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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. Ozone is not emitted directly into the air, but rather formed by a Leontief-like production function of Nitrogen Oxides (NOx) and Volatile Organic Compounds (VOCs) in the presence of sunlight and warm temperatures; hence, affected by climate change (e.g., Jacob and Winner, 2009). Exposure to ambient ozone has important economic implications because it leads to increases in hospitalization, medication expenditure, and mortality (e.g., Neidell, 2009; Moretti and Neidell, 2011; Deschenes, Greenstone and Shapiro, 2017).

Our unifying approach overcomes key challenges of the literature by decomposing meteorological conditions into climatic variation and weather shocks, and estimating climate and weather effects in the *same* panel fixed-effects equation. The pioneer cross-sectional approach to estimate the impact of climate change on economic outcomes (Mendelsohn, Nordhaus and Shaw, 1994) has relied on permanent, anticipated components behind meteorological conditions, but may suffer from omitted variable bias. In contrast, the panel fixed-effects approach (Deschenes and Greenstone, 2007) exploits transitory, unanticipated weather shocks, and deals with that bias, but identification of climate effects using weather

[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.

variation is not trivial. Current hybrid approaches combining cross-sectional and panel data variation also face challenges (see a recent review by Kolstad and Moore, 2020). The partitioning variation approach also decomposes meteorological conditions and estimates climate and weather effects jointly, but typically does not include spatially-disaggregated fixed effects leaving it susceptible to omitted variable bias (e.g., Kelly, Kolstad and Mitchell, 2005; Moore and Lobell, 2014; Merel and Gammans, 2021). The long differences approach leverages panel data variation in weather over a range of timescales (e.g., annual, decadal, and multi-decadal) to identify climate impacts, but does not estimate climate and weather effects jointly (e.g., Dell, Jones and Olken, 2012; Moore and Lobell, 2015; Burke and Emerick, 2016). Our unifying approach combines the strengths of the prior methods while addressing their shortcomings by relying on the properties of the Frisch-Waugh-Lovell theorem.

Influential studies have proposed measuring adaptation as the difference between the estimates of impacts in fixed-effects and cross-sectional approaches (Dell, Jones and Olken, 2009, 2012, 2014). Estimates of climate impacts based on cross-sectional analysis are usually inclusive of adaptation, whereas those from fixed-effects are typically not. 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.

Our unifying approach estimates 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*), Carleton et al. (2020), and Heutel, Miller and Molitor (2021) 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. In a typical climate impact setting, the outcome of interest is (i) affected by temperature, (ii) something of value to the agent, and (iii) responsive to adaptive behavior that dampens the temperature effect. For example, farmers worried about temperature damage may mitigate profit losses by switching crops. Although the consequences of climate change on local air pollution have been understudied (Pestel and Oswald, 2021), it has been pointed out that ambient ozone concentration will increase with rising temperatures (e.g., Jacob and Winner, 2009; Fu and Tian, 2019). In fact, ozone is formed in the atmosphere by combining NOx, VOCs, sunlight and heat. This should be reason for concern due to the well-documented impacts on public health, particularly on those groups of the population with increased vulnerability to air pollution such as children and the elderly. In our context, agents can be individuals responding to pollution information, firms adjusting to environmental regulation, and local regulators implementing federal laws. Our unifying approach should capture these responses altogether, without separating

[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.

them out.

By definition, adaptation involves adjusting to or coping with climatic change with the goal of reducing vulnerability to its harmful effects.[3] In our setting, for agents to be adapting to rising temperatures in a way that changes atmospheric ozone levels, one needs all of the following: (i) agents must be worried about ozone's detrimental impacts, (ii) agents have some knowledge of the process of ozone formation such that they are aware not only of temperature's role but also the impact of an agent's emissions, and (iii) agents believe their actions can sufficiently alter ozone concentrations. There is evidence that on high ozone days, individuals may avoid outdoor exposure (e.g., Neidell, 2009; Graff Zivin and Neidell, 2009) and buy medicines to remediate exposure (e.g., Deschenes, Greenstone and Shapiro, 2017). Also, they may drive less and use public transit in smog alert days (e.g., Cummings and Walker, 2000; Cutter and Neidell, 2009). Indeed, the alerts educate the public on the impact of temperature and the agents' actions on ambient ozone levels. Hence, it not unreasonable to assume that our research setting satisfies the three conditions for adaptation enumerated above.

Our approach has two key features. The first is the decomposition of meteorological variables into "climate" and "weather." The second is identifying responses to weather shocks and longer-term climatic changes in the *same* estimating equation. The difference between those short- and long-run responses is what the literature refers to as adaptation.[4] Indeed, ozone, as with most climate-related outcomes of interest, responds to realized temperature – regardless of how that temperature may be decomposed into weather or climate. It is only agents, by virtue of being able to adjust, e.g., their level of precursor emissions, in response to expected climate, that may affect the ozone response to climate. In the absence

[3]Specifically, the IPCC defines adaptation as "the process of adjustment to actual or expected climate and its effects in order to moderate harm or take advantage of beneficial opportunities," and further states that "[a]daptation plays a key role in reducing exposure and vulnerability to climate change. (...) In human systems, adaptation can be anticipatory or reactive, as well as incremental and/or transformational." (IPCC, 2022).

[4]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).

of any adaptive behavior, the ozone response to equivalent changes in weather or climate would be the same. In our analysis, we merge location-by-day ozone concentration data with temperature data across the United States for the period 1980-2013. For the first feature of our approach, the daily temperature variable is used to construct two variables. The first, $Temp^C$, is operationalized as a 30-year moving average of month-specific average temperatures (e.g., take the average of January daily temperatures for each year and location and then apply a 30 year moving average). This is what we interpret as "climate."[5] The second temperature variable, $Temp^W$, is daily temperature with $Temp^C$ subtracted, interpreted as "weather."

For the second feature of our approach, both variables enter linearly in our estimating equation along with a set of location-by-season-by-year fixed effects, ϕ_{is} (e.g., Chicago-Spring 1990, Chicago-Summer 1990, etc.).[6] Because we create the variable "weather" as a first step, the Frisch-Waugh-Lovell theorem guarantees we do not need to include granular time fixed effects to identify weather effects (Lovell, 1963, Theorem 4.1, p.1001). On the other hand, the inclusion of ϕ_{is} allows us to leverage two sources of climatic variation to identify climate impacts. Conditional on location-by-season fixed effects, the first source of variation comes from adding the most recent year's monthly weather information and dropping the oldest portion from the 30-year moving average. The underlying idea is similar to filtering different frequencies of temperature, as has been done in the time series literature (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003). Note that this updating feature of the moving average mimics the ideal "climate experiment," as, for example, it may make the April climate norm in one year appear more like the May climate norm. For instance, if the average temperature in April 31-years ago was particularly cold, while the average

[5]Climate normals are, by definition, 30-year averages of weather variables such as temperature (WMO, 2017). 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.

[6]Note that while we focus on a linear estimating equation for simplicity in explanation of the method and inferring the implied measure of average adaptation, Section IV.D shows how the approach can be easily extended to a nonlinear setting, examining the nonlinear effects of weather and climate on ozone concentration under multiple nonlinear specifications.

temperature in April of last year was particularly warm, the 30-year moving average climate norm in this year's April may be meaningfully warmer than last year's April climate norm. In other words, we identify the agents' response to their new climate expectation. The second source of variation arises from demeaning $Temp^C$ from a location-specific season-by-year fixed effect.[7] Take, for example, days in April, May, and June in Chicago, all within the spring season of the same year. After demeaning from a spring fixed effect, the average April moving-average measure of climate will likely be a negative value and the average June climate a positive value. Intuitively, it works as if the "climate experiment" assigns changes in the average Chicago May temperature to make it closer to the average April or June temperature, for example. Lastly, the 30-year moving average is purposely lagged in our estimating equation to reflect all the information available to individuals and firms up to the year prior to the measurement of the outcome variables.

Our methodology contributes to the estimation of climate damage functions and the costs of climate change (e.g., Tol, 2009, 2018; Auffhammer, 2018*b*; Miller et al., forthcoming). Our unifying approach to uncover climate impacts and adaptation should be of interest to a broad set of applications due to its simplicity. Our novel application to the impact of climate change on ambient ozone adds an overlooked force behind recent determinants of ozone pollution (e.g., He, Gouveia and Salvo, 2018; Salvo and Wang, 2017; Salvo and Geiger, 2014).

This paper proceeds as follows: Section II provides an overview of the previous methodological approaches used to identify climate impacts and 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. Section IV reports our main findings, examines the robustness of our estimates, and generalizes our approach to nonlinear settings. Section V further explores aspects of heterogeneity. Finally, Section VI concludes.

[7]Note that we use "location" here in the general sense as the spatial unit of analysis. For example, in our empirical setting location is taken as an individual ozone monitor.

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.[8] By using either the short- or long-run variation behind meteorological conditions to identifying climate impacts, those research designs trade off key assumptions.[9] 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 variable of interest, x_i – typically taken as temperature. μ_i represents the vector of all time-invariant 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

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

[9] 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).

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.[10] 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 term, $\hat{\beta}_{FE}$ 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 difference 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

[10] 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).

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.[11] Aside from SUR, it would be possible to statistically test the difference between coefficients recovered via the CS and FE models using re-sampling methods – i.e., block bootstrap or Bayesian bootstrap with random weights assigned at the block-level (Rubin, 1981). However, while these methods may solve the hypothesis testing issue for inferring the significance of adaptation, they would not address the issue of potential bias in the underlying estimating equations, making it difficult to interpret the magnitude 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

[11] As is well known, a SUR system is a generalization of a linear regression model that consists of several regression equations – each having its own dependent variable and potentially different sets of exogenous explanatory variables – that has cross-equation error correlation, that is, the error terms in the regression equations are correlated. Also recall that all equations in a SUR system are estimated jointly, but that such estimation usually requires feasible generalized least squares with a specific assumption on the form of the variance-covariance matrix regarding the structure of the correlation among the error terms. Hence, further structural assumptions are needed for statistical inference of the measure of adaptation.

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.

Notice that emerging hybrid approaches have also relied on such "partitioning variation" (e.g., Kelly, Kolstad and Mitchell, 2005; Moore and Lobell, 2014; Merel and Gammans, 2021). They have attempted to address this collinearity issue by dropping the unit fixed-effect, μ_i, instead including a set of location controls, c_i, in their estimating equation, taking the general form of $y_{it} = f(x_{it} - \bar{x}_i) + g(\bar{x}_i) + c_i\gamma + \epsilon_{it}$, where $f(.)$ and $g(.)$ can take flexible functional forms. While this approach can include spatially-aggregate and time fixed-effects, identification would still ultimately rely on cross-sectional variation within the spatially-aggregate region, and thus may suffer from similar OVB concerns as the CS model.

We therefore propose the following feasible approximation of the ideal Equation (5), which allows for the inclusion of unit fixed-effects by letting the measure of climate vary across time within the sample:[12]

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

As time can be aggregated into multiple subset levels – day, month, season, 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 period 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 – where s is a one-level higher aggregation in time than p – in order to retain relevant variation in $\bar{x}_{i\bar{p}}$.[13] Depending on the study context, μ_i and λ_s may be interacted to flexibly control for unit-level effects that may vary over time.

[12]Observe that for simplicity, and to keep the comparison with the prior CS and FE 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. Later, in Section IV.D, we show how this approach can be easily extended to include higher order nonlinear effects.

[13]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.

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.[14] Subtracting Equation (7) from Equation (6), we highlight the source of variation that allows for the identification of both β_W and β_C:

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

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 while our method does require the researcher to take a stance on the temporal granularity of the climate variable, $\bar{x}_{i\bar{p}}$, and time fixed-effects, λ_s, the recovered measure of adaptation leverages the behavioral responses of the *same* economic agents to both weather shocks and climatic changes via the inclusion of unit fixed effects, μ_i.

[14]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.

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.[15] 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 $j \in \{1, ..., y-2\}$. 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),[16] and in the literature of intergenerational mobility following Solon's (1992) seminal work.[17] 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.

[15]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.

[16]See, for example, Hodrick and Prescott (1981, 1997), Baxter and King (1999), Christiano and Fitzgerald (2003) and Hsiang (2016).

[17]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.

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).[18] 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 $(x_{it} - \bar{x}_{i\bar{p}})$, which allows us to estimate both effects of interest in the same equation.[19]

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 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*.[20]

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

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

[19]"*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).

[20]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.

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 clear 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.[21]

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

[21] It is imperative to recognize, however, that variability may be crucial in some settings. Kala (2019), for example, studies adaptation under different learning models. Hence, variance of climatological variables is a key element of her framework.

(NOx) and volatile organic compounds (VOCs) in the presence of sunlight and warm temperatures.[22] 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.[23] 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.[24]

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.

A. Conceptual Framework

In the context of ozone, economic agents could be polluting firms, households engaging in consumption that produces precursor pollutants, or local regulators concerned with pollution and public health. For example, households may respond to an ozone alert day by mowing their lawns or refueling their cars earlier or later in the day – or on a different day altogether – to avoid VOC emissions, taking public transit, carpooling, or working from home to reduce emissions altogether, or purchasing hybrid or electric vehicles to reduce local emissions. On the other hand, firms may (i) reshuffle their production activities within the day to

[22] See Appendix A.1 for further details.

[23] 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).

[24] 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).

avoid VOC emissions in peak hours, such as painting in construction sites, or even between different months, increasing emissions during colder months in order to reduce emissions during hotter months; (ii) install pollution abatement technologies, or otherwise change their production function, for instance by electrifying emissions-intensive production processes such as switching from oil or gas furnaces to electric. Additionally, local regulators may provide ground-level ozone information to at-risk populations to avoid intense ozone exposure on hot days, e.g., by issuing an ozone alert when a heat wave is forecasted, and coordinating local actions with households and firms to reduce permanently or shift emissions-intensive activities within the day or across days, weeks, or months. Importantly, these agents could be reacting to either the realized or anticipated outcome of climate change, and could be undertaking small or large actions – adjusting behaviors within a day might be a small action that adds up across many agents, for example, while the switch to alternative commuting or production methods may be more transformational.[25]

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, the emission of ozone precursor pollutants (VOCs and NOx) are *de facto* "inputs" into the agent's production schedule.[26] 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.[27] Ceteris paribus, the

[25] Observe that some local regulators are making a direct case for reducing precursor pollutants to control climate change driven increases in ozone (e.g., BAAQMD, 2017), and that the EPA also acknowledges the role of climate change in worsening ozone concentrations, stating that "[i]n addition to being affected by changing emissions, future O3 concentrations may also be affected by climate change" (USEPA, 2015).

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

[27] 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.

agent would thus minimize costs taking into account the implicit shadow prices on these precursors.[28] 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 considering ozone levels whenever they choose the cost-minimizing inputs for production of goods and services.[29]

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 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.[30] 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

[28] Unlike in the agriculture setting, a common focus of prior studies, where markets exist for most inputs, in our context markets for ozone precursors (*de facto* inputs in production) existed only in some areas and in specific periods of time. Notwithstanding, the implicit shadow prices – reflecting social valuation of ambient ozone reductions – may provide incentives for producers similar to those provided by market prices.

[29] 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.

[30] 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.

schedule specific costs, and associated ozone concentrations, vary with temperature. 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,[31] to adapt to the temperature shock and would temporarily produce at 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.

[31] 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.

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 weather stations, 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 stations, indicating that while average temperature has been gradually increasing, temperature variability has remained relatively stable.[32] 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.[33] Our preferred matching algorithm uses information from the two closest weather stations within 30 km of each ozone monitor, as these stations are likely to better reflect the local environment than stations that are further away. The final sample under this matching algorithm includes 97.25% of all daily ozone observations (97.91% of all ozone monitors). However, we also expand the matching algorithm to include

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

[33] We detail the steps taken in Appendix A.2 as well as conduct robustness checks on the sensitivity of our results to changes in the algorithm in Appendix B.1.

the closest five weather stations within 80 km, for a final sample that includes over 99.99% of all daily ozone observations (100% of all ozone monitors). 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.[34] 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.[35] 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 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.

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

[35]For further details regarding the construction of the final dataset for our analysis, see Appendix A.2.

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.[36]

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. At the same time, 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.[37] For example, the 30-year MA associated with May 1982 is the average of May temperatures for all years in the period 1952-1981. 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,

[36]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 special case of) an autoregressive integrated *moving average* (ARIMA) model of climate change.

[37]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.

but not how a particular day of the year has deviated from the norm for that specific day.[38] 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 unexpected temperatures.[39] 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.[40]

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, t stands for day, and s for *season-of-the-sample* (Spring 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.[41] The dependent variable $Ozone$ captures daily maximum ambient ozone concentration. $Temp$'s represent the two components of the decomposition proposed for meteorological variables.[42]

[38] 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.

[39] 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.

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

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

[42] We further explore the nonlinear effects of temperature on ozone in Section IV.D, providing two alter-

The matrix of additional control covariates X_{it} contains a similar decomposition of precipitation.[43] 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.[44] From a theoretical standpoint this change is not necessary – and in fact the empirical results are qualitatively similar in our context 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.[45]

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 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

native approaches for extending the linear model to allow for nonlinearities in the response function of ozone to weather shocks and climate norms.

[43] 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.

[44] 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.

[45] 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.

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, and the magnitude of the average adaptation would be equal to the size of the weather shock effect on ambient ozone concentration.[46] As previously discussed, 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.

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

[46] 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).

temperature shock, represented by the deviation from that long-run norm.[47] Although the effects are uncovered by estimating Equation (13), columns (2) and (3), respectively, 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 1.17 ppb 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 1.68 ppb, and a 1°C change in climate norm increases ozone concentration by 1.16 ppb. To be clear, this does not imply that the cross-sectional approach 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

[47] 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.

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.[48]

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 (1) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under a business-as-usual scenario (RCP 8.5), one would predict an increase in ambient ozone concentrations by the mid and end of the century in the range of 1.9-5.6 ppb, approximately.[49] To be clear, "climate penalty"

[48]See estimates in Appendix B.1 Table B2.

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

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 5 ppb.

B. Measuring Adaptation to Climate Change

Our results indicate that short-run temperature shocks have a larger impact on ozone levels compared to long-run 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 0.51 ppb, suggesting that economic agents may be adapting to climate change. In the case of polluting firms, for example, they might be making adjustments to their production processes 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 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

there may be counter-acting intensification effects.

business-as-usual scenario (RCP 8.5), we would overestimate the climate penalty by 0.82 ppb by mid-century, and 2.47 ppb by the end of the century.

C. Robustness Checks

Measurement Error & Agents' Expectations — 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 expectations 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 expectations 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.[50] 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 concentrations 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,

[50] 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).

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.[51] 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 four additional robustness checks: (i) implementing a *daily* MA rather than *monthly*; (ii) purposefully aggregating our data to the monthly level

[51] We exclude only California in this exercise because Auffhammer and Kellogg (2011) only found effects of gasoline standards on air quality in California. They found no effects for the federal gasoline standards.

to simulate our methodology with lower frequency data; (iii) controlling for wind speed and sunlight with the subset of data for which that information is available; and (iv) examining the sensitivity of our results to inter-regional NOx transport by restricting the estimating sample to exclude, or conversely, only include, the states designated by the EPA as part of the "ozone transport region" (OTR). 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. In addition, that table presents standard errors clustered at the state level. Although they double in magnitude, they do not affect the statistical inference in any meaningful way because the standard errors are still small relative to the magnitude of the estimated coefficients.

D. Estimating Nonlinear Effects of Temperature

In many empirical settings there has been a focus in the economics literature on allowing for nonlinear effects of temperature or climate on the outcome of interest. Thus, while our central model adopts a linear specification for simplicity in interpretation and comparison with prior methods, we note that our proposed approach is easily extendable to any nonlinear setting with nth order polynomial effects. The following equations present the quadratic model as well as the cubic, which appears to fit our empirical setting better due to the "s-shaped" relationship between ozone and temperature. Specifically, one can simply include higher-order polynomial terms for both the weather shock, $(x_{it} - \bar{x}_{i\bar{p}})$, and climate norm, $\bar{x}_{i\bar{p}}$, such that a quadratic model would be estimated as:

$$y_{it} = \alpha + \beta_W(x_{it} - \bar{x}_{i\bar{p}}) + \beta_C\bar{x}_{i\bar{p}} + \beta_{W2}(x_{it} - \bar{x}_{i\bar{p}})^2 + \beta_{C2}\bar{x}_{i\bar{p}}^2 + \mu_i + \lambda_s + \nu_{it}, \qquad (14)$$

while a cubic model would add the terms $\beta_{W3}(x_{it} - \bar{x}_{i\bar{p}})^3$ and $\beta_{C3}\bar{x}_{i\bar{p}}^3$, and so on up to any arbitrary nth degree. Adaptation could then be inferred for the quadratic model as:

$$Adaptation = (\beta_W - \beta_C) + 2(\beta_{W2}(x_{it} - \bar{x}_{i\bar{p}}) - \beta_{C2}(\bar{x}_{i\bar{p}})), \tag{15}$$

while adaptation for a cubic model would add the term $3(\beta_{W3}(x_{it} - \bar{x}_{i\bar{p}})^2 - \beta_{C3}(\bar{x}_{i\bar{p}})^2)$, and so on. Notably, for a marginal deviation of the daily temperature from the climate norm, i.e., $x_{it} - \bar{x}_{i\bar{p}} \approx 0$, Equation (15) simplifies to:

$$Adaptation = \beta_W - \beta_C - 2\beta_{C2}(\bar{x}_{i\bar{p}}), \tag{16}$$

with marginal adaptation in the cubic model additionally including the term $-3\beta_{C3}(\bar{x}_{i\bar{p}})^2$, and so on.

Note that estimating the impacts of climate and weather in a setting with nonlinear effects will also inherently include the interaction of these two channels of temperature response, as discussed by Mendelsohn (2016), because the marginal impact of weather will vary with the underlying climate norm from which it is deviating. To see this mathematically, one need only expand the higher order weather terms to see that they include the interaction effects. For example, the expansion of $(x_{it} - \bar{x}_{i\bar{p}})^2$ includes the term $-2x_{it}\bar{x}_{i\bar{p}}$.

Alternatively, one could construct a set of indicator variables denoting whether realized temperature at location i on day t fell within a certain temperature bin. By interacting these indicators with the shock, norm, and control variables in a linear model, the response function of the outcome variable to both weather and climate would be allowed to flexibly adjust across the temperature distribution in a piece-wise linear fashion.[52] Allowing for a more flexible response function may be especially desirable in settings where the underlying functional form is unknown. Furthermore, by estimating a (locally) linear relationship within each bin, the specification allows for intuitive and easily interpretable measures of weather and climate impacts, and implied measure of adaptation, across the temperature distribution.

Because ozone formation may be intensified with higher temperatures, but also exhibits

[52]In this way, the *marginal* effect of a 1°C change in either component of temperature is constrained to be constant within its respective 5°C temperature bin, but is allowed to vary across each bin.

a shorter half-life (McClurkin, Maier and Ileleji, 2013), we examine the nonlinear effects of weather shocks and climate norms on ambient ozone concentrations across the temperature distribution. The exact functional form of the ozone-temperature relationship is unknown, although we can infer from observed data, e.g., via naive local polynomial smoothing regressions, that it generally follows an "s"-shape. This may be due to competing intensification and shorter half-life effects, or due to higher levels of adaptation at higher temperatures. Thus, in addition to estimating quadratic and cubic models of Equation (13) by including the additional terms outlined in Equation (14), we also estimate a "binned" specification as described above. We start by creating indicator variables denoting whether the contemporaneous daily maximum temperature at a given ozone monitor falls within a certain 5°C temperature bin. The lowest bin is below 20°C (just over the 10th percentile of our temperature distribution), and the highest bin is above 35°C (90th percentile of our temperature distribution), with the middle bin, 25–30°C, approximately centered around the temperature distribution median and mean of 27.8°C and 27.1°C, respectively.

Figure 5 depicts the ozone relationship and marginal response to climate and weather, as well as marginal adaptation, across the temperature distribution for the linear, quadratic, cubic, and "binned" specifications. Recall that the effects of either climate or weather under higher order models depend on the level of the other variable. For the climate norm we assume a weather shock of zero – approximately the sample average as the shocks are constructed as deviations from the norm. Conversely, for the weather shocks we assume the sample average climate norm of approximately 27.5°C. The linear specification appears to provide an adequate first-order approximation of the nonlinearities captured by the cubic and binned specifications, while the quadratic model appears to miss-specify the ozone-weather relationship compared to the other models, implying that adaptation decreases with temperature. Although both the cubic and binned specifications appear to closely match each other over the majority of the temperature distribution, implying a higher level of adaptation when agents face a higher climate norm as might be expected, due to the functional form restrictions of the cubic it also implies a large, and rather unintuitive, level of adaptation at lower temperatures.

With this in mind, our preferred approach for capturing potential nonlinearities in our empirical context is the binned specification. Table B5, column (1), in Appendix B presents the results of our preferred specification when interacting each of the independent variables with the 5°C temperature bin indicators. The implied measure of adaptation is then presented in column (2). Table B6 additionally compares the implied level of adaptation under the linear, binned, quadratic, and cubic specifications. Similar to Figure 5, we find that the ozone/temperature response is increasing at an increasing rate at lower temperature ranges, but increases at a decreasing rate at higher temperatures, particularly for increases in the climate norm. Specifically, below 20°C, a 1°C temperature shock would raise ozone levels by an additional 0.69 ppb, while a similar increase in the climate norm would raise ozone concentrations by 0.14 ppb. Above 20°C, however, both effects drastically increase, with temperature shocks increasing ozone by 1.69 ppb between 20-25°C, and by over 2 ppb above 25°C. While the effect of a 1°C increase in the climate norm is increasing with temperature up to 30°C – at 1.28 ppb and 1.83 ppb for 20-25 and 25-30°C, respectively – the magnitude of the impact is decreasing with temperature above 30°C – at 1.50 ppb and 0.90 ppb for 30-35 and above 35°C, respectively. This would imply a more than doubling of our full-sample measure of adaptation above 35°C, at 1.15 ppb, suggesting that agents may make extra effort to reduce ozone precursor emissions when temperatures are the highest and may otherwise lead to greater ozone formation under business-as-usual precursor levels.

This relatively high level of adaptation above 35°C can be plausibly explained by at least two reasons. First, regions having temperatures above 35°C might have higher incidence of sunlight which might lead to more extensive use of solar panels to generate electricity. Since the U.S. as a whole is predominantly NOx limited, we would expect that changes in electricity usage drastically affect ozone concentrations.[53] Higher temperatures might be

[53]Electricity generation is a major source of NOx, and, since ozone formation has a Leontief-like production function in terms of NOx and VOCs, changes in electricity use in a NOx limited region would imply large

creating an environment that is more suited to shifts away from conventional and dirtier sources of power generation, thus leading to higher levels of adaptation. Second, absent any adaptation, days that are exceptionally hot are more likely to cause exceptionally high levels of ozone, which could trigger additional regulatory oversight. In order to avoid this, firms would be most likely to concentrate adaptation efforts on days where the climate normal temperature is itself the hottest.

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 section examines heterogeneity in adaptive behavior over time in Figure 6 and Appendix B.2 Table B7, and across beliefs in Table 5. Additionally, Appendix B.2 Table B8 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

Figure 6 Panel A 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 norms 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,

changes in ozone formation.

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.[54]

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 single 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 atmospheric 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 and control 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,

[54]Table B7 in Appendix B.2 reports similar results to Figure 6 in tabular format, segmenting the sample into only three time periods for brevity.

while this effect is similar in magnitude but of opposite sign for high-belief counties.[55] 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.

[55] Table B9 in Appendix B.2 conducts a similar analysis, separating counties by their belief in the use of regulation on carbon emissions, while Table B10 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 B9 are qualitatively similar to Table 5, while the results in Table B10 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 from cross-sectional estimates. 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, 2021), 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.[56] 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

[56]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).

of ambient ozone standards should pay attention to the magnitude of this penalty.

When considering the impacts of climate change on air pollution, the application of our unifying methodology led to four 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 1.16 ppb.

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 0.51 ppb, 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 0.82 ppb by mid century, and 2.47 ppb 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 5 ppb. 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, policies specifically targeted at reducing ozone precursors, and the potential non-random siting of ozone monitors.

Third, by extending our central model to flexibly recover estimates accounting for the nonlinear relationship between ozone and temperature, we found that agents – perhaps unsurprisingly – tend to focus their adaptive efforts on the hottest days, which would *ex ante* be likely to lead to higher levels of ambient ozone.

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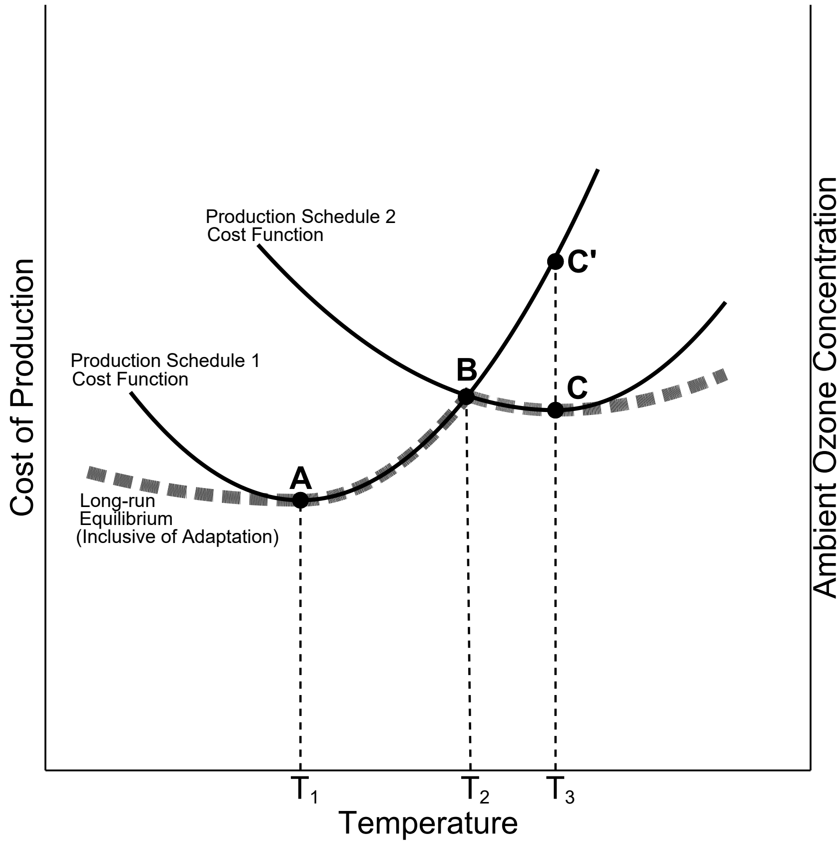
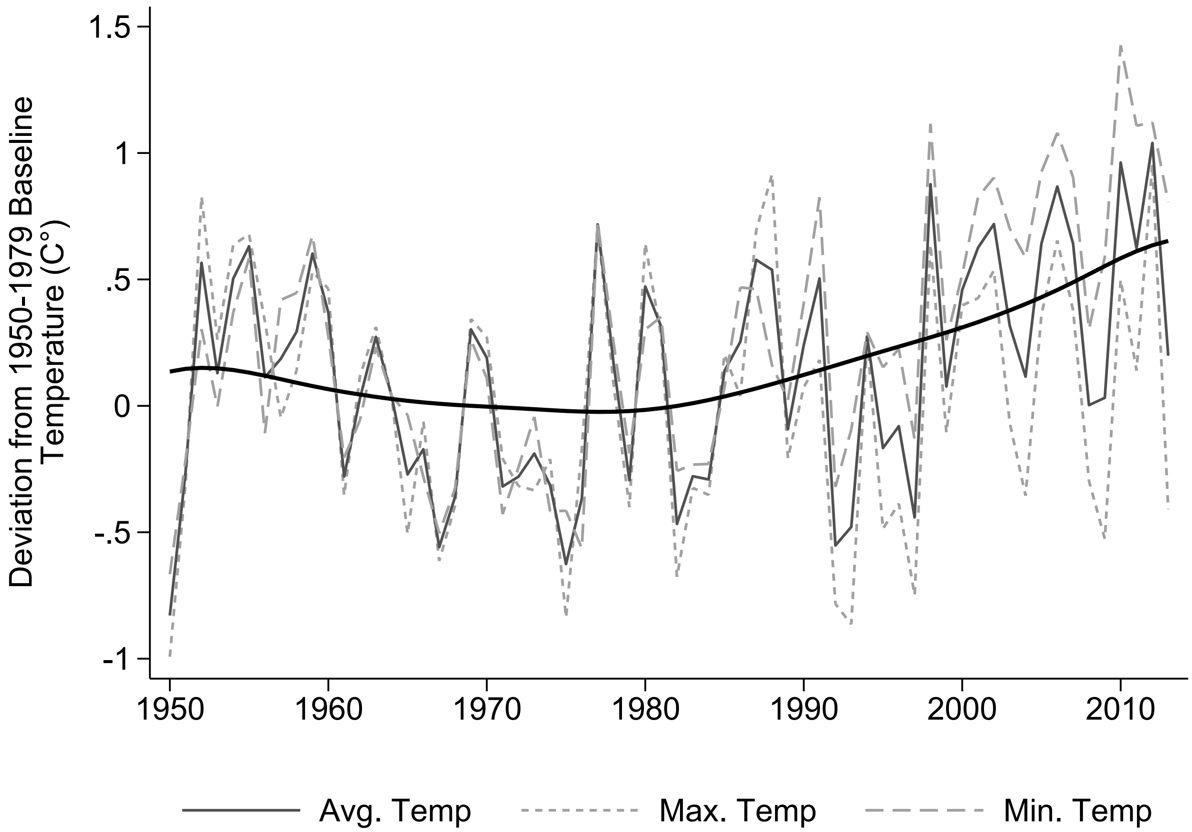
Figure 1: Theoretical Relationship Between Marginal Cost of Dirty Production and Temperature



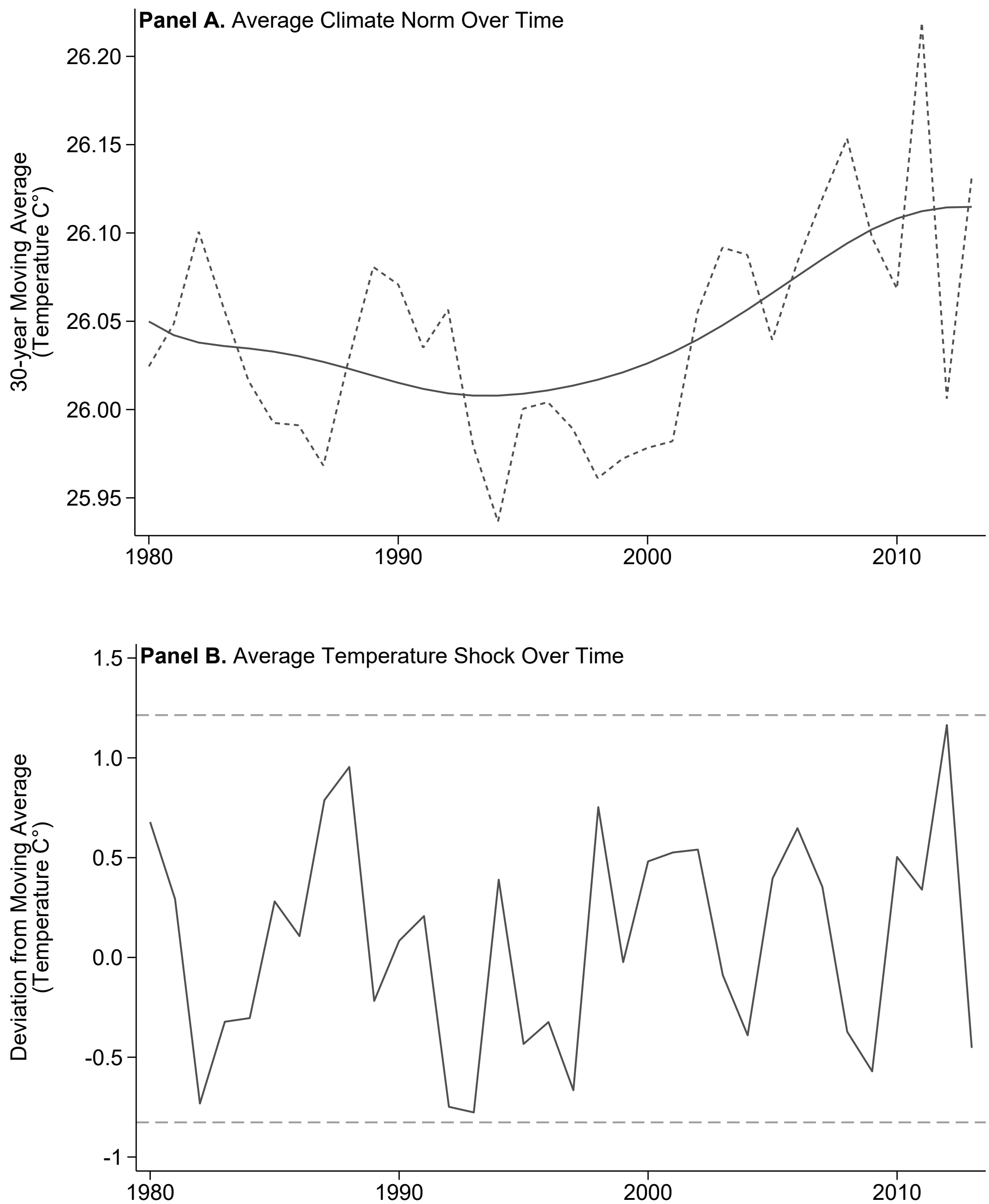
Notes: This figure illustrates a stylized example of how changes in temperature could affect the cost of production through the shadow price on ozone, and thus the implicit shadow prices on VOCs or NOx that are emitted under the chosen production schedule. The profit-maximizing firm minimizes cost – 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)



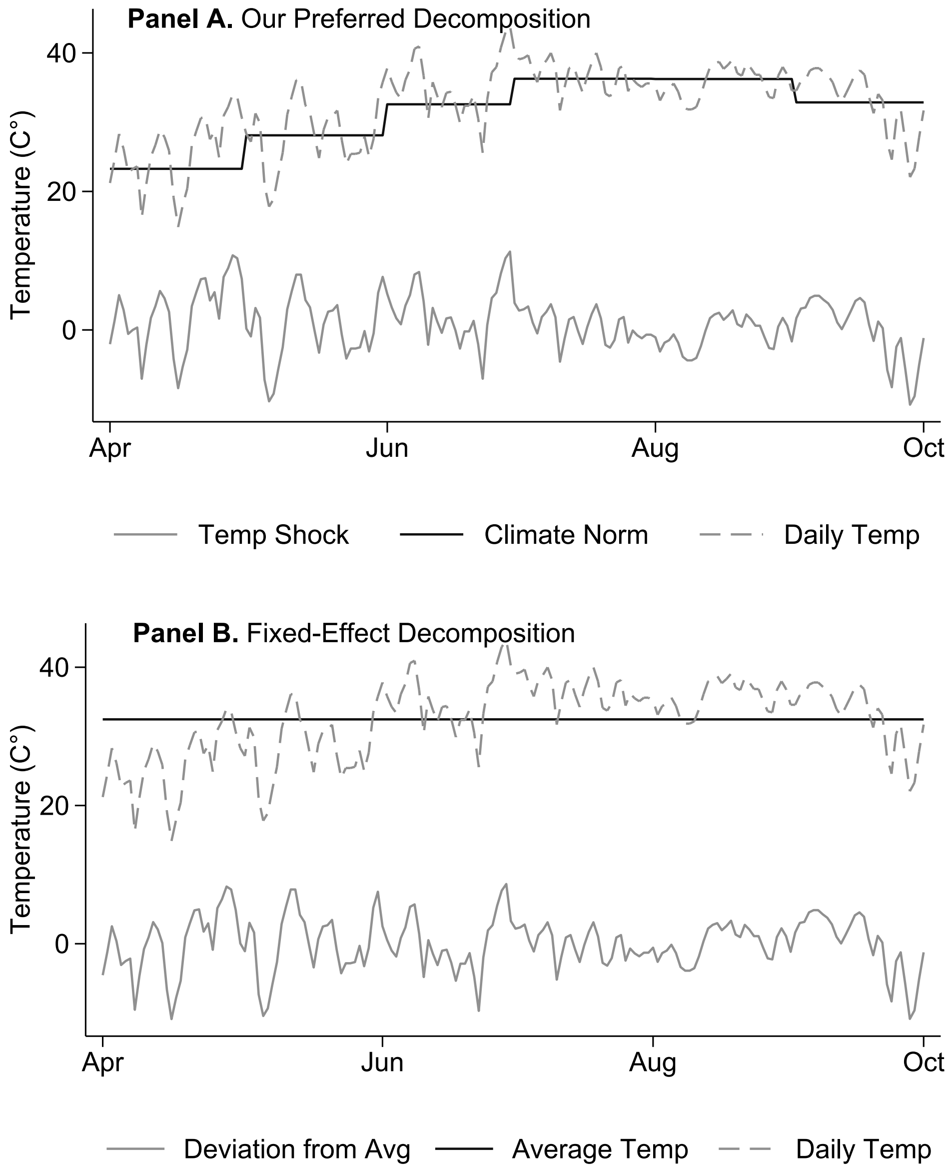
Notes: This figure depicts annual temperature fluctuations and the overall climatic trend for the ozone season in the US relative to a 1950-1979 baseline average. The baseline and the yearly deviations from it are constructed from the comprehensive sample of weather stations across the US from 1950 to 2013 following the data construction steps detailed in Appendix A.2. 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



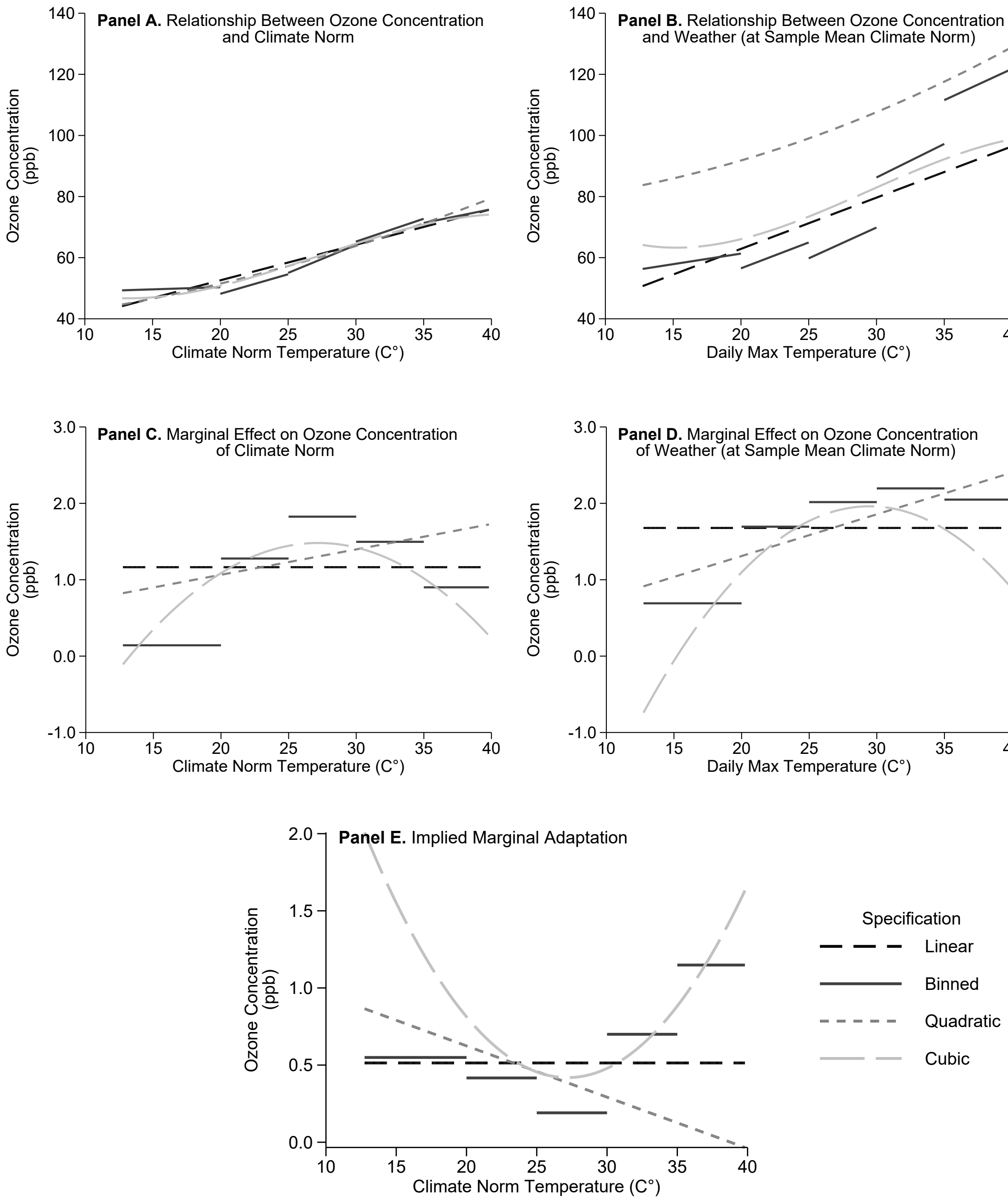
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from a complete, unbalanced panel of weather stations across the US from 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)



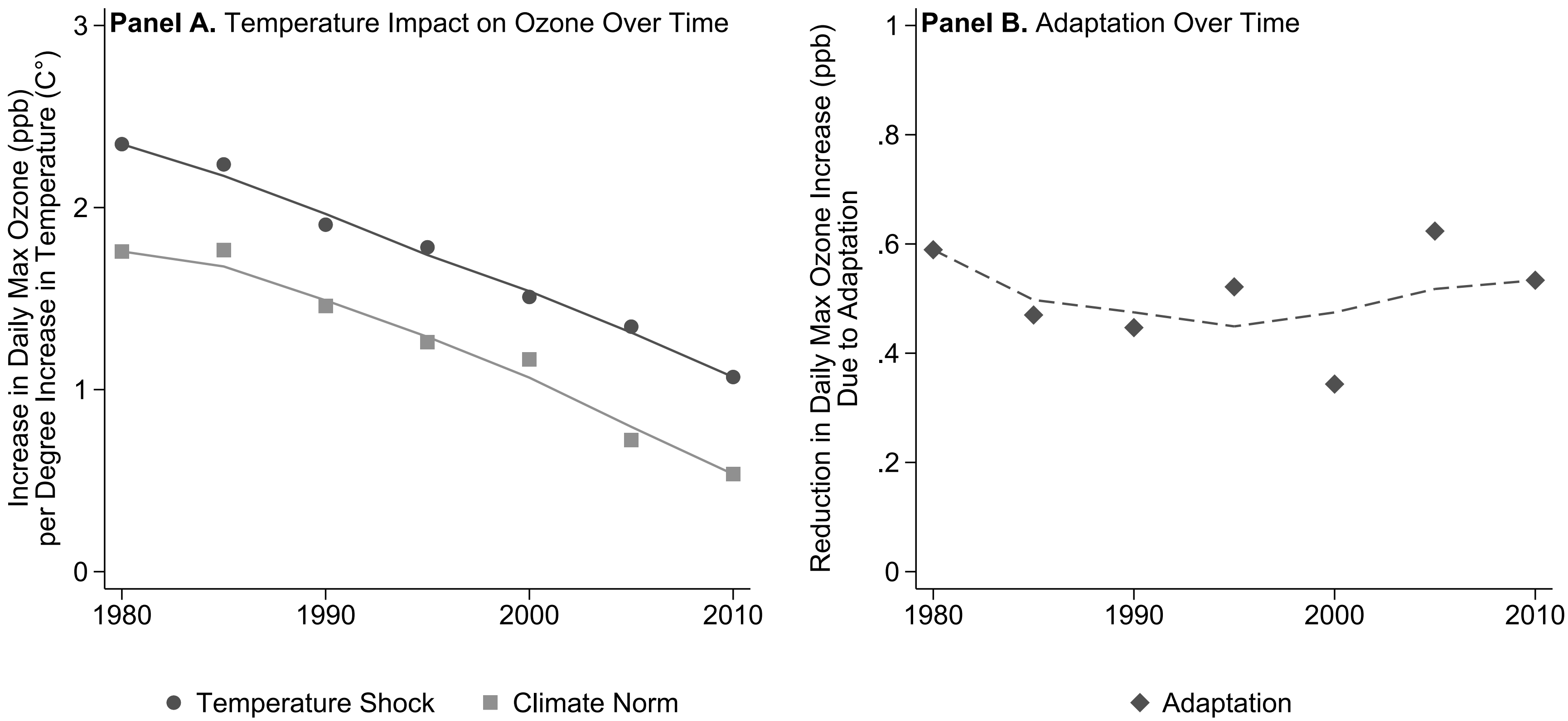
Notes: This figure compares our preferred temperature decomposition method with a standard fixed-effects approach using data from the 2013 Los Angeles ozone season, illustrating the benefit of our unifying approach as outlined in Equation (6) relative to the standard fixed-effects approach outlined in 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: Comparing Linear, Binned, and Nonlinear Specifications



Notes: This figure compares our central linear specification with a 5°C binned linear specification, as well as quadratic and cubic specifications following Equation (14). For clarity in the figures, we trim the top and bottom one-percent of the temperature distribution. Panels A and B depict the relationship between ozone and either climate or weather, respectively, across the temperature distribution. While both relationships exhibit some nonlinearity, the linear specification appears to capture the first-order relationship. Panels C and D depict the marginal impacts of climate and weather on ozone concentration, with both the flexible binned specification and the cubic reflecting an "inverted u" shape, suggesting that while ozone increases with temperature, above a certain temperature it begins to increase at a decreasing rate. Finally, Panel E shows marginal adaptation, wherein both the binned and cubic specifications exhibit a "normal u" shape, suggesting that adaptation is larger when temperature is hotter and could lead to higher ozone formation.

Figure 6: Climate Impacts and Adaptation Over Time



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 B7 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 5.6 ppb, 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 8 ppb, 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). Two major 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), and (ii) the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017). Here we examine the sensitivity of our estimates 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.

Online Appendix for

A Unifying Approach to Measuring Climate Change Impacts and Adaptation

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(for reference only; not for publication)

This appendix provides details on the construction of the data, descriptive figures, and the tabular results of robustness tests and explorations of heterogeneity using alternate specifications. In Appendix A, we provide relevant background information on ozone as a local air pollutant in Section A.1, and further details on the sources of our data and construction of final variables in Section A.2. We additionally include maps of both weather and ozone monitoring station locations, illustrative figures of our decomposition of temperature and its relationship with ozone concentration, and tables of summary statistics. Appendix B includes additional discussion of alternate specifications, split between those investigating robustness in Section B.1, and those examining heterogeneity in Section B.2. Appendix C provides further details on the two sources of variation used to empirically identify the effect of changes in the climate norm on ozone concentration.

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Appendix A. Additional Data Discussion

This appendix section provides background information on ozone pollution in Section A.1, while Section A.2 provides further details on the data sets discussed in Section III, as well as auxiliary data sets used in alternative specifications. It then includes relevant Figures and Tables as outlined below.

A.1. Background Details on Ozone

Background on Ozone — The ozone the U.S. EPA regulates as an air pollutant is mainly produced close to the ground (tropospheric ozone).[1] It results from complex chemical reactions between pollutants directly emitted from vehicles, factories and other industrial sources, fossil fuel combustion, consumer products, evaporation of paints, and many other sources. These highly nonlinear Leontief-like reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NOx) in the presence of sunlight. In "VOC-limited" locations, the VOC/NOx ratio in the ambient air is low (NOx is plentiful relative to VOC), and NOx tends to inhibit ozone accumulation. In "NOx-limited" locations, the VOC/NOx ratio is high (VOC is plentiful relative to NOx), and NOx tends to generate ozone.

As a photochemical pollutant, ozone is formed only during daylight hours, but is destroyed throughout the day and night. It is formed in greater quantities on hot, sunny, calm days. Indeed, major episodes of high ozone concentrations are associated with slow moving, high pressure systems, which are associated with the sinking of air, and result in warm, generally cloudless skies, with light winds. Light winds minimize the dispersal of pollutants emitted in urban areas, allowing their concentrations to build up. Photochemical activity involving these precursors is enhanced because of higher temperatures and the availability of sunlight. Modeling studies point to temperature as the most important weather variable affecting ozone concentrations.[2]

Ambient ozone concentrations increase during the day when formation rates exceed destruction rates, and decline at night when formation processes are inactive.[3] Ozone concen-

[1] It is not the stratospheric ozone of the ozone layer, which is high up in the atmosphere, and reduces the amount of ultraviolet light entering the earth's atmosphere.

[2] Dawson, Adams and Pandisa (2007), for instance, examine how concentrations of ozone respond to changes in climate over the eastern U.S. The sensitivities of average ozone concentrations to temperature, wind speed, absolute humidity, mixing height, cloud liquid water content and optical depth, cloudy area, precipitation rate, and precipitating area extent were investigated individually. The meteorological factor that had the largest impact on ozone metrics was temperature. Absolute humidity had a smaller but appreciable effect. Responses to changes in wind speed, mixing height, cloud liquid water content, and optical depth were rather small.

[3] In urban areas, peak ozone concentrations typically occur in the early afternoon, shortly after solar noon when the suns rays are most intense, but persist into the later afternoon.

trations also vary seasonally. They tend to be highest during the late spring, summer and early fall months.[4] The EPA has established "ozone seasons" for the required monitoring of ambient ozone concentrations for different locations within the U.S.[5] Recently, there is growing concern that the ozone season may prolong with climate change (e.g., Zhang and Wang, 2016).

A.2. Further Details on the Construction of the Data

Weather Data — Meteorological data was obtained 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 which we use the period April-September, 1950-2013, for the contiguous 48 states. In constructing our complete, unbalanced panel of weather stations we make only one restriction: for each weather station in each year, we include only those stations for which valid measurements of maximum and minimum temperature, as well as precipitation, exist for at least 75 percent of the days in the ozone monitoring season (April-September). Figure A1 illustrates the geographical location of the weather stations that we have used from 1950-2013, while Table A1 reports summary statistics for maximum temperature and our decomposed measures of climate norm and temperature shock, averaged across our entire sample for each year 1980-2013. Figure A2 illustrates the variation we have in both components of the maximum temperature, namely, the temperature shocks and the climate norms, using a semi-balanced panel of the comprehensive set of weather stations[6] while Figure A3 depicts similar variation, but using only the temperature assigned to each ozone monitor in our final sample. Notice that there seems to be more variation in the 30-year MA in the latter figure because it includes cross-sectional variation as well. Also, the 30-year MA

[4] In areas where the coastal marine layer (cool, moist air) is prevalent during summer, the peak ozone season tends to be in the early fall.

[5] Appendix Table A3 shows the ozone season for each state during which continuous, hourly averaged ozone concentrations must be monitored.

[6] To create this semi-balanced panel, we impose an additional restriction on our complete, unbalanced sample: for each weather station, we include only those stations with valid readings in every year 1950-2013.

trends down towards the end of the period of our study due to changes in ozone monitor location over time, as shown in Figure A5.

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. Using information on the geographical location of ozone monitors and weather stations, we calculate the distance between each pair of ozone monitor and weather station using the Haversine formula. Then, for every ozone monitor we exclude weather stations that lie beyond a 30 km radius of that monitor. Moreover, for every ozone monitor we use weather information from only the closest two weather stations within the 30 km radius. Once we apply this algorithm, we exclude ozone monitors that do not have any weather stations within 30km. We calculate weather at each ozone monitor location as the weighted average of these two weather stations using the inverse of the squared distance between them. Figure A6 illustrates the proximity of our final sample of ozone monitors to these matched weather stations. We additionally assess the robustness of our results to changes in this algorithm by increasing the radius to 80 km and using the 5 closest weather stations, and by varying the weights used – unweighted arithmetic mean and simple inverse distance weighting – in calculating the approximate daily weather at each ozone monitoring location. The results of our model under these alternative specifications is discussed further in Appendix B.1.

Ozone Data — Ambient ozone concentration data was obtained from the Environmental Protection Agency's Air Quality System (AQS) AirData database, which provides daily readings from the nationwide network of the EPA's air quality monitoring stations. The data was made available by a Freedom of Information Act (FOIA) request. In our preferred specification we use an unbalanced panel of ozone monitors. We make only two restrictions to construct our final sample. First, we include only monitors with valid daily information. According to EPA, daily measurements are valid for regulation purposes only if (i) 8-hour averages are available for at least 75 percent of the possible hours of the day, or (ii) daily maximum 8-hour average concentration is higher than the standard. Second, as a minimum data completeness requirement, for each ozone monitor we include only years for which at least 75 percent of the days in the ozone monitoring season (April-September) are valid; years having concentrations above the standard are included even if they have incomplete data.

We have valid ozone measurements for a total of 5,284,615 monitor-days covering 1980-2013 and the conterminus United States.[7] The number of total valid monitors increased from 1,361 in the 1980s to 1,851 in the 2000s, indicating a growth of 16.6 percent of the ozone monitoring network per decade.[8] The number of monitored counties in our main estimating sample also grew from 585 in the 1980s to 840 in the 2000s. Figure A5 depicts the evolution of our sample monitors over the three decades in our data, and illustrates the expansion of the network over time. Table A2 provides some summary statistics regarding the increase in the number of monitors over time.[9]

Auxiliary Data — In some of our robustness checks and examinations of heterogeneity we incorporate additional datasets. Sources and any necessary data construction steps are described below.

In Table B8 we use measures of whether a county is "VOC-limited" or "NOx-limited." These measures were constructed using data collected by the EPA's network of respective monitoring stations. Note, however, that these are often separate pollution monitors from our main sample of ozone monitors. Additionally, data – especially for VOCs – is relatively sparse compared to ozone data. Due to these data constraints, we construct measures of whether a county is VOC-limited or NOx-limited for each 5-year period in our sample, e.g. 1980-1984, which we then match with our sample of ozone monitors at the county level. To

[7]Note that this value refers to *all* valid ozone measurements, the final samples used in estimation will be smaller due to, e.g., instances where an ozone monitor is not paired with any weather stations under our matching algorithm. For instance, our main estimating sample contains 5,139,523 valid monitor-day observations.

[8]For our main estimating sample, these are 1,285 and 1,701, respectively.

[9]Note that not all monitored counties were monitored in every year, and not all monitoring stations were active in every year. Some monitors were phased in to replace others, while others were simply added to the network over time as needed – thus individual years will generally have less unique monitors and monitored counties than existed across an entire decade or the sample period.

construct these measures we first combine the EPA's VOC and NOx data at the county-day level and generate a daily ratio of VOCs to NOx for each county, where possible. Following the scientific literature, observations with a ratio less than or equal to 4 are coded as VOC-limited, while those greater than 15 are coded NOx-limited, and the remainder are coded as non-limited. We then sum these three measures by county across each 5-year interval and denote a county as VOC-limited, NOx-limited, or non-limited for that interval based on whichever measure was the most prevalent. For example, a county with 50 VOC-limited day, 20 NOx-limited days, and 30 non-limited days would be marked as VOC-limited for this 5-year window. Admittedly, this creates a somewhat coarse measure of whether a county is VOC- or NOx-limited. Given the available data, however, this appears to be the furthest this question can be pursued at this time, and, if anything, should be expected to bias the observed effect from this heterogeneity towards zero.

In Table B3 we include average daily windspeed and total daily sunlight as additional regressors within our main specification. These data, although recorded less frequently, are collected at the same weather monitoring stations as our main temperature and precipitation variables. Due to the sparseness of these data we do not decompose them into a long-run climate norm and transitory weather shock as we do with temperature and precipitation.

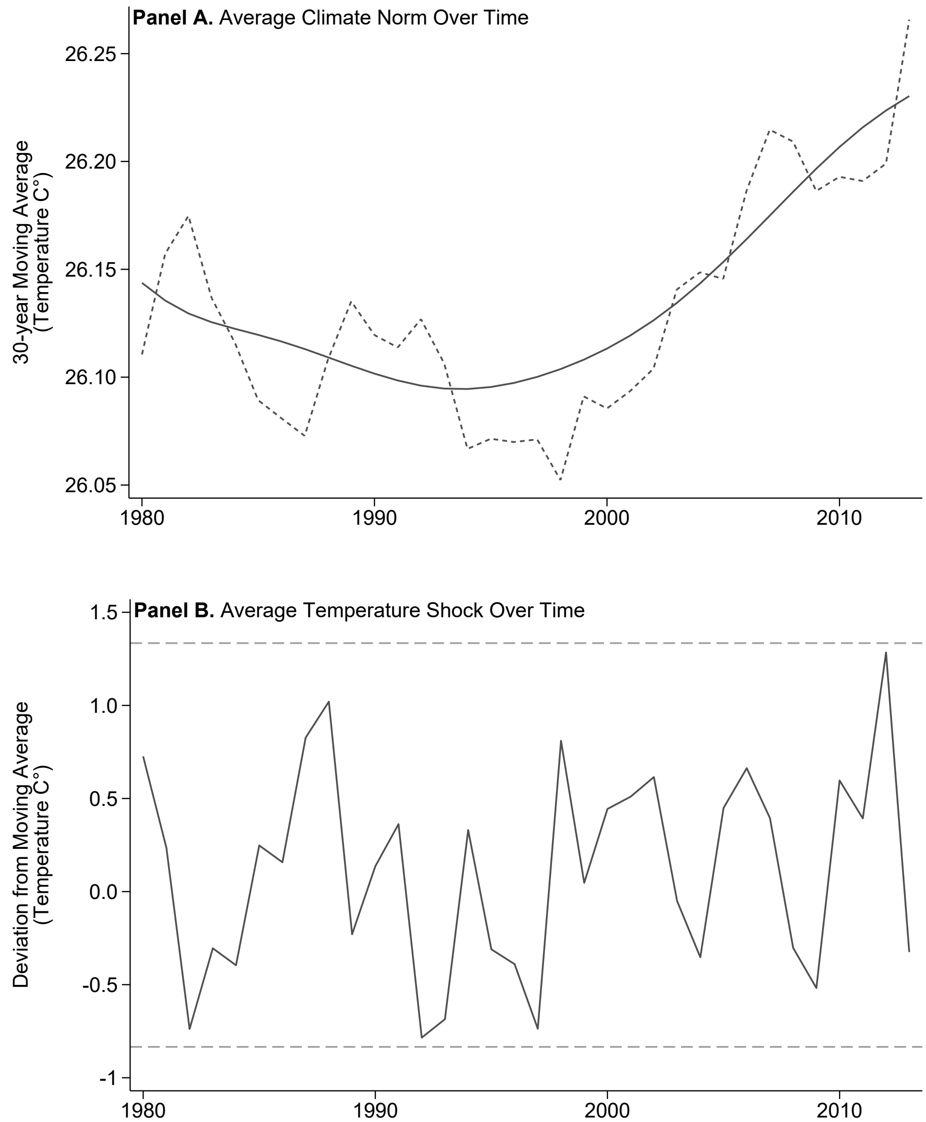
In Tables 5 and B9 we examine heterogeneity in our results when separating counties into low- median- and high-levels of belief regarding the existence of climate change and the use of regulation to reduce carbon emissions. These measures were constructed using county level survey data collected by Howe et al. (2015) in 2013 which estimate the percentage of each county's respective population that hold such beliefs. Notably, we do not rely on the explicitly stated aggregate level of belief, but rather the relative level of belief compared to the rest of our sample. Specifically, we separate counties into low- median- or high-belief terciles based on their stated level of belief in the existence of climate change – and separately by their belief in the use of regulations to reduce carbon emissions. In this way we arrive at three approximately equal sized groups for which we are able to examine heterogeneity in climate impacts and adaptive response. For reference, Table A4 provides summary statistics of basic demographic characteristics across these three county groupings using data from the 2006-2010 5-year American Community Survey.

In Table B10 we approach the question of hetergeneous beliefs from a different angle, using county-level voting results from the 2008 general presidential election obtained from MIT's Election Data and Science Lab (2018). We construct a simple indicator variable for whether Barack Obama or John McCain won the popular vote in that county and denote a county as "Democrat" if the former is true.

Figure A1: Comprehensive Location of all Weather Monitors

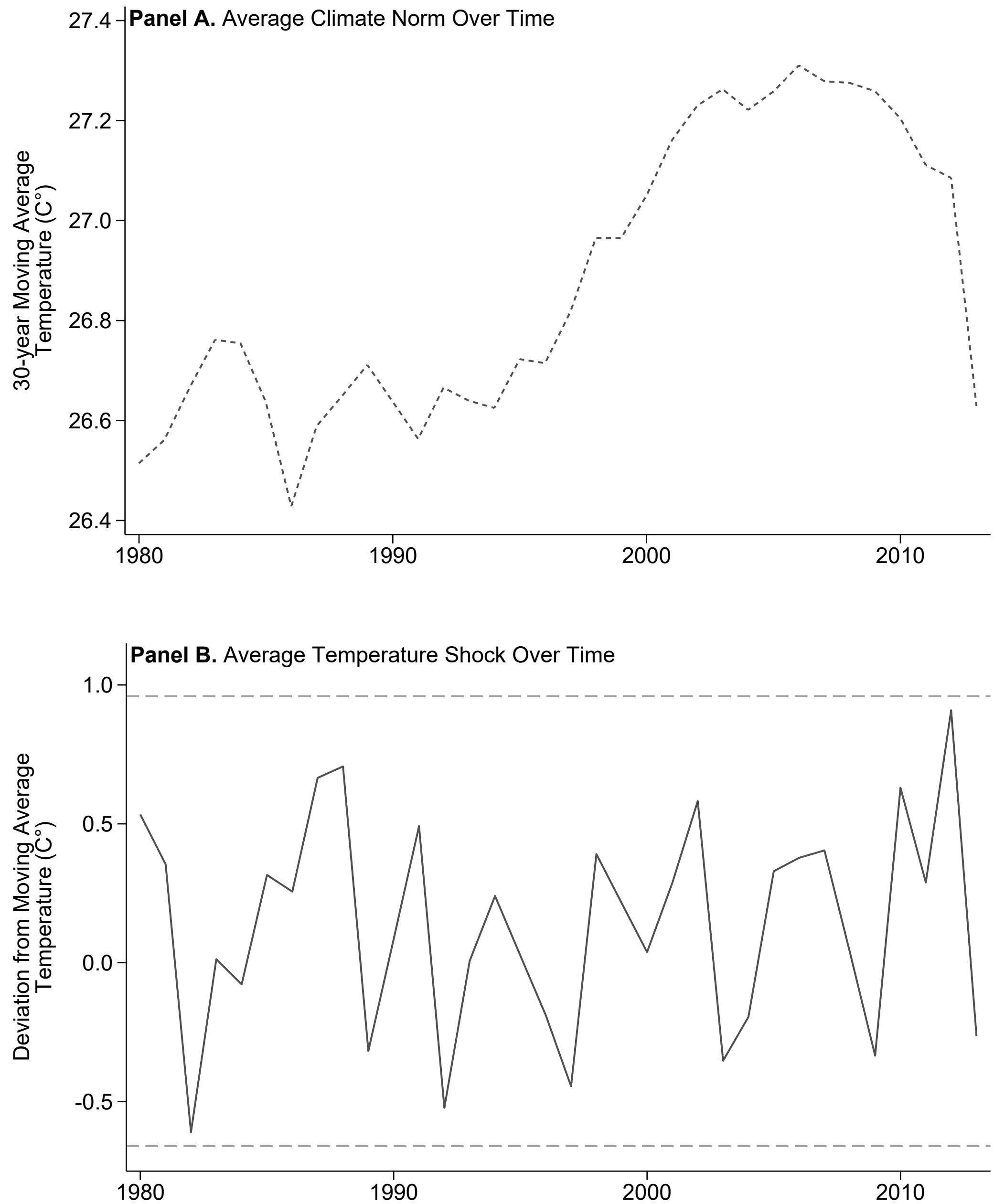
Notes: This figure maps the location of all weather stations across the continental U.S. contained in our complete dataset.

Figure A2: Climate Norms and Shocks (semi-balanced sample)



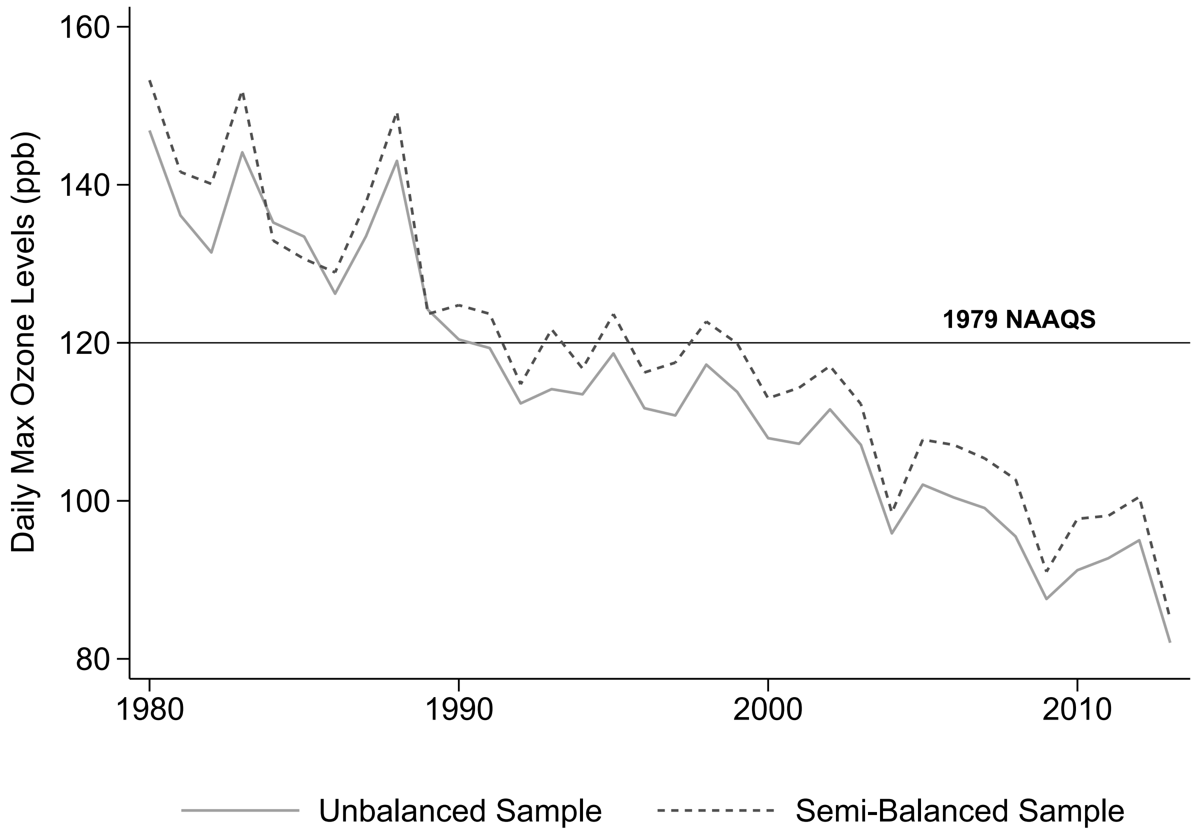
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from a semi-balanced panel of weather stations across the US from 1950 to 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 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. As described in our data construction in Appendix A.2, our full sample of weather stations includes only weather stations with valid measurements for at least 75% of the days in the ozone season. Here we further restrict this to a semi-balanced sample, including only those stations with valid readings in every year of our sample.

Figure A3: Climate Norms and Shocks (main model sample)



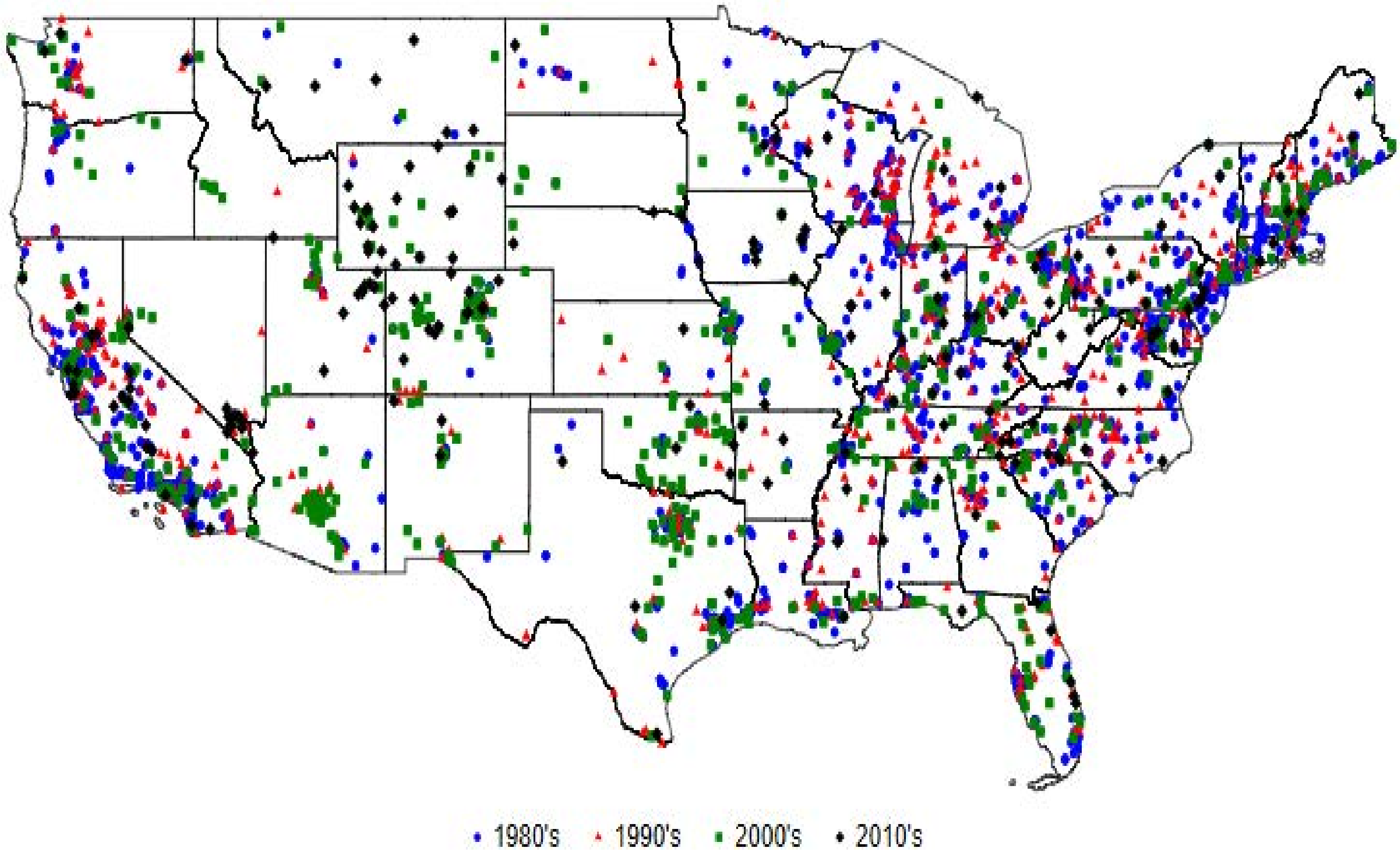
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from the panel of weather stations included in our main model sample across 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 Table A3 for a complete list of ozone seasons by state). The unbalanced feature of our main sample, with ambient ozone monitors moving north over time (see Figure A5), is the likely driving force behind the downward pattern of the average climate norm at the end of our sample period in Panel A. 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 horizontal dashed lines in Panel B highlights that temperature shocks are bounded in our period of analysis.

Figure A4: Evolution of Maximum Ambient Ozone Concentration



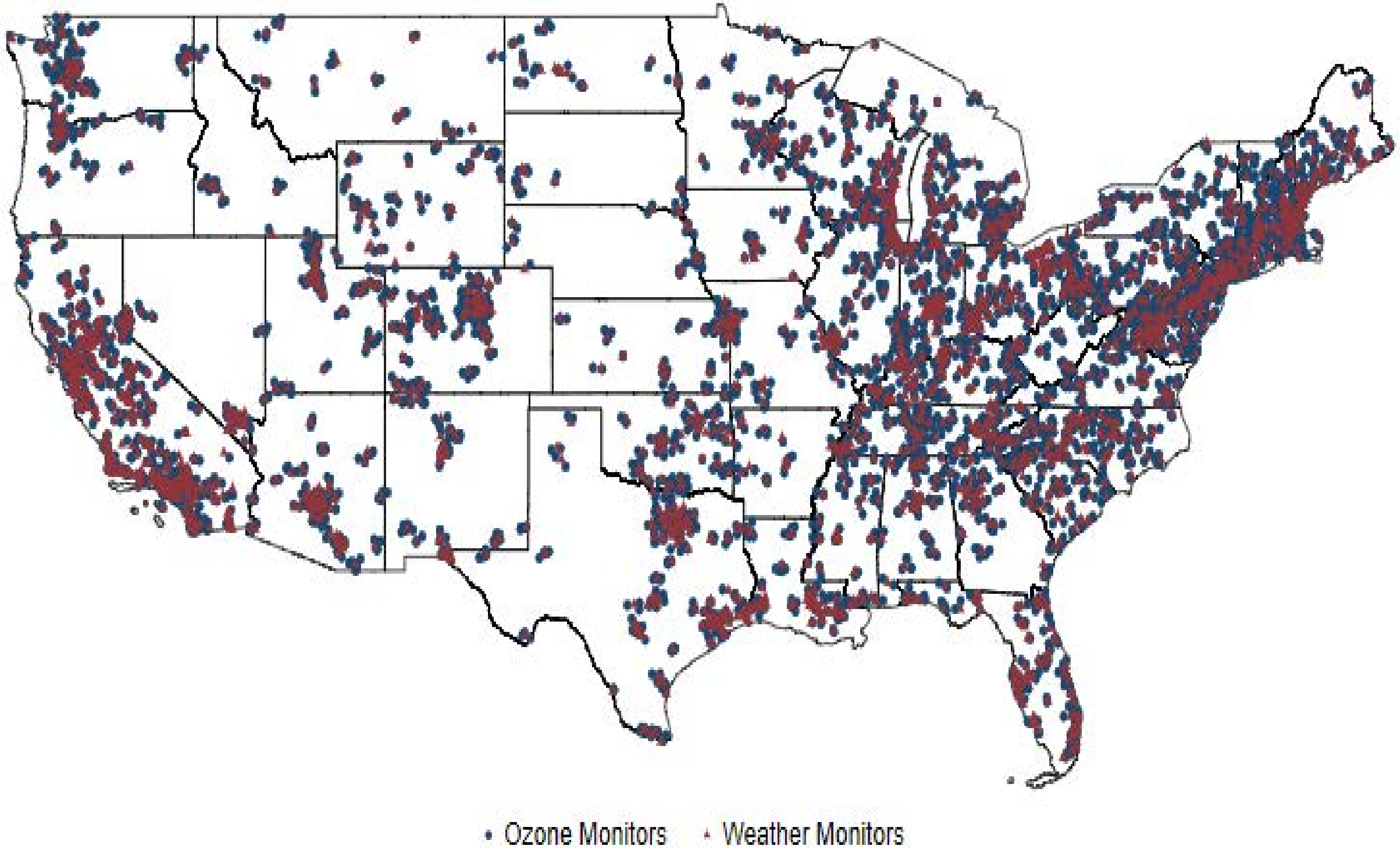
Notes: This figure depicts the evolution of the daily maximum 1-hour ambient ozone concentrations over time in the US for both our complete (unbalanced) sample and our restricted (semi-balanced) sample. For reference the horizontal line depicts the 1979 National Ambient Air Quality Standard for Ozone, which was based on an observed 1-hour maximum ambient ozone concentration of 120 ppb or higher.

Figure A5: Ozone Monitor Location by Decade of First Appearance



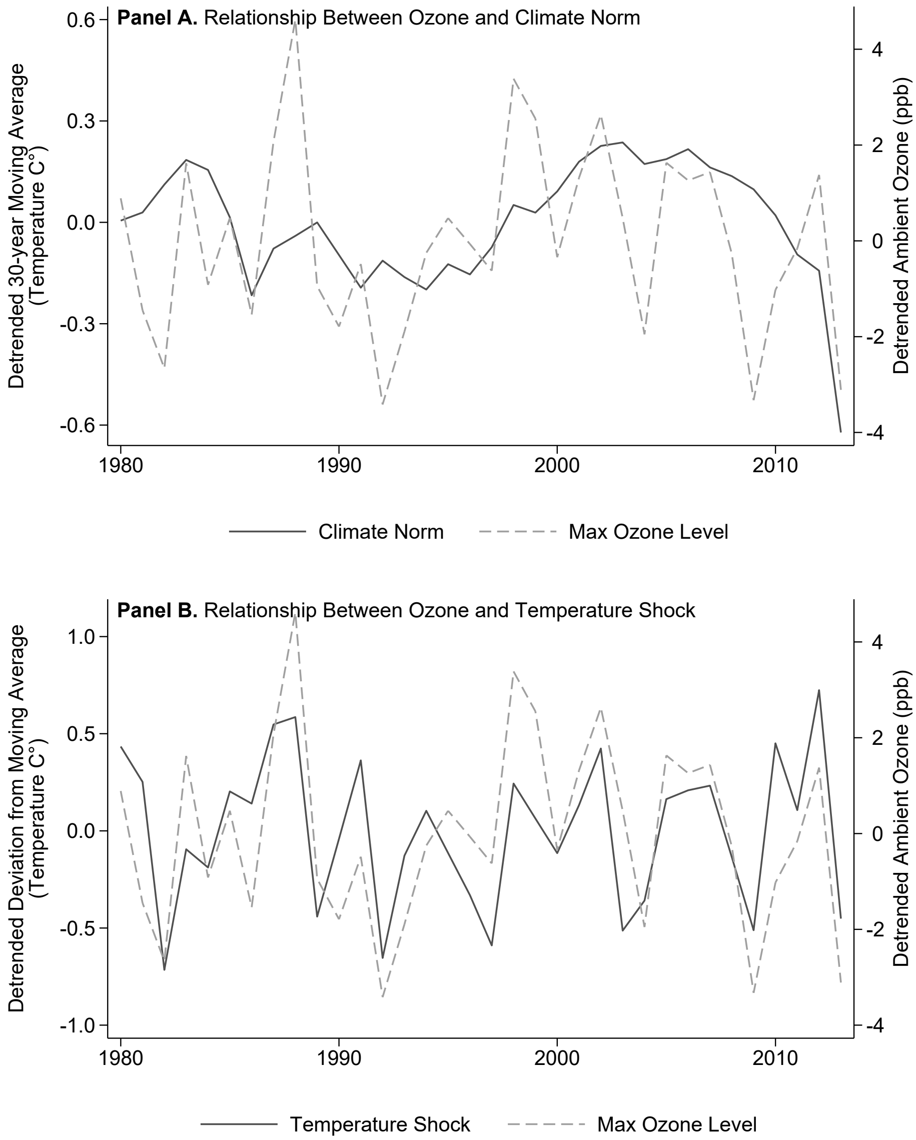
Notes: This figure maps the location of each ozone monitor in our final sample, by decade of first appearance.

Figure A6: Ozone Monitors and their Matched Weather Monitors



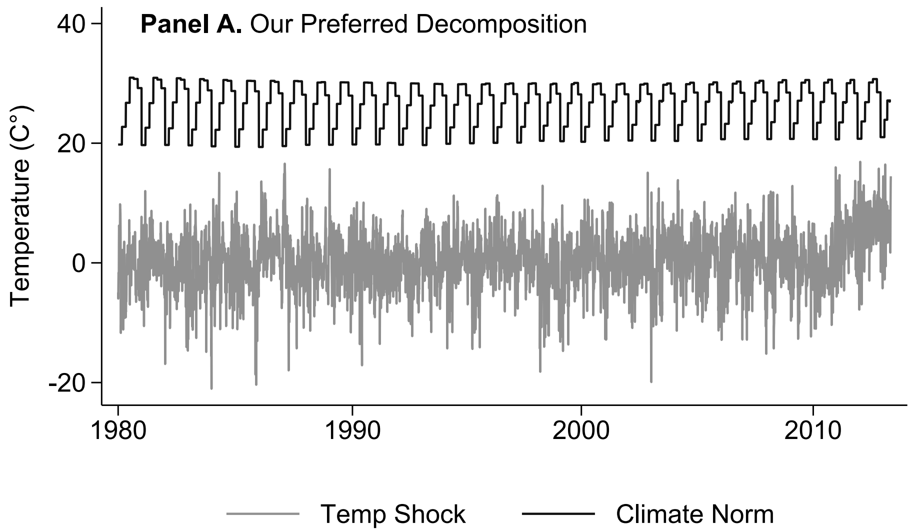
Notes: This figure maps the location of each ozone monitor in our final sample, and their matched weather stations. For each ozone monitor, the closest 2 stations within a 30 km radius have been used in the matching.

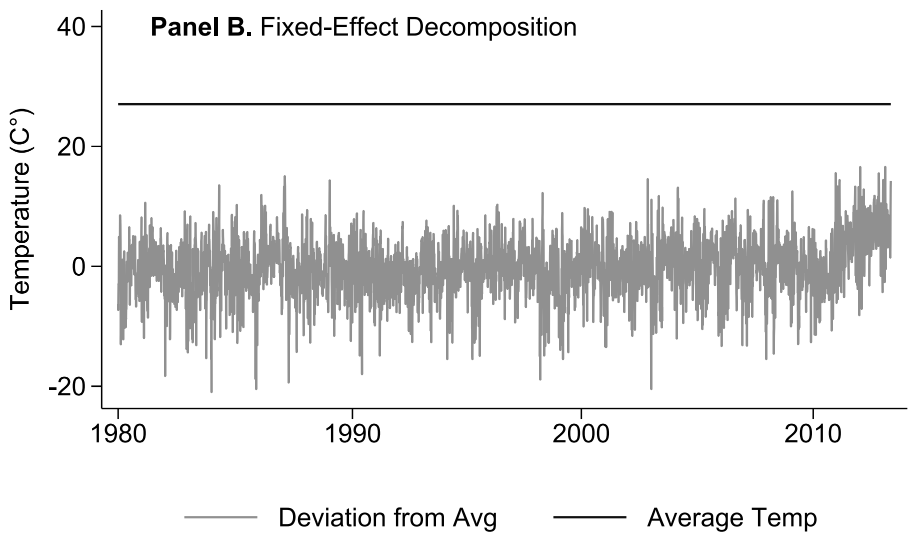
Figure A7: Relationship between Ozone and Decomposed Temperature



Notes: This figure depicts the general relationship between daily maximum ozone concentrations and temperature over the years in our sample (1980-2013) after decomposing temperature into our measure of climate norm and temperature shock and de-trending the data. Both the climate norm (Panel A) and the temperature shock (Panel B) appear to have a close correlation with ozone concentrations, although the relationship in Panel A appears weaker than that in Panel B, providing suggestive evidence of adaptative behavior. 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.

Figure A8: Decomposition of Temp. Norms & Shocks – Illustration (Los Angeles, All Years)





Notes: This figure compares our preferred temperature decomposition method with a standard fixed-effects approach using data for the Los Angeles region duging the ozone season across all years in our sample, 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 month-year fixed-effects. The black solid line at the top of each panel indicates 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.

Table A1: Yearly Summary Statistics for Daily Maximum Temperature

Year	Max Temp	Climate Trend	Temp Shock
(1)	(2)	(3)	(4)
1980	27.0	26.5	0.5
1981	26.9	26.6	0.4
1982	26.1	26.7	-0.6
1983	26.8	26.8	0.0
1984	26.7	26.8	-0.1
1985	27.0	26.6	0.3
1986	26.7	26.4	0.3
1987	27.3	26.6	0.7
1988	27.4	26.6	0.7
1989	26.4	26.7	-0.3
1990	26.7	26.6	0.1
1991	27.1	26.6	0.5
1992	26.1	26.7	-0.5
1993	26.6	26.6	0.0
1994	26.9	26.6	0.2
1995	26.8	26.7	0.0
1996	26.5	26.7	-0.2
1997	26.4	26.8	-0.4
1998	27.3	27.0	0.4
1999	27.2	27.0	0.2
2000	27.1	27.1	0.0
2001	27.4	27.2	0.3
2002	27.8	27.2	0.6
2003	26.9	27.3	-0.4
2004	27.0	27.2	-0.2
2005	27.6	27.3	0.3
2006	27.7	27.3	0.4
2007	27.7	27.3	0.4
2008	27.3	27.3	0.0
2009	26.9	27.3	-0.3
2010	27.8	27.2	0.6
2011	27.4	27.1	0.3
2012	28.0	27.1	0.9
2013	26.4	26.6	-0.3

Notes: This table outlines the evolution of maximum temperature in our sample from the years 1980-2013 in Column (2). Columns (3) and (4) decompose this into our respective measures of climate norm and temperature shock. 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.

Table A2: Yearly Summary Statistics for Ozone Monitoring Network

Year	# Observations	# Counties	# Ozone Monitors
(1)	(2)	(3)	(4)
1980	88426	361	609
1981	100459	399	659
1982	102111	402	661
1983	102429	408	653
1984	103828	390	649
1985	105457	388	648
1986	103820	375	634
1987	110366	392	668
1988	113232	409	686
1989	119938	425	725
1990	126535	443	757
1991	132046	466	792
1992	137754	482	821
1993	146023	511	863
1994	149400	520	876
1995	154230	528	902
1996	153019	530	894
1997	160024	550	931
1998	164491	568	960
1999	168901	585	982
2000	172686	592	999
2001	180872	616	1047
2002	186261	630	1071
2003	188462	641	1082
2004	189868	653	1087
2005	187709	649	1082
2006	188298	650	1075
2007	190824	661	1092
2008	190682	660	1099
2009	194184	678	1116
2010	196439	688	1130
2011	199948	716	1159
2012	199723	703	1148
2013	148306	658	1039

Notes: This table outlines the summary statistics of our main data sample. The construction of our main sample follows EPA guidelines by including all monitor-days for which 8-hour averages were recorded for at least 18 hours of the day and monitor-years for which valid monitor-days were recorded for at least 75% of days between April 1st and September 30th.

Table A3: Ozone Monitoring Season by State

State	Start Month - End	State	Start Month - End
Alabama	March - October	Nevada	January - December
Alaska	April - October	New Hampshire	April - September
Arizona	January - December	New Jersey	April - October
Arkansas	March - November	New Mexico	January - December
California	January - December	New York	April - October
Colorado	March - September	North Carolina	April - October
Connecticut	April - September	North Dakota	May - September
Delaware	April - October	Ohio	April - October
D.C.	April - October	Oklahoma	March - November
Florida	March - October	Oregon	May - September
Georgia	March - October	Pennsylvania	April - October
Hawaii	January - December	Puerto Rico	January - December
Idaho	April - October	Rhode Island	April - September
Illinois	April - October	South Carolina	April - October
Indiana	April - September	South Dakota	June - September
Iowa	April - October	Tennessee	March - October
Kansas	April - October	Texas[1]	January - December
Kentucky	March - October	Texas[1]	March - October
Louisiana	January - December	Utah	May - September
Maine	April - September	Vermont	April - September
Maryland	April - October	Virginia	April - October
Massachusetts	April - September	Washington	May - September
Michigan	April - September	West Virginia	April - October
Minnesota	April - October	Wisconsin	April 15 - October 15
Mississippi	March - October	Wyoming	April - October
Missouri	April - October	American Samoa	January - December
Montana	June - September	Guam	January - December
Nebraska	April - October	Virgin Islands	January - December

Notes: This table shows, for each state, the season when ambient ozone concentration is required to be measured and reported to the U.S. EPA.
[1]The ozone season is defined differently in different parts of Texas.
Source: USEPA (2006, p.AX3-3).

Table A4: County Summary Statistics by Belief in Climate Change

	Panel A. Low Belief Counties				
	Count	Mean	Std. Dev.	Minimum	Maximum
Population (1000's)	334	80.6	106.9	0.8	837.5
Average Education (Years)	334	12.7	0.6	11.0	14.3
Median Income ($1000/year)	334	48.6	10.4	21.9	83.3
Average Income ($1000/year)	334	61.7	11.3	36.9	111.9
	Panel B. Median Belief Counties				
Population (1000's)	335	174.7	297.4	1.9	3,951.0
Average Education (Years)	335	13.2	0.6	11.8	15.1
Median Income ($1000/year)	335	53.8	12.4	26.3	109.8
Average Income ($1000/year)	335	68.2	14.6	39.2	142.2
	Panel C. High Belief Counties				
Population (1000's)	336	466.7	780.8	1.3	9,758.3
Average Education (Years)	336	13.6	0.7	11.5	16.1
Median Income ($1000/year)	336	60.5	16.8	30.4	125.7
Average Income ($1000/year)	336	79.6	21.3	41.1	146.0

Notes: This table reports summary statistics of underlying demographics for each of the terciles of counties used in Table 5. Demographic data were obtained from the 2006-2010 5-year American Community Survey, with income reported in 2015 dollars, and average years of education based on a population weighted average of educational attainment status for the county population over 25 years of age.

Appendix B. Further Robustness Checks and Heterogeneity

Section B.1 of this appendix provides further elaboration of the alternative specifications used for robustness checks, as discussed in Section IV, while Section B.2 does so for our heterogeneity analyses, as discussed in Section V. It then includes relevant Tables as outlined below.

B.1. Further Robustness Checks

Alternative Criteria for Selection of Weather Stations — While our robustness checks presented in Table 2 have addressed potential concerns with the manner in which we construct our regressors by decomposing temperature, a possible additional concern arises from the fact that temperature monitors are not necessarily sited next to ozone monitors. Because of this, we do not have an exact measure of temperature at the same geographic point as our measure of ozone. As discussed in our data section and detailed in Appendix A.2, we define temperature at an ozone monitoring station as the mean of the reported daily maximum temperatures at the two closest weather stations within 30 kilometers, weighted by the inverse squared distance to the ozone monitor. In so doing, we are likely to approximate a good measure of the daily maximum temperature for the local region as a whole, while also maintaining a close geographic boundary around the ozone monitoring station so as not to influence this approximation with temperature readings from a weather station further away that may be subject to a different set of meteorological conditions. It's possible, however, that a less strongly distance-weighted mean would provide a more accurate measure of temperature for the overall local region – although likely less accurate at the ozone monitoring station itself – or that the 2-station and 30-kilometer cutoffs are too restrictive. We investigate the effects of lessening the distance weighting in the calculation of expected temperature at the ozone monitoring station, as well as relaxing the constraints on both the number of included weather stations and distance from the ozone monitor in Table B1. Specifically, columns (1) and (2) report results of our main specification when we maintain the 2-station/30-kilometer restriction, but decrease the weighting scheme to either the simple arithmetic mean in column (1), or a non-squared inverse distance weight in column (2). Columns (3) and (4) use the same weighting schemes as in (1) and (2), but now include temperature readings from the 5 closest weather monitoring stations within 80 kilometers. Results in all four columns are relatively stable and consistent with our main specification.

Non-Random Siting of Ozone Monitors — In recent work, Muller and Ruud (2018) argue that the location of pollution monitors is not necessarily random. The U.S. EPA maintains a dense network of pollution monitors in the country for two major reasons: (i) to provide useful data for the analysis of important questions linking pollution to its varied impacts, and (ii) to check and enforce regulations on criteria pollutants. These are conflicting interests: while monitors should be placed in regions having different levels of pollution to provide representative data, they might be placed in areas where pollution levels are the highest to maintain oversight. Not surprisingly, the authors find that most of the monitors tend to be in areas where pollution levels have been high, and compliance with the regulation is a question.

Following those authors' results, we can expect that ozone monitors that have consistently been in our sample across all years may be located in areas having very high pollution levels, thus commanding constant monitoring and regulation by the EPA. To check if this claim is accurate, we re-run our main analysis using a *balanced* sample of ozone monitors. Starting from our original sample, and using only monitors that have been in the data for every year from 1980-2013, we are left with 89 pollution monitors. The results are reported in Table B2. We find that a 1°C temperature shock leads to a rise in ozone concentrations by 2.03 ppb, while a 1°C increase in the climate norm leads to a rise of 1.49 ppb, implying an adaptation level of 0.54 ppb. As expected, the temperature effects obtained from the balanced panel are *larger* than those in our main results, although the level of adaptation remains largely unchanged. The balanced panel leads to an overestimation of the climate penalty. Therefore, our preferred, unbalanced sample of monitors includes areas with different levels of air pollution, and our estimates should be more representative of the entire country.

Additional Robustness Checks — In addition to all prior robustness checks, we conduct four final checks in Table B3. First, it may be a concern that our climate norm variable structures the long-run climate normal temperature as the 30-year *monthly* moving average, despite the fact that seasonal – or within-season – shifts in temperature are unlikely to exactly follow the calendar at a monthly level. We examine the sensitivity of our results to this decision by alternatively constructing this variable as a 30-year *daily* moving average, allowing it to vary arbitrarily within each month. Results of our main specification, substituting daily moving averages for the standard monthly ones, are presented in column (1). Both coefficients of interest are nearly identical to our original findings. Ultimately, we prefer the monthly moving average because it is likely that individuals recall climate patterns by month, not by day of the year, making the interpretation of adaptation more intuitive. Indeed, broadcast meteorologists 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 a daily norm.

Second, it may be a concern that our proposed methodology is heavily reliant on high-frequency data in order to successfully decompose temperature into its climatological and meteorological components. While this concern does not pose a threat to identification in our context per se, if valid it would reduce the generalizability of our method to other contexts with less temporally rich data. We examine this concept by aggregating our data to the monitor-month level, taking the arithmetic mean of all variables for each ozone monitor, by month, for each year of our sample and running our preferred specification on this aggregate sample. As the climate norm variable is already identified from variation in monthly moving averages, we would not expect this coefficient to change other than due to the aggregation of our dependent variable and the temperature deviations, which both would otherwise vary daily. It is less clear, however, how this "smoothing" of daily ozone and temperature deviations might affect the coefficient on temperature shocks. Although our sample size is greatly reduced, now consisting of 178,175 observations compared to the previous 5,139,523 we find qualitatively similar results, reported in column (2). As expected, the coefficient on climate norm is nearly identical, while the coefficient on temperature shock is slightly larger in magnitude than in our full sample model, though statistically very similar.

Third, although temperature is the primary meteorological factor affecting tropospheric (ambient) ozone concentrations, other factors such as wind speed and sunlight have also been noted as potential contributors. High wind speed may prevent the build-up of ozone precursors locally, and dilute ozone concentrations. Ultraviolet solar radiation should trigger chemical reactions leading to the formation of more ground-level ozone. To test whether our main estimates are capturing part of the effects of wind speed and sunlight, we control for these variables in an alternative specification using a smaller sample containing those variables. Column (3) presents our main results from estimating Equation (13) plus controls for average daily wind speed (meters/second) and total daily sunlight (minutes). As expected, higher wind speeds lead to lower ozone concentrations, and more sunlight leads to higher concentrations. From column (3), we find that a 1 meter/second increase in average daily wind speed would decrease ozone concentrations by 2.3 ppb, whereas a 1 minute increase in daily sunlight leads to 0.02 ppb increase in ozone concentrations. Controlling for these two effects, we find that a shock in daily maximum temperature of 1°C leads to a 1.75 ppb increase in daily maximum ozone whereas a 1°C increase in the climate norm leads to a 1.13 ppb increase in ozone, implying a measure of overall adaptation of 0.62 ppb – all statistically similar to our main results. Our primary estimates of the impact of temperature on ozone concentrations, and hence our measures of adaptation, do not seem to rely crucially on other potentially important meteorological factors.

Finally, one may be concerned that inter-regional pollution transport may be affecting our results. If, for example, pollution was transported into a region, this may affect the estimated level of adaptation in that region as the local agent would not have full control over the pollution outcome. We note two key points relating to this concern. First, neither ozone itself or VOCs, an ozone precursor, are likely to be transported long distances due to their high reactivity, thus it is primarily NOx transport that would pose a concern. Second, as with any real-world setting, local agents may need to take exogenous factors into account when making decisions, such as in a region subject to increased baseline levels of NOx due to transport from other regions. Agent's in such a region may, for example, opt to prioritize reductions in VOCs, a precursor they have more direct control over, in an effort to curb ozone formation. Furthermore, a collection of regions which suffer from such transport concerns may collectively work together to reduce NOx – this may be of their own volition, or imposed by a higher regulatory body, such as the EPA. In fact, the EPA designates 12 states, in whole or part, in the Northeast as part of the "ozone transport region" (OTR).[10] As these states represent the region wherein inter-regional NOx transport poses the greatest concern, we examine the effect of such transport on our central estimates by both explicitly excluding all OTR states from our estimating sample, and, conversely, using only these states as the estimating sample. Columns (4) and (5) present these results, finding that while the coefficients on weather and climate are somewhat higher in the OTR-only sample, as might be expected of a region where ozone is a particular concern, adaptation is statistically indistinguishable from our central estimate.

B.2. Heterogeneity

Results by Decade — To examine temporal heterogeneity, Table B7 mirrors Figure 6 and reports our results by decade. We split our sample into three "decades" 1980-90, 1991-2001, and 2002-2013 so that we have roughly the same number of years in each. We find that the effects of contemporaneous daily maximum temperature, and its two components of our decomposition, are decreasing over time, as shown in column (1). Nevertheless, looking at column (2), we find evidence that adaptation by economic agents reduced slightly from the 1980's to the 1990's, but stabilized back at its original levels in the 2000's. The average adaptation across all counties in our sample drops from 0.54 ppb in the 1980's to 0.43 ppb

[10] *"Ozone Transport Region boundary. As of March 14, 2022, the boundary for the Ozone Transport Region consists of the entire States of Connecticut, Delaware, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont; portions of Maine identified in this section under Table 1; and the Consolidated Metropolitan Statistical Area that includes the District of Columbia and the following counties and cities in Virginia: Arlington County, Fairfax County, Loudoun County, Prince William County, Strafford County, Alexandria City, Fairfax City, Falls Church City, Manassas City, and Manassas Park City."* (USCFR, 2022).

in the 1990's, but increases again to 0.54 ppb in the 2000's.

Heterogeneity by Precursor "Limited" Atmospheric Conditions — As detailed in Appendix Section A.1, ozone is formed from precursor pollutants – volatile organic compounds (VOCs) and oxides of nitrogen (NOx) – in the presence of sunlight and heat. Specifically, ozone formation appears to follow a Leontief-like production function, implying that regions where the ambient supply of one of the two precursor pollutants, VOCs or NOx, are limited might be less susceptible to increased ozone formation when faced with increased temperatures.

To examine potential heterogeneity in the temperature/ozone relationship and adaptation along this channel we collected all available data on VOC and NOx emissions for each county in our sample as reported by the EPA. Due to the sparseness of these data, we construct aggregate indicators of whether a county is VOC-limited, NOx-limited, or neither for each 5-year interval of our overall sample.[11]

Column (1) of Table B8 presents the results of our main specification when using this restricted sample – approximately 20% of our full sample – finding results that are qualitatively similar, albeit larger in magnitude, to our full sample results for the effects of temperature shock, climate norm, and the resulting measure of adaptation – shown in column (2). The magnitude is likely larger because VOCs may be monitored in places with potentially high concentrations. In column (3) we interact the indicators for VOC- and NOx-limited counties with our other regressors to recover a coarse estimate of the effect that being limited in either precursor has on the relationship between our two measures of temperature and ozone. Both main coefficients, and the resulting measure of adaptation – shown in column (4), remain statistically unchanged for non-limited counties. While the difference from these values is statistically indistinguishable from zero in NOx-limited counties. In VOC-limited counties the effects of temperature shock and climate norm are approximately 31 and 79 percent lower

[11] Because ozone formation follows a Leontief-like production function, a county is "VOC-limited" if the ratio of VOC to NOx is too low, while it would be "NOx-limited" if the ratio is too high, and a middle set of counties would not be limited as they face levels of both precursor emissions closer to the "optimal" mix. Further details on this data can be found in Appendix A.2.

and significant, respectively, although the resulting level of adaptation is not precise enough to conclude that it is statistically different from other counties. This finding appears to corroborate the Leontief-like production function of ozone (e.g., Auffhammer and Kellogg, 2011; Deschenes, Greenstone and Shapiro, 2017); when departing from the balanced mix of ozone precursors, the estimated effects of temperature on ambient ozone concentration decline.

Table B1: Alternative Criteria for Selection of Weather Stations

	Daily Max Ozone Levels (ppb)			
	(1)	(2)	(3)	(4)
Temperature Shock	1.721***	1.700***	1.773***	1.764***
	(0.063)	(0.063)	(0.067)	(0.066)
Climate Norm	1.165***	1.165***	1.156***	1.156***
	(0.051)	(0.051)	(0.050)	(0.050)
Implied Adaptation	0.557***	0.535***	0.617***	0.608***
	(0.041)	(0.042)	(0.044)	(0.043)
Distance Cut-off	30 km	30 km	80 km	80 km
Stations Included	2	2	5	5
Weighting Scheme	Simple Avg	1/Dist	Simple Avg	1/Dist
All Controls	Yes	Yes	Yes	Yes
Observations	5,139,523	5,139,523	5,284,420	5,284,420
R^2	0.484	0.483	0.484	0.485

Notes: This table reports estimates from models using alternative criteria to match weather stations to ozone monitors. These estimates are obtained by our main specification, Equation (13), but using different distance radii, number of weather stations, and weights when matching ozone monitors to weather stations. In our main analysis we use a radius of 30 km, the 2 closest stations, and the inverse squared distance as the weight. In the above columns, we give the same weight to both stations (simple average), or use the inverse distance as an alternative weight. In columns (3) and (4) we also increase the radius to 80 km and use the information from the closest 5 weather stations. 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 B2: Comparison to Alternative Estimation Methods (Semi-Balanced Panel)

	Daily Max Ozone Levels (ppb)		
	Unifying	Fixed-Effects	Cross-Section
	(1)	(2)	(3)
Temperature Shock	2.028***		
	(0.109)		
Climate Norm	1.492***		
	(0.084)		
Max Temperature		2.009***	
		(0.109)	
Average Max Temperature			0.904
			(0.950)
Implied Adaptation	0.536***	1.105	
	(0.082)	(0.773)	
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	520,670	520,670	89
R^2	0.475	0.534	0.545

Notes: This table reports our main climate impact results using a semi-balanced panel including only those monitors that exist in every year of our data. 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). 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 the 1%, 5% and 10%, respectively.

Table B3: Further Robustness Checks

	Daily Max Ozone Levels (ppb)				
	Daily Moving Average	Monthly Aggregation	Meteorological Controls	Excluding OTR States	Including Only OTR States
	(1)	(2)	(3)	(4)	(5)
Temperature Shock	1.684***	1.806***	1.749***	1.558***	2.077***
	(0.064)	(0.062)	(0.078)	(0.082)	(0.056)
Climate Norm	1.207***	1.171***	1.126***	1.052***	1.476***
	(0.050)	(0.050)	(0.070)	(0.066)	(0.059)
Average Wind Speed			−2.325***		
			(0.309)		
Total Daily Sunlight			0.015***		
			(0.001)		
Implied Adaptation	0.477***	0.636***	0.624***	0.506***	0.601***
	(0.040)	(0.041)	(0.064)	(0.055)	(0.038)
All Controls	Yes	Yes	Yes	Yes	Yes
Observations	5,139,454	178,175	453,829	4,116,365	1,023,158
R^2	0.480	0.859	0.479	0.497	0.426

Notes: This table reports estimates, obtained by Equation (13), from models that replace our monthly moving average with a daily one in column (1), aggregate our high-frequency daily data to monthly averages in column (2), and include additional meteorological controls in column (3). Specifically, for column (1) we first decompose contemporaneous maximum temperature into an alternative climate norm, represented by the 30-year *daily* moving average, and the respective temperature shock, represented by the difference between this value and the contemporaneous maximum temperature. We then proceed to estimate our main specification as normal, following Equation (13). For column (2), we first aggregate our final sample to the monthly level for each ozone monitor before estimating Equation (13) in order to simulate the application of our model to contexts with less granular data. This reduces our sample from 5,139,523 observations to 178,175. Despite this reduction, our results remain qualitatively similar. In column (3) we augment our main specification by including further meteorological controls, for daily average windspeed and total daily sunlight, in our matrix of additional regressors. While both coefficients are strongly significant, they do not meaningfully affect our coefficients of interest, but drastically restrict our total sample size. Recall that, except for in column (1), 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 B4: Alternative Clustering and Bootstrapped Standard Errors

	Daily Max Ozone Levels (ppb)
	(1)
Temperature Shock	1.678***
(County Cluster)	(0.063)
(State Cluster)	(0.134)
(Bootstrapped)	(0.063)
Climate Norm	1.164***
(County Cluster)	(0.051)
(State Cluster)	(0.091)
(Bootstrapped)	(0.051)
Implied Adaptation	0.514***
(County Cluster)	(0.041)
(State Cluster)	(0.106)
(Bootstrapped)	(0.042)
All Controls	Yes
R^2	0.481
Observations	5,139,523

Notes: This table compares the standard errors of our main estimates with ones obtained by clustering at the state- rather than county-level, and by bootstrap (block method clustered at the county level, 1000 iterations). The latter addresses the potential concern that because our temperature shocks and norm are constructed, they could be seen as generated regressors. 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 B5: Non-Linear Effects of Temperature

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
	Panel A. Below 20°C	
Temperature Shock	0.691***	
	(0.017)	
Climate Norm	0.142***	0.550***
	(0.034)	(0.030)
	Panel B. 20-25°C	
Temperature Shock	1.694***	
	(0.072)	
Climate Norm	1.278***	0.417***
	(0.069)	(0.031)
	Panel C. 25-30°C	
Temperature Shock	2.017***	
	(0.087)	
Climate Norm	1.826***	0.191***
	(0.092)	(0.041)
	Panel D. 30-35°C	
Temperature Shock	2.196***	
	(0.096)	
Climate Norm	1.496***	0.700***
	(0.128)	(0.070)
	Panel E. Above 35°C	
Temperature Shock	2.049***	
	(0.135)	
Climate Norm	0.901***	1.148***
	(0.180)	(0.136)
All Controls	Yes	
Observations	5,139,523	
R^2	0.494	

Notes: This table reports the average marginal effect of a 1°Celsius increase in the temperature shock and climate norm on the daily maximum ambient ozone concentration (ppb) for days in which the daily maximum temperature fell within different temperature bins. We categorize temperature into 5 bins from < 20°C to > 35°C with 5°C intervals in between. Estimates in column (1) correspond to Equation (13), interacting all variables with indicators for each temperature bin, while estimates in column (2) report the implied measure of adaptation. 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, plus the un-interacted indicators for each temperature bin to allow the intercept to vary across bins. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table B6: Adaptation Under Linear, Binned, and Nonlinear Specifications

	Linear	Binned	Quadratic	Cubic
	(1)	(2)	(3)	(4)
	Panel A. Below 20°C			
Implied Adaptation	0.514***	0.550***	0.708***	1.135***
	(0.041)	(0.030)	(0.074)	(0.073)
	Panel B. 20-25°C			
Implied Adaptation	0.514***	0.417***	0.541***	0.587***
	(0.041)	(0.031)	(0.040)	(0.049)
	Panel C. 25-30°C			
Implied Adaptation	0.514***	0.191***	0.375***	0.420***
	(0.041)	(0.041)	(0.061)	(0.048)
	Panel D. 30-35°C			
Implied Adaptation	0.514***	0.700***	0.209*	0.633***
	(0.041)	(0.070)	(0.109)	(0.101)
	Panel E. Above 35°C			
Implied Adaptation	0.514***	1.148***	0.043	1.227***
	(0.041)	(0.136)	(0.161)	(0.210)
All Controls	Yes	Yes	Yes	Yes
Observations	5,139,523	5,139,523	5,139,523	5,139,523
R^2	0.481	0.494	0.483	0.486

Notes: This table reports implied adaptation estimates across the temperature distribution recovered via four alternative specifications. Our central linear specification is shown in column (1), while column (2) depicts the binned specification shown in Table B5, column (3) and (4) show the results of quadratic and cubic specifications, respectively, following Equation (14). Recall that for the quadratic and cubic models, calculating marginal adaptation requires choosing a value for the underlying climate norm. Thus, calculations in columns (3) and (4) use the values of 17.5, 22.5, 27.5, 32.5, and 37.5°Celsius to correspond to the "mid-points" of the respective temperature bins used in column (2). Additionally, recall that implied adaptation reflects the difference between the climate norm, represented by the 30-year monthly moving average of maximum temperature, lagged by one year, and the temperature shock, represented by 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, plus the un-interacted indicators for each temperature bin in column (2). Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table B7: Results by Decade

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
	Panel A. 1980's	
Temperature Shock	2.264***	
	(0.142)	
Climate Norm	1.726***	0.539***
	(0.086)	(0.088)
	Panel B. 1990's	
Temperature Shock	1.768***	
	(0.051)	
Climate Norm	1.339***	0.428***
	(0.049)	(0.037)
	Panel C. 2000's	
Temperature Shock	1.280***	
	(0.030)	
Climate Norm	0.743***	0.537***
	(0.034)	(0.030)
All Controls	Yes	
Observations	5,139,523	
R^2	0.490	

Notes: This table reports our main estimates disaggregated by the three "decades" in our sample: 1980-1990; 1991-2001 and 2002-2013. Estimates in column (1) correspond to Equation (13), while estimates in column (2) report the implied measure of adaptation. 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 B8: Adaptation by VOC- or NOx-limited Atmosphere

	Daily Max Ozone Levels (ppb)			
	Main Specification		VOC/NOx-Limited	
	Restricted Sample	Adaptation	*Restricted Sample*	Adaptation
	(1)	(2)	(3)	(4)
Temperature Shock	2.135***		2.185***	
	(0.165)		(0.206)	
x VOC-limited			−0.674**	
			(0.281)	
x NOx-limited			−0.082	
			(0.115)	
Climate Norm	1.378***	0.757***	1.347***	0.838***
	(0.140)	(0.119)	(0.139)	(0.151)
x VOC-limited			−1.070***	0.397
			(0.335)	(0.284)
x NOx-limited			0.176	−0.258*
			(0.108)	(0.139)
All Controls	Yes		Yes	
Observations	1,007,563		1,007,563	
R^2	0.505		0.506	

Notes: This table reports estimates of temperature shock and climate norm interacted with an indicator of whether the county was, on average, more VOC-limited, NOx-limited, or non-limited. Using 5-year bins (1980-1984, 1985-1989, etc.) a county is designated as VOC-limited, NOx-limited, or neither for each bin based on whichever of these three categories the county observed the most days of during the 5-year period. We restrict our sample to only those counties for which data on these precursor pollutants is available (approximately 20% of our full sample), and depict the results of our main specification under this restricted sample in column (1) for comparison, with the implied measure of adaption in column (2). In column (3), the main effect reflects the result for non-limited counties, while the interaction term depicts the relative difference in the effect of shocks and norms in precursor limited counties. Column (4) reports the implied measure of adaptation in non-limited counties, and the differential effect in limited ones. 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 B9: Adaptation by Belief in Climate Change *Regulation*

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.507***	
	(0.046)	
x Low Belief	−0.397***	
	(0.063)	
x High Belief	0.483***	
	(0.118)	
Climate Norm	1.115***	0.392***
	(0.061)	(0.047)
x Low Belief	−0.344***	−0.053
	(0.085)	(0.068)
x High Belief	0.210**	0.273***
	(0.104)	(0.084)
All Controls	Yes	
Observations	5,139,523	
R^2	0.486	

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 the use of regulations on carbon emissions to combat 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.

Table B10: Adaptation by Political Leaning

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.325***	
	(0.047)	
x Democrat	0.558***	
	(0.100)	
Climate Norm	0.975***	0.349***
	(0.043)	(0.042)
x Democrat	0.302***	0.256***
	(0.085)	(0.071)
All Controls	Yes	
Observations	5,139,523	
R^2	0.484	

Notes: This table reports estimate of temperature shock and climate norm interacted with an indicator of whether the county voted Democrat in the 2008 presidential election. Column (1) follows Equation (13), with an additional interaction term for Democrat political preference depicting the differential effect of shocks and norms in these counties compared to baseline Republican voting counties. Similarly, column (2) reports the implied measure of adaptation for Republican leaning counties, with the differential effect in Democrat leaning counties noted by the interaction effect. 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.

Appendix C. Sources of Variation to Identify Climate Impacts

This appendix provides further elaboration of the two sources of variation used to identify β_C, the coefficient on $\bar{x}_{i\bar{p}}$ in Equation (13) in our empirical application. That estimating equation employs monitor-by-season-by-year fixed effects, a more flexible way to control for a number of unobserved time-varying factors in our ambient ozone setting.

Many least-squares estimators weight heterogeneity with factors that depend on group sizes and the within and between variances of explanatory variables. A univariate regression coefficient, for example, equals an average of coefficients in mutually exclusive (and demeaned) subsamples weighted by size and subsample x-variance (see Goodman-Bacon, 2018, footnote 11):

$$\begin{aligned}\hat{\beta} &= \frac{\sum_i (y_i - \bar{y})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2} \\ &= \frac{\sum_A (y_i - \bar{y})(x_i - \bar{x}) + \sum_B (y_i - \bar{y})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2} \\ &= \frac{n_A s_{xy}^A + n_B s_{xy}^B}{s_{xx}^2} \\ &= \frac{n_A s_{xx}^{2,A}}{s_{xx}^2} \hat{\beta}_A + \frac{n_B s_{xx}^{2,B}}{s_{xx}^2} \hat{\beta}_B, \end{aligned} \tag{C.1}$$

where A and B are mutually-exclusive subsamples, and as usual,

$$\hat{\beta}_j = \frac{s_{xy}^j}{s_{xx}^{2,j}}, \quad j = A, B. \tag{C.2}$$

A simpler version of the estimating equation in our empirical application – Equation (13) – focusing on the time-varying temperature norm, $\bar{x}_{i\bar{p}}$, is:

$$y_{it} = \beta_C \bar{x}_{i\bar{p}} + \phi_{is} + \epsilon_{it}, \tag{C.3}$$

where y represents ambient ozone concentrations, i monitor, t day, and s *season-of-the-sample*, and $\bar{p}$ refers to the aggregation of time – in our case, month – used to construct the climate normals from past observations – the 30-year monthly moving averages of temperature.

Applying a fixed-effects transformation in Equation (C.3), we obtain

$$(y_{it} - \bar{y}_j) = \beta_C (\bar{x}_{i\bar{p}} - \bar{x}_j) + (\epsilon_{it} - \bar{\epsilon}_j), \tag{C.4}$$

where j represents subsamples defined by the trio monitor-by-season-by-year is. Using an alternative notation, we can express the transformed equation as

$$\tilde{y}_{it} = \beta_C \tilde{x}_{i\bar{p}} + \tilde{\epsilon}_{it}. \tag{C.5}$$

By running OLS on the transformed equation, analogous to the decomposition in Equation (C.1), we can express $\hat{\beta}_C$ as:

$$\hat{\beta}_C = \sum_j \frac{n_j s^{2,j}_{\tilde{x}\tilde{x}}}{s^2_{\tilde{x}\tilde{x}}} \hat{\beta}_{C,j}. \tag{C.6}$$

Equation (C.6) helps us understand how we are leveraging both variation across months within the subsample defined by the monitor-by-season-by-year trio, and variation over time to identify β_C. Indeed, $\hat{\beta}_C$ incorporates variation in temperature norms within each subsample j, $s^{2,j}_{\tilde{x}\tilde{x}}$, and variation in how economic agents located around the same monitor respond to temperature norms in different points in time, which is captured by $\hat{\beta}_{C,j}$.

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