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ABSTRACT

A Unifying Approach to Measuring Climate Change Impacts and Adaptation*

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 exploiting simultaneously variation in weather and climatic changes, 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 prior studies' biases in the estimates of climate adaptation.

JEL Classification: Q53, Q54, C51

Keywords: climate change estimation methods, climate impacts, adaptation, local air pollution, ambient ozone concentration, "climate penalty" on ozone

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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 measuring 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 in the estimation of intergenerational mobility (e.g., Solon, 1992, 1999), and the properties of the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963), we develop a novel, unifying approach to measuring climate impacts and adaptation. The proposed approach is then applied to study the impact of climate change on ambient "bad" ozone concentration in U.S. counties over the period 1980-2013.

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

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

Our unifying approach overcomes these key challenges of the literature, and allows for the estimation of the short- and long-run impacts *simultaneously*, 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.[2] First, it recovers a measure of adaptation *directly* from the jointly estimated effects 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), it 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. Barreca et al. (2016), for example, compare the mortality effects of temperature extremes in the first and second half of the twentieth century to conclude that U.S. residents adapted to extreme heat. They point to the diffusion of air conditioning as a key driver of adaptation, but unobserved changes in consumers' preferences for new technologies may have also played a role. More recently, Auffhammer (2018*a*), Carleton et al. (2019), and Heutel, Miller and Molitor (forthcoming) allow for differences across locations in the current relationship between temperature and economic outcomes when dealing with adaptation. But again, unobserved differences in preferences, beliefs, and the experience with the local climate may affect adaptive behavior, potentially making it imprecise the assignment of a profile of temperature responses to another place solely based on observed attributes and the future weather distribution (e.g., Olmstead and Rhode, 2011; Bleakley and Hong, 2017).[3] Instead, we identify adaptation by

[2]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).

[3]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.

comparing how economic agents in the *same* location respond to weather shocks – which by definition limit opportunities to adapt – with their own response to climatic changes, which should incorporate adaptive behavior.

Our approach has two key elements. The first is the decomposition of meteorological variables into two components: long-run trends and weather shocks, the latter defined as deviations from those trends. This decomposition is meant to have economic content. It is likely that individuals and firms respond to information on climatic variation they have observed and processed over the years. In contrast, economic agents may be constrained to respond to weather shocks, by definition. Our measure of adaptation is the difference between those two responses by the *same* economic agents.[4] In our application, we take advantage of high-frequency data, and decompose temperature into a monthly moving average incorporating information from the past three decades, often referred to as climate normal, and a deviation from that lagged 30-year average.[5] Although our choice of the 30-year moving average follows from the climatology literature, in principle any method filtering weather data at some temporal frequency should work (e.g., Baxter and King, 1999; Christiano and Fitzgerald, 2003). The 30-year moving average is purposely lagged in our empirical framework to reflect all the information available to individuals and firms up to the year prior to the measurement of the outcome variables.[6] We then compare the jointly estimated short- and long-run effects to provide a measure of adaptive responses by economic agents.

The second essential element of our approach is indeed identifying responses to weather shocks and longer-term climatic changes in the *same* estimating equation. Our unifying

[4]Alternatively, Shrader (2020) leverages differences in responses to forecasts and realizations of weather to measure adaptation, requiring the assumption of forward-looking behavior. Because economic agents may be myopic or inattentive (e.g., Gabaix and Laibson, 2006; Reis, 2006*a*,*b*), we are agnostic about how agents process and use the information from the past. Also, 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).

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

[6]A graphical representation of our decomposition has been illustrated for Los Angeles county in 2013 in Figure 3, and over the entire sample period of 1980-2013 in Appendix A Figure A8.

approach bridges two strands of the climate-economy literature.[7] We exploit *simultaneously* meteorological variation to identify the causal impact of weather shocks on economic outcomes, and climatological variation to identify the causal effect of longer-term observed climatic changes. The meteorological variation exploited in the estimation is random changes in weather, similar to most of the literature relying on the fixed-effects approach. The climatological variation, however, is new and relies on within-season changes in monthly 30-year moving averages. Intuitively, it works as if the "climate experiment" randomly assigns the average June temperature to April or May in the same location, for example. We are able to leverage both sources of variation in the same estimating equation because of the properties of the Frisch-Waugh-Lovell theorem. The deseasonalization embedded in the fixed-effects approach is equivalent to the construction of weather shocks as deviations from long-run trends as a first step. Furthermore, there is no need to deseasonalize the outcome variable to identify the impact of those shocks (Lovell, 1963, Theorem 4.1, p.1001).[8] As a result, we do not need to include highly disaggregated time fixed effects in the final econometric model; thus, we are able to also exploit variation that evolves slowly over time to identify the impacts of longer-term climatic changes.

This paper proceeds as follows: Section II provides an overview of the two previous methodological approaches used to identify climate impacts, proposes our unifying approach and the resulting measure of adaptation, and explains the conceptual framework that we use to decompose meteorological variables into long-term trends and contemporaneous weather shocks. Section III provides a detailed background on ozone formation and its close relationship with weather, describes our data, and presents our empirical framework. Section IV reports our main findings, and examines the robustness of our estimates. Section V further explores aspects of heterogeneity. Finally, Section VI concludes.

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

[8]In contrast, inspired by Dell, Jones and Olken (2009, 2012, 2014), Burke and Emerick (2016) adopt a "long differences" approach to quantify longer-run adjustment to climate change that requires smoothing out the variables in both sides of the equation. In the methods section, we show that their approach is nested within ours.

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 suffers 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, *exclusive* of adaptation, making the transition to estimated climate effects nontrivial.[9] By using either the short- or long-run variation behind meteorological conditions to identifying climate impacts, those research designs trade off key assumptions. More recent literature (e.g., Dell, Jones and Olken, 2009, 2012, 2014; Burke and Emerick, 2016) 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:

$$y_i = \beta_{CS} x_i + (c_i + u_i) = \beta_{CS} x_i + v_i, \tag{1}$$

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

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

[9] Only in certain conditions weather variation exactly identifies the effects of climate (Hsiang, 2016).

$$y_{it} = \beta_{FE} x_{it} + c_i + \lambda_t + u_{it}, \tag{2}$$

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:

$$\bar{y}_i = \beta_{FE} \bar{x}_i + c_i + \bar{\lambda}_{it} + \bar{u}_i, \tag{3}$$

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

$$(y_{it} - \bar{y}_i) = \beta_{FE}(x_{it} - \bar{x}_i) + \theta_t + (u_{it} - \bar{u}_i), \tag{4}$$

where $\theta_t \equiv (\lambda_t - \bar{\lambda}_{it})$. 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 c_i terms cancelling out, $\hat{\beta}_{FE}$ now identifies the impact of meteorological, rather than climatological, phenomena.

Recently, focus has expanded from simply estimating climate impacts to estimating adaptation to climate change. Some authors have noted that β_{CS} identifies climate impacts *inclusive* of any adaptation, while β_{FE}, by its nature, identifies meteorological impacts which can be taken as an approximation of climate impacts *exclusive* of any adaptation (e.g., Dell, Jones and Olken, 2009, 2012, 2014; Burke and Emerick, 2016). 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, this approach faces two empirical challenges. First, to the extent that OVB impacts $\hat{\beta}_{CS}$ in the cross-sectional model, this will translate directly into bias in the estimate of climate adaptation. Second, even if an unbiased estimate of β_{CS} could be obtained, $\hat{\beta}_{CS}$ and $\hat{\beta}_{FE}$ arise from two different estimating equations. While OLS, equation by equation, allows us to easily test hypotheses about the coefficients within an equation, it does not provide a convenient way for testing hypotheses involving coefficients from different equations. Thus, in practice, we must resort to seemingly unrelated regression (SUR) models to explicitly test whether the measure of adaptation is statistically distinguishable from zero. Recall that a SUR system is a set of equations that has cross-equation error correlation, that is, the error terms in the regression equations are correlated. Also recall that SUR estimation usually amounts to feasible generalized least squares with a specific form of the variance-covariance matrix. Hence, further structural assumptions are needed for statistical inference of the measure of adaptation.

B. Our Unifying Approach

Our unifying approach nests both of these strands of the climate-economy literature in the *same* estimating equation. It simultaneously identifies both long-run climatological impacts and short-run 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; Burke and Emerick, 2016). Specifically, we begin by posing the ideal estimating equation, although infeasible:

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

Here, β_W would identify the effect of meteorological (weather) shocks, while β_C would identify the effect of changes in climatological trends. Unfortunately, β_C cannot be identified because $\bar{x}_i$ is perfectly collinear with c_i. We therefore propose the following feasible approximation of the ideal equation:

$$y_{it} = \beta_W(x_{it} - x_{id}) + \beta_C x_{id} + c_i + \lambda_t + u_{it}, \tag{6}$$

where d represents some longer time period over which climate trends would vary.[10] By

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

averaging each variable in equation (6) for each cross-sectional unit i over time, we obtain:

$$\bar{y}_i = \beta_W(\bar{x}_i - \bar{x}_i) + \beta_C\bar{x}_i + c_i + \bar{\lambda}_{ti} + \bar{u}_i = \beta_C\bar{x}_i + c_i + \bar{\lambda}_{ti} + \bar{u}_i, \tag{7}$$

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

$$(y_{it} - \bar{y}_i) = \beta_W(x_{it} - x_{id}) + \beta_C(x_{id} - \bar{x}_i) + \theta_t + (u_{it} - \bar{u}_i), \tag{8}$$

where, once again, $\theta_t \equiv (\lambda_t - \bar{\lambda}_{ti})$. Thus, 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. Observe that this measure leverages the behavioral responses of the *same* economic agents to both weather shocks and climatic changes. We do not need to extrapolate responses to weather realizations over time or space to account for adaptation, as it has been done in the literature (e.g., Deschenes and Greenstone, 2011; Barreca et al., 2016; Auffhammer, 2018*a*; Carleton et al., 2019; Heutel, Miller and Molitor, forthcoming). In addition, we do not have to assume forward-looking behavior in order to obtain a measure of adaptation, as in Shrader (2020). Our measure is agnostic about how economic agents process and use the information from the past. It does not matter whether agents are forward-looking, inattentive (e.g., Reis, 2006*a*,*b*), or myopic(e.g., Gabaix and Laibson, 2006), for example; our measure is informative either way.

Notice that because $(x_{id} - \bar{x}_i)$ in equation (8) varies slowly over time, we propose replacing θ_t with θ_s, where s is defined as a longer time frame relative to the temporal unit of observation t. For example, if t represents days, s could be a season of the year. This is for simplicity, model parsimony, and clarity in the exposition. In practice, researchers will be able to exploit variation under a much richer set of time fixed effects.[11] Additionally, observe that while $\hat{\beta}_C$ is identified from this within-season variation in long-run climate, $\hat{\beta}_W$ is identified using the short-run *deviations* from this longer-run value, $(x_{it} - x_{id})$. Constructing the regression model in this way attenuates the need to saturate the econometric specification with high-frequency time fixed effects.

In a panel data approach, we would usually include time fixed effects at the level of the temporal unit of analysis to deseasonalize the time series, and control for observed and unobserved macroeconomic factors, before uncovering the causal effects of interest. From the Frisch-Waugh-Lovell theorem, however, we know that the deseasonalization embedded in the highly-saturated model is equivalent to the use of deviations in the final regression model (Frisch and Waugh, 1933; Lovell, 1963). Moreover, although equation (8) is instructive regarding variable decomposition, we do not need to transform the outcome variable to identify β_W (Lovell, 1963, Theorem 4.1, p.1001), which preserves all the variation in y_{it} for the estimation of all parameters of interest. Therefore, by decomposing x_{it} into its long-run and short-run components, we are also able to exploit variation that evolves slowly over time by including only lower-frequency time fixed effects in θ_s. Using seasonal rather than monthly or daily fixed effect allows us to take advantage of how climate varies across different months or days within a season and location. Intuitively, we exploit how economic agents respond when April temperature in a particular area is assigned the May temperature, for instance. In fact, several researchers have pointed out that with climate change, springs could start earlier and falls could last longer in some locations (e.g., Zhang and Wang, 2016).

Alternative recent advancements in the literature, termed "hybrid approaches" by Kolstad and Moore (2020), have similarly aimed to address the issues inherent in either the cross-sectional or fixed-effects approaches. The long-differences method (Burke and Emerick, 2016) is one such a hybrid that addresses the OVB issues in the cross-sectional approach

[11] Later, in the application of our unifying approach to the impact of climate change on ambient ozone concentration, we will demonstrate this point by exploiting a much more granular set of fixed effects in the econometric specification.

while still identifying long-run climatological impacts rather than short-run effects of meteorological shocks. This approach is, in essence, a special case of our unifying approach in which both the dependent and independent variables are similarly transformed to reflect long-run changes. As in our approach, the long-differences method estimates the impact of long-run climate variation in x_{id} on an outcome variable, although this variable now also only varies at a lower temporal frequency by construction, and should thus be thought of as y_{id} rather than y_{it}. Again, the reason why we do not transform the dependent variable in the same way in our approach is to allow for the identification of the short-term weather effect in the same estimating equation. That is feasible because the Frisch-Waugh-Lovell theorem does not require the transformation of the dependent variable in order to identify that coefficient of interest (Lovell, 1963, Theorem 4.1, p.1001). Empirically, the long-differences approach recasts the fixed-effects approach, equation (2), using two long time periods, a and b, each spanning n years, with some number of gap years, g, between the midpoints of both periods such that all years in the final sample are exclusive to one period.[12] For each of these two periods a cross-sectional model is constructed as in equation (1):

$$\bar{y}_{ia} = \beta_a \bar{x}_{ia} + \bar{\lambda}_a + (c_i + \bar{u}_{ia}), \tag{9a}$$

$$\bar{y}_{ib} = \beta_b \bar{x}_{ib} + \bar{\lambda}_b + (c_i + \bar{u}_{ib}), \tag{9b}$$

where $\bar{y}_{ia} \equiv 1/n \sum_{t \in a} y_{it}$, the same holds for $\bar{y}_{ib}$, and the other variables are defined similarly. Taking the "long difference" (LD) of equation (9a) from (9b), we obtain:

$$(\bar{y}_{ib} - \bar{y}_{ia}) = \beta_{LD}(\bar{x}_{ib} - \bar{x}_{ia}) + (\bar{\lambda}_b - \bar{\lambda}_a) + (\bar{u}_{ib} - \bar{u}_{ia}). \tag{10}$$

Note that since a and b are g years separated, $\bar{x}_{ib} - \bar{x}_{ia}$ reflects the long-run variation in x_i, and can be rewritten as $x_{id} - \bar{x}_i$, just as in equation (6), and all other variables can

[12] For example, Burke and Emerick (2016) use the years 1978-1982 and 1998-2002 in constructing their two time periods, such that $n = 5$ and $g = 20$.

be rewritten similarly. Additionally, as the long-differences approach makes use of only two periods, it is algebraically the same as a two-period fixed-effects model, and equation (10) can be rewritten to highlight the source of variation that allows for the identification of β_{LD}:

$$(y_{id} - \bar{y}_i) = \beta_{LD}(x_{id} - \bar{x}_i) + \theta_d + (u_{id} - \bar{u}_i), \tag{11}$$

where $\theta_d \equiv (\lambda_d - \bar{\lambda}_{id})$. Thus, in equation (11) we can observe that $\hat{\beta}_{LD}$ is identified from climatic changes in the same way as $\hat{\beta}_C$ in equation (8).

C. Decomposition of Meteorological Variables: Climate Trends 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, x_{id}, and its short-run deviation from this value, $(x_{it} - x_{id})$. A similar idea has been used in macroeconomics to measure business cycles since the seminal contribution of Bums and Mitchell (1946),[13] and in the literature of intergenerational mobility following Solon's (1992) seminal work. 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. Importantly, the averaging is not needed for sons income, the dependent variable (Lovell, 1963, Theorem 4.1, p.1001). We proceed in a similar way: we decompose only meteorological variables, not the main economic outcomes of interest. Illustrating the decomposition with temperature ($Temp$), we can express it as:

$$Temp = Temp^C + Temp^W, \tag{12}$$

where $Temp^C$ represents climate patterns, and $Temp^W$ ($\equiv Temp - Temp^C$) deviations from those long-run patterns. Again, this decomposition highlights the two sources of variation

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

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. Now, 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*.

Two types of variation are often associated with a changing climate: changes in averages, and changes in the frequency of extreme weather events (IPCC, 2013). For simplicity, and to keep the comparison with prior approaches as simple as possible, our temperature decomposition focuses on increases in averages, not on variability. In fact, in the following section we show that our weather data, comprised of the comprehensive set of national weather monitors, suggests a gradual increase in average temperature, but evidence 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 trends take into account the frequency and intensity of daily temperature extremes. 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.

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. Forward-looking agents, as considered by Shrader (2020), will respond optimally to all information at hand when deciding the degree of adaptation. 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.

III. Empirical Application: Climate Impacts on Ambient Ozone

We apply our novel, unifying approach to measure climate impacts on ambient ozone concentration, and adaptation, and examine the heterogeneity in adaptive behavior. The application is particularly ideal for four reasons. First, ozone is not emitted directly into the air, but rather rapidly formed by Leontief-like chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight and warm temperatures. Hence, meteorological conditions do matter in determining surface ozone levels, and climate change may increase ozone concentration in the near future (e.g., Jacob and Winner, 2009). Furthermore, ozone is rapidly destroyed during the night; thus, correlation between ambient concentrations across two consecutive days is limited. Second, nationwide high-frequency data on ambient ozone and meteorological conditions are publicly available for a long period of time in the United States: we use daily measurements for the typical ozone season from 1980-2013. Third, our "climate experiment" is quite simple to understand in the ozone context, as 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). Fourth, 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.[14]

In this section, we present the data used in our analysis – we utilize information from two major sources of data[15] – and the empirical strategy to carry out the estimation of the impacts of weather shocks and longer-term climatic changes on ambient ozone concentration.

A. Data

Weather Data — For meteorological data, we use daily measurements of maximum temperature as well as total precipitation from the National Oceanic and Atmospheric Administrations's Global Historical Climatology Network databse (NOAA, 2014). This dataset provides detailed weather measurements at over 20,000 weather stations across the country for the period 1950-2013. Figure 1 presents the yearly temperature fluctuations and overall climate trend in the US as measured by these monitors, relative to a 1950-1979 baseline average temperature, while Figure A1, in Appendix A, illustrates the geographical location of the complete sample of weather stations from 1950-2013. Figure 2, by comparison, depicts the variation and trend of our decomposed temperature variables, $Temp^C$ and $Temp^W$, between 1980 and 2013 for the comprehensive set of national weather monitors, indicating that while average temperature has been gradually increasing since the 1980's, temperature variability has remained relatively stable.[16] 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.[17] 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.

[14]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).

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

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

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

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.[18] 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. 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 temperature trend also seems to be affecting it, although perhaps to a lesser extent. We leverage both relationships in the empirical framework we now describe.

B. 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

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

in day t of month m and year y, and decompose it into $Temp^C$ and $Temp^W$ as in Section II. We define $Temp^C$ as the 30-year monthly moving average (MA) of past temperatures.[19] To make this variable part of the information set held by economic agents at the time that the outcome of interest is measured, we lag it by one year. 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 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.[20] We use monthly MAs because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed, meteorologists on TV and social media often talk about how a month has been the coldest or warmest in the past 10, 20, or 30 years, but not how a particular day of the year has deviated from the trend.[21] $Temp^W$ represents weather shocks and is defined as the deviation of the daily temperature from the lagged 30-year monthly MA. By definition, these shocks are revealed to economic agents only at the time ambient ozone is being measured. Thus, in this case agents may have had only a few hours to adjust, limiting their ability to respond to such unexpected temperatures.[22] Figure 3 provides an illustrative example of our preferred

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

[20]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.

[21]As another robustness check, we use *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.

[22]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

decomposition in Panel A, compared to a traditional fixed-effect decomposition in Panel B, using data for Los Angeles in 2013.[23]

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:

$$Ozone_{it} = \beta_W Temp^W_{it} + \beta_C Temp^C_{it} + X'_{it}\gamma + Z_i\lambda_{sy} + \eta_i + \phi_{rsy} + \epsilon_{it}, \tag{13}$$

where i represents an ozone monitor located in NOAA climate region r, and t stands for day, s for season (Spring or Summer), and y for 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.[24] The dependent variable $Ozone$ captures daily maximum ambient ozone concentration. $Temp$'s represent the two components of the decomposition proposed for meteorological variables.[25] The matrix of additional control covariates X contains a similar decomposition of precipitation[26] as well as a binary indicator variable for whether a county is out of compliance with the Clean Air Act ambient ozone standard.[27] Z represents time-invariant covariates (latitude and longitude of ozone monitors), which are interacted with season-by-year fixed effects in our econometric specification to control for differential trends associated with topographical and other geographical features of a location, η represents monitor fixed effects, ϕ NOAA climate region-by-season-by-year fixed effects,[28] and ϵ an

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.

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

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

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

[26]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.

[27]The Clean Air Act nonattainment county designation is a binary status for counties not complying with the National Ambient Air Quality Standards (NAAQS) for ambient ozone. This variable is lagged by three years because EPA gives heavy-emitters at least three years to comply with ozone NAAQS (USEPA, 2004, p.23954).

[28]Recall that once we have constructed weather shocks appropriately, the Frisch-Waugh-Lovell theorem allows us to identify the effects of those shocks without deseasonalizing the dependent variable and without highly saturating the econometric model with time fixed effects. Notwithstanding, in the robustness checks,

idiosyncratic term. In all estimations, standard errors are clustered at the county level.[29]

As should be clear by now, we exploit plausibly random, monthly variation in climate normals, and daily variation in weather within a season to estimate the impact of climate change on ambient ozone concentration. Identification of the effect of weather shocks relies on monitor-level daily variation in the deviation of meteorological variables from *lagged* climate normals after controlling non-parametrically for regional shocks to ozone concentration at the season-by-year level. For instance, let us consider the variation of May 1st, 1982 relative to the Spring (April-June) of 1982 in the Northeast region. The question we ask is the following: what happens to ozone concentration in a May 1982 day when the deviation of temperature from the May 1981 climate normal is 1°C above the average daily temperature shock in the Northeast in the Spring (April-June) of 1982? Conditional on business-as-usual ozone precursor emissions, a higher temperature should lead to more ozone formation and, consequently, higher ozone concentration.[30]

Identification of the effect of climatic changes on ambient ozone levels relies on plausibly random, monitor-level monthly variation in *lagged* 30-year MAs of meteorological variables after controlling non-parametrically for regional shocks to ozone concentration at the season-by-year level. As an example, let us consider variation of *lagged* 30-year MA temperature in May 1982 relative to the Spring (April-June) of 1982 in the Northeast region. Again, the question we ask is the following: what happens to ozone concentration in a May 1982 day when the normal temperature around the monitor in May 1981 is 1°C warmer than the average of all 30-year monthly MAs of temperature in the Northeast in the Spring (April-June) of 1981? If economic agents pursued full adaptive behavior, the unexpected increase in normal temperature would lead to reductions in ozone precursor emissions to avoid an

we provide estimates from a number of less parsimonious specifications with a much richer set of time fixed effects, and not surprisingly the results are remarkably similar to our main findings.

[29] There may be a concern that our temperature shocks and trends are both constructed, so they could be considered generated regressors. Estimating bootstrapped standard errors, we find little variation relative to the county-level clustered standard errors, discussed further in the robustness checks. Given such a small variation, we opted to report the regular clustered standard errors.

[30] Robustness checks with richer sets of location by time fixed effects also control for a variety of time-varying unobserved heterogeneity in emissions. Again, the results are remarkably similar to our main findings.

increase in ozone concentration of identical magnitude of the weather shock effect in the same month of the following year. In other words, agents would respond to "permanent" changes in temperature by adjusting their behavior or production processes to offset that increase in normal temperature. Unlike weather shocks, which influence ozone formation by triggering chemical reactions conditional on a level of ozone precursor emissions, changes in the 30-year MA affect the level of emissions.

To understand better the identification strategy for the climate effects, let us compare it to the ideal experiment. In that experiment, we could have a glass dome covering each county, assign climate to each of them randomly and inform residents that the assigned climate is permanent, and collect information on a number of economic outcomes after some time. To approximate such an ideal setting, we use plausibly random, within-season variation in the *lagged* 30-year moving averages. Agents know the normal temperature in the spring for having observed it in the last thirty years, but it turns out that the substitution of last year's average March temperature in the 30-year MA for the average March temperature three decades ago could generate some random variation in March climate. March could be randomly assigned April or May temperature, for instance. Likewise, April could experience March temperature randomly. Because individuals and firms have observed the temperature in the last three decades, they should interpret such changes as permanent, and update their climate information. As a result, they may make adjustments to cope with those changes, leading to adaptive (or intensifying) behavior.

Measuring Adaptation — Once we credibly estimate the impact of the two components of temperature – shocks and within-season changes in long-run trends – on ambient ozone concentration, we uncover our measure of adaptation. The average adaptation across all counties 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. As explained before, agents would react to "permanent" increases in temperature by reducing ozone precursor emissions to offset potential increases in ozone concentration.

In our preferred econometric specification, behavioral responses are allowed to occur only in the year after the change in temperature trend 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 (3) of Table 1 presents the effects on ambient ozone of the two components of observed temperature: climate, represented by the *lagged* 30-year monthly MA, and weather shock, represented by the deviation from that long-run trend.[31] Although they are uncovered by estimating equation (13), columns (1) and (2) benchmark them against effects that would have been found if one had exploited either only the cross-sectional (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005) or only the longitudinal (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) structure of the data.

Column (1) reports results from a cross-sectional estimation of daily maximum ozone concentration on daily maximum temperature around each monitor, averaged over the entire

[31] 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 B4.

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 1.02 parts per billion (ppb) in ozone concentration, approximately. Column (2) reports the effect of temperature on ozone identified by exploiting within-monitor daily variation in maximum temperature after controlling for climate region-by-month-by-year fixed effects. The coefficient indicates that a 1°C increase in maximum temperature leads to a 1.72ppb increase in maximum ambient ozone concentration. When we decompose daily maximum temperature into our two components in column (3), as expected the effect on ambient ozone changes for the lagged 30-year MA, relative to the column (1) result, but is statistically the same as column (2) for the effect of weather shocks. A 1°C shock increases ozone concentration by 1.68ppb, and a 1°C change in trends in the same month of the previous year increases ozone concentration by 1.23ppb. Therefore, by including the two components of temperature – the lagged 30-year MA and deviations from it – the impact of a 1°C change in long-run maximum temperature increases roughly 20 percent when compared to cross-sectional estimate.

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 roughly equivalent to the use of deviations from 30-year trends in our regression model.

Even with the larger estimate of the impact of rises in long-term temperature on ambient ozone concentrations, our estimates imply a so-called "climate penalty" on ozone on the lower end of the ranges found in the literature. Indeed, Jacob and Winner (2009), in their review of the effects of climate change on air quality, find that climate change alone may lead to a rise in summertime surface ozone concentrations by 1-10 ppb – a wide interval partly driven by the different regional focuses of the studies they review. The U.S. EPA, in its 2009 Interim Assessment, claims that "*the amount of increase in summertime average ... O3 concentrations across all the modeling studies tends to fall in the range 2-8 ppb*" (USEPA, 2009, p.25). Combining our estimates in column (3) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5), one would also predict an increase in ambient ozone concentrations by the mid and the end of the century in the range of 2-5.9 ppb, approximately. To be clear, "climate penalty" in our setting is the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation, as it will be discussed below. If one would wrongly use the responses to temperature shocks as the penalty, which is *exclusive* of adaptation, the range would be 2.7-8 ppb, a nontrivial shift to the right. In fact, this may be one of the reasons why our estimate of the penalty is on the lower ranges of the values produced by simulation studies (again, for a review, see Jacob and Winner, 2009); they usually do not take into account behavioral responses. To put those values in perspective, each of the last few times EPA revised the air quality standards for ambient ozone, they decreased it by 5ppb.

B. Measuring Adaptation to Climate Change

Our results indicate that temperature shocks have a larger impact on ozone levels compared to long-term temperature trends. 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; Burke and Emerick, 2016). Given the bias of the cross-sectional approach, by comparing the impact of long-run temperature on ozone concentration in column (1) of Table 1 with the effect of a temperature shock in column (2), adaptation would be overestimated – approximately 0.69ppb. Our measure of adaptation – also a comparison between the impact of the long-run temperature (lagged 30-year MA) and the effect of the temperature shock (deviation from the MA) – is 35 percent smaller: 0.45ppb. Notwithstanding, this suggests that economic agents might be adapting to climate change.

If we ignored such adaptive responses by economic agents, then we would be overestimating the "climate penalty" on ozone by over 36 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 business-as-usual scenario (RCP 8.5), we would overestimate the climate penalty by 0.72ppb by mid century, and 2.15ppb by the end of the century. For comparison, recall that each of the last few times EPA revised the air quality standards for ambient ozone, they decreased it by 5ppb.

C. Robustness Checks

Measurement Error & Agents' Beliefs — A concern regarding our decomposition of meteorological variables in equation (12) might be measurement error. Because both components are intrinsically unobserved, we define the long-run trend 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 longitudinal 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" – three-decade averages of meteorological variables including temperature and precipitation[32] – are close to the "optimal" long-run trends. The improvements from reducing measurement error might be offset by the panel-driven attenuation bias between 20- and 30-year time windows.

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

[32] "*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).

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 trend, 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 trend 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.[33] 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.

Controlling for Precursor Emissions — As discussed previously in Section III, ozone is formed from precursor pollutants – volatile organic compounds (VOCs) and oxides of nitrogen (NOx) – in the presence of sunlight and heat. It may be of concern, then, that the levels of such precursor pollutants are not explicitly included as regressors in our main specification. Data on these precursors, especially VOCs, however, is unfortunately limited. We thus investigate this concern via two approaches: Table 4 presents the results of our main specification when using a richer set of fixed effects to account for systematic variation in local precursor levels over time; while Table 5 presents the results of specifications using the restricted sample for which precursor data exists.

The ideal experiment would be to have two locations with the same levels of ozone precursors, but facing different changes in temperature. If precursor levels are different, but approximately unchanging over time, our standard monitor fixed-effects approach would mimic this ideal setting. Additionally, our region-by-season-by-year fixed effects maintain this ideal setting while allowing precursor levels to vary arbitrarily across NOAA climate regions, seasons, and years as long as levels are similar for monitors each day within a region in a given season and year. Precursor emissions may, however, vary at a more localized level, whether it be seasonally, by day of the week, or trending over time. Table 4 presents the results of four additional specifications in which we enrich our standard set of fixed effects to account for potential localized variation in precursor levels. Column (1) allows

[33] Although the recovered coefficients of temperature shock, climate trend, 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).

the monitor fixed effect to vary by season, column (2) allows the monitor fixed effect to vary by weekday/weekend, column (3) allows the monitor fixed effect to vary linearly over time, and column (4) allows for all three. In all cases the magnitude of the change in our coefficients of interest is economically negligible and statistically insignificant, providing reassuring evidence in favor of our preferred parsimonious specification expressed in equation (13).

As an alternative approach to implementing further fixed effects, 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.[34] Column (1) of Table 5 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, for the effects of temperature shock, climate trend, and the resulting measure of adaptation. The magnitude is probably larger because VOCs may be monitored in places with likely higher concentrations. In column (2) we interact the indicators for VOC- and NOx-limited counties with our other regressors to both investigate whether their inclusion impacts our main coefficients of interest, and 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.[35] Both main coefficients, and the resulting measure of adaptation, remain unchanged for non-limited counties, while the difference from these values is statistically indistinguishable from zero in VOC-limited counties. In NOx-limited counties the effects of both temperature shock and climate trend are approximately 27 percent lower and significant, but the resulting level of adaptation is statistically indifferent from other counties. Taken together, these pieces of evidence provide not only further support

[34] 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.1.

[35] Table B1 in Appendix B.1 combines both of these approaches, using this VOC/NOx-interacted specification with the richer set of fixed effects employed in Table 4. Results are qualitatively similar.

for our preferred parsimonious econometric specification expressed in equation (13), but also 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 on ambient ozone concentration decline.

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 B2, B3, and B4. Specifically, Table B2 examines the sensitivity of our results to our algorithm for matching ozone and temperature monitoring stations. Table B3 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 B4 contains three additional robustness checks: implementing a *daily* MA rather than *monthly*, purposefully aggregating our data to the monthly level to simulate our methodology with lower frequency data, and controlling for wind speed and sunlight with the subset of data for which that information is available. Across all of these models results remain qualitatively similar to our central findings. Finally, Appendix B.1 Table B5 provides bootstrapped standard errors for our main estimates, and shows that they vary from -5 percent to +11 percent, relative to the standard errors clustered at the county level.

V. Exploring Heterogeneity

Earlier studies have inferred adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks, then assessing climate damages through shifts in the future weather distribution. We have pointed out the shortcomings of that approach in the spirit of the Lucas Critique (Lucas, 1976). Importantly, once we have recovered a measure of adaptation from responses to weather shocks and longer-term climatic changes by the *same* economic agents, then we are able to explore the heterogeneity in their degree of adaptation. The following subsections examine heterogeneity in adaptive behavior over time and space in Figure 4 and Table 6, respectively, while Appendix B.2 Table B6 explores heterogeneous effects of temperature in a nonlinear fashion.

A. *Results by Decade*

Panel A of Figure 4 illustrates the evolution of temperature's impact 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 trend on ozone formation are decreasing over time, likely due – at least in part – to regulations (see, for example, our companion paper Bento, Mookerjee and Severnini, 2020). The early 1980's, which marked the initial phases of ozone monitoring and awareness, and when the average pollution levels were also higher, exhibit the largest impacts of climate on ambient ozone, as well as the largest degree of adaptation. In fact, in the beginning of the sample period adaptation is at approximately 0.65ppb, but then appears to level off at slightly over 0.40ppb by 1990, and remains in that range through 2013.[36]

Notice in Figure 4 that responses to temperature shocks a decade ahead approximately mirror responses to longer-term climatic changes a decade before. Nevertheless, the difference between those responses at any point in time since the 1990's has been relatively stable. This suggests that there may be limits to adaptation unless new technologies are able to affect atmosphere composition, such as in the case of geoengineering (e.g., Heutel, Moreno-Cruz and Ricke, 2016; Flegal et al., 2019). It also suggests that adaptation opportunities for reducing ambient ozone may have shrunk or become more costly, and highlights the risks of extrapolating flexibly-estimated weather responses over time to address adaptation (Olmstead and Rhode, 2011; Bleakley and Hong, 2017), analogous to the Lucas Critique (Lucas, 1976).

[36]Table B7 in Appendix B.2 reports similar results to Figure 4 in tabular format, segmenting the sample into only three time periods for brevity.

B. Adaptation by Beliefs in Climate Change Across Counties

Using the results of a 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 6 presents the results of our preferred specification when interacting indicator variables for high- and low-belief counties with our temperature variables in column (1). The implied measure of adaptation is presented 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 trend. High-belief counties, by comparison, observe approximately 23 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 39 percent lower in low-belief counties than median ones, while this effect is statistically similar but of opposite sign for high-belief counties.[37] 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 novel, unifying approach to measuring climate change impacts 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

[37]Table B8 in Appendix B.2 conducts a similar analysis, separating counties by their belief in the use of regulation to combat climate change, while Table B9 in Appendix B.2 instead splits the sample into two groups based on whether they leaned Republican or Democrat in the 2008 presidential election using data from MIT (2018). Results in Table B8 are qualitatively similar to Table 6, while the results in Table B9 paint a similar picture under the assumption that belief or dis-belief in climate change approximately maps to Democratic or Republican political affiliation. Table A4 in Appendix A provides summary statistics of basic characteristics for the three sets of counties used in Table 6. High-belief counties tend to be more populous, better educated, and richer than low-belief ones.

– 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 in long-run trends and 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.

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 same fixed-effects model; hence, less susceptible to omitted variable biases. In addition, it compares the responses of the same economic agents to both weather shocks and climatic changes, overcoming the challenges of identifying adaptation by comparing the profiles of weather responses across time and space (e.g., Deschenes and Greenstone, 2011; Barreca et al., 2016; Auffhammer, 2018*a*; Carleton et al., 2019; Heutel, Miller and Molitor, forthcoming), which requires that preferences be constant across those dimensions. In other words, our strategy to identifying adaptation does not require the imprecise assignment of a profile of temperature responses to other locations solely based on observed attributes and the future weather distribution, as pointed out by Olmstead and Rhode (2011) and Bleakley and Hong (2017).

We applied our unifying approach to study the impact of climate change on ambient "bad" ozone in U.S. counties over the period 1980-2013. Others have relied on atmospheric-sciences simulation models to study the so-called "climate penalty" on ozone (see a review in Jacob and Winner, 2009). By ignoring the adaptive behavior of economic agents, they may have substantially overestimated the magnitude of this penalty. Based on our central estimates, we suspect this can be as large as 36 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.[38] Indeed, in a companion paper (Adler et al., 2020) we examine the role of this "climate penalty" in partially undoing the benefits of the Clean Air Act Amendments, implying that any future discussions related to the tightening of ambient ozone standards should pay attention to the magnitude of this penalty.

When considering the impacts of climate change on air pollution, the application of our unifying methodology led to three main findings. *First*, a changing climate appears to be affecting ambient ozone concentrations in two ways. A 1°C shock in temperature increases ozone levels by 1.68 parts per billion (ppb) on average, which is expectedly what would have been found in the standard fixed-effects approach. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.23ppb, which is 20 percent higher than what would have been found in the standard cross-sectional approach.

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 0.45ppb, 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 36 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 0.72ppb by mid century, and 2.15ppb by the end of the century. To put these values in perspective, the last few times EPA revised

[38] 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).

the air quality standards for ambient ozone, they have decreased it by 5ppb. These findings were robust to a wide variety of specification tests and sample restrictions accounting, for instance, for measurement error in climate variables, the timing of adaptation, the production function of ozone, and the potential non-random siting of ozone monitors.

Third, we provided evidence of nontrivial heterogeneity in the degree of adaptation across time and space, which highlights the potential biases of existing approaches in assigning 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 higher degree of adaptation in the 1980s relative to the following decades, but a similar magnitude for the estimates of adaptation in the 1990s and 2000s. This suggests that adaptation opportunities in the context of ambient ozone might be shrinking or becoming more costly. 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 the 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 trends could reflect changes over a number of years or decades.

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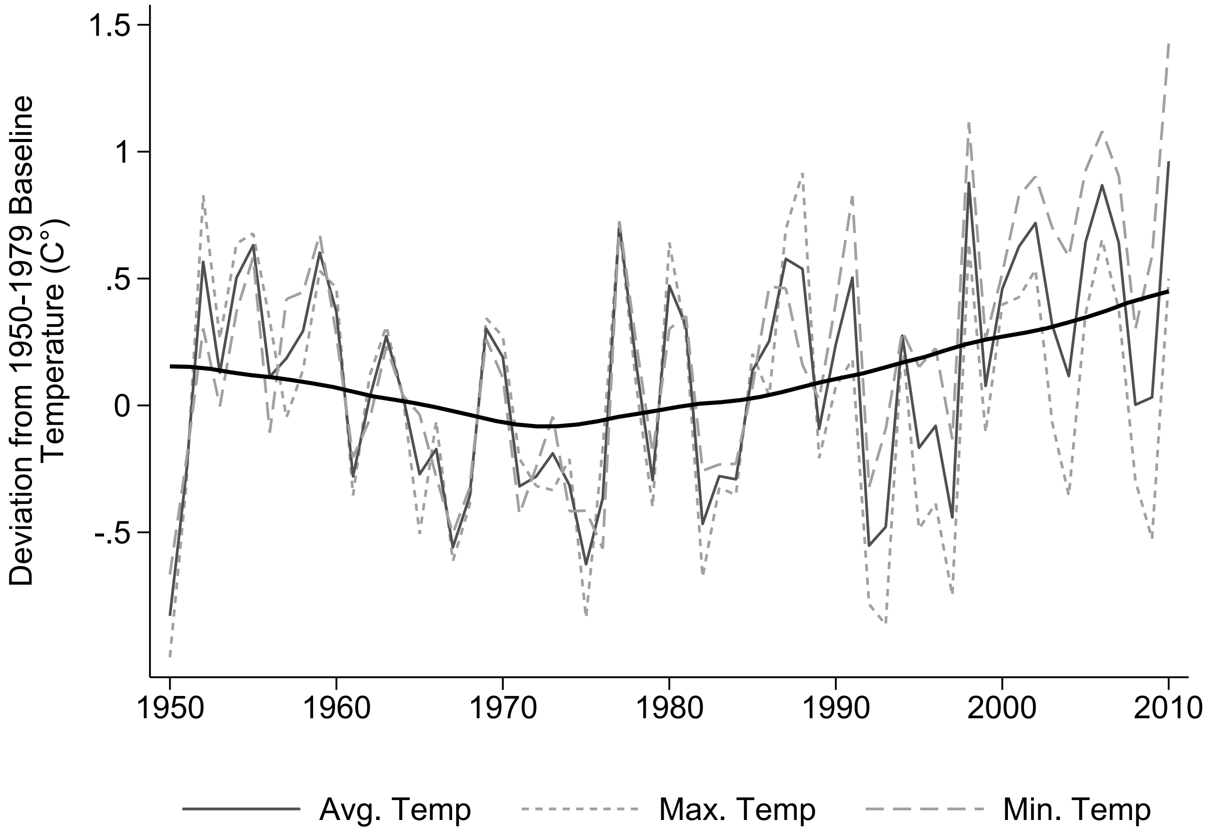
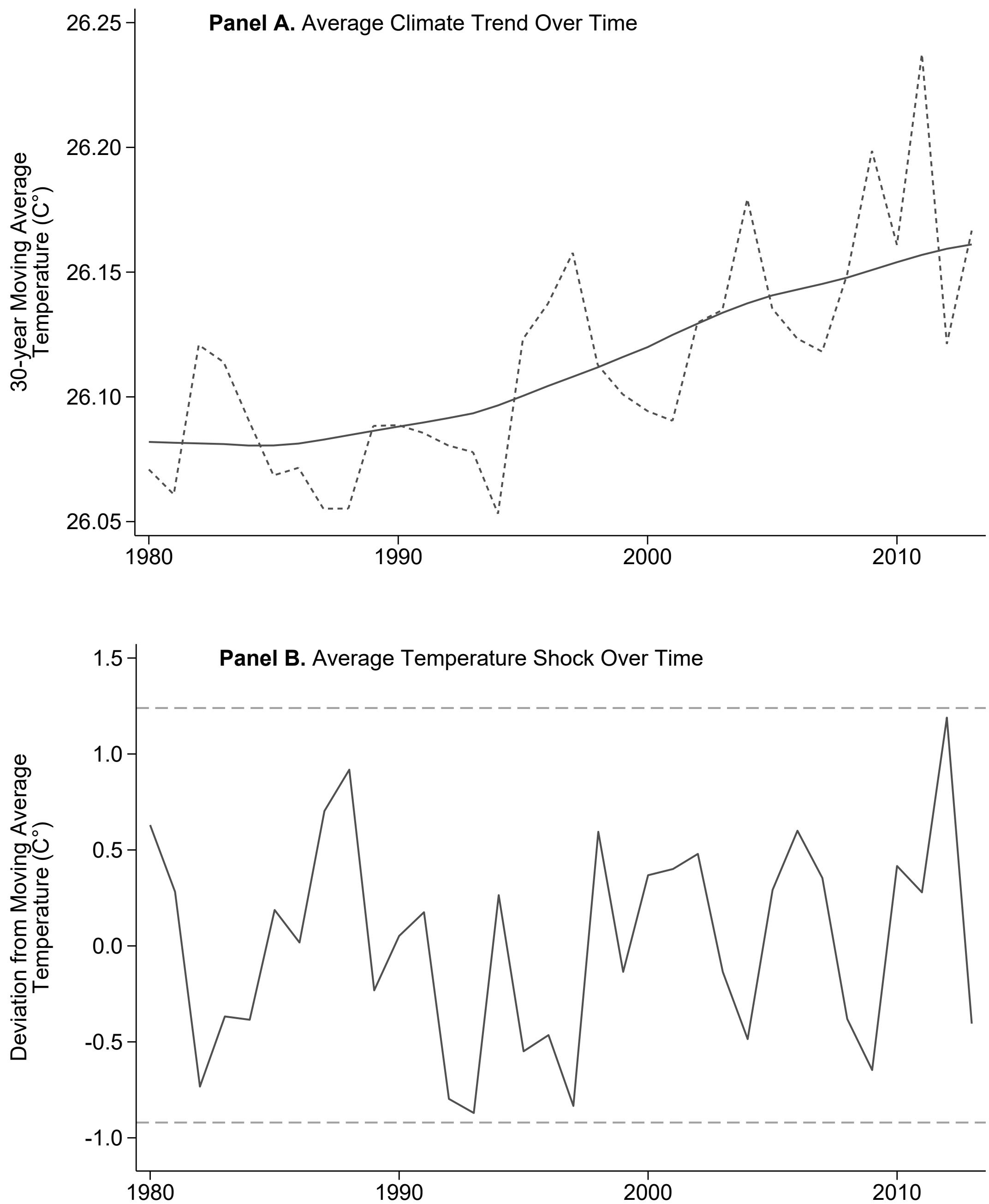
Figure 1: Temperature Relative to Baseline (1950-1979)



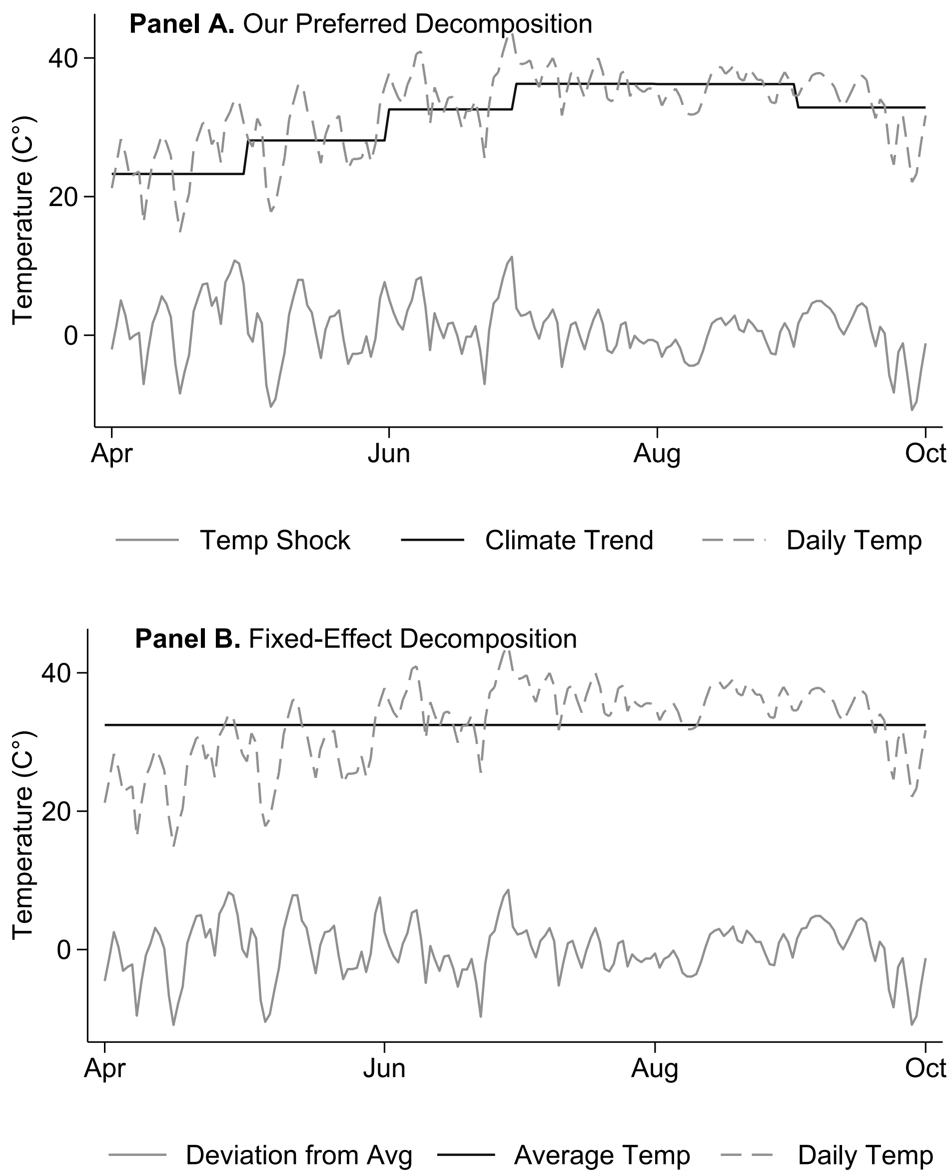
Notes: This figure depicts annual temperature fluctuations and the overall climate trend in the US relative to a 1950-1979 baseline average. The baseline and the yearly deviations from it are constructed from a balanced panel of weather stations across the US from 1950 to 2013. The 1950-1979 baseline represents, generally speaking, the pre-climate change awareness era. The climate trend 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 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 2: Climate Trends and Shocks



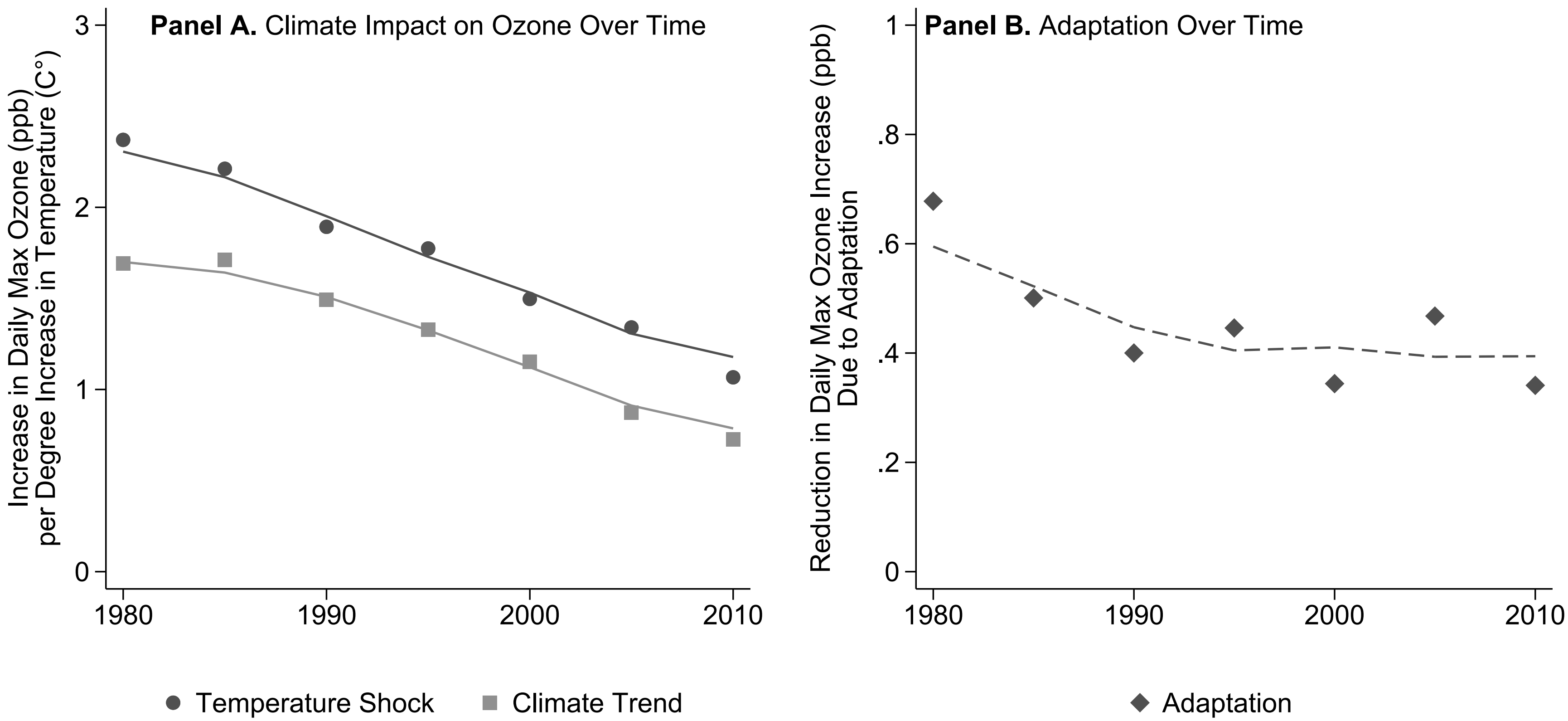
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate trend and temperature shock components. The climate trend (Panel A) and temperature shocks (Panel B) are constructed from a complete, unbalanced panel of weather stations across the US from 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 Trend 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 trends 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 3: Decomposition of Temperature Trends & 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 Trend 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 trends. 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 Trend 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 4: Climate Impacts and Adaptation Over Time in the Context of Ambient Ozone Concentration



Notes: This figure displays the impacts of temperature rises on ambient ozone concentrations over time in the US, as well as the implied measures of adaptation. Splitting the main sample into 5-year periods (e.g., 1980-1984, 1985-1989, etc.), Panel A depicts the estimated coefficients on the Climate Trend 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 from the differences between the estimated coefficients associated with shocks and trends. Recall that the Climate Trend 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 derived 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)		
	Cross-Section	Fixed-Effects	Unifying
	(1)	(2)	(3)
Average Max Temperature	1.025***		
	(0.095)		
Max Temperature		1.718***	
		(0.054)	
Temperature Shock			1.677***
			(0.059)
Climate Trend			1.229***
			(0.055)
Implied Adaptation		0.693***	0.448***
		(0.240)	(0.037)
Non-Attainment Control	Yes	Yes	Yes
Precipitation Controls	Yes	Yes	Yes
Latitude & Longitude	Yes		
Fixed Effects:			
Climate Region	Yes		
Month-by-Year		Yes	
Monitor		Yes	Yes
Season-Year x Latitude		Yes	Yes
Season-Year x Longitude		Yes	Yes
Seasdon-Year-Region		Yes	Yes
Observations	2,514	4,924,099	4,923,932
R^2	0.258	0.435	0.423

Notes: This table reports the weather and climate impacts on ambient ozone concentrations, estimated by different methodologies. Column (1) 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. 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. In Column (3), we decompose daily maximum temperature into climate trends and weather shocks, and exploit variation in both components in the same estimating equation – our Equation 13. These are the estimates of our unifying approach, which represents climate trends as 30-year moving averages, lagged by 1 year to allow for economic agents to potentially adapt, and weather shocks by deviations from the trends. Combining our estimates in column (3) with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017) under the business-as-usual scenario (RCP 8.5) – 1.6°C temperature increase by 2050, and 4.8°C by 2100 – ambient ozone concentrations would rise by 2 and 5.9ppb, respectively. This should be the so-called "climate penalty" – the response of economic agents to longer-term climatic changes, which is *inclusive* of adaptation. Wrongly using the response to temperature shocks as the penalty, which is *exclusive* of adaptation, those numbers would be larger: 2.7 and 8ppb, respectively. For a comparison, modelling studies find increases in summertime ambient ozone concentrations by 1-10 ppb (for a review, see Jacob and Winner, 2009). Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 2: Addressing Measurement Error with Alternative Lengths for the Climate Trends

	Daily Max Ozone Levels (ppb)			
	3-yr MA	5-yr MA	10-yr MA	20-yr MA
	(1)	(2)	(3)	(4)
Temperature Shock	1.680***	1.678***	1.674***	1.674***
	(0.061)	(0.061)	(0.060)	(0.060)
Climate Trend	1.209***	1.220***	1.234***	1.236***
	(0.052)	(0.053)	(0.055)	(0.055)
Implied Adaptation	0.472***	0.458***	0.440***	0.438***
	(0.037)	(0.037)	(0.038)	(0.037)
All Controls	Yes	Yes	Yes	Yes
Observations	4,923,932	4,923,932	4,923,932	4,923,932
R^2	0.422	0.422	0.422	0.423

Notes: This table addresses primarily measurement error in climate variables, but also sheds light on how economic agents process weather information. The table reports estimates from Equation (13) but using alternative definitions for the climate trends, which are now defined as moving averages of temperature from different time windows – averages of 3, 5, 10, and 20 years. Recall that all moving averages are lagged by one year to allow for the potential adaptation responses by individuals and firms. 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. Our estimates 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. Because group fixed effects absorb a lot of the signal in the weather variables, the signal:noise ratio might decrease. Again, our estimates 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 (Column 3 of Table 1). This latter result suggests that the widely used "climate normals" – three-decade averages of meteorological variables including temperature – are close to the "optimal" long-run trends. The improvements from reducing measurement error might be offset by the panel-driven attenuation bias between 20- and 30-year time windows. The row entitled "implied adaptation" reports the implied measure of adaptation as the difference between the estimated responses to temperature shocks, which are *exclusive* of adaptation, and the estimated responses to climate trends, which are *inclusive* of adaptation. The full list of controls are the same as in the main specification, depicted in Column (3) of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 3: The Timing of 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	1.676***	1.677***	1.195***
	(0.059)	(0.059)	(0.029)
Climate Trend	1.225***	1.218***	0.629***
	(0.055)	(0.055)	(0.037)
Implied Adaptation	0.451***	0.459***	0.566***
	(0.035)	(0.034)	(0.031)
Temp Shock x Action Day			0.037
			(0.186)
All Controls	Yes	Yes	Yes
Action Day Interactions			Yes
Observations	4,917,371	4,914,113	1,771,194
R^2	0.422	0.422	0.413

Notes: This table addresses the timing of potential adaptation responses. It 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 the usual 1-year lag. By doing so, agents are provided with more time to potentially adjust to climate change. Even though we would expect that the effects of the weather shocks to be similar, we expected the effects of the climate trend to be slightly smaller than before, as agents should now be able to adapt more than before. Yet, our estimates are remarkably close to our main results (Column 3 of Table 1), providing support to our main specification expressed in Equation (13). Column (3), then, continues using the 1-year lag of the main specification, but adds an interaction term of temperature shock with "ozone action day" announcements at the county-level to account for potential short-run adaptive behavior. These are 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. Individuals and firms are urged to take *voluntary* action to reduce the emissions of pollutants that are conducive to ozone formation. The estimate for the interaction between temperature shocks and action days is economically and statistically insignificant, pointing to limited opportunities for economic agents to adjust in the short run. Note that although action day policies first began in the 1990's, EPA only provided data beginning in 2004, leading to a restricted overall sample (approximatley 36% of our full sample). The row entitled "implied adaptation" reports the implied measure of adaptation as the difference between the estimated responses to temperature shocks, which are *exclusive* of adaptation, and the estimated responses to climate trends, which are *inclusive* of adaptation. The full list of controls are the same as in the main specification, depicted in column 3 of Table 1. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 4: Addressing Climate Experiment Issues with Alternative Specifications

	Daily Max Ozone Levels (ppb)			
	(1)	(2)	(3)	(4)
Temperature Shock	1.677***	1.677***	1.690***	1.689***
	(0.060)	(0.059)	(0.062)	(0.063)
Climate Trend	1.188***	1.229***	1.230***	1.189***
	(0.051)	(0.055)	(0.056)	(0.052)
Implied Adaptation	0.489***	0.448***	0.460***	0.500***
	(0.038)	(0.037)	(0.040)	(0.042)
Non-Attainment Control	Yes	Yes	Yes	Yes
Precipitation Controls	Yes	Yes	Yes	Yes
Fixed Effects:				
Monitor-by-Season	Yes			Yes
Monitor-by-Weekday/end		Yes		Yes
Monitor x Year			Yes	Yes
Season-Year x Latitude	Yes	Yes	Yes	Yes
Season-Year x Longitude	Yes	Yes	Yes	Yes
Seasdon-Year-Region	Yes	Yes	Yes	Yes
Observations	4,923,931	4,923,932	4,923,932	4,923,931
R^2	0.434	0.425	0.442	0.456

Notes: This table addresses deviations from the ideal climate experiment with alternative specifications. The ideal experiment would have two locations with the same levels of ozone precursors (NOx and VOCs), but facing different changes in temperature. Unfortunately, data on these precursors, especially VOCs, is limited – only available to approximately 20% of our full sample, as reported in Table 5. If precursor levels are different, but approximately unchanging over time, our standard monitor fixed-effects approach expressed in Equation (13) would mimic this ideal setting. This table presents estimates of four additional specifications in which the standard set of fixed effects is enriched to account for potential unobserved localized variation in precursor levels. Column (1) allows the monitor fixed effect to vary by season, column (2) allows the monitor fixed effect to vary by weekday/weekend, column (3) allows the monitor fixed effect to vary linearly over time, and column (4) allows for all three. In all cases, the estimates are remarkably similar to our main results depicted in column (3) of Table 1, providing reassuring evidence in favor of our preferred parsimonious specification expressed in Equation (13). The row entitled "implied adaptation" reports the implied measure of adaptation as the difference between the estimated responses to temperature shocks, which are *exclusive* of adaptation, and the estimated responses to climate trends, which are *inclusive* of adaptation. Standard errors are clustered at the county level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table 5: Climate Impacts and Adaptation by VOC- or NOx-limited Atmosphere

	Daily Max Ozone Levels (ppb)	
	Main Specification *Restricted Sample*	VOC/NOx-Limited *Restricted Sample*
	(1)	(2)
Temperature Shock	2.059***	2.109***
	(0.139)	(0.179)
x VOC-limited		−0.090
		(0.108)
x NOx-limited		−0.548**
		(0.253)
Climate Trend	1.457***	1.469***
	(0.149)	(0.157)
x VOC-limited		0.008
		(0.083)
x NOx-limited		−0.423***
		(0.149)
Implied Adaptation	0.602***	0.641***
	(0.103)	(0.113)
x VOC-limited		−0.098
		(0.092)
x NOx-limited		−0.125
		(0.211)
All Controls	Yes	Yes
Observations	1,006,748	1,006,748
R^2	0.452	0.453

Notes: This table addresses the Leontief-like production function of ozone, and the heterogeneity of climate impacts and adaptation according to conditions of the local atmosphere. The table reports estimates of temperature shocks and climate trends interacted with indicators for whether the county is VOC-limited or NOx-limited. The production of ozone is often VOC-limited in urban areas with a high population concentration, but is generally NOx-limited in rural areas and downwind suburban areas. 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 was observed in most days. The sample is restricted to only those counties for which data on these precursor pollutants are available (approximately 20% of our full sample), but for comparison the table depicts in column (1) the results of our main specification expressed in Equation (13) estimated under this restricted sample. In column (2), the main effect reflects the result for non-limited counties, while each interaction term depicts the relative difference in the effect of shocks and trends in precursor-limited counties. The rows entitled "implied adaptation" report the implied measure of adaptation as the difference between the estimated responses to temperature shocks, which are *exclusive* of adaptation, and the estimated responses to climate trends, which are *inclusive* of adaptation. In this case, they also report the differential adaptation effects in limited counties. Overall, the estimates are lower in limited counties, corroborating the Leontief-like production function of ozone. The full list of controls are the same as in the main specification, depicted in column 3 of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 6: Climate Impacts and Adaptation by Beliefs in Climate Change

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.519***	
	(0.042)	
x Low Belief	−0.173***	
	(0.059)	
x High Belief	0.374***	
	(0.108)	
Climate Trend	1.112***	0.407***
	(0.049)	(0.048)
x Low Belief	−0.014	−0.159***
	(0.054)	(0.050)
x High Belief	0.243***	0.131*
	(0.080)	(0.079)
All Controls	Yes	Yes
Observations	4,923,932	4,923,932
R^2	0.425	0.425

Notes: This table addresses heterogeneity in climate impacts and adaptation according to beliefs in climate change. It reports estimates of temperature shocks and climate trends interacted with indicators for whether the residents of a 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 middle 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 middle-belief counties along with the differential effects in the low- and high-belief counties. The implied measure of adaptation is the difference between the estimated responses to temperature shocks, which are *exclusive* of adaptation, and the estimated responses to climate trends, which are *inclusive* of adaptation. Overall, high-belief counties seem to make more efforts to adapt to climate change, and low-belief counties less efforts. For reference, high-belief counties tend to be more populous, better educated, and richer than low-belief ones. The full list of controls are the same as in the main specification expressed in Equation (13), depicted in column 3 of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 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 further details on the sources of our data and construction of final variables in Subsection A.1, and relevant background on ozone as a local air pollutant in Subsection 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 Subsection B.1, and those examining heterogeneity in Subsection B.2.

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Appendix A. Additional Data Discussion

This appendix section provides further details on the datasets discussed in Section III, as well as auxiliary datasets used in alternative specifications. It then includes relevant Figures and Tables as outlined below.

A.1. 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 dataset provides detailed weather measurements at over 20,000 weather stations across the country, for which we use the period 1950-2013. 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 trend 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 shocks and the long-term trends, using a semi-balanced panel of the comprehensive set of weather stations 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 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 pollution monitors and weather stations, we calculate the distance between each pair of pollution monitor and weather station using the Haversine formula. Then, for every pollution monitor we exclude weather stations that lie beyond a 30 km radius of that monitor. Moreover, for every pollution 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 — Ground-level ozone concentration data was obtained from the Environmental Protection Agency's , we use 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 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 5,037,851 monitor-days. The number of monitors increased from 672 in the 1980s to 1026 in the 2000s, indicating a growth of 17.6 percent of the ozone monitoring network per decade. The number of monitored counties in our sample also grew from 390 in the 1980s to 601 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. We have valid ozone measurements for a total of 4,974,155 monitor-days. The number of monitors increased from about 650 in the 1980s to over a thousand in the 2000s, indicating an important growth of the ozone monitoring network per decade. The number of monitored counties in our sample also grew from about 380 in the 1980s to over 600 in the 2000s.

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

In Tables 5 and B1 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 construct these measures we first combine the EPA's VOC and NOx data at the county-day and generate a daily ratio of VOCs to NOx for each county. 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 pushed, and, if anything, should be expected to bias the observed effect from this heterogeneity towards zero.

In Table B4 we include average daily windspeed and total daily sunlight as additional regressors within our main specification. These data, although less frequently available, 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 component and transitory weather shock as we do with temperature and precipitation.

In Tables 6 and B8 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 changes – and separately by their belief in the use of regulations on carbon. In this way we arrive at three equally sized groups for which we are able 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 B9 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.

A.2. 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)

[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 earths atmosphere.

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 concentrations also vary seasonally. They tend to be highest during the 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).

[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.

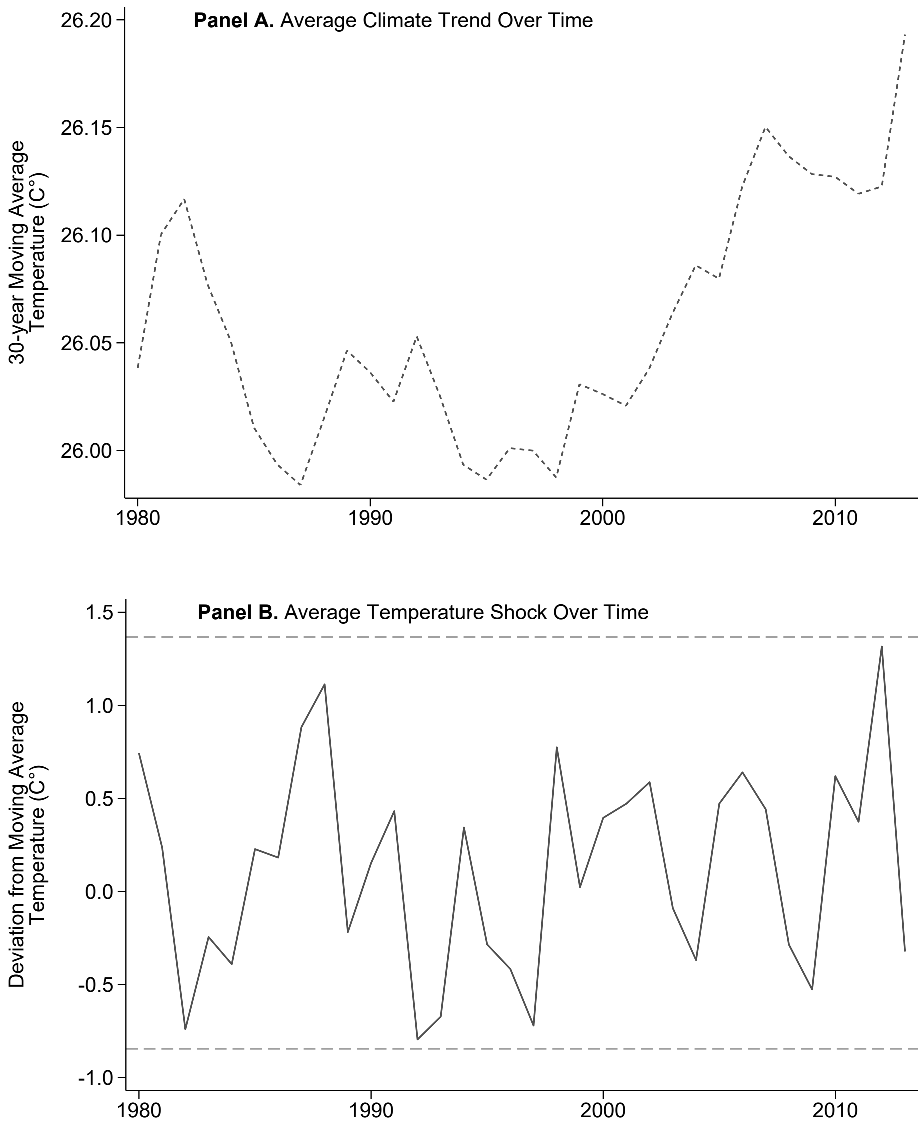
[4]In areas where the coastal marine layer (cool, moist air) is prevalent during summer, the peak ozone season tends to be in the early fall.

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

Figure A1: Comprehensive Location of all Weather Monitors

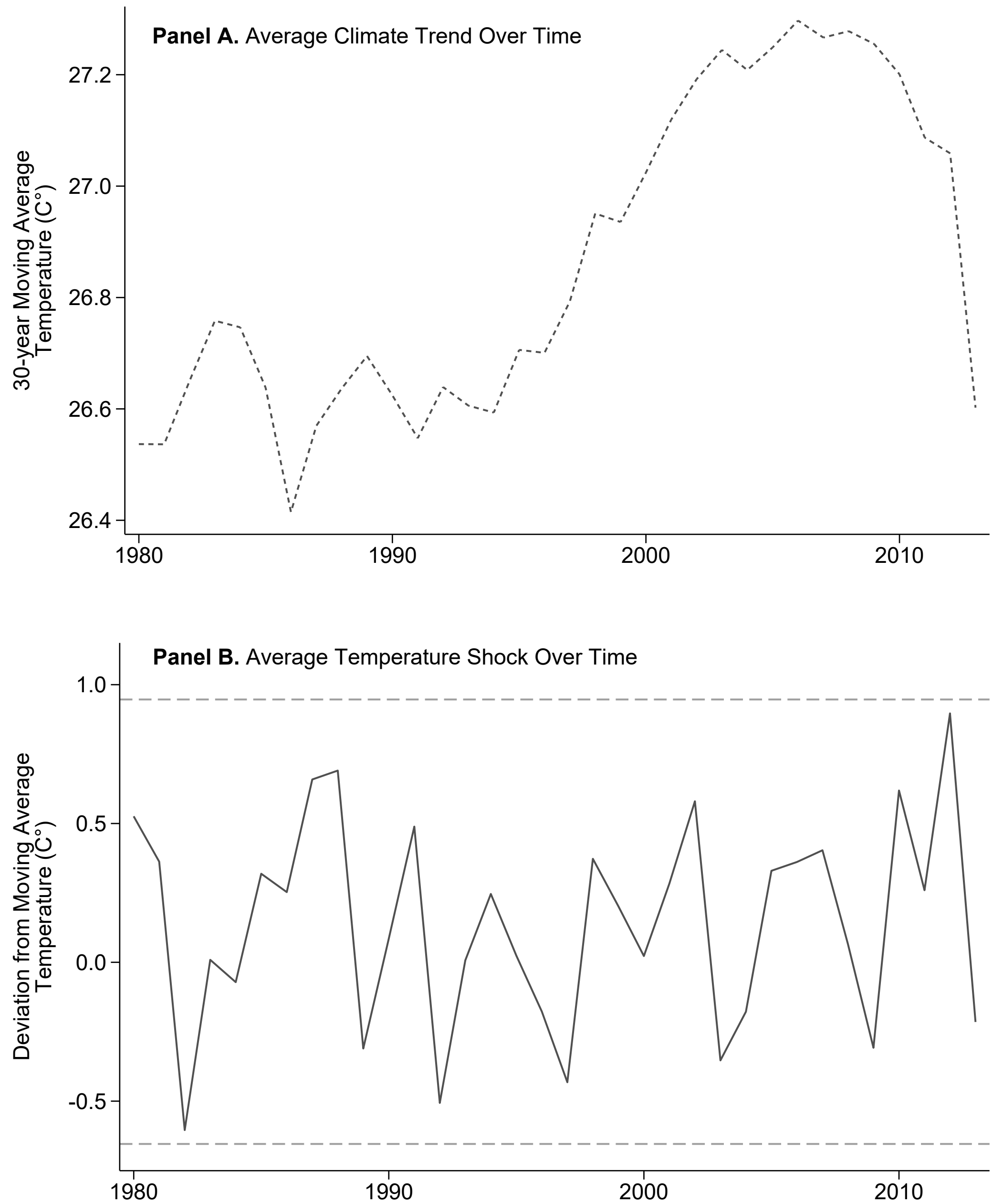
Notes: This figure maps the location of all weather stations across the continental U.S. contained in our complete dataset.

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



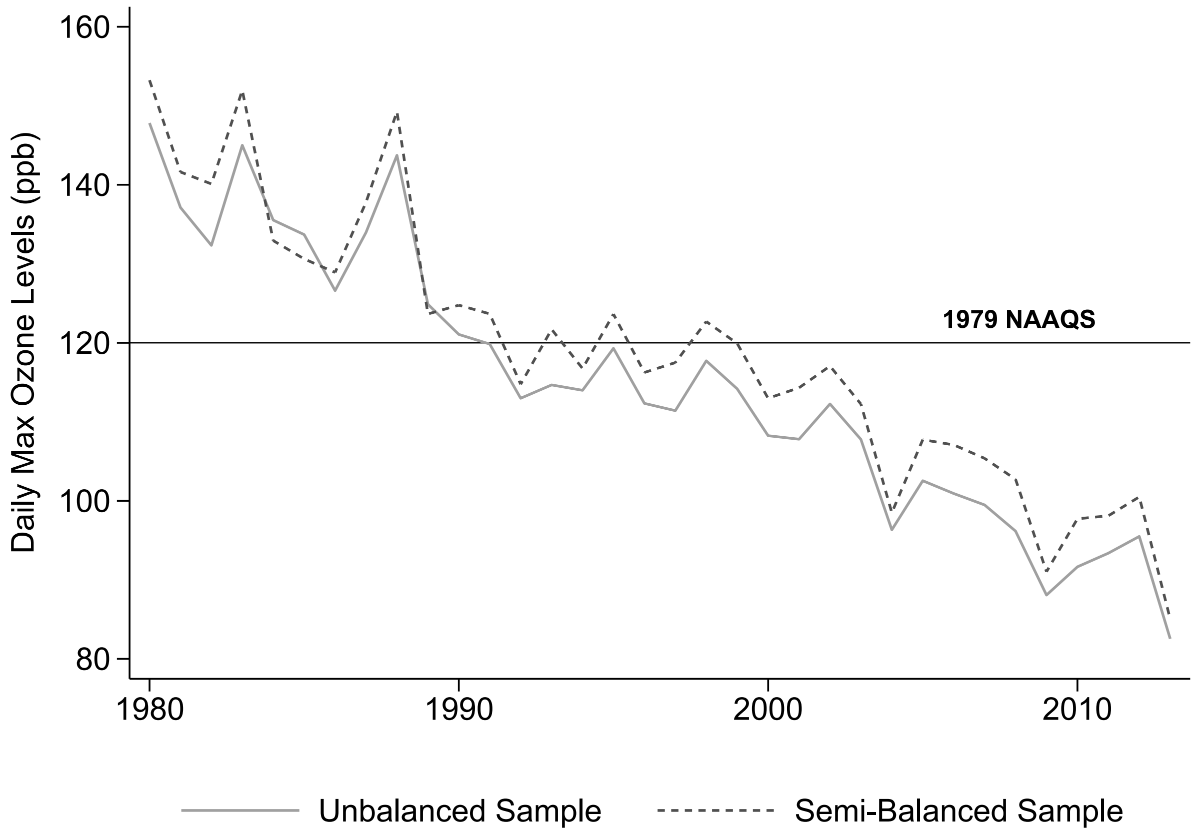
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate trend and temperature shock components. The climate trend (Panel A) and temperature shocks (Panel B) are constructed from a panel of weather stations matched to a semi-balanced panel of ozone monitoring 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 Trend 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 A3: Climate Trends and Shocks (main model sample)



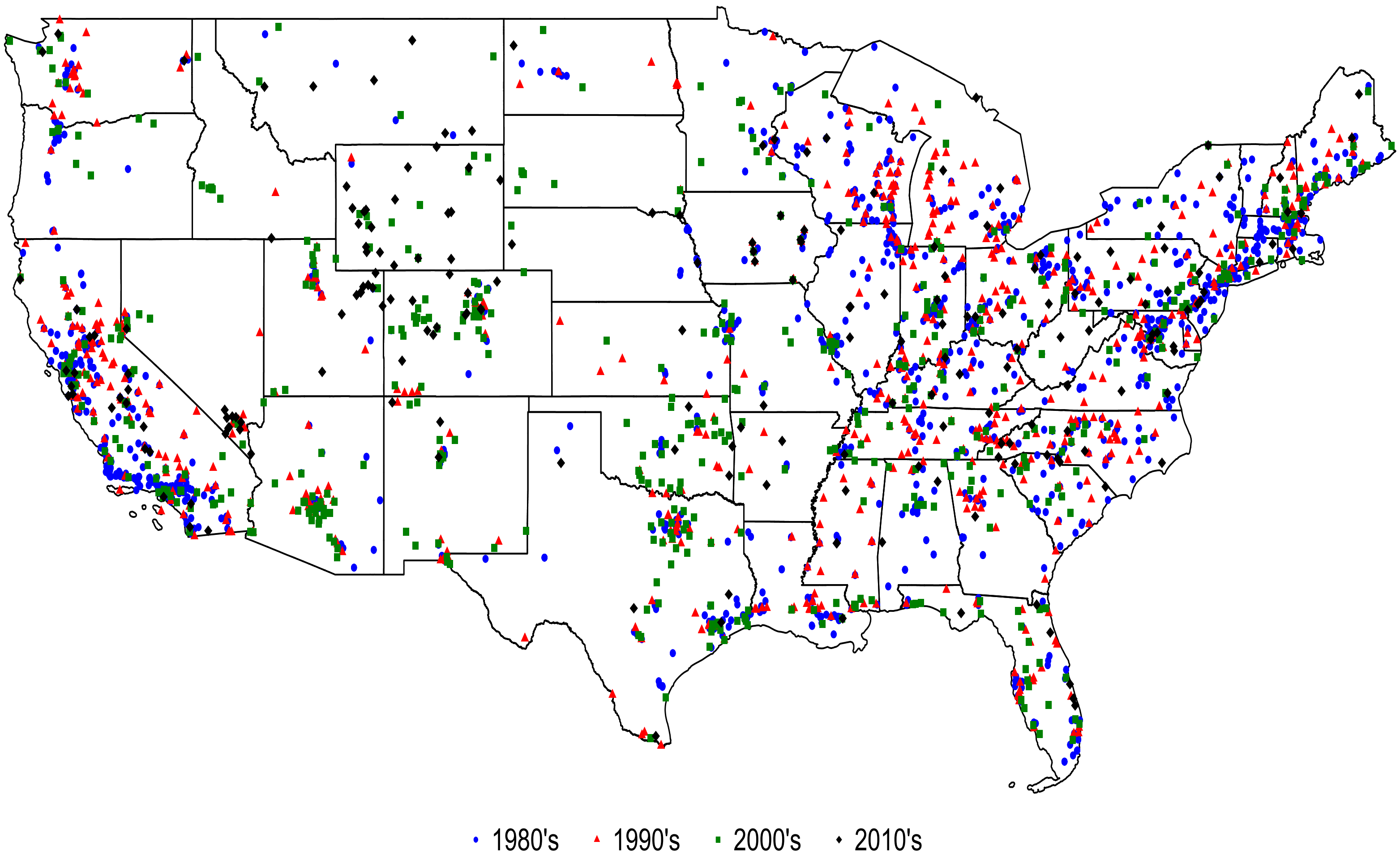
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate trend and temperature shock components. The climate trend (Panel A) and temperature shocks (Panel B) are constructed from the panel of weather stations included in our main model sample across 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 A4), is the likely driving force behind the downward pattern of the average climate trend at the end of our sample period in Panel A. Recall that the Climate Trend 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



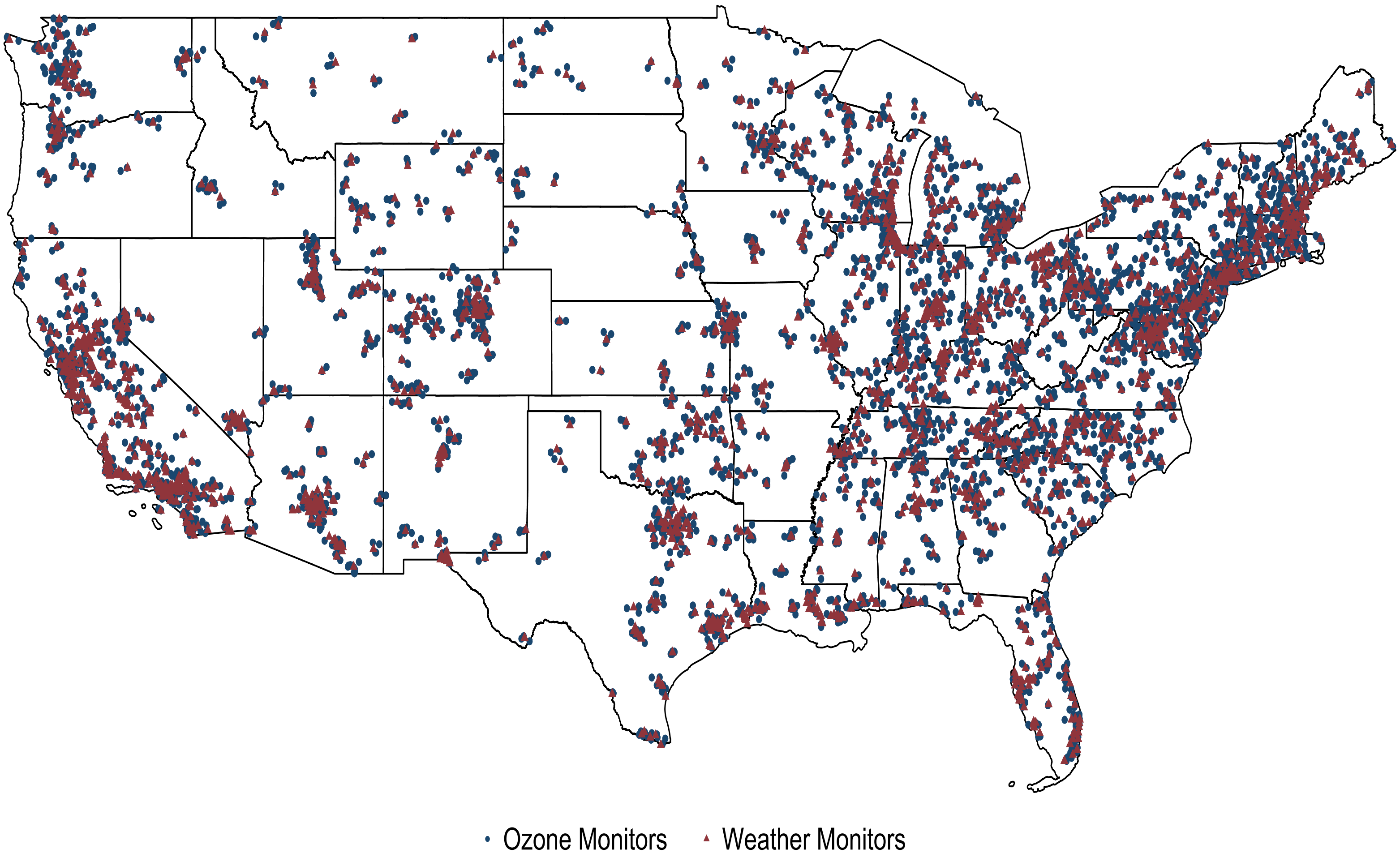
Notes: This figure depicts the evolution of the daily maximum 1-hour ambient ozone concentrations over time in the US for both our complete (unbalanced) sample and our restricted (semi-balanced) sample. The 1979 NAAQS for designating a county's attainment status was based on an observed 1-hour maximum ambient ozone concentration of 120 ppb or higher. Here we contrast this attainment status cutoff with the maximum yearly ozone concentrations of Attainment and Non-Attainment counties.

Figure A5: Ozone Monitor Location by Decade of First Appearance



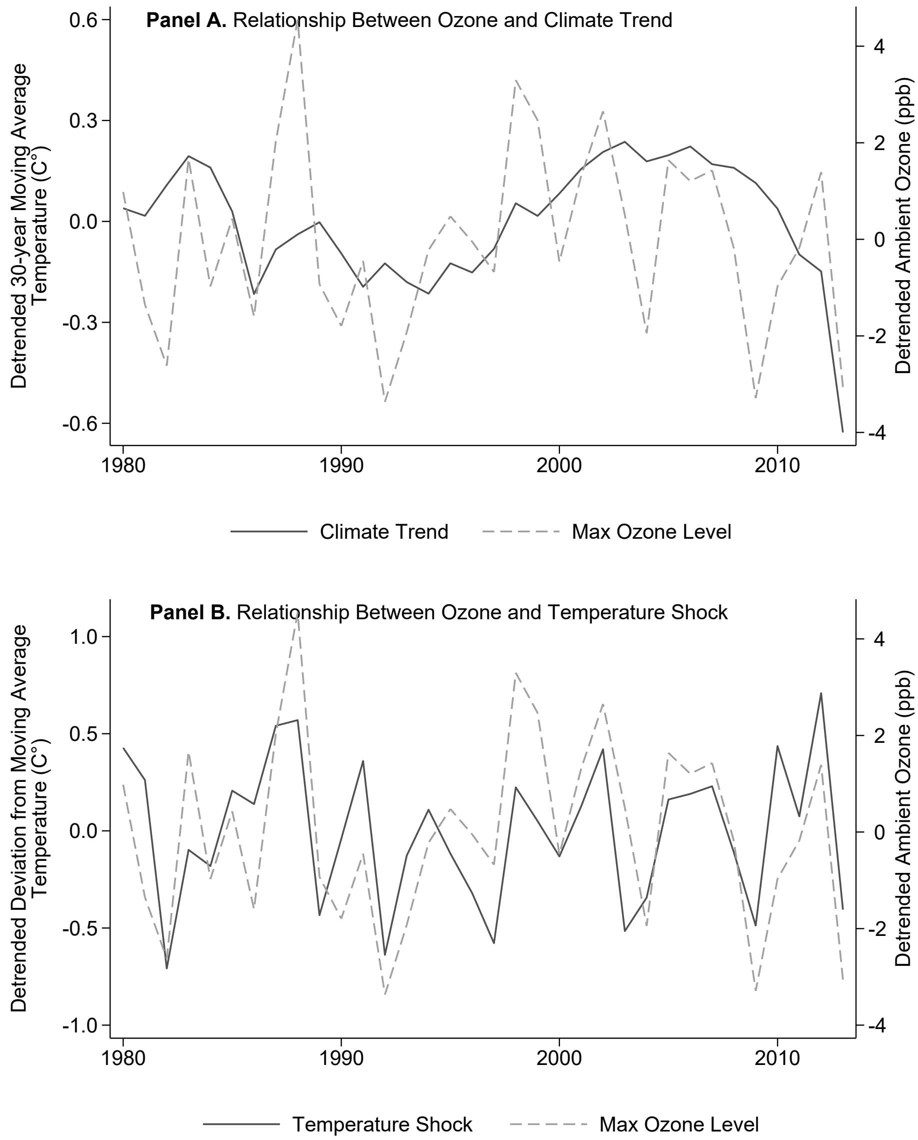
Notes: This figure maps the location of each ozone monitor in our final sample, by decade of first appearance.

Figure A6: Ozone Monitors and their Matched Weather Monitors



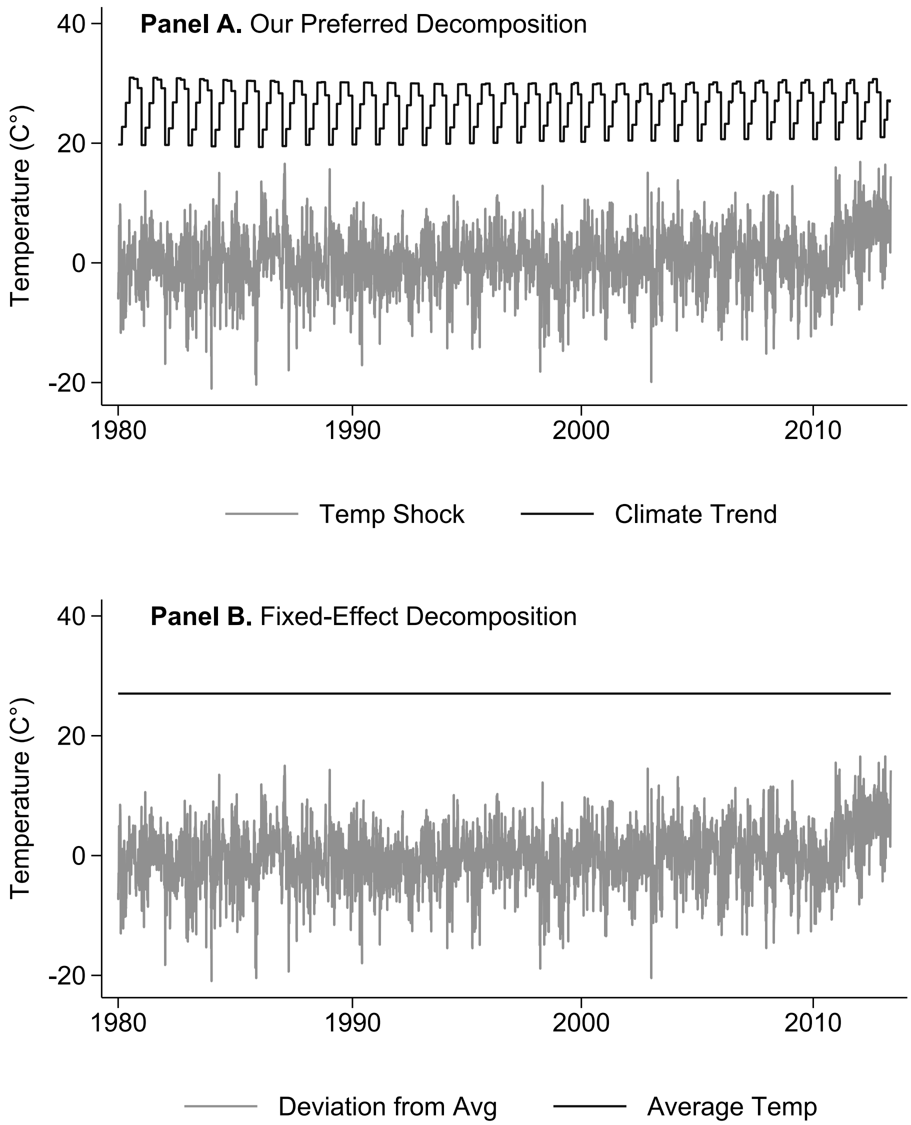
Notes: This figure maps the location of each ozone monitor in our final sample, and their matched weather stations. For each ozone monitor, the closest 2 stations within a 30 km radius have been used in the matching.

Figure A7: Relationship between Ozone and Climate Trend



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 trend and temperature shock and detrending the data. Both the climate trend (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 Trend 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. Trends & 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 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 Trend 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 trends. 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 Trend 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	27.1	26.5	0.5
1981	26.9	26.5	0.4
1982	26.0	26.7	-0.6
1983	26.8	26.8	0.0
1984	26.7	26.7	-0.1
1985	27.0	26.6	0.3
1986	26.7	26.4	0.3
1987	27.2	26.6	0.7
1988	27.3	26.6	0.7
1989	26.4	26.7	-0.3
1990	26.7	26.6	0.1
1991	27.0	26.5	0.5
1992	26.1	26.6	-0.5
1993	26.6	26.6	0.0
1994	26.8	26.6	0.2
1995	26.7	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	27.1	26.9	0.2
2000	27.0	27.0	0.0
2001	27.4	27.1	0.3
2002	27.8	27.2	0.6
2003	26.9	27.2	-0.4
2004	27.0	27.2	-0.2
2005	27.6	27.2	0.3
2006	27.7	27.3	0.4
2007	27.7	27.3	0.4
2008	27.3	27.3	0.1
2009	26.9	27.3	-0.3
2010	27.8	27.2	0.6
2011	27.3	27.1	0.3
2012	28.0	27.1	0.9
2013	26.4	26.6	-0.2

Notes: This table outlines the evolution of maximum temperature in our sample from the years 19802013 in Column (2). Columns (3) and (4) decompose this into our respective measures of Climate Trend and Temperature Shock. Recall that the Climate Trend 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	86087	344	591
1981	98072	383	643
1982	99730	385	644
1983	100079	392	637
1984	102574	382	641
1985	104426	381	641
1986	102344	365	624
1987	107987	377	652
1988	110821	394	670
1989	116845	406	705
1990	122819	422	733
1991	128011	442	766
1992	133182	455	793
1993	141009	483	833
1994	144289	490	845
1995	148388	493	866
1996	147483	498	861
1997	154349	516	896
1998	158136	531	921
1999	161903	544	941
2000	165457	550	957
2001	172576	570	998
2002	177289	581	1019
2003	178539	587	1025
2004	179354	596	1026
2005	177700	595	1024
2006	178545	597	1019
2007	180561	605	1033
2008	180701	604	1040
2009	183956	621	1056
2010	185046	625	1064
2011	186312	642	1079
2012	187408	638	1077
2013	137783	589	962

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

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: Belief in Climate Change - Summary Stats

	Count	Mean	Std. Dev.	Minimum	Maximum
	(1)	(2)	(3)	(4)	(5)
Panel A. Low Belief Counties					
Population	285	129502	280485	897	3950000
Average Years of Education	285	12.89	0.64	11.41	16.14
Median Household Income	285	50008.23	11640.85	26886.00	112706.00
Average Household Income	285	63997.09	13116.08	39672.50	127666.37
Panel B. Median Belief Counties					
Population	285	215797	321536	6002	3750000
Average Years of Education	285	13.28	0.64	11.81	15.21
Median Household Income	285	55660.92	13972.39	32261.00	125680.00
Average Household Income	285	71189.31	17167.79	45256.98	146007.51
Panel C. High Belief Counties					
Population	286	476383	808003	1659	9760000
Average Years of Education	286	13.55	0.65	11.63	15.74
Median Household Income	286	61038.05	15607.28	30445.00	112304.00
Average Household Income	286	79401.26	20103.51	43136.86	142153.61

Notes: This table reports summary statistics of underlying demographics for each of the terciles of counties used in Table 6. 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 population over 25 years of age.

Appendix B. Further Robustness Checks and Heterogeneity

This appendix provides further elaboration of the alternative specifications used for robustness checks as discussed in Section IV and examining heterogeneity 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 previous robustness checks 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, 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. Its 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 B2. 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 out 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 must 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 run our 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 92 pollution monitors. The results are reported in Table B3. We find that a 1°C temperature shock leads to a rise in ozone concentrations by 2.05ppb, while a 1°C increase in the climate trend leads to a rise of 1.61ppb, implying an adaptation level of 0.44ppb. 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 the 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.

Further Robustness Checks — In addition to all prior robustness checks, we conduct three final checks in Table B4. First, it may a concern that our climate trend 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, as mentioned before, 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 the trend.

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 monthly level, taking the arithmetic mean of all variables by month for each year of our sample and running our preferred specification on this aggregate sample. As the climate trend 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. On the other hand, to the extent that daily temperature shocks covary more strongly with daily ozone concentration levels, as we have seen to be the case throughout our analyses, the smoothing of these two variable by aggregating to the monthly level may reduce the extent to which temperature shocks appear to impact ozone formation, attenuating this coefficient towards the coefficient on climate trend. Although our sample size is greatly reduced, now consisting of 170,960 observations compared to the previous 4,974,115 we find qualitatively similar results, reported in column (2). As expected, the coefficient on climate trend is nearly identical, while the coefficient on temperature shock is slightly smaller than in our full sample model.

Lastly, although temperature is the primary meteorological factor affecting tropospheric 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 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/sec) and total daily sunlight (mins). 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/sec increase in average daily wind speed would decrease ozone concentrations by 2.2ppb, whereas a 1 min increase in daily sunlight leads to 0.02ppb increase in ozone concentrations. More importantly, by comparing Column (3) with our main result, even though our main climate impacts are somewhat reduced after the inclusion of these other meteorological variables, their patterns are qualitatively identical and our measure of adaptation is quantitatively similar. A shock in daily maximum temperature of 1°C leads to a 1.24ppb increase in daily maximum ozone whereas a 1°C increase in the climate trend leads to a 0.72ppb increase in ozone. Our measure of overall adaptation is 0.52ppb. Therefore, 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.

B.2. Heterogeneity

Nonlinear Effects of Temperature — Because ozone formation may be intensified with higher temperatures, we also examine the heterogeneous nonlinear effects of daily maximum temperature on ambient ozone concentrations. Similar to our previous investigations 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). Table B6 presents the results of our preferred specification when interacting each of these temperature bin indicators with our other covariates in column (1), taking the below 20°C bin as reference. The implied measure of adaptation is presented in column (2). In this way, the marginal effect of a 1°C change in either component of temperature is allowed to vary across each 5°C temperature bin. As expected, we find that higher temperatures increasingly lead to higher ozone concentrations.

Between 20°C and 25°C, a 1°C temperature shock would raise ozone levels by an additional 0.79 ppb on average compared to a similar shock on a day below 20°C. A 1°C increase in the long-run climate trend, by comparison, would only raise ozone levels by an additional 0.31 ppb on average compared to a similar increase on a day below 20°C. This implies that adaptation accounts for approximately 0.48 ppb, or 30.45 percent of the total effect with zero adaptation.[6] Above 35°C the temperature impacts are 1.94 ppb and 0.74 ppb respectively, for an implied adaptation measure of 1.20 ppb, or 30.95 percent of the effect. Interestingly, although the marginal impacts of both components of temperature are monotonically increasing with temperature bin, this is not the case with adaptation. Between 25-30°C adaptation is only 0.26 ppb approximately 16.15 percent, while between 30-35°C

[6] Adaptation percentages for each bin have been calculated by comparing the level of adaptation to twice the effect of the weather shock i.e. the impact of a 1°C increase in temperature that we would have observed in the absence of any adaptation.

adaptation is 0.68 approximately 24.83 percent.

Since the U.S. as a whole is predominantly NOx limited, we would expect that changes in electricity usage drastically affect ozone concentrations.[7] In the below 20°C bin or at temperature above 25°C people are generally more dependent on either the heater or the air conditioner and hence might not be able to adjust their electricity use. Temperatures between 20-25°C, however, represent very pleasant weather which might potentially induce people to cut down on electricity demand and, hence, reduce NOx emissions, which might be driving the high degrees of adaptation in this bin. Indeed, Deschenes and Greenstone (2011) analyze the nonlinear effects of daily average temperature on residential energy consumption, and document a U-shaped function such that the hottest and coldest days are the highest energy consumption ones. Energy consumption at intermediate levels of temperature of around 60-80°F (comparable to our intermediate temperature bin of 20-25°C) is the lowest, conforming to our estimates of adaptation at different levels of temperature. At intermediate levels of daily temperature, economic agents can adjust and bring down their energy consumption, hence leading to large decreases in ozone concentrations. It is also interesting to see a relatively high level of adaptation above 35°C. This 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. Thus, higher temperatures might be 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.

Results by Decade — To examine temporal heterogeneity, Table B7 reports our results by

[7] 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 changes in ozone formation.

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 reduces from the 1980s to the 1990s, but stabilizes afterwards. The average adaptation across all counties in our sample drops from 0.58ppb in the 1980s to 0.39ppb in the 1990s, but it is still 0.41ppb in the 2000s.

Table B1: Alternative Monitor Fixed-Effects with VOC/NOx Interactions

	Daily Max Ozone Levels (ppb)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature Shock	2.056***	2.111***	2.059***	2.107***	2.097***	2.089***	2.093***	2.140***
	(0.139)	(0.181)	(0.138)	(0.178)	(0.155)	(0.171)	(0.155)	(0.192)
x VOC-Limited		−0.100		−0.086		−0.063		−0.079
		(0.110)		(0.107)		(0.098)		(0.100)
x NOx-Limited		−0.572**		−0.545**		−0.527**		−0.606**
		(0.251)		(0.252)		(0.247)		(0.258)
Climate Trend	1.388***	1.413***	1.457***	1.469***	1.450***	1.638***	1.381***	1.371***
	(0.142)	(0.152)	(0.149)	(0.157)	(0.148)	(0.196)	(0.141)	(0.142)
x VOC-Limited		−0.033		0.008		−0.077		0.085
		(0.091)		(0.084)		(0.102)		(0.061)
x NOx-Limited		−0.371**		−0.423***		−0.514***		−0.454***
		(0.163)		(0.148)		(0.165)		(0.160)
Implied Adaptation	0.668***	0.698***	0.602***	0.638***	0.647***	0.451***	0.711***	0.769***
	(0.104)	(0.115)	(0.103)	(0.112)	(0.113)	(0.117)	(0.116)	(0.132)
x VOC-Limited		−0.066		−0.094		0.014		−0.165*
		(0.085)		(0.091)		(0.095)		(0.099)
x NOx-Limited		−0.201		−0.122		−0.013		−0.152
		(0.214)		(0.210)		(0.195)		(0.222)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:								
Monitor-by-Season	Yes	Yes					Yes	Yes
Monitor-by-Weekend			Yes	Yes			Yes	Yes
Monitor x Year					Yes	Yes	Yes	Yes
Observations	1,006,748	1,006,748	1,006,748	1,006,748	1,006,748	1,006,748	1,006,748	1,006,748
R^2	0.463	0.464	0.458	0.458	0.470	0.427	0.487	0.487

Notes: This table combines both approaches implemented in Tables 4 and 5 of Section IV. Columns (1) and (2) allows the monitor fixed effect to vary by season, while columns (3) and (4) vary by weekday/weekend, columns (5) and (6) vary linearly over time, and columns (7) and (8) allow for all three. Within each of these column pairs, the second column reports the results of our model when further including the interaction terms for VOC- and NOx-limited counties as in Table 5, while the first column – for comparison – reports the results of our model without these terms, as in Table 4. Results are qualitatively similar across all specifications. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B2: Alternative Criteria for Selection of Weather Stations

	Daily Max Ozone Levels (ppb)			
	(1)	(2)	(3)	(4)
Temperature Shock	1.723***	1.701***	1.797***	1.783***
	(0.060)	(0.060)	(0.067)	(0.066)
Climate Trend	1.229***	1.230***	1.217***	1.219***
	(0.055)	(0.055)	(0.054)	(0.054)
Implied Adaptation	0.493***	0.471***	0.580***	0.564***
	(0.035)	(0.036)	(0.040)	(0.040)
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	4,923,932	4,923,932	5,051,745	5,051,745
R^2	0.426	0.424	0.427	0.428

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 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. We also increase the radius to 80 km and use the information from the closest 5 weather stations. Recall that the Climate Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B3: Comparison to Alternative Estimation Methods (Semi-Balanced Panel)

	Daily Max Ozone Levels (ppb)		
	Cross-Section	Fixed-Effects	Proposed
	(1)	(2)	(3)
Average Max Temperature	0.982*		
	(0.547)		
Max Temperature		2.040***	
		(0.094)	
Temperature Shock			1.998***
			(0.098)
Climate Trend			1.531***
			(0.089)
Implied Adaptation		1.057*	0.467***
		(0.542)	(0.069)
Non-Attainment Control	Yes	Yes	Yes
Precipitation Controls	Yes	Yes	Yes
Latitude & Longitude	Yes		
Fixed Effects:			
Climate Region	Yes		
Month-by-Year		Yes	
Monitor		Yes	Yes
Season-Year x Latitude		Yes	Yes
Season-Year x Longitude		Yes	Yes
Seasdon-Year-Region		Yes	Yes
Observations	88	515,050	515,050
R^2	0.330	0.418	0.404

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 cross-sectional estimates using average maximum temperature and ambient ozone concentrations at each of the 88 ozone monitors in this restricted sample. Having averaged the variables over all the years from 1980-2013, this estimate captures the effect of a change in climate. 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. In Column (3), we decompose daily maximum temperature into climate trends and weather shocks, and exploit variation in both components in the same estimating equation – our Equation (13). Recall that the Climate Trend 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. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B4: Further Robustness Checks

	Daily Max Ozone Levels (ppb)		
	Daily Moving Average	Monthly Aggregation	Meteorological Controls
	(1)	(2)	(3)
Temperature Shock	1.682***	1.525***	1.758***
	(0.060)	(0.050)	(0.078)
Climate Trend	1.266***	1.224***	1.140***
	(0.054)	(0.053)	(0.070)
Average Wind Speed			−2.231***
			(0.292)
Total Daily Sunlight			0.014***
			(0.001)
Implied Adaptation	0.416***	0.301***	0.618***
	(0.036)	(0.057)	(0.063)
All Controls	Yes	Yes	Yes
Observations	4,923,894	171,135	451,801
R^2	0.421	0.721	0.428

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 a Climate Trend, represented by the 30-year *daily* moving average, and a 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 4,923,932 observations to 171,135. Despite this reduction, our results remain qualitatively similar – although over-smoothing has led to slight attenuation of the coefficient on Temperature Shock. 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 Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B5: Alternative Standard Errors

	Daily Max Ozone Levels (ppb)
	(1)
Temperature Shock	1.677
(County Cluster)	(0.059)***
(State Cluster)	(0.120)***
(Bootstrapped)	(0.028)***
Climate Trend	1.229
(County Cluster)	(0.055)***
(State Cluster)	(0.105)***
(Bootstrapped)	(0.026)***
All Controls	Yes
Observations	4,923,932
R^2	0.4423

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 monitor level). This latter addresses the potential concern that because our temperature shocks and trends are constructed, they could be seen as generated regressors. Recall that the Climate Trend 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 (3) of Table 1. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B6: Non-Linear Effects of Temperature

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
	Panel A. 20-25°C	
Temperature Shock	0.834***	
	(0.040)	
Climate Trend	0.375***	0.459***
	(0.031)	(0.029)
	Panel B. 25-30°C	
Temperature Shock	0.760***	
	(0.045)	
Climate Trend	0.532***	0.228***
	(0.040)	(0.036)
	Panel C. 30-35°C	
Temperature Shock	1.341***	
	(0.071)	
Climate Trend	0.686***	0.654***
	(0.051)	(0.072)
	Panel D. Above 35°C	
Temperature Shock	1.796***	
	(0.120)	
Climate Trend	0.638***	1.158***
	(0.056)	(0.120)
All Controls	Yes	Yes
Observations	4,923,932	4,923,932
R^2	0.435	0.435

Notes: This table reports the non-linear effects of a 1°Celsius increase in temperature shocks and climate trends on ambient ozone levels across multiple temperature bins. We categorize temperature into 5 bins from < 25°C to > 35°C with 5°C intervals in between. Estimates in column (1) correspond to Equation (13), while estimates in column (2) report the implied measure of adaptation. Recall that the Climate Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B7: Results by Decade

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
	Panel A. 1980's	
Temperature Shock	2.260***	
	(0.139)	
Climate Trend	1.672***	0.587***
	(0.095)	(0.101)
	Panel B. 1990's	
Temperature Shock	1.757***	
	(0.049)	
Climate Trend	1.372***	0.385***
	(0.050)	(0.037)
	Panel C. 2000's	
Temperature Shock	1.278***	
	(0.028)	
Climate Trend	0.875***	0.402***
	(0.050)	(0.044)
All Controls	Yes	Yes
Observations	4,923,932	4,923,932
R^2	0.431	0.431

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 Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B8: Adaptation by Belief in Climate Change Regulation

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.538***	
	(0.049)	
x Low Belief	−0.336***	
	(0.064)	
x High Belief	0.414***	
	(0.112)	
Climate Trend	1.185***	0.353***
	(0.062)	(0.041)
x Low Belief	−0.245***	−0.090
	(0.071)	(0.060)
x High Belief	0.193**	0.222***
	(0.098)	(0.077)
All Controls	Yes	Yes
Observations	4,923,932	4,923,932
R^2	0.426	0.426

Notes: This table reports estimates of temperature shock and climate trend 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 Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B9: Adaptation by Political Leaning

	Daily Max Ozone Levels (ppb)	Adaptation
	(1)	(2)
Temperature Shock	1.377***	
	(0.049)	
x Democrat	0.459***	
	(0.094)	
Climate Trend	1.133***	0.244***
	(0.051)	(0.045)
x Democrat	0.151*	0.308***
	(0.078)	(0.060)
All Controls	Yes	Yes
Observations	4,923,932	4,923,932
R^2	0.424	0.424

Notes: This table reports estimate of temperature shock and climate trend 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 trends in these counties compared to the 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 Trend 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 (3) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

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