ante adaptation is here impossible and ex-post adaptation is here not affected by previous decisions.

either Assumption 1 or 2,

$$\frac{\mathrm{d}E_0[\pi_t]}{\mathrm{d}C} = \bar{\pi}_w + \underbrace{\bar{\pi}_A \frac{\mathrm{d}\bar{A}}{\mathrm{d}C}}_{=0} + \underbrace{\bar{\pi}_K \frac{\mathrm{d}K}{\mathrm{d}C}}_{=0} = \bar{\pi}_w \tag{6}$$

for $t > 2$. When agents optimize, the effects of climate on short-run and long-run actions vanish and we need to recover only the direct effect of weather. This envelope theorem intuition is familiar from previous literature (Hsiang, 2016; Deryugina and Hsiang, 2017).[24] ,[25]

Consider the following regression

$$\pi_{jt} = \alpha_j + \theta w_{jt} + \eta_{jt}, \tag{7}$$

where $\alpha_j$ is a fixed effect for unit $j$ and $\eta_{jt}$ is an error term. Use a hat to denote each estimator. I study the probability limits of this and other estimators as we increase the number of units in the sample. By standard results,

$$\text{plim}\,\hat{\theta} = \frac{Cov[\pi_{jt}, w_{jt} - C]}{Var[w_{jt} - C]}.$$

The following proposition relates this estimator to theoretical primitives.

**Proposition 1** (Conventional Estimator)**.** *Let Assumption 1 hold, or let Assumptions 2 and 3 hold. If* $\pi_S = 0$*, then* $\text{plim}\,\hat{\theta} = \bar{\pi}_w$.

*Proof.* See Appendix E.2. Sketch: Approximates $\pi$ to second-order around the deterministic steady state and analyzes $Cov[\pi_{jt}, w_{jt} - C]/Var[w_{jt} - C]$. □

Therefore, from equation (6),

$$\frac{\mathrm{d}E_0[\pi_t]}{\mathrm{d}C} = \text{plim}\,\hat{\theta}$$

for $t > 2$. When $\pi_S = 0$, the simplest weather regression recovers the average marginal effect of weather and thus recovers the long-run effects of climate.[26]

This is an optimistic result, but this environment with $\pi_S = 0$ is rather specialized. First, we have assumed that history does not matter. Yet capital stocks and storage

[24] I recover the setting of Hsiang (2016) and Deryugina and Hsiang (2017) if I further eliminate the choice of $A_t$ and make $\pi$ depend on $C$ directly rather than on $w_t$. In that case, the only available action (the choice of $K$) is made independently of weather realizations and there is no scope for either ex-post or ex-ante adaptation.

[25] Guo and Costello (2013) show that this envelope theorem intuition breaks down when choice variables are discrete, which could be especially relevant to long-lived infrastructure.

[26] Much literature regresses outcomes other than payoffs on weather. In the restricted setting of Section 3, the coefficient on weather in a regression with actions as the dependent variable also recovers the long-run effect of climate on actions.

may adjust only slowly over time and resource constraints may compound over time, as several authors have informally noted (e.g., Deschênes and Greenstone, 2007; Fisher et al., 2012). Capital stocks and resource constraints are potentially important in many applications, whether agricultural, industrial, or household. Second, we have assumed away any ability to proactively protect oneself against future weather (i.e., to undertake ex-ante adaptation). Yet evidence suggests that farmers adjust planting decisions based on beliefs about the coming season's weather (Rosenzweig and Udry, 2013), fishers adjust plans based on multi-month forecasts of El Niño events (Shrader, 2020), markets price in hurricane forecasts (Kruttli et al., 2019), and people use weather forecasts to reduce mortality risk (Shrader et al., 2023). We next turn to the full setting to see how far the optimism engendered by the present specialization has to run.

# 4 Estimating Climate Impacts in the Presence of Dynamics

In a general environment with $\pi_S \neq 0$, agents must account for future consequences when choosing their actions. Appendix E.4 establishes that the deterministic special case (with $\zeta = 0$ and thus $w_t = f_{i,t} = C$) has a unique steady state and is saddle-path stable. Label steady-state actions $\bar{A}$, the steady-state stock $\bar{S}$, and steady-state payoffs $\bar{\pi}$. I write $\bar{A}(K, C)$, so that $\mathrm{d}\bar{A}/\mathrm{d}C = \partial\bar{A}/\partial C + [\partial\bar{A}/\partial K][\mathrm{d}K/\mathrm{d}C]$. I assume henceforth that agents are not too far from the steady state at time 0 (i.e., that $(S_0 - \bar{S})^2$ is not too large).

I first define the true effect of climate. I then describe how past and future weather affect agents' choices. I finally consider an empirical researcher's ability to estimate the true effect of climate from variation in payoffs induced by past and future weather.

## 4.1 The True Effect of Climate on Payoffs

Following the empirical literature, we are interested in the long-run effects of altered climate on average payoffs. Appendix E.7 shows that, if either Assumption 1 or 2 holds,

$$\begin{aligned}\lim_{t\to\infty} \frac{\mathrm{d}E_0[\pi_t]}{\mathrm{d}C} =& \bar{\pi}_w + \bar{\pi}_A \frac{\mathrm{d}\bar{A}}{\mathrm{d}C} + \bar{\pi}_S \frac{\mathrm{d}\bar{S}}{\mathrm{d}C} + \overbrace{\bar{\pi}_K \frac{\mathrm{d}K}{\mathrm{d}C}}^{=0} \\ =& \underbrace{\bar{\pi}_w}_{\text{direct effects}} + \underbrace{\left[\bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g}\right] \frac{\mathrm{d}\bar{A}(K,C)}{\mathrm{d}C}}_{\text{adaptation effects}} . \qquad (8)\end{aligned}$$

The direct effects of alterations to long-lived infrastructure $K$ again vanish because agents optimize this infrastructure around long-run payoffs. However, adaptation choices $A_t$ can now can have first-order consequences for average payoffs, both directly and through their effects on the stock. Their effects on the stock become increasingly important as the stock becomes more persistent (i.e., as $g$ approaches 1).

Why do adaptation responses now have first-order effects on payoffs? In Section 3, changing these actions had no effect because the first-order condition ensured that $\pi_A = 0$. However, in a dynamic environment, agents set $V_A = 0$, not $\pi_A = 0$. Optimal actions satisfy the Euler equation, derived in Appendix E.5:

$$-\pi_A(w_t, A_t, S_t; K) = \beta h'(A_t)\, E_t \left[ \pi_S(w_{t+1}, A_{t+1}, S_{t+1}; K) + g \frac{-\pi_A(w_{t+1}, A_{t+1}, S_{t+1}; K)}{h'(A_{t+1})} \right]. \tag{9}$$

Agents equate the marginal effect of actions on contemporary payoffs (the left-hand side) to the marginal effect of actions on expected future payoffs (the right-hand side), which includes the direct effect $\pi_S$ of altering the stock and the effect of adjusting subsequent actions to return to the original stock trajectory. An agent may, for instance, choose an action whose marginal effect on immediate payoffs is negative if that action increases expected future payoffs. We recover the static efficiency condition that $\pi_A = 0$ only as agents become myopic ($\beta \to 0$) or as the stock becomes independent of actions ($h' \to 0$).

Around the deterministic steady state, equation (9) implies (see (A-8)):

$$h'(\bar{A})\bar{\pi}_S = -\frac{1 - \beta g}{\beta} \bar{\pi}_A.$$

Substitute into (8) to obtain:

$$\lim_{t \to \infty} \frac{\mathrm{d}E_0[\pi_t]}{\mathrm{d}C} = \bar{\pi}_w - \frac{1}{1-g} \frac{1-\beta}{\beta} \bar{\pi}_A \frac{\mathrm{d}\bar{A}(K, C)}{\mathrm{d}C}. \tag{10}$$

If the steady-state adaptation response to climate change increases per-period payoffs for a given stock (i.e., if $\bar{\pi}_A \frac{\mathrm{d}\bar{A}(K,C)}{\mathrm{d}C} > 0$), then it reduces steady-state payoffs. For instance, if the stock has no persistence ($g = 0$), the effect on the stock in (8) becomes $h'(\bar{A})\bar{\pi}_S$, which from the Euler equation (9) is equal to $-\bar{\pi}_A/\beta$. This term is larger than the effect $\bar{\pi}_A$ on contemporary payoffs in (8): a dynamically optimizing agent trades off short-run increases in per-period payoffs against long-run costs imposed through the stock, and discounting means those costs must be larger in current value terms. As agents become perfectly patient ($\beta \to 1$), the long-run costs are exactly offset by the short-run benefits, but as agents become myopic ($\beta \to 0$), those short-run benefits are obtained by imposing especially large costs on the future through a depleted stock. When we add the short-run benefits and long-run costs together in a steady-state calculation, the long-run costs dominate.

An empirical researcher will therefore need to estimate how climate affects actions around the deterministic steady state $\bar{A}$ if they are to recover the effect of climate on average payoffs. Appendix E.8 shows that

$$\frac{\mathrm{d}\bar{A}(K,C)}{\mathrm{d}C} \propto \underbrace{\overbrace{\bar{\pi}_{wA}}^{\text{ex-post adaptation}} + \overbrace{\beta\left[h'(\bar{A})\bar{\pi}_{wS} - g\,\bar{\pi}_{wA}\right]}^{\text{ex-ante adaptation}}}_{\propto \partial\bar{A}(K,C)/\partial C} + \overbrace{\underbrace{\left[(1-\beta g)\bar{\pi}_{AK} + \beta h'(\bar{A})\bar{\pi}_{SK}\right]}_{\propto \partial\bar{A}(K,C)/\partial K} \frac{\mathrm{d}K}{\mathrm{d}C}}^{\text{interactions with long-lived infrastructure}}. \tag{11}$$

There are three terms. The first captures what the literature has called reactive or ***ex-post adaptation*** to realized changes in weather (Fankhauser et al., 1999; Mendelsohn, 2000). Here the reaction is to observed changes in weather induced by climate change. It depends on how weather shifts the marginal benefit of short-run actions, controlled by $\pi_{wA}$. For instance, farmers may water crops during a heat wave. Ex-post adaptation can also reflect a firm's production responses to price signals generated by weather events.

The second term captures what the literature has called anticipatory or ***ex-ante adaptation*** (Fankhauser et al., 1999; Mendelsohn, 2000). Here the anticipation reflects understanding of how climate change shifts all future weather. It depends on how weather shifts the marginal benefit of the stock, controlled by $\pi_{wS}$. For instance, farmers may conserve groundwater today in order to reduce the costs of irrigating in coming hot weather. Ex-ante adaptation also reflects agents anticipating that future actions will alter the stock in still-later periods. They therefore begin investing now to reduce distortions in the later stock. For instance, farmers may cut back on groundwater use today to make sure there is still enough groundwater left after the hot weather passes. Unsurprisingly, myopic agents ($\beta = 0$) do not undertake ex-ante adaptation.

The remaining terms depend on how long-lived infrastructure $K$ responds to the change in climate. Changes in this infrastructure do not directly affect payoffs when optimized (i.e., $\bar{\pi}_K = 0$), but they do indirectly affect payoffs when the marginal benefit of either short-run actions ($\bar{\pi}_{AK}$) or the stock ($\bar{\pi}_{SK}$) depends on the choice of long-lived infrastructure. For instance, building irrigation canals might change the marginal cost of watering crops during a heat wave or the marginal benefit of having more groundwater.

## 4.2 How Weather Affects Decisions

So an empirical researcher needs to recover effects of climate on actions from effects of weather on actions. I next build intuition for how weather determines actions in this environment.

Figure 1 illustrates the determinants of time $t$ actions. Formally, time $t$ optimal

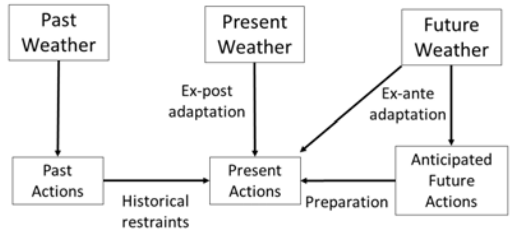


Figure 1: The determinants of present actions.

actions are (Appendix E.5)

$$A_t = \bar{A} + \overbrace{\frac{\bar{\pi}_{wA}}{h'(\bar{A})\,\bar{\chi}}(w_t - C)}^{\text{effects of present weather}} + \overbrace{\bar{Z}(S_t - \bar{S})}^{\text{effects of past weather}} + \overbrace{\frac{\beta\Gamma}{h'(\bar{A})\,\bar{\chi}}\left[(f_{1,t} - C) + \frac{\beta\Psi}{h'(\bar{A})\bar{\chi}}(f_{2,t} - C)\right]}^{\text{effects of future weather}}, \tag{12}$$

where $h'(\bar{A})\,\bar{\chi} > 0$. The $\bar{\chi}$ and $\bar{Z}$ are functions of derivatives of $\bar{\pi}$. They derive from a backward recursion that captures forward-looking optimization. I discuss $\Psi$ below.

Present weather affects present actions through an ex-post adaptation channel. This channel is controlled by $\bar{\pi}_{wA}$, with actions aiming to mitigate the immediate harm or amplify the immediate benefits of weather outcomes. This term is proportional to the ex-post adaptation channel in equation (11).

Past weather and forecasts affect present actions by altering the past actions that determine the present stock. The history of weather thereby restrains present actions. For $g$ small, $\bar{Z}$ is proportional to $\bar{\pi}_{AS}$. When $\bar{\pi}_{AS} > 0$, past actions that increased the stock justify higher present actions, but when $\bar{\pi}_{AS} < 0$, past actions that increased the stock favor less present action.[27]

Future weather affects present actions through forecasts of that weather. The coefficients on forecasts in (12) are each proportional to $\beta\Gamma$, where

$$\Gamma \triangleq \overbrace{\left[h'(\bar{A})\bar{\pi}_{wS} - g\bar{\pi}_{wA}\right]}^{\text{ex-ante adaptation from (11)}} + \overbrace{\Psi\frac{\bar{\pi}_{wA}}{h'(\bar{A})\,\bar{\chi}}}^{\text{preparatory actions}} \tag{13}$$

[27] Appendix E.5 shows that $\bar{Z} \to 0$ as either $h'(\bar{A})$ goes to zero or as $\bar{\pi}_{AS}$ and $g$ jointly go to zero. As $h'(\bar{A}) \to 0$, past actions do not affect the stock around the steady state. As $\bar{\pi}_{AS} \to 0$, changes in the stock do not directly affect the marginal benefit of current actions, and as $g \to 0$, the time $t$ stock does not affect the desired time $t+1$ stock or the time $t$ actions taken to reach it.

and

$$\Psi \triangleq h'(\bar{A})\bar{\pi}_{AS} + g \overbrace{\left(-\bar{\pi}_{AA} + \frac{h''(\bar{A})}{h'(\bar{A})}\bar{\pi}_A\right)}^{>0 \text{ by } (2)} \tag{14}$$
$$\propto \left.\frac{\mathrm{d}A_t}{\mathrm{d}A_{t+1}}\right|_{w_t, f_{1,t}, f_{2,t}=C}.$$

Unsurprisingly, the coefficients on forecasts in (12) go to zero as agents become myopic. For forward-looking agents, three terms in equation (13) control how actions depend on forecasts of future weather. First, when $\bar{\pi}_{wS} \neq 0$, agents choose today's actions in order to directly mitigate the consequences (or enhance the benefits) of expected future weather. This is the most direct form of ex-ante adaptation. Second, expecting higher weather outcomes in the future changes how agents trade-off time $t$ and $t+1$ actions when trying to reach the desired time $t+2$ stock. If, for instance, a higher forecast makes future actions more valuable ($\bar{\pi}_{wA} > 0$), then agents cut back on current actions. This effect vanishes as $g \to 0$ because the time $t+2$ stock then depends only on time $t+1$ actions. This is an indirect form of ex-ante adaptation. These first two terms are proportional to the ex-ante adaptation channel in equation (11).

Third, agents anticipate how today's choices impose historical restraints on future choices and undertake preparatory actions that can enable beneficial future actions. $\bar{\pi}_{wA}/[h'(\bar{A})\bar{\chi}]$ captures how a higher forecast shifts desired future actions. The term labeled $\Psi$ captures how today's actions change with expectations of future actions. Equation (14) shows that $\Psi$ depends on two terms. The first term within $\Psi$ reflects intertemporal substitutability or complementarity among actions. When actions are intertemporal complements ($h'(\bar{A})\,\bar{\pi}_{AS} > 0$), a forecast that increases desired future actions leads agents to choose high actions today as a means of reducing future adjustment costs, but when actions are intertemporal substitutes ($h'(\bar{A})\,\bar{\pi}_{AS} < 0$), a forecast that increases desired future actions leads agents to choose low actions today as a means of conserving resources for the future. The second term within $\Psi$ reflects how changes in desired future actions affect the tradeoff between time $t$ and $t+1$ investments in reaching the desired time $t+2$ stock. This effect vanishes as $g \to 0$. The preparatory action term in equation (13) was absent from the effects of climate change derived in equation (11), a point that will be important for subsequent analysis.

## 4.3 Recovering the Effect of Climate from Weather Regressions

Now consider the possibility of estimating long-run climate impacts from variation in weather. By affecting people's lived experience of weather, a change in climate affects actions reactively chosen to deal with present weather. It also affects the past weather experienced by agents once they have been living in the counterfactual climate. This channel will make it important to estimate the effects of past weather. Finally, a change in climate also affects agents' expectations of future weather, manifested as systematically higher forecasts. This channel will make it important to estimate the effects of forecasts.

I here assume that the empirical researcher can observe payoffs (e.g., profits) and weather variables.[28] I do not assume that the empirical researcher observes all of the actions that agents take or the level of the stock.[29] Consider the following distributed lag regression with fixed effects:

$$\pi_{jt} = \alpha_j + \sum_{i=0}^{I} \Lambda_i w_{j(t-i)} + \sum_{i=0}^{I} \lambda_i f_{j1,(t-i)} + \sum_{i=0}^{I} \gamma_i f_{j2,(t-i)} + \eta_{jt}, \tag{15}$$

where units are again labeled $j$, where $\alpha_j$ is a fixed effect for agent $j$, where $I \geq 0$ controls the number of lags, and where $\eta_{jt}$ is an error term. As before, a hat denotes estimated coefficients.

The proposition describes the effect of summing the estimated coefficients on an arbitrarily large number of lags:[30]

**Proposition 2** (Summing Many Lags)**.** *Let Assumption 1 hold, or let Assumptions 2 and 3 hold. Then:*

$$\lim_{I\to\infty} \operatorname{plim} \sum_{i=0}^{I-2} \left[\hat{\Lambda}_i + \hat{\lambda}_i\right] = \bar{\pi}_w + \omega \left[\bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g}\right] \left(\frac{\partial \bar{A}(K,C)}{\partial C} + \Omega\right), \tag{16}$$

*where*

$$\Omega \propto \beta\Psi \frac{\bar{\pi}_{wA}}{h'(\bar{A})\,\bar{\chi}}$$

*and* $\Psi$ *is defined in equation* (14)*. If* $\beta\Psi > 0$*, then* $\omega < 1$*. If* $\beta\Psi = 0$*, then* $\omega = 1$*. If* $\beta\Psi < 0$*, then* $\omega > 1$*.*

*Proof.* See Appendix E.9. Sketch: Approximates $\pi_t$ around the deterministic steady state, calculates each coefficient as the covariance of the associated variable with $\pi_t$ divided by the variance of that variable, defines $\Omega$ and $\omega$ to reconcile the summed lags with the effect of climate change, and then analyzes these terms. □

[28] The analysis straightforwardly extends to the case where the empirical researcher instead observes actions, not payoffs, and seeks the effect of climate on actions.

[29] In Section 5, I will analyze cases in which the empirical researcher does not observe forecasts.

[30] The requirement that we estimate at least $I$ lags even though we use only $I-2$ lags avoids ancillary complications from omitted variables bias at the longest lags used in (16).

The good news is that we come somewhat close to the true effect of climate derived in equation (8). In particular, we successfully capture the direct effect of weather and we capture effects proportional to ex-post and ex-ante adaptation.

However, we also see three wedges between the true effect in equation (8) and the estimated effect in equation (16). First, the change in steady state actions in equation (16) holds $K$ fixed, but equation (11) showed that $\mathrm{d}\bar{A}/\mathrm{d}C$ depends on changes in $K$ when either $\bar{\pi}_{AK} \neq 0$ or $\bar{\pi}_{SK} \neq 0$. The problem is that long-lived infrastructure does not vary with weather shocks, so fluctuations in payoffs do not identify the consequences of adapting $K$ to an altered climate. Even though these long-run adaptations do not have first-order consequences for payoffs when chosen optimally (i.e., $\bar{\pi}_K = 0$), equation (11) shows that these long-run adaptations can affect short-run actions that do have first-order consequences for payoffs. This wedge vanishes if long-lived infrastructure is in fact fixed over the timescale of climate change (i.e., if $\mathrm{d}K/\mathrm{d}C = 0$ in equation (11)) or if it does not directly interact with other decisions (i.e., if $\bar{\pi}_{AK} = \bar{\pi}_{SK} = 0$ in equation (11)).

The remaining two wedges arise from the durability of shorter-run decisions. $\Omega$ is a bias in estimated ex-ante adaptation. It is proportional to the preparatory actions defined in equation (13). Ex-ante adaptation is identified from transient shocks to forecasts. Preparatory actions reflect that an idiosyncratically high forecast implies idiosyncratically high future weather, for which current actions are not the most suited. An increase in the climate index $C$ also increases forecasts but does so systematically rather than idiosyncratically: because increasing $C$ also increases current and past weather, preparations for a change in weather are not relevant to the long-run effects of climate. Forecasts are critical to identifying ex-ante adaptation, but agents do not respond to higher-than-average forecasts in exactly the same way as they respond to forecasts that reflect higher average weather.[31]

The final wedge is $\omega$. This term reflects the difference between the historical restraints on current actions imposed by transient weather shocks and those imposed by a change in climate that affects all past weather realizations and all past forecasts. By the proposition and (14), we have $\omega < 1$ when actions are intertemporal complements. In this case, historical restraints prevent an agent from adjusting too much to any particular transient weather shock, but when that shock has been repeated many times in the past (as eventually happens following a change in climate), the many small adjustments eventually add up to a much greater adjustment. Responses to transient shocks therefore overstate historical restraints, which is why $\omega < 1$. Consistent with conjectures in Deschênes and Greenstone (2007), observable short-run

[31] One could eliminate $\Omega$ by not using the forecast coefficients $\hat{\lambda}_i$, instead relying on $\lim_{I\to\infty}\sum_{i=0}^{I-2}\hat{\Lambda}_i$. However, this calculation would introduce a new bias, as it would miss all ex-ante adaptation terms in equation (11). One might also consider including additional forecast horizons in the summation. Summing the first and second horizons multiplies the ex-ante adaptation component and $\Omega$ by $1 + \beta\Psi/[h'(\bar{A})\bar{\chi}]$, introducing a new bias. If we had infinite forecast horizons, summing them would multiply the ex-ante adaptation component and $\Omega$ by $1/\{1 - \beta\Psi/[h'(\bar{A})\bar{\chi}]\}$, again introducing a new bias. Neither formulation clearly improves on (16).

adaptation is less than long-run adaptation.

In contrast, we can have $\omega > 1$ when actions are intertemporal substitutes. In this case, an agent can experience more severe historical restraints following a change in climate than following a transient weather shock. For instance, if actions depend on scarce resources, agents may respond strongly to a transient weather shock but be unable to maintain this response for a long period of time. Their response to a change in climate may thus be relatively muted. Responses to transient shocks can understate historical restraints, which is why $\omega > 1$. Consistent with conjectures in Fisher et al. (2012) and Blanc and Schlenker (2017), observable short-run adaptation is greater than long-run adaptation.[32]

Proposition 2 described the results of estimating a model with infinite lags and summing the coefficients. The following corollary describes feasible regressions, with fewer lags:[33]

**Corollary 3** (Summing Some Lags)**.** *Let $I' \geq 1$ and $I \geq I'+2$. Also let Assumption 1 hold, or let Assumptions 2 and 3 hold. Then:*

$$\operatorname{plim} \sum_{i=0}^{I'} \left[\hat{\Lambda}_i + \hat{\lambda}_i\right] = \bar{\pi}_w + \omega_{I'} \left[\bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g}\right] \left(\frac{\partial \bar{A}(K,C)}{\partial C} + \Omega\right),$$

*where $\Omega$ is as in Proposition 2. If $\Psi = 0$, then $\omega_{I'} = \omega = 1$. If $\Psi > 0$, then $\omega_{I'} \in (0, \omega)$ with $\omega < 1$ and $\omega_{I'}$ increasing in $I'$. If $\Psi < 0$, then $\omega_{I'} > \omega > 1$ for $I'$ odd.*

*Proof.* See Appendix E.10. □

The number of summed lags only affects $\omega$. When $\omega < 1$, responses to weather shocks underestimate responses to long-run changes in climate. Corollary 3 shows that this underestimation is more severe when based on a shorter history of weather shocks. Matters are more complicated when $\omega > 1$. In this case, the bias $\omega_{I'}$ fluctuates around $\omega$ as we increase $I'$, clearly introducing more bias than $\omega$ when $I'$ is odd.[34]

The net bias introduced by the wedges $\Omega$ and $\omega$ cannot be signed in general. However, both wedges do vanish in some intuitive special cases, leaving only the wedge induced by $K$ being fixed:

[32]If $g > 0$, we can have $\omega < 1$ even when actions are intertemporal substitutes (via the second term in (14)). The reason is that an agent living in an altered climate would choose actions to loosen historical restraints over time.

[33]The requirement that we estimate at least $I$ lags even if we use only $I'$ lags avoids complications from omitted variables bias at the longest lags.

[34]Appendix A analyzes "long difference" estimators, which average over $\Delta$ timesteps and estimate a conventional weather regression on the transformed data (e.g., Dell et al., 2012; Burke and Emerick, 2016). While long difference estimators are motivated by the possibility that climate change has manifested itself over long timesteps, Appendix A shows that long difference estimators are identified by sequences of transient weather shocks even when the climate has been constant. At best, these estimators conflate the two sources of variation, and at worst they are identified off nothing but the transient weather shocks. In the latter case, Appendix A shows that long difference estimators are inferior to simply estimating regression (15) with $I \geq \Delta + 2$ lags.

**Corollary 4** (Special Cases)**.** *Let Assumption 1 hold, or let Assumptions 2 and 3 hold. Let $I' \geq 1$ and $I \geq I'+2$. Then:*

$$\lim_{\beta\to 0}\lim_{I\to\infty} \operatorname{plim} \sum_{i=0}^{I-2} \hat{\Lambda}_i = \lim_{g,\bar{\pi}_{AS}\to 0} \operatorname{plim} \sum_{i=0}^{I'} \left[\hat{\Lambda}_i + \hat{\lambda}_i\right] = \bar{\pi}_w + \left[\bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g}\right] \frac{\partial \bar{A}(K,C)}{\partial C}.$$

*Proof.* See Appendix E.11. □

First, in a special case with myopic agents who do not undertake ex-ante adaptation ($\beta = 0$), the wedge introduced by preparatory actions vanishes because myopic agents are not concerned about future actions. The sign of the bias then depends only on the wedge $\omega$ induced by historical restraints, as even myopic agents respond to their own past decisions (see also Keane and Wolpin, 2002). And this wedge vanishes as we sum an infinite number of lags: myopic agents respond to a long sequence of transient weather shocks in exactly the same way as they respond to living in a world with an altered climate.[35] Therefore we recover the effect of climate when we estimate infinite lags as long as agents are myopic and long-lived infrastructure either is fixed or does not interact with shorter-run adaptation decisions.[36]

Second, each period's decisions are independent of other periods' decisions in a special case without interactions between different periods' actions ($\bar{\pi}_{AS}, g = 0$). In equation (12), we lose the effects of past weather (see footnote 27). Estimating effects of realized weather suffices to recover the direct effects of climate as well as the effects of ex-post adaptation, and estimating effects of forecasts suffices to recover the effects of ex-ante adaptation. In fact, in this special case we do not even need to estimate all of the lags. When actions are chosen independently over time, the coefficients on lags longer than the first are all zero. These can be dropped from the regression without causing bias. But it is still important to include the first lag of both weather and forecasts. This lag picks up effects of time $t-1$ weather and forecasts on time $t$ payoffs, via the effects of time $t-1$ actions on the time $t$ stock. In equation (8), the contemporary effects identify $\bar{\pi}_w + \bar{\pi}_A \frac{\partial \bar{A}(K,C)}{\partial C}$ and the lagged effects identify $h'(\bar{A})\bar{\pi}_S \frac{\partial \bar{A}(K,C)}{\partial C}$. Therefore we recover the effect of climate when we estimate at least one lag of weather and forecasts as long as $\bar{\pi}_{AS}, g = 0$ and long-lived infrastructure either is fixed or does not interact with shorter-run adaptation decisions.

[35]The bias introduced by $\omega_{I'}$ in Corollary 3 does not vanish as $\beta \to 0$: even myopic agents respond to the weather they lived through and experience the historical restraints imposed by their responses. Only by estimating infinite lags of weather can we replicate the long-run effect of living in an altered climate.

[36]When agents are myopic, we do not need to estimate responses to forecasts (and should obtain $\operatorname{plim} \hat{\lambda}_i = 0$ and $\operatorname{plim} \hat{\gamma}_i = 0$ if we do). On the other hand, when agents are not myopic but forecasts do not exist, we lose the bias induced by preparatory actions but we also fail to estimate the ex-ante adaptation terms from (11) (i.e., we no longer recover $\partial \bar{A}/\partial C$ in (16)).

# 5 An Indirect Least Squares Estimator of Climate Impacts

We have thus far seen that we can exactly recover the effects of climate change from simple weather regressions only under restrictive assumptions: if agents are not affected by resource or capital stocks, if agents are myopic and long-lived infrastructure either is fixed or does not interact with shorter-run adaptation decisions, or if agents make decisions independently over time and long-lived infrastructure either is fixed or does not interact with shorter-run adaptation decisions. But while we have described the biases that arise when these conditions do not hold, we have not been able to sign any parts of those biases.

I now show how an indirect least squares estimator can disentangle direct effects from each type of adaptation and bound climate impacts, modulo only effects of altered long-lived infrastructure. I derive this new estimator by solving for the probability limit of each estimated coefficient in terms of model primitives and then rearranging those equations to solve for the combinations of model primitives needed to calculate climate change impacts. Importantly, this new approach maintains precisely the same credible identification as the reduced-form specifications in Section 4.

I derive the estimator first when agents and the empirical researcher observe forecasts, then when agents observe forecasts but the empirical researcher does not, and finally when neither agents nor the empirical researcher observe forecasts.

## 5.1 When Agents and the Empirical Researcher Observe Forecasts

Begin by considering the case we have analyzed so far, in which agents see specialized forecasts of coming weather and the empirical researcher has data on those forecasts. For example, in Shrader (2020), the empirical researcher observes forecasts of the El Niño seasonal climate index. The following proposition presents the indirect least squares estimator for climate impacts:

**Proposition 5** (Indirect Least Squares With Forecasts)**.** *Let Assumption 1 hold, or let Assumptions 2 and 3 hold. Consider estimating regression* (15)*, with* $\operatorname{plim} \hat{\lambda}_0, \hat{\lambda}_1, \hat{\Lambda}_1 \neq 0$*. Then, for* $I > 2$*,*

$$\operatorname{plim}\left( \underbrace{\hat{\Lambda}_0 - \hat{\Lambda}_1 \frac{\hat{\lambda}_0}{\hat{\lambda}_1}}_{\textit{direct effects}} \underbrace{- \frac{1-\beta}{\beta}\hat{\Lambda}_1 \frac{\hat{\lambda}_0}{\hat{\lambda}_1}}_{\textit{ex-post adaptation}} \overbrace{\underbrace{- \frac{1-\beta}{\beta}\hat{\lambda}_0}_{\textit{estimated}} \underbrace{+ \frac{1-\beta}{\beta}\frac{\hat{\gamma}_0}{\hat{\lambda}_0}\hat{\Lambda}_1 \frac{\hat{\lambda}_0}{\hat{\lambda}_1}}_{\textit{prep. action adjustment}}}^{\textit{ex-ante adaptation}} \right)$$

$$= \bar{\pi}_w + \tilde{\omega}\left[\bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g}\right] \frac{\partial \bar{A}(K, C)}{\partial C}, \tag{17}$$

*and*

$$\Psi \propto \text{plim}\, \frac{\hat{\Lambda}_2}{\hat{\Lambda}_1}.$$

*If $\Psi > 0$, then $\tilde{\omega} < 1$. If $\Psi = 0$, then $\tilde{\omega} = 1$. If $\Psi < 0$, then $\tilde{\omega} > 1$.*

*Proof.* See Appendix E.12. Sketch: Follows proof of Proposition 2 to derive the probability limits of estimated coefficients and then solves the system for the desired terms. □

The indirect least squares estimator provides an estimate of the effect of climate change and also provides estimates of the channels that determine that effect.[37] Comparing the right-hand side of (17) to (8), we see the usual bias due to $K$ being fixed and an additional bias when $\tilde{\omega} \neq 1$ that is signed from estimated coefficients.

The estimated coefficient $\hat{\Lambda}_0$ on contemporary weather identifies the sum of direct weather effects and the immediate payoffs from ex-post adaptation to that weather. However, as discussed around (10), the steady-state effects of ex-post adaptation to climate change must account for its dynamic consequences, not just its immediate payoffs. Conditional on past forecasts, past weather matters for current payoffs only by having induced ex-post adaptation that has dynamic consequences. The ratio of forecast coefficients identifies the adjustment due to dynamics, allowing us to isolate the immediate payoffs from ex-post adaptation. Subtracting these immediate payoffs from $\hat{\Lambda}_0$ isolates direct effects, and converting these immediate payoffs into a steady-state effect (via $-(1-\beta)/\beta$) isolates the long-run effect of ex-post adaptation to climate change.

The estimated coefficient $\hat{\lambda}_0$ on contemporary forecasts identifies a term related to ex-ante adaptation. But that term also includes preparatory actions irrelevant to changes in climate (see discussions of $\Psi$ in (13) and $\Omega$ in (16)). Fortunately, longer-horizon forecasts identify preparatory actions, as there is no other channel through which longer-horizon forecasts can affect current payoffs in this environment. Formally, the coefficient $\hat{\gamma}_0$ on longer-horizon forecasts contains $\Psi$ from equation (12), $\Psi$ is the term that drives preparatory actions in (13), and the adjustment to $\hat{\gamma}_0$ accounts for effects such as $\bar{\pi}_{wA}$ in (13).[38] The indirect least squares estimator adjusts the ex-ante adaptation channel to remove the preparatory action bias.

Finally, the ratio of coefficients on lagged weather identifies how actions are linked over time. As mentioned above, past weather matters for current weather via ex-post adaptation, which in turn matters for current payoffs via actions' dynamic consequences. We can infer the sign of $\Psi$ from $\hat{\Lambda}_2/\hat{\Lambda}_1$, which is important because the sign

[37]The indirect least squares estimator defined in Proposition 5 is a consistent estimator of the indicated theoretical primitives, but because it is a nonlinear function of the estimated ordinary least squares coefficients, it is not unbiased. A similar comment will apply to subsequent results.

[38]That adjustment is reminiscent of the ex-post adaptation term because $\bar{\pi}_{wA}$ defines ex-post adaptation (see (11)).

of $\Psi$ controls the bias from $\tilde{\omega}$, as it did for $\omega$ in (16).[39] We thus learn from the ratio of lagged weather coefficients whether $\tilde{\omega}$ dampens or inflates the adaptation channels.

There are two cases. First, if the ratio of coefficients on lagged weather is positive, then $\Psi > 0$ and $\tilde{\omega} < 1$. Adaptation to climate is greater than implied by responses to weather, as when adjustment costs constrain short-run responses more than long-run responses (i.e., actions are intertemporal complements).[40] In that case, the top line of (17) gives a lower (upper) bound on the true effect of climate if the adaptation terms are positive (negative). Because adaptation could be arbitrarily large, we have only a one-sided bound. If, instead, the ratio of coefficients on lagged weather is negative, then $\Psi < 0$ and $\tilde{\omega} > 1$. Adaptation to climate is less than implied by responses to weather, as when resource constraints bind in the long run but not in the short run (i.e., actions are intertemporal substitutes). In that case, the top line of (17) and the estimated direct effects bound the effect of climate from either side.

Either way, we have bounded the effect of climate if long-lived infrastructure either is fixed or does not interact with shorter-run adaptation decisions. And remarkably, we have done so without needing to observe either the stock or actions and without needing to assume particular functional forms for payoffs or stock accumulation. In contrast, the purely reduced-form approaches in Sections 3 and 4.3 do not generally bound the effects of climate and can exactly recover the effects of climate only when the decision-making environment is sufficiently simple: Proposition 1 required $\pi_S = 0$, and Corollary 4 required either that agents are myopic ($\beta = 0$) or that actions are independent over time ($g, \bar{\pi}_{AS} = 0$), in addition to long-lived infrastructure either being fixed or not interacting with shorter-run adaptation decisions. Of course, the present section's calculations also exactly recover the effects of climate when these special conditions are met. The indirect least squares approach therefore directly weakens the assumptions required by reduced-form approaches in dynamic environments, without sacrificing anything in terms of identification.[41]

## 5.2 When Agents Have Forecasts But the Empirical Researcher Does Not Observe Them

In some cases, the empirical researcher cannot observe the same forecasts that agents observe. Appendix D shows that leads of weather can proxy for the unobserved forecasts. However, in this case the estimate of ex-ante adaptation is too small: the empirical researcher estimates relatively small responses to subsequent realized

[39] Deschênes and Greenstone (2012) noted the importane of estimating lags when thinking about actions such as storage.

[40] Although note, from (14), that if $g > 0$, then intertemporal substitutes can be consistent with positive $\Psi$.

[41] In dynamic environments, both reduced-form and indirect least squares calculations require that infrastructure either is fixed or does not interact with shorter-run adaptation decisions. Relaxing that constraint will require either data with variation in infrastructure or assumptions about how infrastructure interacts with other adaptation choices.

weather because only a fraction of the variation in subsequent realized weather was forecasted ahead of time. A similar bias also affects the estimate of $\Omega$. If the empirical researcher can calibrate the quality of agents' average forecasts, then Appendix D shows how the researcher can undo these biases and recover the same pieces as in Section 5.1.

## 5.3 When Neither Agents Nor the Empirical Researcher Observe Forecasts

What if agents do not have specialized forecasts of future weather, so they predict future weather solely from their climate zone? For instance, farmers may lack quality forecasts of temperature and rainfall months or more ahead. In this case, effects of future weather drop out of (12). However, the lack of forecasts does not absolve us from needing to estimate the ex-ante adaptation to climate change described in (11): whether or not agents have specialized forecasts of future weather, they can recognize when the climate has changed and can understand what a changed climate means for average weather.

Consider the following regression, which is similar to (15) but omits the nonexistent forecasts:

$$\pi_{jt} = \alpha_j + \sum_{i=0}^{I} \phi_i w_{j(t-i)} + \eta_{jt}. \tag{18}$$

The following proposition presents the indirect least squares estimator for climate impacts in this setting without forecasts:

**Proposition 6** (Indirect Least Squares Without Forecasts)**.** *Let Assumption 1 hold, or let Assumptions 2 and 3 hold. Consider estimating regression* (18)*, assuming that* $\operatorname{plim} \hat{\phi}_1 \neq 0$ *and* $\operatorname{plim} \hat{\phi}_2/\hat{\phi}_1 \neq 1/\beta$*. For* $I > 2$*,*

$$\operatorname{plim}\left( \overbrace{\hat{\phi}_0 - \frac{\hat{\phi}_1}{\frac{\hat{\phi}_2}{\hat{\phi}_1} - \frac{1}{\beta}}}^{\textit{direct effects}} \overbrace{- \frac{1-\beta}{\beta} \frac{\hat{\phi}_1}{\frac{\hat{\phi}_2}{\hat{\phi}_1} - \frac{1}{\beta}}}^{\textit{ex-post adaptation}} \right) = \bar{\pi}_w + \tilde{\omega} \left[ \bar{\pi}_A + \bar{\pi}_S \frac{h'(\bar{A})}{1-g} \right] \lim_{\beta \to 0} \frac{\partial \bar{A}(K, C)}{\partial C},$$

*and*

$$\Psi \propto \operatorname{plim} \frac{\hat{\phi}_2}{\hat{\phi}_1}.$$

*If* $\Psi > 0$*, then* $\tilde{\omega} < 1$*. If* $\Psi = 0$*, then* $\tilde{\omega} = 1$*. If* $\Psi < 0$*, then* $\tilde{\omega} > 1$*.*

*Proof.* See Appendix E.13. Sketch: Follows proof of Proposition 2 to derive estimated coefficients and then solves the system for the desired terms. □

The intuition for identification is much as given following Proposition 5. The biases introduced by the possibility of endogenous $K$ and by $\tilde{\omega} \neq 1$ are also as in Proposition 5. However, we now have a new bias due to the inability to estimate ex-ante adaptation, which means that we recover effects on actions only as agents become myopic (hence the $\lim_{\beta \to 0}$ on the right-hand side). Nothing in the data can identify ex-ante adaptation without variation in agents' expectations of weather.

# 6 Application: Impacts of Climate Change on the U.S. Economy

I demonstrate the new indirect least squares approach by analyzing the relationship between temperature and output in U.S counties.

## 6.1 Data and Methods

At the macro level, the analogue of flow payoffs $\pi$ is aggregate production or income. I obtain county-level output from the Bureau of Economic Analysis for the continental U.S. states from 2001–2019. In the base specification, I exclude the financial crisis years 2007 and 2008. I obtain output per capita by using population data available from the NIH Surveillance, Epidemiology, and End Results (SEER) Program. Weather data follow Schlenker and Roberts (2006, 2009).[42] I aggregate weather on a 4 km by 4 km grid to county-average weather, weighting grid cells by area in the base specification and weighting grid cells by Census tract population in a robustness check. I calibrate $\beta$ to a 15% annual discount rate in the base specification. Appendix B reports descriptive statistics.

Quality forecasts are unlikely to be available to economic agents at the timescale of these data. The analysis of Section 5.3 is therefore the most relevant to this application. Adapting regression (18), I estimate:

$$\pi_{jt} = \alpha_j + \sum_{r=1}^{4} \sum_{i=0}^{3} \mathbb{1}_{j \in r} \phi_{ir} w_{j(t-i)} + \nu_t + \eta_{jt}, \tag{19}$$

where $\pi_{jt}$ is log output per capita in county $j$ and year $t$.[43] In order to compare to

[42] I first estimate the relationship between a stable set of weather station observations from the NOAA Global Historical Climatology Network and 4km-by-4km weather interpolations from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). I then use the estimated relationship to aggregate weather station observations to a 4km-by-4km grid. This method creates a record of daily data that accounts for the physical characteristics used by PRISM while also limiting the scope for nonclassical measurement error induced by endogenous entry of weather stations over time.

[43] Newell et al. (2021) show that models relating the level of output to temperature perform better in cross-validation tests and model uncertainty assessments than do models relating the growth rate of output to temperature.

conventional approaches, I also adapt regression (7):

$$\pi_{jt} = \alpha_j + \sum_{r=1}^{4} \mathbb{1}_{j\in r}\theta_r w_{jt} + \nu_t + \eta_{jt}. \tag{20}$$

In both cases, I allow the effects of weather to vary by Census region $r$ in order to mitigate concerns about heterogeneous treatment effects in linear fixed effects estimators (see Carter et al., 2018). $\mathbb{1}_{j\in r}$ is an indicator for whether county $j$ is in Census region $r$. The weather variable $w$ of interest is average annual temperature, in degrees Celsius. The $\alpha_j$ are county fixed effects, and the $\nu_t$ are year fixed effects. Regressions are weighted by each county's average log output over the sample years, which downweights outlier counties that contain very few people (in particular, oil-rich rural counties) and makes the central estimates reflect impacts on the average unit of (log) output rather than on the average county. Standard errors are two-way clustered by county (to account for within-county temporal correlation) and state-year (to account for a year's within-state spatial correlation), following Deryugina and Hsiang (2017).

## 6.2 Results

Table 1 reports estimates of equations (19) and (20). In either specification, a 1°C higher average temperature reduces contemporary output in each Census region by around 2–3%. Lagged temperatures typically have meaningful effects (significant at the 5% level in two cases) and that work in the same direction as contemporary temperature. Finding that lags of temperature affect output is contrary to the assumption of $\pi_S = 0$ in Section 3 that I showed would justify conventional calculations of climate impacts. The indirect least squares estimator is thus necessary for theoretically grounded estimates of climate impacts.

So consider the indirect least squares estimates of channels for climate change impacts. The calculations in Table 2 use the estimated $\hat{\phi}$ from regression (19) in Proposition 6. Standard errors are from the delta method, using the cluster-robust covariance matrix estimated in regression (19).[44]

The first column shows that the estimated direct effects of higher temperature are more deleterious than what one might expect from the coefficient on contemporary weather: an increase of 1°C in average temperature has the direct effect of reducing output by 3–10% (depending on the region), whereas the coefficients on contemporary temperature in Table 1 implied a reduction of only 1.5–3%. The reason for the gap is that the reduced-form coefficient in Table 1 entwines direct effects of temperature with ex-post adaptation that responds to temperature, and the latter masks the former. The indirect least squares estimator properly separates these two channels. In addition, although ex-post adaptation provides short-run benefits, it has dynamic

[44] Implemented by Stata's `nlcom` command.

Table 1: Estimating effects of temperature on county output per capita.

| | Regression (19) | Regression (20) |
|---|---|---|
| Temperature, Midwest | -0.0282*** | -0.0213*** |
| | (0.0072) | (0.0062) |
| Temperature, Northeast | -0.0161** | -0.0171*** |
| | (0.0075) | (0.0064) |
| Temperature, South | -0.0273*** | -0.0318*** |
| | (0.0088) | (0.0076) |
| Temperature, West | -0.0150** | -0.0206*** |
| | (0.0068) | (0.0064) |
| Temperature, Midwest, Lag 1 | -0.0138* | |
| | (0.0072) | |
| Temperature, Northeast, Lag 1 | -0.0127 | |
| | (0.0079) | |
| Temperature, South, Lag 1 | -0.0126 | |
| | (0.0112) | |
| Temperature, West, Lag 1 | -0.0150** | |
| | (0.0075) | |
| Temperature, Midwest, Lag 2 | -0.0133* | |
| | (0.0070) | |
| Temperature, Northeast, Lag 2 | -0.0070 | |
| | (0.0071) | |
| Temperature, South, Lag 2 | -0.0080 | |
| | (0.0104) | |
| Temperature, West, Lag 2 | -0.0018 | |
| | (0.0071) | |
| County FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 52326 | 52326 |

Standard errors in parentheses
Standard errors clustered by county and state-year, with at least 217 county clusters in each Census Region and at least 153 state-year clusters in each Census Region.
Regressions weighted by each county's average log output over the sample.
Years: 2001–2019, excluding 2007 and 2008.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Indirect least squares estimates, from Proposition 6 and regression (19).

| | Direct Effects | Ex-Post Adaptation | Total Effects | $\Psi$ |
|---|---|---|---|---|
| Midwest | -0.102 | -0.011 | -0.113 | 0.963 |
| | (0.2800) | (0.0417) | (0.3217) | (0.7730) |
| Northeast | -0.037* | -0.003 | -0.040* | 0.550 |
| | (0.0212) | (0.0029) | (0.0240) | (0.6858) |
| South | -0.052 | -0.004 | -0.055 | 0.633 |
| | (0.0454) | (0.0063) | (0.0516) | (1.2313) |
| West | -0.030*** | -0.002* | -0.032*** | 0.119 |
| | (0.0096) | (0.0013) | (0.0106) | (0.4894) |

Standard errors in parentheses
Standard errors clustered by county and state-year, with at least 217 county clusters in each Census Region and at least 153 state-year clusters in each Census Region.
Regressions weighted by each county's average log output over the sample.
Years: 2001–2019, excluding 2007 and 2008.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

consequences that add up to reduce output by an additional 0.2–1% in steady state (second column). Combining these results, an extra degree of warming reduces output in the Northeast and West by a decently precise 3–4% in steady state (third column). The central estimates for the South and Midwest project even more severe impacts, but these regions also have the noisiest estimates.

The final column shows that the central estimates for $\Psi$ are positive, which follows from the estimates on the first two lags having the same sign in Table 1.[45] Finding a positive $\Psi$ is consistent with a story of adjustment costs (i.e., with actions being intertemporal substitutes), as when the stock variable represents capital. From Proposition 6, $\Psi > 0$ implies that adaptation to climate change is likely to be greater than estimated from variation in weather, making the estimates in the second and third columns lower bounds on the cost of climate change (i.e., the true effect of ex-post adaptation and the true steady-state costs of climate change are each more negative than calculated here) in the absence of offsetting ex-ante adaptation.

## 6.3 Robustness

Table 3 contains robustness checks. The main takeaways are fairly robust: temperature is harmful, the ILS estimator projects more severe total effects than does the OLS estimator, and (not shown) the central estimate of $\Psi$ is positive.

The first check includes region-specific time trends. Many estimates are attenu-

[45] Appendix C reports that point estimates of $\Psi$ are also positive at the industry level.

Table 3: Indirect least squares estimates of total effects, from Proposition 6 and regression (19), versus ordinary least squares estimates, from Proposition 1 and regression (20).

| | Midwest | | Northeast | | South | | West | |
|---|---|---|---|---|---|---|---|---|
| | ILS | OLS | ILS | OLS | ILS | OLS | ILS | OLS |
| Base | -0.113 | -0.021*** | -0.040* | -0.017*** | -0.055 | -0.032*** | -0.032*** | -0.021*** |
| | (0.322) | (0.006) | (0.024) | (0.006) | (0.052) | (0.008) | (0.011) | (0.006) |
| Region Trends | -0.637 | -0.011* | -0.021 | -0.007 | -0.011 | -0.011 | -0.029*** | -0.017*** |
| | (49.225) | (0.006) | (0.015) | (0.006) | (0.010) | (0.008) | (0.010) | (0.006) |
| With 07–08 | -0.129 | -0.019*** | -0.037** | -0.014** | 0.342 | -0.025*** | -0.032*** | -0.022*** |
| | (0.378) | (0.006) | (0.018) | (0.006) | (20.668) | (0.007) | (0.010) | (0.006) |
| Alt Weather | -0.113 | -0.021*** | -0.040* | -0.017*** | -0.056 | -0.032*** | -0.033*** | -0.021*** |
| | (0.310) | (0.006) | (0.024) | (0.006) | (0.052) | (0.008) | (0.011) | (0.006) |
| Pop-Weighted | -0.111 | -0.021*** | -0.036 | -0.016*** | -0.056 | -0.031*** | -0.028*** | -0.019*** |
| | (0.312) | (0.006) | (0.023) | (0.006) | (0.057) | (0.007) | (0.010) | (0.006) |
| Unweighted | -0.111 | -0.023*** | -0.043* | -0.018*** | -0.057 | -0.033*** | -0.035*** | -0.022*** |
| | (0.271) | (0.007) | (0.023) | (0.007) | (0.049) | (0.008) | (0.012) | (0.007) |
| Small Disc | -0.161 | -0.021*** | -0.042 | -0.017*** | -0.058 | -0.032*** | -0.032*** | -0.021*** |
| | (0.870) | (0.006) | (0.029) | (0.006) | (0.068) | (0.008) | (0.011) | (0.006) |
| Large Disc | -0.093 | -0.021*** | -0.039* | -0.017*** | -0.053 | -0.032*** | -0.032*** | -0.021*** |
| | (0.169) | (0.006) | (0.021) | (0.006) | (0.041) | (0.008) | (0.010) | (0.006) |

Standard errors in parentheses
Standard errors clustered by county and state-year, with at least 217 county clusters in each Census Region and at least 153 state-year clusters in each Census Region.
Regressions weighted by each county's average log output over the sample, unless otherwise noted.
Years: 2001–2019, excluding 2007 and 2008, unless otherwise noted.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Projected end-of-century percentage change in average county's output due to business-as-usual climate change's effect on temperature.

| | Midwest | | Northeast | | South | | West | |
|---|---|---|---|---|---|---|---|---|
| | ILS | OLS | ILS | OLS | ILS | OLS | ILS | OLS |
| Direct Effects | -46.8 | | -16.5* | | -18.7 | | -11.6*** | |
| | (128.1) | | (9.4) | | (16.5) | | (3.8) | |
| Ex-Post Adaptation | -5.1 | | -1.4 | | -1.3 | | -0.9* | |
| | (19.1) | | (1.3) | | (2.3) | | (0.5) | |
| Total Effects | -51.8 | -9.8*** | -17.9* | -7.6*** | -20.0 | -11.5*** | -12.4*** | -8.1*** |
| | (147.1) | (2.8) | (10.7) | (2.8) | (18.7) | (2.8) | (4.1) | (2.5) |

Standard errors in parentheses
Standard errors clustered by county and state-year, with at least 217 county clusters in each Census Region and at least 153 state-year clusters in each Census Region.
Projected change in regional average temperature from CMIP6 SSP3-7.0 multi-model ensemble, for 2080–2100 relative to 1995–2014. Projected temperature change is 4.6 degC in the Midwest, 4.4 degC in the Northeast, 3.6 degC in the South, and 3.9 degC in the West. Column (1) multiplies projected temperature change by indirect least squares estimate, from Proposition 6 and (19). Column (2) multiplies projected temperature change by $\hat{\theta}$ from equation (20).
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

ated, although the estimate in the Midwest becomes even larger and noisier. The ILS estimator still projects more severe impacts.

The next checks assess robustness to data and estimation options. Results are very similar to the base case when including the crisis years of 2007 and 2008, alternately measuring a county's weather using its population-weighted weather (rather than its area-weighted weather), weighting counties in the regression by the average of their log population over the sample, or declining to weight counties within the regression. The exception is that the ILS estimate in the South becomes exceptionally noisy when including the crisis years.

The final checks reduce or increase the discount rate by 50%. Either change alters the ILS estimate mechanically: raising the discount rate reduces estimated direct effects but increases the cost of ex-post adaptation, and reducing the discount rate has opposite effects. In either case, the main conclusions are barely affected.

## 6.4 Climate Change Impacts

Finally, I project the effects of end-of-century climate change on U.S. output. Climate projections for 2080–2100 come from a multi-model ensemble of the Coupled Model Intercomparison Project Phase 6 (CMIP6), as compiled by the World Bank.[46]

[46] `https://climateknowledgeportal.worldbank.org/country/united-states/climate-data-projections`

Following recommendations in Hausfather and Peters (2020), I use SSP3-7.0 as a no-policy scenario. Taking an area-weighted average of the states in a Census region, these models project warming of around 4°C in each region relative to 1995–2014, with the least change in the South and the most change in the Midwest.

Table 4 reports the channels from the indirect least squares estimator as well as the results one would obtain if, following the convention in prior literature, one naively multiplied the coefficient $\hat{\theta}$ from the OLS regression (20) by the projected change in temperature. The conventional approach would project that the average county's output will fall by 8–12% with climate change, which is consistent with the calibration in Hänsel et al. (2020) that implies losses of 12% from 4°C of warming. From Proposition 1, this conventional approach is justified if there is no stock variable such as capital that affects output, but such a requirement contradicts both intuition about the importance of capital and the significant coefficients on lagged weather reported in Table 1.

The theoretically derived ILS estimates relax this requirement. They predict a much larger reduction in output. In the more precisely estimated Northeast and West, projected impacts cost 12–18% of output. In the less precisely estimated Midwest and South, projected impacts cost 20–52% of output. As in Table 2, much of the reduction in output is due to the direct effects of altered weather. These effects are masked in the OLS estimates by ex-post adaptation. Because we saw in Table 2 that $\Psi$ is positive, we know from Proposition 6 that ex-post adaptation will tend to have larger effects than the approximately 1% reduction in output estimated here, suggesting that the estimated total losses are a lower bound for the combination of direct effects and ex-post adaptation. The large estimated losses from end-of-century climate change suggest that some combination of ex-ante adaptation and emission reductions will be critical to limiting the drag on U.S. output from climate change.[47]

# 7 Discussion

I have explored the limits of our ability to estimate the long-run effects of climate change purely from short-run, panel variation in weather that is clearly exogenous, without postulating variation in climate either cross-sectionally or over time and without postulating that we can observe agents' adaptation choices. I have shown that we can bound long-run effects by using a new indirect least squares estimator. In an application to U.S. counties' output, I have shown that the new estimator can generate very different conclusions from conventional estimators that are not grounded in theory. Future work should apply these new methods to other settings, including ones in which observable forecasts enable estimates of ex-ante adaptation.

Instead of writing down a model of everything, I have highlighted the dynamic

[47]The industry-level analysis in Appendix C shows that losses from climate change derive from agriculture, mining, utilities, and construction.

differences between transient weather shocks and permanent shifts in climate. Of course, weather shocks and climate change differ in other ways, including in their spatial structure and thus in their general equilibrium implications. Future work should explore how to credibly conduct inference about climate change from weather in these other dimensions. In addition, I have followed the empirical literature in estimating the effects of changing one stationary climate to another. Future work should consider the process of changing the climate. Finally, by imposing stronger assumptions on the decision-making environment and constraining its parameters to replicate the long-run costs implied by the methods presented here, future work could simulate counterfactual climate trajectories and thereby estimate the costs of transitioning from one climate to another.

# References

Aldy, Joseph E. and Richard Zeckhauser (2020) “Three prongs for prudent climate policy,” *Southern Economic Journal*, Vol. 87, No. 1, pp. 3–29.

Aragón, Fernando M., Francisco Oteiza, and Juan Pablo Rud (2021) “Climate change and agriculture: Subsistence farmers’ response to extreme heat,” *American Economic Journal: Economic Policy*, Vol. 13, No. 1, pp. 1–35.

Auffhammer, Maximilian (2018) “Quantifying economic damages from climate change,” *Journal of Economic Perspectives*, Vol. 32, No. 4, pp. 33–52.

——— (2022) “Climate adaptive response estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption,” *Journal of Environmental Economics and Management*, Vol. 114, p. 102669.

Barker, David (2022) “Temperature and U.S. Economic Growth: Comment on Colacito, Hoffmann, and Phan,” *Econ Journal Watch*, Vol. 19, No. 2, pp. 176–189.

Blakeslee, David, Ram Fishman, and Veena Srinivasan (2020) “Way down in the hole: Adaptation to long-term water loss in rural India,” *American Economic Review*, Vol. 110, No. 1, pp. 200–224.

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 and Kyle Emerick (2016) “Adaptation to climate change: Evidence from US agriculture,” *American Economic Journal: Economic Policy*, Vol. 8, No. 3, pp. 106–140.

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

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang (2022) "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits," *The Quarterly Journal of Economics*, Vol. 137, No. 4, pp. 2037–2105.

Carter, Colin, Xiaomeng Cui, Dalia Ghanem, and Pierre Mérel (2018) "Identifying the economic impacts of climate change on agriculture," *Annual Review of Resource Economics*, Vol. 10, No. 1, pp. 361–380.

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, Riccardo, Bridget Hoffmann, and Toan Phan (2019) "Temperature and growth: A panel analysis of the United States," *Journal of Money, Credit and Banking*, Vol. 51, No. 2-3, pp. 313–368.

Cui, Xiaomeng (2020) "Beyond yield response: Weather shocks and crop abandonment," *Journal of the Association of Environmental and Resource Economists*, Vol. 7, No. 5, pp. 901–932, Publisher: The University of Chicago Press.

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.

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.

——— (2012) "The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Reply," *American Economic Review*, Vol. 102, No. 7, pp. 3761–3773.

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.

Graff Zivin, Joshua and Matthew Neidell (2009) "Days of haze: Environmental information disclosure and intertemporal avoidance behavior," *Journal of Environmental Economics and Management*, Vol. 58, No. 2, pp. 119–128.

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.

Hagerty, Nick (2020) "Adaptation to water scarcity in irrigated agriculture," working Paper.

Hamermesh, Daniel S. (1995) "Comment," *ILR Review*, Vol. 48, No. 4, pp. 835–838.

Hausfather, Zeke and Glen P. Peters (2020) "Emissions—the 'business as usual' story is misleading," *Nature*, Vol. 577, No. 7792, pp. 618–620.

Heal, Geoffrey and Jisung Park (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.

Heckman, James J. (2010) "Building bridges between structural and program evaluation approaches to evaluating policy," *Journal of Economic Literature*, Vol. 48, No. 2, pp. 356–398.

Hennessy, Christopher A. and Ilya A. Strebulaev (2020) "Beyond random assignment: Credible inference of causal effects in dynamic economies," *Journal of Finance*, Vol. 75, No. 2, pp. 825–866.

Hornbeck, Richard and Pinar Keskin (2014) "The historically evolving impact of the Ogallala aquifer: Agricultural adaptation to groundwater and drought," *American Economic Journal: Applied Economics*, Vol. 6, No. 1, pp. 190–219.

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.

Hänsel, Martin C., Moritz A. Drupp, Daniel J. A. Johansson, Frikk Nesje, Christian Azar, Mark C. Freeman, Ben Groom, and Thomas Sterner (2020) "Climate economics support for the UN climate targets," *Nature Climate Change*, Vol. 10, No. 8, pp. 781–789.

Jagnani, Maulik, Christopher B. Barrett, Yanyan Liu, and Liangzhi You (2021) "Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers," *The Economic Journal*, Vol. 131, No. 633, pp. 392–419.

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.

Keane, Michael P. and Kenneth I. Wolpin (2002) "Estimating welfare effects consistent with forward-looking behavior. Part I: Lessons from a simulation exercise," *The Journal of Human Resources*, Vol. 37, No. 3, pp. 570–599.

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.

Kolstad, Charles D. and Frances C. Moore (2020) "Estimating the economic impacts of climate change using weather observations," *Review of Environmental Economics and Policy*, Vol. 14, No. 1, pp. 1–24.

Kruttli, Mathias, Brigitte Roth Tran, and Sumudu W. Watugala (2019) "Pricing Poseidon: Extreme weather uncertainty and firm return dynamics," Finance and Economics Discussion Series 2019-054, Board of Governors of the Federal Reserve System.

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.

Lucas, Robert E., Jr. (1972) "Econometric testing of the natural rate hypothesis," in Otto Eckstein ed. *The Econometrics of Price Determination*: Board of Governors of the Federal Reserve System, pp. 50–59.

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.

——— (2019) "An examination of recent revealed preference valuation methods and results," *Review of Environmental Economics and Policy*, Vol. 13, No. 2, pp. 267–282.

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.

Mérel, Pierre and Matthew Gammans (2021) "Climate econometrics: Can the panel approach account for long-run adaptation?" *American Journal of Agricultural Economics*, Vol. 103, No. 4, pp. 1207–1238.

Newell, Richard G., Brian C. Prest, and Steven E. Sexton (2021) "The GDP-temperature relationship: Implications for climate change damages," *Journal of Environmental Economics and Management*, Vol. 108, p. 102445.

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.

——— (2017) "Revisiting the social cost of carbon," *Proceedings of the National Academy of Sciences*, Vol. 114, No. 7, pp. 1518–1523.

Quiggin, John and John Horowitz (2003) "Costs of adjustment to climate change," *Australian Journal of Agricultural and Resource Economics*, Vol. 47, No. 4, pp. 429–446.

Quiggin, John and John K. Horowitz (1999) "The impact of global warming on agriculture: A Ricardian analysis: Comment," *The American Economic Review*, Vol. 89, No. 4, pp. 1044–1045.

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.

Schlenker, Wolfram and Michael J. Roberts (2006) "Nonlinear effects of weather on corn yields," *Applied Economic Perspectives and Policy*, Vol. 28, No. 3, pp. 391–398.

——— (2009) "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, Vol. 106, No. 37, pp. 15594–15598.

Severen, Christopher, Christopher Costello, and Olivier Deschênes (2018) "A forward-looking Ricardian approach: Do land markets capitalize climate change forecasts?" *Journal of Environmental Economics and Management*, Vol. 89, pp. 235–254.

Shrader, Jeffrey (2020) "Expectations and adaptation to environmental risks," working paper.

Shrader, Jeffrey G., Laura Bakkensen, and Derek Lemoine (2023) "Fatal errors: The mortality value of accurate weather forecasts," Working Paper 31361, National Bureau of Economic Research.

Sorkin, Isaac (2015) "Are there long-run effects of the minimum wage?" *Review of Economic Dynamics*, Vol. 18, No. 2, pp. 306–333.

Tinbergen, J. (1930) "Bestimmung und deutung von angebotskurven ein beispiel," *Zeitschrift für Nationalökonomie*, Vol. 1, No. 5, pp. 669–679.

——— (1995) "Determination and interpretation of supply curves: An example [Bestimmung und deutung von angebotskurven. ein beispiel] (Zeitschrift fur Nationalokonomie, vol. 1, 1930, pp. 669–79)," in David F. Hendry and Mary S. Morgan eds. *The Foundations of Econometric Analysis*, Cambridge: Cambridge University Press, pp. 233–246.

Weyl, E. Glen (2019) "Price theory," *Journal of Economic Literature*, Vol. 57, No. 2, pp. 329–384.