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ABSTRACT

We develop a unifying approach to estimating climate impacts and adaptation, and apply it to study the impact of climate change on local air pollution. Economic agents are usually constrained when responding to daily weather shocks, but may adjust to long-run climatic changes. By simultaneously exploiting variation in weather and climate, we identify both the short- and long-run impacts on economic outcomes, and measure adaptation directly as the difference between those responses. As a result, we identify adaptation without making extrapolations of weather responses over time or space, and overcome omitted variable bias concerns in prior approaches.

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I. Introduction

Failure to achieve climate mitigation goals puts increasing pressure on climate adaptation strategies.[1] Therefore, it is crucial to develop methods to measure climate impacts and adaptation, and examine heterogeneity in adaptive response. Inspired by the macroeconomic literature on the effects of unanticipated versus anticipated shocks on the economy (e.g., Lucas, 1972, 1976), the labor literature on the importance of distinguishing transitory versus permanent income shocks (e.g., Solon, 1992, 1999), and the properties of the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963), we develop a unifying approach to measuring climate impacts and adaptation. The proposed approach is then applied to examine the impact of climate change on ambient "bad" ozone concentration in U.S. counties over the period 1980-2013.

The pioneer cross-sectional approach to estimate the impact of climate change on economic outcomes (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005) has relied on permanent, anticipated components behind meteorological conditions, but may suffer from omitted variable bias. In contrast, the panel fixed-effects approach (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) exploits transitory, unanticipated weather shocks, and deals with that bias, but identification of climate effects using weather variation is not trivial. Estimates of climate impacts based on cross-sectional studies are inclusive of adaptation, whereas those from fixed-effects are not. Naturally, in the absence of a unifying approach that simultaneously exploits both variation in unexpected weather and long-run climatic changes, influential studies have proposed measuring adaptation as the difference between the estimates of impacts in fixed-effects and cross-sectional approaches (e.g., Dell, Jones and Olken, 2009, 2012, 2014). While this measure of adaptation is rather intuitive and theoretically sound, if one relies on biased cross-sectional estimates of climate impacts, this derived measure will likely be biased as well.

[1] According to the Fifth Assessment Report from the Intergovernmental Panel on Climate Change (IPCC, 2013), the warming of the climate system is unequivocal, and global temperatures are likely to rise from 1.5 to 4 degree Celsius over the 21st century, depending on the emissions scenario.

Our unifying approach overcomes these key challenges of the literature, and allows for the estimation of the short- and long-run impacts in the same equation. As a result, our approach enables a straightforward test for the statistical significance of the measure of adaptation. Further, our approach to identifying adaptation addresses two other shortcomings from existing approaches. First, it recovers a measure of adaptation *directly* from the jointly estimated impacts of weather and climate. In contrast, a common approach in the literature tackles adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks, then assessing climate damages by using shifts in the future weather distribution predicted by climate models (e.g., Deschenes and Greenstone, 2011).

Second, and analogous to the Lucas Critique (Lucas, 1976), our approach overcomes the challenges of identifying adaptation by comparing the profiles of weather responses across time and space, under the assumption that preferences are constant across those dimensions. For example, Barreca et al. (2016), Auffhammer (2018*a*), and Heutel, Miller and Molitor (forthcoming) allow for differences across time or location in the relationship between temperature and economic outcomes when dealing with adaptation. But, the assignment of a profile of temperature responses to another time or place solely based on observed attributes and the future weather distribution may be imprecise due to unobserved differences in preferences, beliefs, and experience with the local climate that may affect adaptive behavior (e.g., Olmstead and Rhode, 2011; Bleakley and Hong, 2017).[2] Instead, we identify adaptation by comparing how economic agents in the *same* season and location respond to weather shocks – which, by definition, limit opportunities to adapt – with their own response to climatic changes, which should incorporate adaptive behavior.

We apply our unifying approach to the context of daily temperature and ambient ozone concentration across the continental United States. This provides an ideal setting for examining the difference between agents' responses to transitory temperature shocks and permanent

[2]One way to address this issue is to use experimental or quasi-experimental variation in those attributes in order to causally capture the extent to which they offset weather effects. One example is Garg, McCord and Montfort (2020), who leverage quasi-experimental variation in eligibility to a cash transfer program in Mexico to identify how income may mitigate the temperature-homicide relationship.

shifts in climate because the effects of temperature changes on ozone are almost instantaneous. Furthermore, economic agents, whether directly or indirectly, may have market and non-market incentives for reducing ozone concentrations. For example, a polluting firm faced with regulatory or public pressures, or technological advancements, could alter its input mix with potential cost implications. Similarly, a commuter provided with new air pollution information may adjust their transport mode choice or timing, which may not be costless either. In this context, agents may minimize cost, analogously to the profit maximizing approach for agriculture implemented by Deschenes and Greenstone (2007) which can be restated as its dual cost-minimization problem.

Our approach has two key elements. The first is the decomposition of meteorological variables into two components: long-run climate normals and weather shocks, the latter defined as deviations from those norms. This decomposition is meant to have economic content. It is likely that individuals and firms respond to information on climatic variation they have observed and processed over the years. In contrast, economic agents may be constrained in their response to short-term, unanticipated weather shocks. Our measure of adaptation is the difference between those two responses by the *same* economic agents.[3] In our application, we take advantage of high-frequency data, and decompose temperature into a monthly moving average incorporating information from the past three decades, often referred to as climate normal (WMO, 2017), and a deviation from that lagged 30-year average.[4] Although our choice of the 30-year moving average follows from the climatology literature, in principle any method filtering weather data at some temporal frequency should work (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003). The 30-year moving average is purposely lagged in our empirical framework to reflect all the information available to individuals and firms up to the year prior to the measurement of the outcome variables. We then compare

[3]Although we focus on adaptive behavior, we are agnostic about the true impacts. There may be adaptation or intensification effects (Dell, Jones and Olken, 2014).

[4]Climate normals are, by definition, 30-year averages of weather variables such as temperature. The *monthly* frequency for the moving averages in our empirical decomposition is without loss of generality. All we need is a time frame that economic agents can easily remember information from the past. Our robustness checks using *daily* moving averages provide nearly identical results.

the jointly estimated short- and long-run effects to provide a measure of adaptive response by economic agents.

The second essential element of our approach is identifying responses to weather shocks and longer-term climatic changes in the *same* estimating equation. Our unifying approach bridges two strands of the climate-economy literature.[5] We *simultaneously* exploit meteorological variation to identify the causal effect of weather shocks on economic outcomes, and climatological variation to identify the causal impact of longer-term observed climatic changes. The meteorological variation exploited in the estimation is random changes in weather, similar to most of the literature relying on the fixed-effects approach. The climatological variation, however, is new and relies on within-season changes in local, monthly 30-year moving averages. Intuitively, it works as if the "climate experiment" randomly assigns changes in the average May temperature that makes it closer to average June temperature in the same location, for example. We are able to leverage both sources of variation in the same estimating equation because of the properties of the Frisch-Waugh-Lovell theorem. The deseasonalization embedded in the fixed-effects approach is equivalent to the construction of weather shocks as deviations from climate norms as a first step. Furthermore, there is no need to deseasonalize the outcome variable to identify the impact of those shocks (Lovell, 1963, Theorem 4.1, p.1001).[6] As a result, we do not need to include highly disaggregated time fixed effects in the final econometric model; thus, we are able to also exploit variation that evolves slowly over time to identify the impacts of longer-term climatic changes.

This paper proceeds as follows: Section II provides an overview of the two previous methodological approaches used to identify climate impacts, proposes our unifying approach and the resulting measure of adaptation. Section III provides a conceptual framework of an agent's adaptation decision-making, describes our data, and presents our empirical strategy.

[5]For reviews of this literature, see Dell, Jones and Olken (2014), Hsiang (2016), Massetti and Mendelsohn (2018), Auffhammer (2018*b*), and Kolstad and Moore (2020).

[6]As in Dell, Jones and Olken (2009, 2012, 2014), Burke and Emerick (2016) also quantify longer-run adjustments to climate change in an application to agriculture by smoothing out the variables on both sides of the equation.

Section IV reports our main findings, and examines the robustness of our estimates. Section V further explores aspects of heterogeneity. Finally, Section VI concludes.

II. Prior Methods and Our Unifying Approach to Measuring Climate Change Impacts and Adaptation

A. Prior Methods

Prior literature on estimating climate impacts and adaptation has usually relied on two approaches. The first is the cross-sectional approach (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005), which exploits permanent, anticipated components behind meteorological conditions, leveraging climate variation across locations to estimate climate impacts *inclusive* of adaptation, but may suffer from omitted variable bias. The other is the panel fixed-effects approach (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), which deals with that bias but identifies the effect of transitory, unanticipated weather shocks, most likely *exclusive* of adaptation, making the transition to estimated climate effects nontrivial.[7] By using either the short- or long-run variation behind meteorological conditions to identifying climate impacts, those research designs trade off key assumptions.[8] More recent literature (e.g., Dell, Jones and Olken, 2009, 2012, 2014) has proposed various hybrid approaches for combining these two strands of the literature, but face issues of their own (Kolstad and Moore, 2020).

The cross-sectional (CS) approach estimates the following equation:

$$y_i = \alpha + \beta_{CS} x_i + (\mu_i + \nu_i) = \alpha + \beta_{CS} x_i + e_i, \tag{1}$$

where y_i is an outcome variable measured at location i, and is affected by the climatological

[7] Only in certain conditions does weather variation exactly identify the effects of climate (e.g., Hsiang, 2016; Lemoine, 2020).

[8] All this literature takes climate variation as given, under the assumption that relatively small spatial units of analysis can be thought of as "climate takers" rather than "climate setters." Notwithstanding, there is a literature that carries out analyses at a global scale, and accounts for the bi-directional feedback between climate and the economy (e.g., Kaufmann, Kauppi and Stock, 2006; Pretis, 2020).

variable of interest, x_i – typically taken as temperature. μ_i represents the vector of all time-constant unobserved covariates that are correlated to x_i, while ν_i reflects the standard idiosyncratic error term. Thus, if μ_i is non-empty and $cov(x_i, \mu_i) \neq 0$, $\hat{\beta}_{CS}$ suffers from omitted variable bias (OVB).

The panel fixed-effects (FE) approach instead estimates the following equation:

$$y_{it} = \alpha + \beta_{FE} x_{it} + \mu_i + \lambda_t + \nu_{it}, \tag{2}$$

where the outcome variable, y_{it}, and climatic variable of interest, x_{it}, are now additionally measured at some recurring time interval t. By averaging each variable in Equation (2) for each unit i over time, we obtain:

$$\bar{y}_i = \alpha + \beta_{FE} \bar{x}_i + \mu_i + \bar{\nu}_i, \tag{3}$$

where $\bar{y}_i \equiv 1/T \sum_{t=1}^{T} y_{it}$, and the other variables are defined similarly.[9] Subtracting Equation (3) from Equation (2), we highlight the source of variation in the identification of β_{FE}:

$$(y_{it} - \bar{y}_i) = \beta_{FE}(x_{it} - \bar{x}_i) + \lambda_t + (\nu_{it} - \bar{\nu}_i). \tag{4}$$

Because $(x_{it} - \bar{x}_i)$ is the deviation of observed temperature from its local long-run value, β_{FE} is clearly identified from temperature shocks. Thus, in this approach, although most OVB problems are resolved by the μ_i terms cancelling out, $\hat{\beta}_{FE}$ now identifies the impact of meteorological, rather than climatological, phenomena.

Recently, focus has expanded from simply estimating climate impacts to estimating adaptation to climate change. Some authors have noted that β_{CS} identifies climate impacts *inclusive* of any adaptation, while β_{FE}, by its nature, identifies meteorological impacts which can be taken as an approximation of climate impacts *exclusive* of any adaptation (e.g., Dell, Jones and Olken, 2009, 2012, 2014). Thus, they propose measuring adaptation as the differ-

[9] Note that via the inclusion of the intercept, the λ_t and μ_i fixed effects are both relative to the same baseline, α, and thus the λ_t term drops out when averaging over time by the restriction that $\sum_t \lambda_t = 0$ (Suits, 1984; Baltagi, 2008).

ence between $\hat{\beta}_{FE}$ and $\hat{\beta}_{CS}$. Although this principle to recovering a measure of adaptation is accurate, the approach faces two empirical challenges. First, to the extent that OVB may impact $\hat{\beta}_{CS}$ in the cross-sectional model, this will translate directly into bias in the estimate of climate adaptation. Second, even if an unbiased estimate of β_{CS} could be obtained, $\hat{\beta}_{CS}$ and $\hat{\beta}_{FE}$ arise from two different estimating equations. While OLS, equation by equation, allows us to easily test hypotheses about the coefficients within an equation, it does not provide a convenient way for testing hypotheses involving coefficients from different equations. Thus, in practice, one must resort to seemingly unrelated regression (SUR) models to explicitly test whether the measure of adaptation is statistically distinguishable from zero. As is well known, a SUR system is a set of equations that has cross-equation error correlation, that is, the error terms in the regression equations are correlated. Also recall that SUR estimation usually amounts to feasible generalized least squares with a specific form of the variance-covariance matrix. Hence, further structural assumptions are needed for statistical inference of the measure of adaptation.

B. Our Unifying Approach

Our unifying approach nests both of those strands of the climate-economy literature in the *same* estimating equation. It simultaneously identifies long-run climatological impacts and short-run effects of meteorological shocks, and thus allows for an explicitly testable measure of adaptation in the spirit of prior comparisons between short- and long-run effects (e.g., Dell, Jones and Olken, 2009, 2012, 2014). Specifically, we begin by posing the ideal estimating equation, although infeasible:

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_i) + \beta_C\bar{x}_i + \mu_i + \lambda_t + \nu_{it}. \tag{5}$$

If this infeasible equation were estimable, β_W – the effect of weather shocks – would exactly identify β_{FE} by the Frisch-Waugh-Lovell theorem. On the other hand, β_C – the effect of changes in climate – would identify β_{CS} minus *OVB* due to the inclusion of fixed effects.

Unfortunately, β_C cannot be identified because $\bar{x}_i$ is perfectly collinear with μ_i. We therefore propose the following feasible approximation of the ideal equation:[10]

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C \bar{x}_{i\bar{p}} + \mu_i + \lambda_s + \nu_{it}. \tag{6}$$

As time can be aggregated into multiple subset levels – day, month, quarter, year, decade, etc. – we first define a time period, p, as a weakly larger aggregation of t. Agents, however, may observe and react to the slow evolution of climate. Thus, we define $\bar{p}$ to incorporate data from the same time frame p in the past. Furthermore, agents may need time to adjust, so we additionally restrict $\bar{p}$ to exclude contemporaneous data. We also replace λ_t with λ_s – with s a one-level higher aggregation in time than p – in order to retain relevant variation in $\bar{x}_{i\bar{p}}$.[11] Defined in this way, variation in $\bar{x}_{i\bar{p}}$ comes from two separate sources. First, although more aggregate than t, $\bar{p}$ still varies across time within the the higher level time period s. Second, $\bar{p}$ is defined to include historical data, and thus "updates" its value from year to year. Following the same steps as with the fixed-effects model and averaging each variable in Equation (6) for each cross-sectional unit i over time, we obtain:

$$\bar{y}_i = \alpha + \beta_W(\bar{x}_i - \bar{x}_i) + \beta_C \bar{x}_i + \mu_i + \bar{\nu}_i = \alpha + \beta_C \bar{x}_i + \mu_i + \bar{\nu}_i, \tag{7}$$

where, once again, $\bar{y}_i \equiv 1/T \sum_{t=1}^{T} y_{it}$, and the other variables are defined similarly.[12] Subtracting Equation (7) from Equation (6), we highlight the source of variation that allows for the identification of both β_W and β_C:

$$(y_{it} - \bar{y}_i) = \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C(\bar{x}_{i\bar{p}} - \bar{x}_i) + \lambda_s + (\nu_{it} - \bar{\nu}_i). \tag{8}$$

[10]Observe that for simplicity, and to keep the comparison with those two strands of the literature as clear as possible, our unifying approach uses a linear specification, which should also capture the first-order effects of potentially nonlinear responses.

[11]Note that just as t, by convention, represents a specific time-step *of the sample*, e.g. day-of-the-sample, we take s as similarly representing a more aggregate time-step *of the sample*, e.g. season-of-the-sample.

[12]Note that in Equation (7) the $\bar{x}_i$ derived from the $\bar{x}_{i\bar{p}}$ term would rely on a longer time-series of information than the $\bar{x}_i$ derived from the x_{it} term. Still, they are approximately equivalent, with correlation between these two terms above 0.95 in our empirical application.

In Equation (8) we can observe that $\hat{\beta}_W$ is identified from temperature shocks, therefore approximately equivalent to $\hat{\beta}_{FE}$, whereas $\hat{\beta}_C$ is identified from climatic changes, approximately equivalent to $\hat{\beta}_{CS}$, though now critically free from a number of OVB concerns. We thus naturally define adaptation as the difference $\hat{\beta}_W - \hat{\beta}_C$. Because both coefficients of interest are estimated in a single equation, statistical inference on the measure of adaptation is straightforward. Furthermore, observe that this measure leverages the behavioral responses of the *same* economic agents to both weather shocks and climatic changes.

C. Decomposition of Meteorological Variables: Climate Norms vs. Weather Shocks

As mentioned above and seen in Equation (6), implementing our approach requires that we first decompose x_{it} into its long-run component, $\bar{x}_{i\bar{p}}$, and its short-run deviation from this value, $(x_{it} - \bar{x}_{i\bar{p}})$. Econometrically, from the Frisch-Waugh-Lovell theorem, we can decompose x_{it} into its longer term seasonal component and a contemporaneous de-seasonalized component. For example, as weather varies day-to-day, t, and local climate varies both seasonally (e.g., month-to-month within a year) and over time (e.g., year-to-year), we could take "month-of-the-sample," my, as representing the seasonal component and pose the following first-stage regression:

$$x_{it} = \gamma_{imy} + \epsilon_{it}, \tag{9}$$

such that temperature in location i on day t (of month m in year y) is regressed on a set of location-by-month-by-year fixed effects. In this case, the matrix of coefficients $\hat{\gamma}_{imy}$ would constitute the matrix of monthly average temperature values $\bar{x}_{imy}$, while the estimated residuals $(x_{it} - \bar{x}_{imy})$ $(\equiv \hat{\epsilon}_{it})$ would reflect the de-seasonalized daily local deviations of temperature. Because this regression simply de-means x_{it} over the my period in the time-series dimension for each individual location i, we could instead recover the $x_{it} - \bar{x}_{imy}$ values in Equation (9) arithmetically via the following:

$$\underbrace{Temp}_{x_{it}} = \underbrace{Temp^C}_{\bar{x}_{imy}} + \underbrace{Temp^W}_{(x_{it}-\bar{x}_{imy})}, \tag{10}$$

such that $Temp^C$ ($\equiv \bar{x}_{imy}$) represents climate patterns, and $Temp^W$ ($\equiv x_{it} - \bar{x}_{imy}$) deviations from those longer-run patterns. Notice that although the above example uses daily temperatures, de-seasonlized at the monthly level, the choice of timing can be selected to match the study context. To use the example of agriculture, a common focus in the climate literature, it may be that a year, or the growing seasons within a year, would be better suited to the analysis than the months of the year example illustrated in equations (9) and (10).

Economically, however, this presents a potential problem. As mentioned in the previous section, agents may need time to adapt, and prior information sets likely inform agents' beliefs. Thus, $\bar{x}_{imy}$ is not strictly equivalent to $\bar{x}_{i\bar{p}}$ as defined in Equation (6). To address this, we propose, as a first step, replacing $\bar{x}_{imy}$ with a lagged function of its historical values:

$$\bar{x}_{i\bar{p}} \equiv \frac{1}{J}\sum_{j=1}^{J<y} \omega_j \bar{x}_{imj} \approx \bar{x}_{imy}, \tag{11}$$

where ω_j represents a scalar weighting of $\bar{x}_{imj}$, such that the function defining $\bar{x}_{i\bar{p}}$ can be generalized to fit various contexts.[13] Returning to the agriculture example, it's possible that farmers need more than a single year to adjust production processes or change crop choice, in which case the $(\omega_{y-k}, ..., \omega_{y-1})$ weighting scalars of Equation (11) could all simply be set to zero, with $k > 1$. Furthermore, the functional form of Equation (11) itself can be chosen to best suit the application by changing the specific values of ω_j. Myopic and Bounded agents may simply assume that contemporaneous monthly temperature will be equal to what it was in the previous year, that is, ω_j simply evaluates to zero for all $j \in \{1, ..., y-2\}$.

[13] These weights, ω_j, can be defined by values derived from other literatures, such as climatology for example, which defines a climate normal as the average temperature over the last 30 years: "*The 30 year interval was selected by international agreement, based on the recommendations of the International Meteorological Conference in Warsaw in 1933. The 30 year interval is sufficiently long to filter out many of the short-term interannual fluctuations and anomalies, but sufficiently short so as to be used to reflect longer term climatic trends*" (Climatology Office, 2003). Alternative filtering techniques could also be implemented (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003), and would implicitly follow from this expression by varying the values of ω_j.

Other agents may flexibly fit values of ω_j to the historical data in an attempt to predict $\bar{x}_{i\bar{p}}$ through statistical means. A similar idea has been used in macroeconomics to measure business cycles since the seminal contribution of Bums and Mitchell (1946),[14] and in the literature of intergenerational mobility following Solon's (1992) seminal work.[15] Note that $\bar{x}_{i\bar{p}}$ can be calculated from a longer time-series of x to take into account historical information beyond the sample period of the outcome variable.

We then return to Equation (10), substituting $\bar{x}_{i\bar{p}}$ for $\bar{x}_{imy}$ in representing $Temp^C$, and recovering $x_{it} - \bar{x}_{i\bar{p}}$ ($\approx x_{it} - \bar{x}_{imy}$) for $Temp^W$, giving us all the components necessary for estimating Equation (6).[16] Notice that by the properties of the Frisch-Waugh-Lovell theorem (specifically, point 4 of Lovell (1963, Theorem 4.1, p.1001)) it is unnecessary to de-seasonalize the outcome variable y_{it} in the same way as $(x_{it} - \bar{x}_{i\bar{p}})$.[17]

This decomposition highlights the two sources of variation that have been used in the climate-economy literature. $Temp^C$ and $Temp^W$ in the decomposition above are associated with different sets of information. On the one hand, $Temp^C$ includes climate patterns that economic agents can only gather by experiencing weather realizations over a long period of time, and can be thought of as the "climate normal" temperature. On the other hand, $Temp^W$ represents weather shocks, which by definition are revealed to economic agents virtually at the time of the weather realization. Usually one adjusts to something they happen to know by experience. Therefore, adaptation can be measured as the difference between responses to changes in $Temp^C$ relative to effects of weather shocks $Temp^W$. This is analogous to Lucas' powerful insight that economic agents respond differently depending

[14] See, for example, Hodrick and Prescott (1981, 1997), Baxter and King (1999), and Christiano and Fitzgerald (2003).

[15] In Solon's context, observed income is noisy: it includes a permanent and a transitory component. To establish a relationship between permanent income of sons and fathers, Solon proposes averaging fathers' income for a number of years to reduce the errors-in-variables bias.

[16] In our preferred decomposition detailed in the following section, $Cor(\bar{x}_{i\bar{p}}, \bar{x}_{imy}) > 0.95$ and $Cor((x_{it} - \bar{x}_{i\bar{p}}), (x_{it} - \bar{x}_{imy})) > 0.90$.

[17] "*Theorem 4.1: Consider the following alternative regression equations, where the subscript α indicates that the data have been adjusted by the least squares procedure with D as the matrix of explanatory variables: 1. $Y = Xb_1 + D_{\alpha 1} + e_1$ 2. $Y_\alpha = X_\alpha b_2 + e_2$ 3. $Y = Xb_3 + e_3$ 4. $Y = X_\alpha b_4 + e_4$ ... The identity $b_2 = b_4$ reveals that it is immaterial whether the dependent variable is adjusted or not, provided the explanatory variables have been seasonally corrected*" (Lovell, 1963).

on the set of information that is available to them. Lucas (1977), for instance, provides an example of a producer that makes no changes in production or works less hard when facing a *permanent* increase in the output price, but works harder when the price increase is *transitory*.[18]

It is also important to emphasize that this decomposition does not make any assumption on how individuals and firms process and use the information from the past. Rational agents would respond optimally to all information at hand when deciding the degree of adaptation, while myopic and inattentive agents (e.g., Gabaix and Laibson, 2006; Reis, 2006*a*,*b*), on the other hand, may find it costly to absorb and process all the information at all times, and may respond only to partial information or only sporadically. Our measure of adaptation is agnostic to either type of behavior; the goal of our approach is to empirically assess the economic and statistical significance of adaptation, regardless of how economic agents make decisions on whether to adapt, or the extent of adaptation.

Finally, notice that this decomposition represents a first-order Taylor approximation of a potentially nonlinear relationship between climate and realized temperature. Two types of variation are often associated with a changing climate: changes in averages, and changes in the frequency of extreme weather events (IPCC, 2013). For simplicity, and to keep the comparison with prior approaches as simple as possible, our temperature decomposition focuses on increases in averages, not on variability. In fact, in the following section we show that our weather data, comprised of the comprehensive set of national weather monitors, suggests a gradual increase in average temperature, but that the magnitude of temperature shocks, defined as deviations from the 30-year moving averages, are relatively stable over time, and narrowly bounded. Therefore, in our approach, dispersion shows up only implicitly in the sense that long-run norms take into account the frequency and intensity of daily temperature extremes.[19]

[18]Notably, in our context the behavior would be reversed. Due to the contemporaneous nature of *transitory* weather shocks, little to no change in production is possible, while the producer would be able to change behavior in response to *permanent* changes in climate.

[19]It is imperative to recognize, however, that variability may be crucial in some settings. Kala (2019), for

III. Empirical Application: Climate Impacts on Ambient Ozone

We apply our unifying approach to measure climate impacts on ambient ozone concentration, and adaptation to climate change in this context, and examine the heterogeneity in adaptive behavior. This application is ideal for three reasons. First, ozone is not emitted directly into the air, but rather rapidly formed by Leontief-like chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight and warm temperatures. Hence, meteorological conditions do matter in determining surface ozone levels, and climate change may increase ozone concentration in the near future (e.g., Jacob and Winner, 2009). Furthermore, ozone is rapidly destroyed during the night; thus, correlation between ambient concentrations across two consecutive days is limited. Second, nationwide high-frequency data on ambient ozone and meteorological conditions are publicly available for a long period of time in the United States: we use daily measurements for the typical ozone season from 1980-2013.[20] Third, this is a highly policy-relevant issue. The so-called "climate penalty" on ozone means that climate change might deteriorate air quality in the near future, with important implications for public health and labor productivity.[21]

In this section, we present a conceptual framework for why agents may undertake adaptive measures, describe the data used in our analysis, and the empirical strategy used to carry out the estimation of the impacts of weather shocks and longer-term climatic changes on ambient ozone concentration.

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example, studies adaptation under different learning models. Hence, variance of climatological variables is a key element of her framework.

[20]The ozone season varies by state and usually consists of only six months (typically April-September), but concerns are mounting that longer spring and fall would expand the ozone season in some states (e.g., Zhang and Wang, 2016).

[21]Exposure to ambient ozone has been causally linked to asthma hospitalization, pharmaceutical expenditures, mortality, and labor productivity (e.g., Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2012; Deschenes, Greenstone and Shapiro, 2017).

A. Conceptual Framework

In the context of ozone, economic agents could be polluting firms, or households engaging in consumption that produces precursor pollutants. For simplicity of exposition, consider the case of a polluting firm. The agent minimizes cost by selecting the optimal production schedule for the given input costs, climate, and other local factors faced by the agent. But, ambient ozone itself can impose an additional shadow price on the agent's chosen production schedule, implied by, e.g., public or regulatory pressures. Specifically, for the agent engaging in dirty production, ozone precursor pollutants (VOCs and NOx) are *de facto* "inputs" into the agent's production schedule.[22] Any shadow price on ozone faced by the agent would thus translate into an implicit shadow price on the emission of either of these precursors as inputs in their production process, conditional on local climate and atmospheric composition.[23] Ceteris paribus, the agent would thus minimize costs taking into account the implicit shadow prices on these precursors. In practice, the optimizing decisions are often over changes in input mix or timing of production (Henderson, 1996). In other words, the agent is implicitly minimizing ozone levels whenever they choose inputs for production of goods and services.[24]

To better understand why agents may adapt to climatic changes in ways that reduce ambient ozone, compare the ozone context to a standard agricultural setting. As has been shown in that context (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), the agent maximizes profit by optimizing over their choice of crop and other inputs such as irrigation, conditional on anticipated or realized climate, controlling for other local factors such as soil

[22] That is, they are emitted in proportion to the choice, and quantity used, of actual production inputs.

[23] Naturally, there may also be regulatory pressures for the precursors themselves, therefore explicitly defining (shadow) prices for them as well (Auffhammer and Kellogg, 2011; Deschenes, Greenstone and Shapiro, 2017). In the robustness checks, however, we provide evidence that these regulations do not seem to play an important role in agents' adaptation measures regarding climatic changes. This is not surprising, given that it is ozone formation, not the precursors, that primarily depends on climate.

[24] Of course there are other factors that may affect ambient ozone concentrations, climate being the obvious one, but precursor emissions are the only source that is controllable by the agent. While this could lead to measurement error in the direct relationship between agents' decisions and ozone concentration, ozone – in this context – is the outcome variable, and any measurement error in ozone would simply be absorbed by the error term in a reduced form model.

quality. Restated, the agent minimizes cost by selecting the optimal production schedule for the given set of input costs, climate, and other local factors faced by the agent.

Figure 1 illustrates this "cost-minimizing" optimization decision agents face with respect to ozone and its precursors, depicting the envelope of minimum-cost production schedules, conditional on realized climate, in the spirit of Deschenes and Greenstone (2007). Cost of production is on the left y-axis, associated ozone concentration is on the right y-axis, and temperature is on the x-axis.[25] For simplicity in illustration, we assume that factors such as precipitation and other exogenous determinants have been adjusted for. The production schedule 1 and 2 cost functions reveal the relationship between cost and temperature, as well as ozone and temperature, when these production schedules are chosen. It is evident that schedule specific costs, and associated ozone concentrations, vary with temperatures. Further, the cost-minimizing production schedule varies with temperature. For example, production schedule 1 minimizes cost between T_1 and T_2; the agent would be indifferent between the two at T_2 where the cost functions cross (i.e., point B); and production schedule 2 minimizes cost between T_2 and T_3. The long-run equilibrium is denoted by the dashed gray line and represents the long-run optimum when the agent can freely adjust their production schedule in response to changes in temperature.

Consider first an agent that is initially faced with a climate normal temperature of T_1. Their optimal choice would thus be to minimize cost under production schedule 1, at point A. Now consider two alternative scenarios: one in which the agent is faced with a transitory temperature shock of T_3, and a second in which the agent is faced with a permanent change to a new climate normal temperature of T_3. Under the first scenario, the agent would be unable, or unwilling,[26] to adapt to the temperature shock and would temporarily produce at

[25] Notice that from the cost minimization problem, we observe a derived demand function for VOCs and NOx, conditional on the agent's chosen level of output. In turn, that demand for precursors maps into resultant ambient ozone levels, conditional on the temperature.

[26] From a purely mechanical standpoint, the agent may be technologically unable to adjust their production schedule on such short notice – i.e., daily. From an economic standpoint, even if such adjustments were technologically feasible, they may not be economically sound, as such adjustments would likely incur greater costs than could be saved by avoiding the additional cost associated with transitory sub-optimal production.

point C', with higher associated ozone concentration and higher cost of production. Under the second scenario, the agent would adjust to this permanent change in the climate normal temperature and change to production schedule 2, now producing at point C rather than C'. Notice, however, that while point C is lower cost than point C', it still implies a higher cost of production and associated ozone concentration than point A. This is to be expected. Adaptation is typically not costless (e.g., Kelly, Kolstad and Mitchell, 2005; Carleton et al., 2020) – as production schedule 1 was cost-minimizing under the original climate norm of T_1, this implies that schedule 2 must be (weakly) more costly to implement in the absence of any climatic changes.

Finally, notice that our unifying approach estimates *simultaneously* both of these reduced form relationships between ambient ozone concentration and temperature, accounting for agents' differential responses to temperature shocks versus changes in the climate norm. The recovered estimate for temperature shocks – β_W in Equation (6) – reflects the difference between the ozone concentrations associated with points C' and A, while the recovered estimate for changes in the climate norm – β_C in Equation (6) – reflects the difference between points C and A, and thus adaptation can be clearly taken as the difference between C' and C.

B. Data

Weather Data — For meteorological data, we use daily measurements of maximum temperature as well as total precipitation from the National Oceanic and Atmospheric Administration's Global Historical Climatology Network database (NOAA, 2014). This data-set provides detailed weather measurements at over 20,000 weather stations across the country for the period 1950-2013. Figure 2 presents the yearly temperature fluctuations and overall climate trend in the US as measured by these monitors, relative to a 1950-1979 baseline average temperature, while Figure A1, in Appendix A, illustrates the geographical location of the complete sample of weather stations from 1950-2013. Figure 3, by comparison, depicts the variation and trend of our decomposed temperature variables, $Temp^C$ and $Temp^W$, between 1980 and 2013 for the comprehensive set of national weather monitors, indicating that while average temperature has been gradually increasing, temperature variability has remained relatively stable.[27] These weather stations are typically not located adjacent to the ozone monitors. Hence, we develop an algorithm to obtain a weather observation at each ozone monitor in our sample.[28] Table A1, in Appendix A, reports the summary statistics for daily temperature and our decomposed variables, for each year in our sample from 1980-2013.

Ozone Data — For ground-level ozone concentrations, we use daily readings from the nationwide network of the EPA's air quality monitoring stations. In our preferred specification we use an unbalanced panel of ozone monitors.[29] Appendix A Figure A4 illustrates the evolution of ambient ozone concentrations over our sample period for both the full unbalanced panel of monitors, as well as a smaller balanced panel. Figure A5, in Appendix A, depicts the evolution of our sample of ozone monitors over the three decades in our data, and illustrates the expansion of the network over time. Table A2, in Appendix A, describes some features of the sample of ozone monitors used in our analysis, for every year between 1980 and 2013.

Consolidating information from the above sources, we reach our final unbalanced sample of ozone monitors over the period 1980-2013.[30] Appendix A Figure A6 illustrates the proximity of our final sample of ozone monitors to the matched weather stations.

We carry out the analysis focusing on the effect of daily maximum temperature on daily maximum ozone concentration since 1980. We choose this relationship because increases in temperature are expected to be the principal factor driving increases in ambient ozone concentrations (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our

[27] Figures A2 and A3 in Appendix A present similar patterns using a semi-balanced sample of monitors, and our final sample of weather monitors once matched to ozone monitors.

[28] We detail the steps taken in Appendix A.1 as well as conduct robustness checks on the sensitivity of our results to changes in the algorithm in Appendix B.1.

[29] We discuss the reasoning for this approach as well as our results using a balanced panel in Appendix B.1.

[30] For further details regarding the construction of the final dataset for our analysis, see Appendix A.1.

sample, plotted in Appendix A Figure A7, highlights the close correlation between these two variables. Interestingly, we see that not only does contemporaneous temperature have an effect on ambient ozone, but the long-term climate normal temperature also seems to be affecting it, although perhaps to a lesser extent. We leverage both relationships in the empirical framework we now describe.

C. Empirical Strategy

Decomposition of Meteorological Variables: An Empirical Counterpart — Focusing on temperature ($Temp$), our primary variable of interest, we express it around ozone monitor i in day t of month m and year y, and decompose it into $Temp^C$ ($\equiv \bar{x}_{i\bar{p}}$) and $Temp^W$ ($\equiv x_{it} - \bar{x}_{i\bar{p}}$) as in Section II. For our application, we define:

$$\bar{x}_{i\bar{p}} = \frac{1}{30} \sum_{j=y-30}^{y-1} \bar{x}_{imj}, \tag{12}$$

Implicitly defining ω_j as equal one for all $j \in \{y-30, ..., y-1\}$ – where y denotes the contemporaneous year – and zero otherwise, such that $Temp^C$ ($\equiv \bar{x}_{i\bar{p}}$) is equal to the 30-year monthly moving average (MA) of past temperatures.[31]

We choose a one-year lag to make this variable part of the information set held by economic agents at the time that the outcome of interest is measured, and we average temperature over 30 years because it is how climatologists usually define climate normals, and because we wanted individuals and firms to be able to observe climate patterns for a long period of time, enough to potentially make adjustments.[32] For example, the 30-year MA associated with May 1982 is the average of May temperatures for all years in the period 1952-

[31] Our decomposition of meteorological variables into a 30-year moving average (norms) and deviations from it (shocks), as discussed in Section II, is a data filtering technique to separate the "signal" from the "noise." This should not be confused with a moving-average model of climate change.

[32] It is possible, however, that agents form beliefs regarding expected climate over much shorter and more recent time windows (e.g., Kaufmann et al., 2017), or that organizational inertia slows the rate at which firms adapt to a changing climate (e.g., Kelly and Amburgey, 1991). In our robustness checks we provide similar estimates using 3-, 5-, 10-, and 20-year moving averages, as well as longer lag lengths between the contemporaneous weather shock and the defined climate normal.

1981. Therefore, economic agents should have had at least one year to respond to unexpected changes in climate normals at the time ambient ozone is measured. We use monthly MAs, rather than daily or seasonal, because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed, meteorologists on TV and social media often talk about how a month has been the coldest or warmest in the past 10, 20, or 30 years, but not how a particular day of the year has deviated from the norm for that specific day.[33] Taking this approach, $Temp^W$ represents weather shocks and is defined as the deviation of the daily temperature from the lagged 30-year monthly MA.

By definition, these shocks are revealed to economic agents only at the time ambient ozone is being measured. Thus, in this case agents may have had only a few hours to adjust, limiting their ability to respond to such unexpected temperatures.[34] Figure 4 provides an illustrative example of our preferred decomposition in Panel A, compared to a traditional fixed-effects decomposition in Panel B, using data for Los Angeles in 2013.[35]

Econometric Model — Given the decomposition of meteorological variables into two sources of variation, our parsimonious econometric specification to estimate the impact of temperature on ambient ozone is the following:

$$Ozone_{it} = \beta_W Temp^W_{it} + \beta_C Temp^C_{i\bar{p}} + X'_{it}\delta + \phi_{is} + \epsilon_{it}, \tag{13}$$

where i represents an ozone monitor, and t stands for day, s for *season-of-the-sample* (Spring

[33]There may be a concern that because temperature can have a within-month trend, defining temperature as a monthly average (climate norm) with daily (weather) shocks could mechanically lead to a stronger relationship between ozone and weather than between ozone and climate. As another robustness check, we redefine $\bar{x}_{i\bar{p}}$ in Equation (12) to the special case in which $p = t$, using *daily* instead of *monthly* moving averages, discussed further in the following subsection. Economic agents, however, may still associate a day with its corresponding month when making adjustment decisions.

[34]Because precise weather forecasts are made available only a few hours before its realization, economic agents may have limited time to adjust prior to the ozone measurement. This might be true even during Ozone Action Days (OAD). An OAD is declared when weather conditions are likely to combine with pollution emissions to form high levels of ozone near the ground that may cause harmful health effects. Individuals and firms are urged to take action to reduce emissions of ozone-causing pollutants, but usually only a day in advance or in the same day. Unlike what happens in a few developing countries, however, neither production nor driving is forced to stop in those days, limiting the impact of short-run adjustments. In the robustness checks, we find no evidence of any additional adaptation occurring due to OAD announcements. That is, short-run adjustments, if any, do not seem large enough to be comparable to what happens in the long run.

[35]Figure A8, in Appendix A, illustrates this same concept but over the entire 34-year sample period.

or Summer, in each year). As mentioned in the prior section, our analysis focuses on the most common ozone season in the U.S. – April to September – in the period 1980-2013.[36] The dependent variable $Ozone$ captures daily maximum ambient ozone concentration. $Temp$'s represent the two components of the decomposition proposed for meteorological variables.[37] The matrix of additional control covariates X_{it} contains a similar decomposition of precipitation.[38] Finally, we replace the monitor fixed effects, μ_i, and time fixed effects, λ_s, from the generalized model presented in Equation (6) with ϕ_{is} – fixed effects for monitor-by-season-by-year, and include ϵ_{it}, an idiosyncratic term.[39] From a theoretical standpoint this change is not necessary – and in fact the empirical results are qualitatively similar when implemented using μ_i and λ_s as separate fixed effects. We nevertheless combine them to more flexibly control for local factors that may have changed across seasons and years, allowing us to more closely approximate the ideal experiment.[40]

Analogous to Isen, Rossin-Slater and Walker (2017), notice that by including fixed effects for monitor-by-season-by-year, it is as if we regressed our main specification monitor by monitor, individually, for each season of the sample, and then took the weighted average of all recovered coefficients. Conceptually, consider the following thought experiment that we observe in our data many thousands of times for both daily temperature shocks and monthly climate norms: Take two days (months) in the same location, same season, and same year. Now, suppose that one of the days (months) experiences a larger temperature shock (hotter climate norm) than the other. Our estimation strategy quantifies the extent to which this difference in temperature shock (climate norm) affected the ozone concentration

[36]Table A3 in Appendix A lists the official ozone season by state following USEPA (2006).

[37]We also explore the nonlinear effects of temperature on ozone in Appendix B.1.

[38]Although Dawson, Adams and Pandisa (2007) find it to be less important than temperature, Jacob and Winner (2009) point out that higher water vapor in the future climate may decrease ground-level ozone concentration. Our estimates are in line with those authors' assessment, and are available upon request.

[39]Appendix C details how both sources of monitor-level variation in $\bar{x}_{i\bar{p}}$, within-season and across-year, are still leveraged within this monitor-by-season-by-year fixed-effects structure.

[40]One may be concerned that we do not include fixed effects for "predictable" within-season variation such as the "ozone weekend effect." As a robustness check we re-estimated Equation (13) after further extending our monitor-by-season-by-year fixed effects, ϕ_{is}, to monitor-by-season-by-year-by-weekday/end. Our results were quantitatively unchanged to the third decimal digit.

observed on that day (month). Therefore, this approach controls for a number of potential time-invariant and time-varying confounding factors that one may be concerned with, such as the composition of the local atmosphere, regulatory burden, and technological progress.

Measuring Adaptation — Once we credibly estimate the impact of the two components of temperature – daily shocks and within-season changes in climate normals – on ambient ozone concentration, we uncover our measure of adaptation. The average adaptation across all monitored locations in our sample is the difference between the coefficients $\hat{\beta}_W$ and $\hat{\beta}_C$ estimated in Equation (13). If economic agents engaged in full adaptive behavior, $\hat{\beta}_C$ would be zero,[41] and the magnitude of the average adaptation would be equal to the size of the weather shock effect on ambient ozone concentration. As explained before, agents would react to "permanent" increases in temperature by reducing ozone precursor emissions to offset potential increases in ozone concentration.

In our preferred econometric specification, behavioral responses are allowed to occur only in the year after the change in temperature norm is observed. Those adjustments, however, might be related to innovations in temperature happening both in the previous year and 30 years before. Indeed, the "moving" feature of the 30-year MA is, by definition, associated with the removal of the earliest observation included in the average – 31 years before, and the inclusion of the most recent observation – one year before. Nevertheless, in the robustness checks we consider cases where economic agents can take a decade or two to adjust.

IV. Results

In this section we report our findings of the application of our unifying approach to the impact of temperature changes on ambient ozone concentration, and the extent to which economic agents adapt to climate change in the context of ambient ozone pollution.

[41] This outcome is unlikely because, as noted previously, adaptation is typically not costless and thus the costs of engaging in 'full adaptive behavior' likely outweigh the benefits (Kelly, Kolstad and Mitchell, 2005; Carleton et al., 2020).

A. Impacts of Temperature on Ambient Ozone Concentration

Column (1) of Table 1 presents the effects on ambient ozone of the two components of observed temperature: climate norm, represented by the *lagged* 30-year monthly MA, and temperature shock, represented by the deviation from that long-run norm.[42] Although they are uncovered by estimating Equation (13), columns (2) and (3) benchmark them against effects that would have been found if one had exploited either only the panel (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) or only the cross-sectional (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005) structure of the data.

Column (2) reports the effect of temperature on ozone identified by exploiting within-monitor daily variation in maximum temperature after controlling for monitor-by-month-by-year fixed effects. The coefficient indicates that a 1°C increase in maximum temperature leads to a 1.66 parts per billion (ppb) increase in maximum ambient ozone concentration. Column (3) reports results from a cross-sectional estimation of daily maximum ozone concentration on daily maximum temperature around each monitor, averaged over the entire period of analysis 1980-2013. These variables capture information for all the years in our sample and are good proxies for the average pollution and climate around each monitor. The estimate suggests that a 1°C increase in average maximum temperature is associated with an increase of 1.17ppb in ozone concentration, approximately. When we decompose daily maximum temperature into our two components in column (1), as expected the estimated effect of temperature shocks on ambient ozone is statistically the same as the fixed-effects approach in column (2). Coincidentally, the effect for the lagged 30-year MA climate norm is also statistically the same as its counterpart in column (3). Specifically, a 1°C temperature shock increases ozone concentration by 1.68ppb, and a 1°C change in climate norm increases ozone concentration by 1.16ppb. To be clear, this does not imply that the cross-sectional approach

[42] As mentioned before, even though we use monthly moving averages in our main analysis, as a robustness check we also estimate our preferred specifications using daily moving averages. The results are virtually identical, and are reported in Appendix B.1 Table B3.

is free of omitted variable bias concerns. More likely there happens to simply be both upward and downward bias simultaneously affecting the estimate in this specific context (Griliches, 1977). In fact, when we re-estimate our model on a more balanced sample of monitors as a robustness check the bias in the cross-sectional approach becomes much more evident, leading to an over-estimation of the implied measure of adaptation by more than 100 percent.[43]

It is widely recognized that the cross-sectional approach is plagued with omitted variable bias. In our context, if more informed/concerned local monitoring agencies inspect heavy emitters of ozone precursors more often when average temperature rises, and more intense enforcement of environmental regulations induces reductions in ozone concentration, then this unobserved behavior might lead to underestimation of the long-run impact of temperature. On the other hand, as emphasized in the conceptual framework, estimates from the standard panel data fixed-effects methodology and our approach should be statistically the same due to the properties of the Frisch-Waugh-Lovell theorem. The deseasonalization embedded in the fixed-effects model is approximately equivalent to the use of deviations from 30-year norms in our regression model.

Our estimates imply a so-called "climate penalty" on ozone on the lower end of the ranges found in the literature. Indeed, Jacob and Winner (2009), in their review of the effects of climate change on air quality, find that climate change alone may lead to a rise in summertime surface ozone concentrations by 1-10 ppb – a wide interval partly driven by the different regional focuses of the studies they review. The U.S. EPA, in its 2009 Interim Assessment, claims that "*the amount of increase in summertime average ... O3 concentrations across all the modeling studies tends to fall in the range 2-8 ppb*" (USEPA, 2009, p.25). Combining our estimates in column (3) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5), one would also predict an increase in ambient ozone concentrations by the mid and the end of the century in the range of 1.9-5.6 ppb, approximately.[44] To be clear, "climate

[43]See estimates in Table B2 in Appendix B.

[44]To be clear, while our estimate of adaptation does not rely on extrapolation, any prediction of the

penalty" in our setting is the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation, as it will be discussed below. If one would wrongly use the response to temperature shocks as the penalty, which is *exclusive* of adaptation, the range would be 2.7-8 ppb, a nontrivial shift to the right. In fact, this may be one of the reasons why our estimate of the penalty is on the lower ranges of the values produced by simulation studies (again, for a review, see Jacob and Winner, 2009); they usually do not take into account behavioral responses. To put those values in perspective, each of the last few times EPA revised the air quality standards for ambient ozone, they decreased it by 5ppb.

B. Measuring Adaptation to Climate Change

Our results indicate that temperature shocks have a larger impact on ozone levels compared to long-term temperature norms. The comparison between the short- and long-run effects of temperature may provide a measure of adaptive responses by economic agents (Dell, Jones and Olken, 2009, 2012, 2014). Our measure of adaptation – also a comparison between the impact of changes in the long-run climate normal temperature (lagged 30-year MA) and the effect of the temperature shock (deviation from the MA) – is 0.51ppb, suggesting that economic agents might be adapting to climate change. In the case of polluting firms, for example, they might be making adjustments to the production process so that whenever average temperature rises, the emissions of ozone precursors reduce to keep ambient ozone at controllable levels. Such adjustments might be driven by public and regulatory pressures and/or technological innovation.

If we ignored such adaptive responses by economic agents, then we would be overestimating the "climate penalty" on ozone by more than 44 percent. Again, we would be making the

future "climate penalty" must do so by construction. In that sense, the "climate penalty" implied by our estimates may still be an upper bound. As we will show in Section V, although our measure of adaptation has remained relatively constant over time, the impact of the climate norm on ozone has decreased. This could imply that long-run changes in the economic or regulatory landscape, driven, e.g., by technological advancement or shifting preferences, could lead to further decreases in this impact in the future. At the same time, we also find non-linear and increasing effects of temperature on ozone formation, indicating that there may be counter-acting intensification effects.

mistake of taking the effect of weather shocks as the penalty, when we should be looking at the impact of climatic changes, which incorporates adaptive responses by economic agents. Using the climate projections from the U.S. Fourth National Climate Assessment under the business-as-usual scenario (RCP 8.5), we would overestimate the climate penalty by 0.82ppb by mid century, and 2.47ppb by the end of the century.

C. Robustness Checks

Measurement Error & Agents' Beliefs — A concern regarding our decomposition of meteorological variables in Equation (10) might be measurement error. Because both components are intrinsically unobserved, we define the long-run climate norm as the 30-year MA, and weather shocks as deviations from that moving average. If there is classical measurement error, the estimates of the coefficients of interest in Equation (13) will suffer from attenuation bias. Moreover, the bias will be magnified in fixed-effect regressions.

To investigate the robustness of our results to measurement error, we carry out analyses using moving averages of different length. We start by using a 3-year MA, then 5-, 10-, and 20-year MAs, relative to our preferred specification using 30 years. As argued seminally by Solon (1992), as we increase the time window of a moving average, the permanent component of a variable that also includes a transitory component will be less mismeasured. If this is the case, we should observe the coefficients of interest increasing as longer windows are used for the moving averages. Our estimates in Table 2 remain remarkably stable over the different lengths of the moving averages, but if anything they get slightly larger until the 20-year moving average.

As pointed out by Angrist and Pischke (2009) and Blanc and Schlenker (2017), a fixed-effects regression with variables under classical measurement error is plagued by larger attenuation bias. The identifying variation in a standard panel analysis comes from deviations from the cross-sectional averages in the panel structure. Once the variables of interest are demeaned, the share of measurement error variation is magnified, and the coefficients of interest will be even more attenuated. Again, our estimates in Table 2 remain largely unchanged over the different lengths of the moving averages, with a slight attenuation of the coefficient of the moving average when we move from the 20- to the 30-year moving average. This latter result suggests that the widely used climate normals are close to the "optimal" long-run norms. The improvements from reducing measurement error might be offset by the panel-driven attenuation bias between 20- and 30-year time windows.

At the same time, it is possible that agents form climate beliefs in a way that exhibits recency weighting (e.g., Kaufmann et al., 2017). This presents a second trade-off. Longer, 20- to 30-year MAs, guided by climatology, appear "optimal" in our setting for navigating the first trade-off between potential measurement error and fixed effect induced attenuation bias for the purposes of estimating a long-run climate impact. Shorter, 3- to 5-year MAs, however, may better reflect agents' internalized information set with regards to forming beliefs over the current climate conditions and thus better capture medium-run adaptive behavior (Moore et al., 2019). It is plausible, therefore, that the observed increases, however slight, in the coefficient on climate norm as we move from a 3- to a 20-year MA are, at least in part, due to agents' stronger adaptive response to recent events than to longer-run trends in the climate norm.

Lagged & Short-run Adaptive Responses — Another potential concern with our preferred specification might be the fact that we have used the 1-year lagged 30-year moving average to capture the long-term climate norm, implying that agents adapt within one year. Hence, we check the sensitivity of our results when agents have 10 or 20 years to adapt, instead of just one. In columns (1) and (2) of Table 3, we provide estimates from our preferred specification but using respectively 20-year moving averages of temperature *lagged by 10 years*, and 10-year moving averages *lagged by 20 years*. By doing so, we are providing agents more time to potentially adjust to climate change. Even though we would expect that the effects of the weather shocks to be similar, we anticipate the effects of the climate norm to be slightly smaller than before, as agents should now be able to adapt more than before.

This is what we find from our estimates reported in Table 3, although the magnitude of the coefficients is remarkably close to that of our main results.

Alternatively, one might be concerned that agents are in fact able to respond rapidly and adapt to weather shocks, in which case the coefficient on temperature deviations would be inclusive of any such adaptive responses, and thus our estimate of adaptation would be biased downwards. In column (3) we make use of a widespread policy of "Ozone Action Day" (OAD) alerts, where a local air pollution authority would issue an alert, usually a day in advance, that meteorological conditions are expected to be more conducive to a high concentration of ambient ozone in the following day. If agents are adapting to contemporaneous weather shocks, these "action days" would be the days we would be most likely to observe an adaptive response. Indeed, individuals are urged to take *voluntary* action to reduce emissions of ozone precursors such as working from home, carpooling to work, or using public transportation; combining auto trips while running errands; and reducing home landscaping projects. Firms are also urged to provide work schedule flexibility, reduce refueling of the corporate fleet during daytime, and save AC-related energy usage by adjusting indoor temperature (USEPA, 1997, 2004). Interacting an indicator variable for days in which OAD alerts were issued for a given county with our other covariates, we find that such alerts have a negligible and statistically insignificant impact on the effect of a 1°C change in the contemporaneous temperature shock.[45] Although previous studies have provided evidence of some decline in driving and increases in the use of public transportation in a few locations (e.g., Cummings and Walker, 2000; Cutter and Neidell, 2009; Sexton, 2012), we find little indication that agents engage in meaningful short-run adaptive responses across the country.

Accounting for Policies Targeting Ozone Precursors — During our period of analysis (1980-2013) there were two other major policies aimed at reducing ambient ozone concentra-

[45] Although the recovered coefficients of temperature shock, climate norm, and implied adaptation are quantitatively different for column (3) than columns (1) and (2), this is due to a difference in the underlying sample. EPA data on "action day" alerts were only provided from 2004 onwards, leading to a restricted overall sample (approximately 36% of our full sample).

tions implemented in the United States: (i) regulations restricting the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources (Auffhammer and Kellogg, 2011), and (ii) the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017). There may be concern that these input regulations targeted at ozone precursors could be influencing our results.

Table 4 examines the sensitivity of our results to the exclusion of the regions and periods affected by these regulations from our estimating sample. Column (1) reports the results of our main specification re-estimated on a sample excluding all observations from California starting in 1996, when new state-wide regulations went into effect – aimed at reducing VOC emissions between April and September by requiring a more stringently regulated type of reformulated gasoline (RFG) be sold. Column (2) reports the results of re-estimating our main specification after excluding all states that participated in the NOx Budget Trading Program (NBP) starting in 2003, when the program went into effect. Finally, column (3) re-estimates our model on a sample excluding both subsets of observations. In all three cases the recovered estimates of temperature shock, climate norm, and implied adaptation are statistically indistinguishable from our full-sample estimates. This is not too surprising, because predominantly it is ozone formation, rather than precursors, that depend on climate. Thus, while these policies may have affected precursor *levels*, they would not necessarily have affected how agents respond to changes in climate.

Further Robustness Checks — We conduct additional robustness checks regarding features in the construction of the data, selection of the estimating sample, and alternative econometric specifications in Appendix B.1 Tables B1, B2, and B3. Specifically, Table B1 examines the sensitivity of our results to our algorithm for matching ozone and temperature monitoring stations. Table B2 restricts our sample of ozone monitors to a semi-balanced panel, including only monitors with data for every year of our sample; however, as pointed out by Muller and Ruud (2018), our preferred unbalanced panel is likely more nationally representative. Finally, Table B3 contains three additional robustness checks: implementing a *daily* MA rather than *monthly*; purposefully aggregating our data to the monthly level to simulate our methodology with lower frequency data; and controlling for wind speed and sunlight with the subset of data for which that information is available. Across all of these models results remain qualitatively similar to our central findings. Finally, Appendix B.1 Table B4 provides bootstrapped standard errors for our main estimates, finding little difference relative to the standard errors clustered at the county level.

V. Exploring Heterogeneity

Earlier studies have inferred adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks, then assessing climate damages through shifts in the future weather distribution. We have pointed out the shortcomings of that time/space extrapolation approach in the spirit of the Lucas Critique (Lucas, 1976). Importantly, once we have recovered a measure of adaptation from responses to weather shocks and longer-term climatic changes by the *same* economic agents, then we are able to explore the heterogeneity in their degree of adaptation. The following subsections examine heterogeneity in adaptive behavior over time and space in Figure 5 and Table 5, respectively, while Appendix B.2 Table B5 explores the heterogeneous effects of temperature on ambient ozone concentration in a nonlinear fashion. Additionally, Appendix B.2 Table B7 examines how the effect of temperature on ozone may be attenuated if the local atmosphere has limited levels of *one* of the key ozone precursors (NOx or VOCs) relative to the other.

A. Results Over Time

Panel A of Figure 5 illustrates the evolution of temperature's impacts on ozone formation across our sample period in 5-year increments, while Panel B reports the resulting level of adaptation. As seen in Panel A, the effects of both temperature shocks and the climate norm on ambient ozone concentration are decreasing over time, likely due – at least in part – to regulations (see, for example, our companion paper Bento et al., 2020). The early 1980's, which marked the initial phases of ozone monitoring and awareness, and when the average pollution levels were also higher, exhibit the largest impacts of climate on ambient ozone.[46]

Notice in Panel A that responses to temperature shocks a decade ahead approximately mirror responses to longer-term climatic changes a decade before. Nevertheless, the difference between those responses at any point in time since the 1980's has been relatively stable, as illustrated by Panel B. This suggests that there may be limits to adaptation unless new technologies are able to affect atmosphere composition, such as in the case of geoengineering (e.g., Heutel, Moreno-Cruz and Ricke, 2016; Flegal et al., 2019). It also highlights the risks of extrapolating flexibly-estimated weather responses over time to estimate adaptation (Olmstead and Rhode, 2011; Bleakley and Hong, 2017), analogous to the Lucas Critique (Lucas, 1976).

B. Adaptation by Beliefs in Climate Change Across Counties

Using the results of a relatively recent county-level survey regarding residents beliefs in climate change (Howe et al., 2015), we split the set of counties in our sample into terciles of high, median, and low beliefs. Table 5 presents the results of our preferred specification when interacting indicator variables for high- and low-belief counties with our temperature variables in column (1). The implied measure of adaptation is reported in column (2). We find that low-belief counties, on average, observe a smaller ozone response to a 1°C temperature shock, relative to the median set of counties, but that this difference is statistically insignificant with regards to changes in the climate norm. High-belief counties, by comparison, observe approximately 31-35 percent larger and statistically significant ozone responses to a 1°C increase in both components of temperature. As might be expected of counties at opposite ends of the spectrum regarding beliefs that climate is changing, we find that adaptation is roughly 42 percent lower in low-belief counties than median ones, while this effect

[46] Table B6 in Appendix B.2 reports similar results to Figure 5 in tabular format, segmenting the sample into only three time periods for brevity.

is statistically similar but of opposite sign for high-belief counties.[47] This evidence suggests that greater caution is called for when extrapolating flexibly-estimated weather responses over space when dealing with adaptation to climate change. Economic agents might respond heterogeneously according to unobserved preferences, beliefs, and the experience with the local climate.

VI. Concluding Remarks

We have developed a unifying approach to measuring climate change impacts and adaptation that considers both responses to weather shocks and longer-term climatic changes in the *same* estimating equation. By bridging the two earlier strands of the climate-economy literature – cross-sectional studies that relied on permanent, anticipated components behind meteorological conditions (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005), and panel fixed effects that exploit transitory, unanticipated weather shocks (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) – we have overcome identification concerns from earlier cross-sectional studies, improved on the measurement of adaptation, provided a test for the statistical significance of this measure, and addressed the changing relationship between meteorological variables and economic outcomes, in the spirit of the Lucas Critique (Lucas, 1976). Our approach rests on two rather simple but powerful ideas. First, the decomposition of meteorological variables into long-run climate norms and contemporaneous weather shocks. Second, the properties of the Frisch-Waugh-Lovell theorem, which enables the simultaneous identification of short- and long-run impacts of climate change.

[47] Table B8 in Appendix B.2 conducts a similar analysis, separating counties by their belief in the use of regulation to combat climate change, while Table B9 in Appendix B.2 instead splits the sample into two groups based on whether they leaned Republican or Democrat in the 2008 presidential election using data from MIT (2018). Results in Table B8 are qualitatively similar to Table 5, while the results in Table B9 paint a similar picture under the assumption that belief or dis-belief in climate change approximately maps to Democratic or Republican political affiliation. Table A4 in Appendix A provides summary statistics of basic characteristics for the three sets of counties used in Table 5. High-belief counties tend to be more populous, better educated, and richer than low-belief ones.

In the spirit of Dell, Jones and Olken (2009, 2012, 2014), we recovered a measure of adaptation defined as the difference between those short- and long-run responses. Unlike previous studies, however, this measure was derived *directly* from coefficients estimated in the same fixed-effects model; hence, less susceptible to omitted variable biases. In addition, it compares the responses of the *same* economic agents to both weather shocks and climatic changes, overcoming the challenges of identifying adaptation by comparing the profiles of weather responses across time and space (e.g., Deschenes and Greenstone, 2011; Barreca et al., 2016; Auffhammer, 2018*a*; Heutel, Miller and Molitor, forthcoming), which requires that preferences be constant across those dimensions. In other words, our strategy to identifying adaptation does not require the imprecise assignment of a profile of temperature responses to other locations solely based on observed attributes and the future weather distribution, as pointed out by Olmstead and Rhode (2011) and Bleakley and Hong (2017).

We applied our unifying approach to study the impact of climate change on ambient "bad" ozone in U.S. counties over the period 1980-2013. Others have relied on atmospheric-sciences simulation models to study the so-called "climate penalty" on ozone (see a review in Jacob and Winner, 2009). By ignoring the adaptive behavior of economic agents, they may have substantially overestimated the magnitude of this penalty. Based on our central estimates, we provided evidence that this can be as large as 44 percent. In addition to its atmospheric and chemistry properties and richness of data, the ozone application is particularly relevant from a policy perspective. The "climate penalty" on ozone implied in our study suggests that climate change might deteriorate air quality in the near future, with important implications for public health and labor productivity.[48] Indeed, in a companion paper (Adler et al., 2020) we examine the role of this "climate penalty" in partially undoing the benefits of the Clean Air Act Amendments, implying that any future discussions related to the tightening of ambient ozone standards should pay attention to the magnitude of this penalty. When

[48]Exposure to ambient ozone has been causally linked to asthma hospitalization, pharmaceutical expenditures, mortality, and labor productivity (e.g., Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2012; Deschenes, Greenstone and Shapiro, 2017).

considering the impacts of climate change on air pollution, the application of our unifying methodology led to three main findings. *First*, a changing climate appears to be affecting ambient ozone concentrations in two ways. A 1°C shock in temperature increases ozone levels by 1.68 parts per billion (ppb) on average, which is expectedly what would have been found in the standard fixed-effects approach. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.16ppb.

Second, we found strong evidence of adaptive behavior. For a 1°C change in temperature, our measure of adaptation in terms of ozone concentration is 0.51ppb, which is statistically and economically significant. If adaptive responses were not taken into account in the estimation of the impact of climate change, then the climate penalty on ozone would be overestimated by approximately 44 percent. Using the climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5), we would overestimate the climate penalty by 0.82ppb by mid century, and 2.47ppb by the end of the century. To put these values in perspective, the last few times EPA revised the air quality standards for ambient ozone, they have decreased it by 5ppb. These findings were robust to a wide variety of specification tests and sample restrictions accounting, for instance, for measurement error in climate variables, the timing of adaptation, the production function of ozone, and the potential non-random siting of ozone monitors.

Third, we provided evidence of nontrivial heterogeneity in the degree of temperature response and adaptation across time and space, which highlights the potential biases of existing approaches in assigning weather responses or adaptation from one period and/or location to other periods and locations, consistent with insights by Olmstead and Rhode (2011) and Bleakley and Hong (2017). We found a larger temperature response for ozone in the 1980's which declined over the following decades, but similar magnitudes for the estimate of adaptation throughout the sample period. We also uncovered an interesting pattern of adaptation regarding county residents' beliefs about climate change. Our measure of adaptation is much larger in counties where those beliefs are stronger. This suggests that local social norms may play a key role in shaping future responses to climate change.

Notably, although we made use of high frequency data in this study, our unifying framework is generalizable to any empirical setting where one can obtain short-term variation in weather associated with limited opportunities to adapt, and long-term climatological variation allowing for adaptation. Settings in which opportunities to adapt are limited at the daily level, but may exist at the monthly or seasonal level are reliant on temporally disaggregated data, while those in which such opportunities are limited even at the monthly or seasonal level may be able to use more aggregate data. Take, for example, the classical application in agriculture (e.g, Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005; Schlenker and Roberts, 2009; Blanc and Schlenker, 2017; Mendelsohn and Massetti, 2017), in which planting decisions are made in advance, crops typically cannot be changed once planted, and an outcome of interest, harvest yields, are observed seasonally rather than daily. In this context, weather shocks may be taken as a more coarse measurement of meteorological conditions over the growing season, while climate norms could reflect changes over a number of years or decades.

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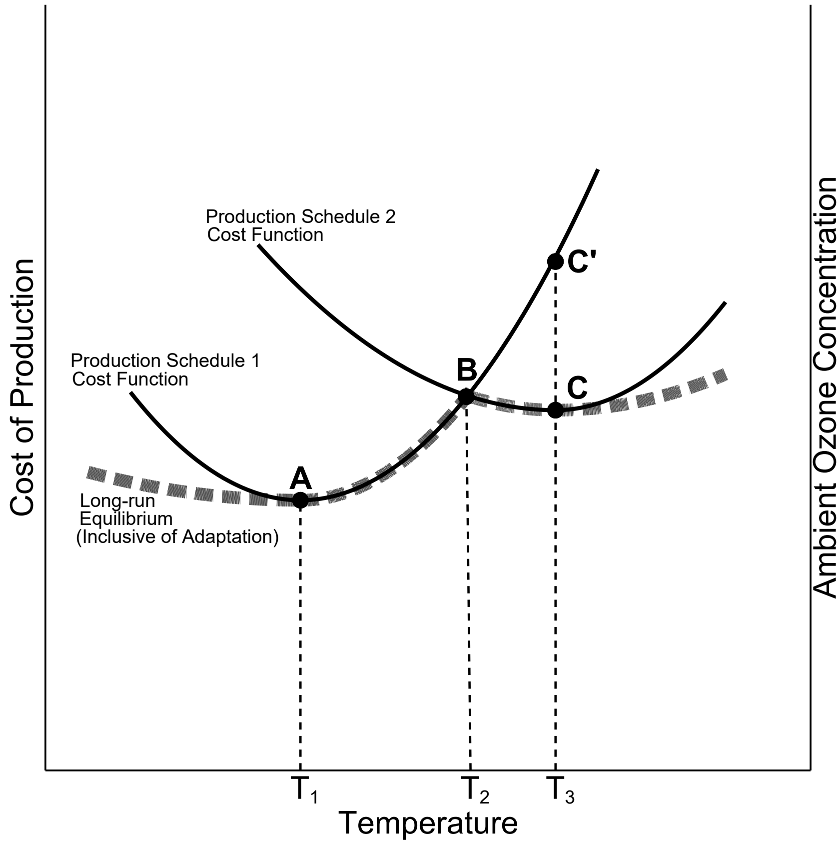
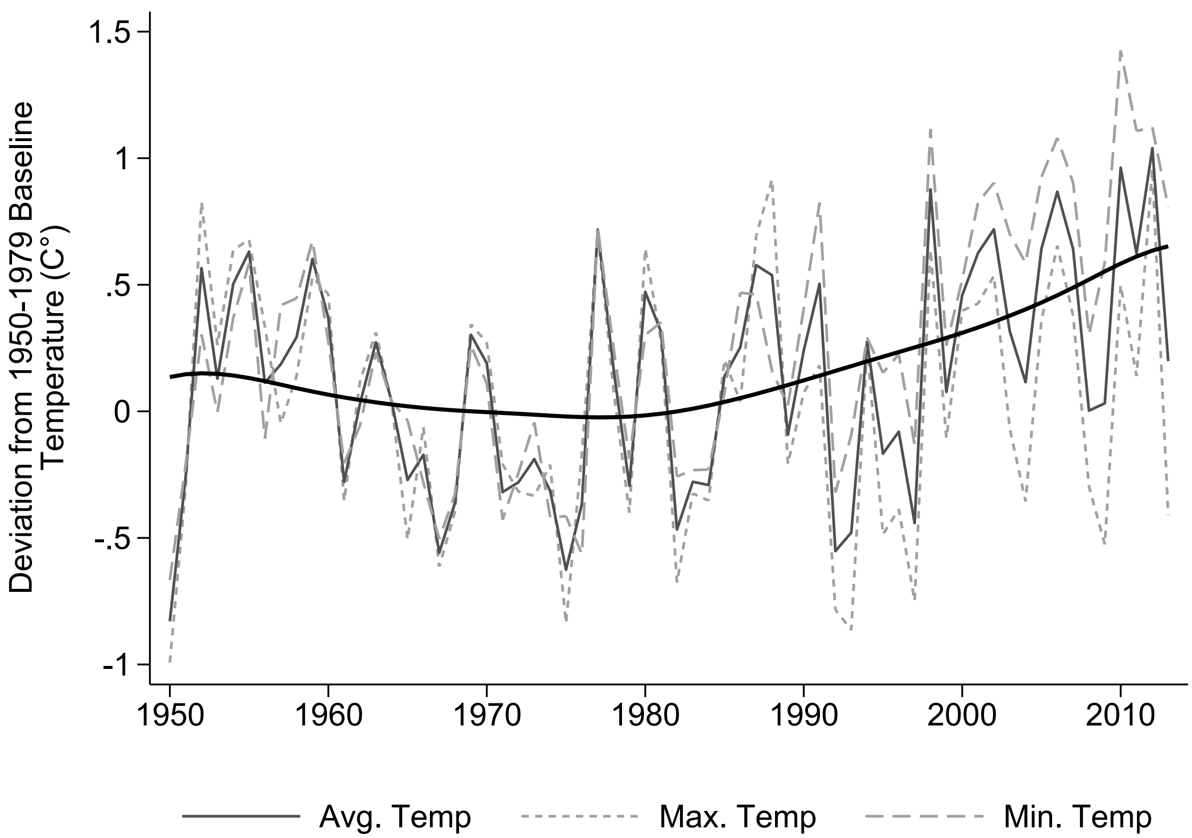
Figure 1: Theoretical Relationship Between Marginal Cost of Dirty Production and Temperature



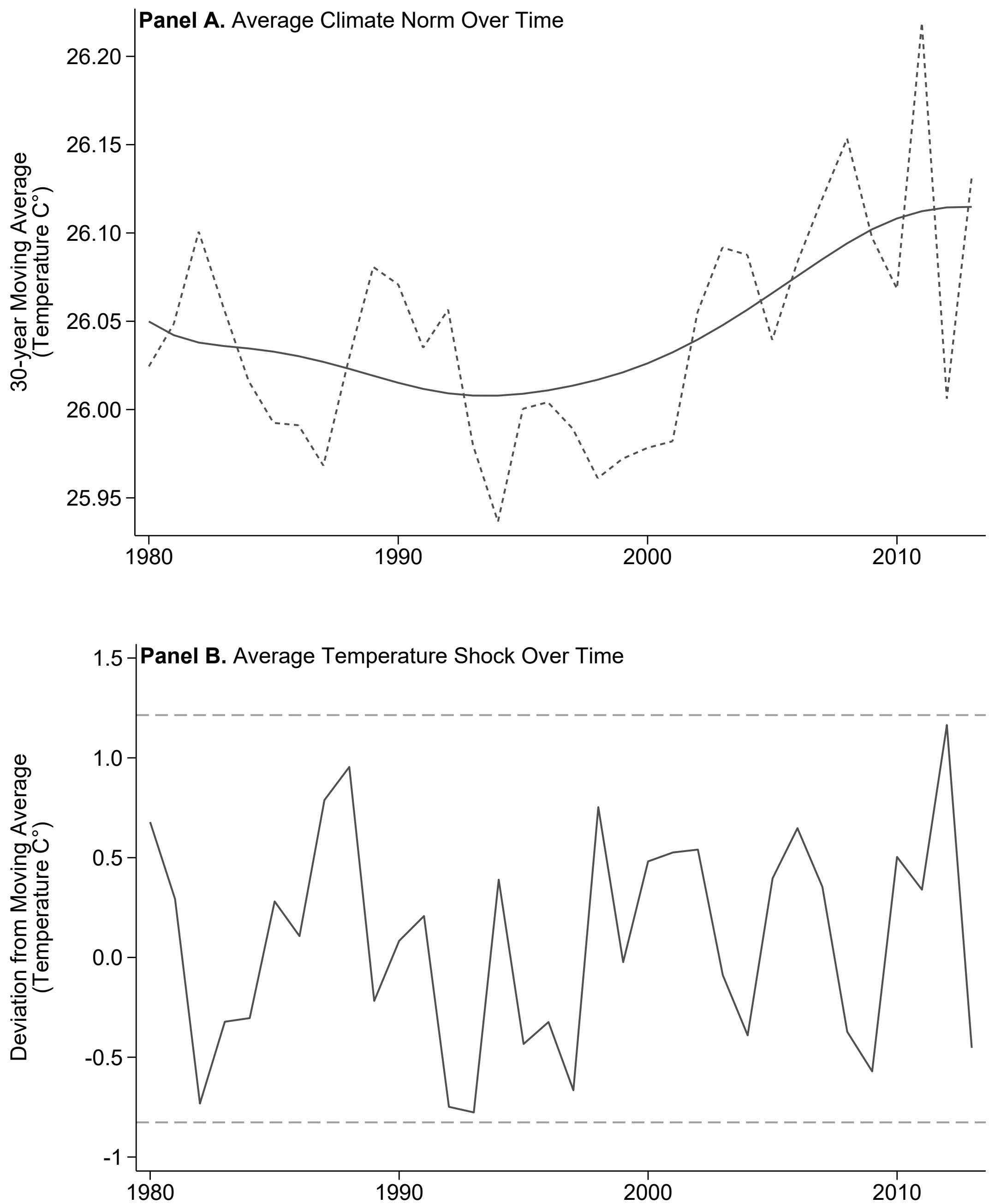
Notes: This figure illustrates a stylized example of how changes in temperature could affect the cost of production through the shadow price on ozone, and thus the implicit shadow prices on VOCs or NOx that are emitted under the chosen production schedule. The profit-maximizing firm minimizes cost – the amounts inputs used in production multiplied by their respective prices, as well as the quantity of VOCs and NOx produced under the chosen production schedule multiplied by the shadow prices of these ozone precursor pollutants implied by the local shadow price on ozone and conditions of the local atmosphere. While in many cases firms may not face an observable market price for their emissions of VOCs or NOx, they may face a shadow price for doing so based on, for example, public or regulatory pressures. As depicted, at a temperature of T_1, production schedule one dominates schedule two, and the firm minimizes cost at point A, with associated daily maximum ozone concentration. At a temperature of T_2 the firm is indifferent between either production schedule one or two at point B. At a temperature of T_3, however, production schedule two now dominates schedule one, and the firm minimizes cost at point C. A firm may not, however, be capable of adjusting their production schedule on a day-to-day basis. Thus, a firm facing a *climate normal* temperature of T_1 may opt to produce at point A, but end up producing at point C', and a much higher ozone concentration, when faced with a *temperature shock* of T_3. A firm that experiences many such shocks would thus update their beliefs about the underlying climate norm and shift their production schedule towards schedule two.

Figure 2: Temperature Relative to Baseline (1950-1979)



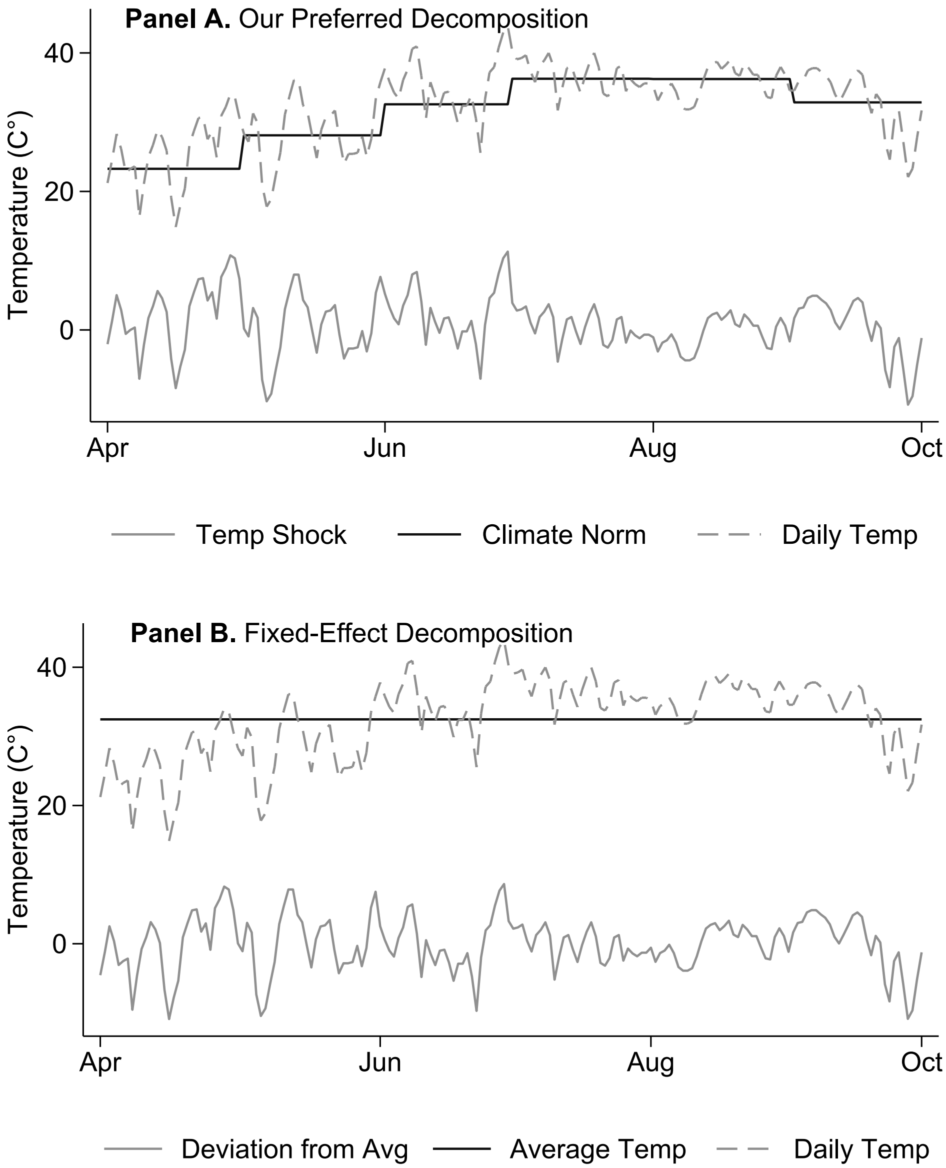
Notes: This figure depicts annual temperature fluctuations and the overall climatic trend for the ozone season in the US relative to a 1950-1979 baseline average. The baseline and the yearly deviations from it are constructed from the comprehensive sample of weather stations across the US from 1950 to 2013 following the data construction steps outlined in Appendix A. The 1950-1979 baseline represents, generally speaking, the pre-climate change awareness era. The average temperature, relative to this baseline, has been slowly but steadily increasing since the early- to mid-1970's, with an increase in the average temperature of approximately 0.5 degree Celsius (°C) by 2010. For clarity, the thin solid line, the short-dashed line, and long-dashed line refer to annual averages for daily average, maximum, and minimum temperature, respectively, as coded in the legend. The thick solid line smooths out the annual observations for average temperature over the period covered in the graph.

Figure 3: Climate Norms and Shocks



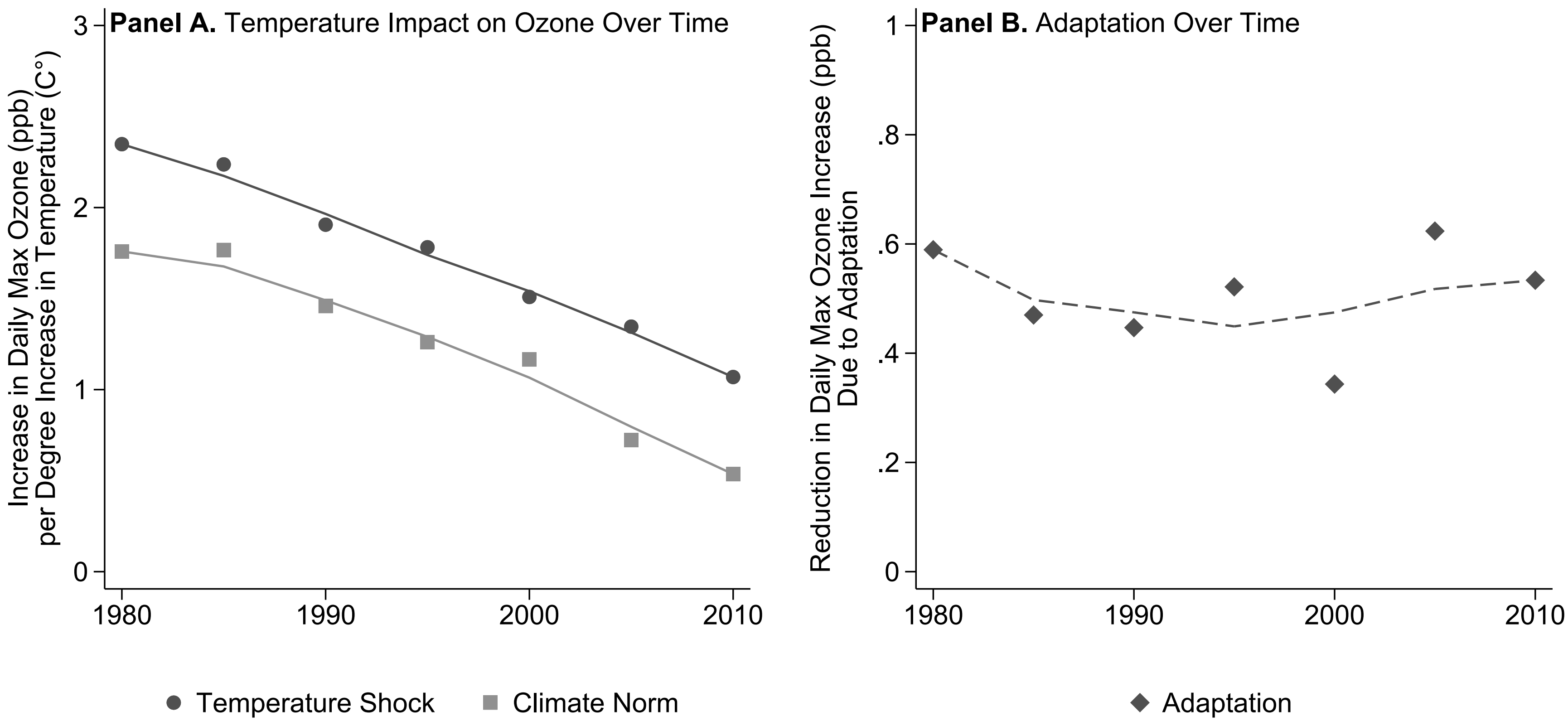
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from a complete, unbalanced panel of weather stations across the US from 1950 to 2013, restricting the months over which measurements were gathered to specifically match the ozone season of April–September, the typical ozone season in the US (see Appendix A Table A3 for a complete list of ozone seasons by state). Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The solid line in Panel A smooths out the annual averages of the 30-year moving averages, and the horizontal dashed lines in Panel B highlights that temperature shocks are bounded in our period of analysis. Appendix A Figure A2 depicts these same norms and shocks when restricting the dataset to include only a semi-balanced panel of weather stations, while Appendix A Figure A3 depicts these when the dataset is restricted to only those weather stations that are matched to an ambient ozone monitor for our main estimation sample.

Figure 4: Decomposition of Temperature Norms & Shocks – Illustration (Los Angeles, 2013)



Notes: This figure compares our preferred temperature decomposition method with a standard fixed-effects approach using data from the 2013 Los Angeles ozone season, illustrating the benefit of our unifying approach as outlined in Equation (6) relative to the standard fixed-effects approach outlined in Equation (2). Specifically, Panel A depicts the daily measure of temperature, as well as its decomposition into climate norm and temperature shock. By contrast, Panel B depicts the same daily measure of temperature, but instead decomposed into a typical fixed-effect average temperature and the deviations from this constant value after additionally controlling for monthly fixed effects. The dashed line at the top of each panel indicates observed daily maximum temperature while the black solid line represents long-run norms. The gray solid line at the bottom of each panel indicates temperature shocks. Notice that the Temperature Shocks in our preferred decomposition are nearly identical to the deviations in the fixed-effects decomposition, as would be expected from the Frisch-Waugh-Lovell theorem, and illustrate the source of variation used for identifying β_W and β_{FE} respectively. Additionally, Panel A highlights the source of variation in climate used to identify β_C in our proposed approach, while the fixed-effects decomposition lacks any such variation in the measure of climate, as the LA fixed effect is collinear with average temperature. Recall that for our proposed approach the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

Figure 5: Climate Impacts and Adaptation Over Time in the Context of Ambient Ozone Concentration



Notes: This figure displays the impacts of temperature increases on ambient ozone concentrations over time in the US (in Panel A), as well as the implied measures of adaptation (in Panel B). Splitting the main sample into 5-year periods (e.g., 1980-1984, 1985-1989, etc.), Panel A depicts the estimated coefficients on the climate norm and temperature shock variables for each of these periods. All these coefficients were estimated by Equation (13), extended to include interactions between each of the two components of temperature and indicators for each of the 5-year periods considered here. Panel B, on the other hand, depicts the respective measures of adaptation as the differences between the estimated coefficients associated with shocks and norms. Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The solid lines in Panel A smooth out each set of estimated coefficients plotted in the graph, and the dashed line in Panel B smooths out the implied measures of adaptation. Appendix B.2 Table B6 examines these same patterns by decade in tabular form. All point estimates included in the figure are statistically significant at the 1% level.

Table 1: Climate Impacts and Adaptation – Our Unifying Approach vs. Prior Approaches

	Daily Max Ozone Levels (ppb)		
	Unifying	Fixed-Effects	Cross-Section
	(1)	(2)	(3)
Temperature Shock	1.678***		
	(0.063)		
Climate Norm	1.164***		
	(0.051)		
Max Temperature		1.659***	
		(0.063)	
Average Max Temperature			1.166***
			(0.106)
Implied Adaptation	0.514***	0.493**	
	(0.041)	(0.225)	
Fixed Effects:			
Monitor-by-Season-by-Year	Yes		
Monitor-by-Month-by-Year		Yes	
State			Yes
Precipitation Controls	Yes	Yes	Yes
Latitude & Longitude			Yes
Non-Attainment Control			Yes
Observations	5,139,523	5,139,523	2,712
R^2	0.481	0.542	0.352

Notes: This table reports the weather and climate impacts on ambient ozone concentrations, estimated by different methodologies. Column (1) reports the estimates of our unifying approach, in which we decompose daily maximum temperature into climate norms and weather shocks, and exploit variation in both components in the same estimating equation – our Equation (13). Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year to allow for economic agents to potentially adapt, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. Column (2) reports the effect of daily maximum temperature on ambient ozone from the panel fixed-effects approach, exploiting day-to-day variation in temperature, hence capturing the effect of a change in weather. Column (3) reports cross-sectional estimates using average maximum temperature and ambient ozone concentrations for each ozone monitor in the sample. Having averaged the variables over all the years from 1980-2013, this estimate captures the effect of a change in climate. Note that while estimates in column (3) must additionally control for whether a county is in violation of the CAA ozone standards, this is implicitly controlled for via the fixed-effects in columns (1) and (2). Combining our estimates in column (1) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5) – 1.6°C temperature increase by 2050, and 4.8°C by 2100 – ambient ozone concentrations would rise by 1.9 and 5.6ppb, respectively. This should be the so-called "climate penalty" – the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation. Wrongly using the response to temperature shocks as the penalty, which is *exclusive* of adaptation, those numbers would be larger: 2.7 and 8ppb, respectively. For a comparison, modelling studies find increases in summertime ambient ozone concentrations by 1-10 ppb (for a review, see Jacob and Winner, 2009). Standard errors are clustered at the county level in columns (1) and (2), while column (3) uses standard heteroskedastic robust errors. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 2: Alternative Lengths of Climate Norm

	Daily Max Ozone Levels (ppb)			
	3-yr MA	5-yr MA	10-yr MA	20-yr MA
	(1)	(2)	(3)	(4)
Temperature Shock	1.669***	1.670***	1.670***	1.673***
	(0.063)	(0.062)	(0.062)	(0.062)
Climate Norm	1.158***	1.166***	1.176***	1.175***
	(0.049)	(0.050)	(0.051)	(0.051)
Implied Adaptation	0.511***	0.504***	0.495***	0.499***
	(0.040)	(0.040)	(0.041)	(0.041)
All Controls	Yes	Yes	Yes	Yes
Observations	5,139,523	5,139,523	5,139,523	5,139,523
R^2	0.481	0.481	0.481	0.481

Notes: This table reports the results for alternative definitions for the climate norm by constructing the climate norm (moving averages of temperature) using different time windows. Recall that the 3- to 30-yr moving average is lagged by 1 year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The full list of controls are the same as in the main model, depicted in column (1) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 3: Adaptation Responses

	Daily Max Ozone Levels (ppb)		
	Long-Run 10-year Lag	Long-Run 20-year Lag	Short-Run *2004-2013 only*
	(1)	(2)	(3)
Temperature Shock	1.681***	1.685***	1.179***
	(0.063)	(0.063)	(0.029)
Climate Norm	1.155***	1.143***	0.581***
	(0.050)	(0.049)	(0.034)
Implied Adaptation	0.527***	0.542***	0.597***
	(0.041)	(0.041)	(0.029)
Shock x Action Day			0.068
			(0.188)
All Controls	Yes	Yes	Yes
Action Day Interaction			Yes
Observations	5,131,943	5,127,886	1,879,041
R^2	0.481	0.481	0.444

Notes: This table reports estimates when allowing more or less time for economic agents to engage in adaptive behavior. The estimates in columns (1) and (2) are obtained by Equation (13), but using 10- and 20-year lags between the moving average and contemporaneous temperature, rather than 1-year lag. Column (3) continues using the 1-year lag of the main specification, but adds an additional interaction term on temperature shock using clean air action day announcements (days in which the relevant air quality authority observes, or expects to observe, unhealthy levels of pollution on the Air Quality Index and releases a public service announcement to this effect) at the county-level to estimate short-run adaptive behavior. Note that although action day policies first began in the 1990's, EPA data only begins from 2004 onwards, leading to a restricted overall sample (approximatley 35% of our full sample). The full list of controls are the same as in the main model, depicted in column (1) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 4: Excluding Areas with Regional Air Pollution Policies

	Daily Max Ozone Levels (ppb)		
	Gasoline Policy (RFG)	NOx Budget Program	Both
	(1)	(2)	(3)
Temperature Shock	1.672***	1.723***	1.722***
	(0.060)	(0.073)	(0.073)
Climate Norm	1.175***	1.218***	1.234***
	(0.045)	(0.060)	(0.054)
Implied Adaptation	0.498***	0.506***	0.488***
	(0.040)	(0.049)	(0.048)
All Controls	Yes	Yes	Yes
Observations	4,631,407	4,338,178	3,830,062
R^2	0.463	0.491	0.473

Notes: This table reports results from our main specification in Equation (13) but excluding locations with input regulations aimed at reducing ozone precursors (VOCs and NOx). Three of these regulations were implemented in the United States over our sample period 1980-2013: (i) regulations restricting the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources (Auffhammer and Kellogg, 2011), (ii) the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017), and (iii) the Regional Clean Air Incentives Market (RECLAIM) NOx and SOx emissions trading program (Fowlie, Holland and Mansur, 2012). Here we examine the sensitivity of our estimates of when taking into account these input regulations. Column (1) excludes California from 1996 onwards, when stringent VOC regulations were in place. Column (2) excludes the states participating in the NBP from 2003 onwards, when the program was in effect. Column (3) excludes both subsets of observations. Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The full list of controls are the same as in the main model, depicted in column (1) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 5: Adaptation by Belief in Climate Change

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.442***	
	(0.040)	
x Low Belief	−0.141**	
	(0.061)	
x High Belief	0.503***	
	(0.114)	
Climate Norm	0.998***	0.445***
	(0.054)	(0.051)
x Low Belief	0.047	−0.188***
	(0.071)	(0.063)
x High Belief	0.310***	0.193**
	(0.102)	(0.085)
All Controls	Yes	
Observations	5,139,523	
R^2	0.484	

Notes: This table reports estimates of temperature shock and climate norm interacted with an indicator of whether the residents of the county generally believed in climate change or not. Specifically, all counties in the sample were split into terciles based on the results of a survey conducted on climate change beliefs (Howe et al., 2015). In column (1) the main effect reflects the result for the median tercile of counties, while the interacted effects reflect the difference from this value observed in the lower and higher tercile counties. Column (2) reports the implied measure of adaptation for the median counties along with the differential effect in the low and high belief counties. Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The full list of controls are the same as in the main model, depicted in column (1) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.