# A New Approach to Measuring Climate Change Impacts and Adaptation

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***Abstract:*** *We propose a novel approach to estimate climate impacts and adaptation based on a decomposition of meteorological variables into long-run trends and deviations from them (weather shocks). Our estimating equation simultaneously exploits weather variation to identify the impact of shocks, and climatic variation to identify the effect of longer-run observed changes. We compare the simultaneously estimated short- and long-run effects to test for the presence and magnitude of adaptation. We apply our approach to the impact of climate change on air quality, estimating the climate penalty on ozone. Leveraging ambient ozone regulations, we find evidence of regulation-induced and residual adaptation.*

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## 1. Introduction

It is unlikely that international organizations and the U.S. government will make progress on comprehensive mitigation programs to avoid damaging climate change[1]. Failure to achieve climate mitigation goals puts even more pressure on climate adaptation strategies, making it crucial to estimate climate impacts and adaptation properly, and understand the margins of adaptive response. Inspired by the macroeconomic literature on the effects of unanticipated versus anticipated shocks on the economy (e.g. Lucas, 1972, 1976), and by the labor literature on the importance of distinguishing transitory versus permanent income shocks in the estimation of intergenerational mobility (e.g. Solon, 1992, 1999), this study develops a new approach to measuring climate impacts and adaptation.

The pioneer hedonic, 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 the permanent, anticipated components behind meteorological conditions, but faces serious omitted variable bias. The panel fixed-effects approach (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) exploits the transitory, unanticipated weather shocks, and deals with the bias, but identification of climate effects using weather variation is not trivial (Hsiang, 2016). Our unifying approach addresses those key challenges of the literature, provides a measure of adaptation by comparing short- and long-run effects (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016), and, because these effects are novelly estimated in the same regression model, tests whether the magnitude of adaptation is statistically significant at conventional levels.

A key element of our approach is the decomposition of meteorological variables into two components: long-run trends and weather shocks, the latter defined as deviations from those trends. Taking advantage of high-frequency data, we decompose temperature (and precipitation) into a monthly moving average incorporating information from the past three decades, often referred to as climate normal[2], and a deviation from that lagged 30-year average[3]. This decomposition is meant to have economic content. Agents can only respond to climatic variables

[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°C over the 21st century, depending on the emissions scenario.
[2] Climate normals are three-decade averages of meteorological variables including temperature and precipitation.
[3] A graphical representation of our decomposition has been illustrated for Los Angeles county over the entire sample period of 1980-2013 in Figures A1 and A2, and for 2013 only in Figures A3 and A4 in Appendix A.

they observe. The 30-year moving average is purposely lagged to capture all the information available to individuals and firms up to the year prior to the measurement of the outcome variables. In contrast, agents cannot respond to weather shocks by definition. Our measure of adaptation is the difference between the *simultaneously* estimated responses to weather shocks and responses to changes in lagged 30-year moving averages[4].

Once weather shocks and longer-run climatic changes are obtained, our novel approach proceeds by bridging two strands of the climate-economy literature. In the same estimating equation, we exploit meteorological variation to identify the impact of weather shocks on economic outcomes, and climatological variation to identify the causal effect of longer-run observed climatic changes. We then compare the *simultaneously* estimated short- and long-run effects to provide a measure of adaptive responses by economic agents. The meteorological variation exploited in the estimation is day-to-day changes in weather, similar to most of the literature. 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, for example.

We apply our novel approach to study the impact of climate change on ambient "bad" ozone in U.S. counties over the period 1980-2013. This is an ideal application for four reasons. First, ozone is not emitted directly into the air, but rather quickly created by 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). Second, 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 (usually 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). Third, ground-level ozone is one of the six criteria air pollutants regulated by the U.S. Environmental Protection Agency (EPA). Counties in violations with the National Ambient Air Quality Standards (NAAQS) for ozone

[4] Although we present our methodology focusing on adaptation, we are agnostic about the true impacts. There may be adaptation or intensification effects (Dell, Jones, and Olken, 2014). If economic outcomes are more affected by climatic changes than by weather shocks, agents may be not only abstaining from adjusting to climate change, but also slacking on any previous efforts. Perhaps they see those adjustments as too costly for what comes next.

face more stringent regulations, allowing us to investigate a potential mechanism of adaptation[5] – adaptation induced by regulations[6]. Fourth, from the policy point of view, the so-called climate penalty on ozone means that climate change might offset some of the improvements in air quality expected from reductions in emissions of ozone precursors, and therefore some of the improvements in public health[7]. Thus, stronger emission controls may be needed to meet a given air quality standard[8].

We identify the impacts of climate change on ambient ozone by focusing on the effect of daily maximum temperature on daily maximum ozone concentration in the U.S. since 1980. We take advantage of (i) daily measurements of ambient ozone levels from hundreds of air quality monitors across the nation during 1980-2013; (ii) daily measurements of temperature (and precipitation) from the widespread network of thousands of weather stations across the U.S. during 1950-2013 and (iii) the rich spatial and temporal variation with which Clean Air Act regulations were rolled out. We choose the highest ozone concentration because EPA's ambient ozone standards have been built around it. Likewise, increases in temperature are expected to be the principal factor in driving any ozone increases (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our sample, plotted in Figure 1, highlights the close relationship between these two variables. Lastly, the Clean Air Act Amendments (CAAA) marked an unprecedented attempt by the federal government to mandate lower levels of air pollution. If pollution concentrations in a county exceed the federally determined ceiling, then EPA designates that county as "non-attainment". Heavy emitters in non-attainment counties face far more stringent regulations than their counterparts in attainment counties. We use a standard

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[5] The measure of adaptation assumes that economic agents cannot respond to weather shocks. In reality, there might be some opportunities to make short-run adjustments in the context of ground-level ozone. Even though developed countries have usually not taken drastic measures to attenuate unhealthy levels of ozone because concentrations are generally low, developing countries have often constrained operation of industrial plants and driving in days of extremely high levels of ambient ozone.

[6] To understand this mechanism, consider a county where emissions of ozone precursors are under control in the baseline. If a rise in temperature leads to higher ozone formation and to the violation of NAAQS for ozone, that county may be forced to install equipment to reduce ozone concentration. Since that technology would have to be used because of higher temperatures rather than higher emissions, we interpret the decline in ozone levels as adaptation to climate change induced by clean air regulations.

[7] Graff Zivin and Neidell (2012), for instance, provide robust evidence that exposure to ozone levels well below federal air quality standards have a significant impact on labor productivity.

[8] In fact, when strengthening the standards for ground-level ozone from 75 to 70 ppb recently, the EPA has recognized the role climate change may play in driving air pollution in coming decades: "*In addition to being affected by changing emissions, future $O_3$ concentrations will also be affected by climate change. (…) If unchecked, climate change has the potential to offset some of the improvements in $O_3$ air quality (…) that are expected from reductions in emissions of $O_3$ precursors."* (EPA, 2015, p.65300)

fixed-effect approach, but replace the direct measurements of temperature with the two components of our decomposition – weather shocks and climatic changes. In our preferred specification, we interact such components with CAA “non-attainment” designations.

We have four main findings. First, a changing climate appears to be affecting ground-level ozone concentrations in two ways. A 1°C shock in temperature increases ozone levels by 1.7 parts per billion (ppb) on average, which is expectedly what would have been found in the standard fixed-effect approach. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.2ppb, which is 14 percent higher than what would have been found in the standard cross-section approach. Second, we find evidence of adaptive behavior. For a 1°C change in temperature, our measure of adaptation in terms of ozone concentration is 0.45ppb. When we compare our estimate of adaptation to the direct effect of the CAAA “non-attainment” designations, it is equivalent to over one third of that effect. Also, if adaptive responses were not taken into account in the measurement of the impact of climate change, then the climate penalty on ozone would be overestimated by approximately 17 percent.

Third, adaptation in counties with levels of ozone above the EPA’s standards is estimated to be over 66 percent larger than baseline adaptation in “attainment” counties[9], and is equivalent to about 45 percent of the direct effect of the CAAA “non-attainment” designations. Indeed, counties out of attainment must reduce ozone concentration by making costly adjustments in their production processes (Greenstone, List, and Syverson, 2012). For those counties, regulation-induced adaptation represents 40 percent of the total adaptation. Lastly, we have 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 ground-level ozone might be shrinking or becoming more costly.

This paper proceeds as follows: Section 2 explains the conceptual framework that we use to decompose meteorological variables into long-term trends and contemporaneous weather shocks, and describes our measures of adaptation. Section 3 provides a detailed background on ozone formation, its relationship with weather, and ambient ozone regulations. Section 4 describes our

[9] This is what we call residual adaptation. Counties complying with EPA’s ozone standards might still adapt by exploiting technological advances such as photovoltaic panels (e.g.,Barreca et al, 2015, 2016), or by unconscious behavioral responses (e.g., Graff Zivin, Hsiang, and Neidell, 2018).

data, Section 5 presents our empirical methodology, and Section 6 reports our main findings. Section 7 illustrates the robustness of our estimates, and Section 8 concludes.

## 2. Conceptual Framework

We propose a unifying approach to estimating climate impacts, and ultimately measuring adaptation. Prior literature has exploited permanent, anticipated components behind meteorological conditions – the hedonic approach (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005), which utilizes cross-sectional climate variation but suffers from omitted variable bias – or transitory, unanticipated weather shocks – the fixed effect approach (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), which deals with the bias but makes the transition from weather to climate effects nontrivial[10].

By using either the short- or long-run variation behind meteorological conditions to identifying climate impacts, those research designs trade off key assumptions. Our unifying approach bridges those two strands of the climate-economy literature, and provides a measure of adaptation in the spirit of the comparison between short- and long-run effects (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016). In our approach, climate impacts refer to responses to variation in long-run trends, which may incorporate adaptive behavior, but we also allow for responses to weather shocks, which may only capture a limited number of adaptive actions. Because estimates associated with different time horizons have distinct informational content, the comparison between them should measure the degree of adaptation to climate change[11].

*Decomposition of Meteorological Variables: Long-Run Trends vs. Weather Shocks*

In order to estimate the impacts of climate on economic outcomes, and ultimately uncover a measure of adaptation, we exploit both meteorological and climatological variation. The same estimating equation uses meteorological variation to identify the impact of weather shocks, as in the standard fixed-effect approach, and climatological variation within a season to identify the causal effect of longer-run observed climatic changes. The use of within-season variation in

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[10] Only in certain conditions weather variation exactly identifies the effects of climate (Hsiang, 2016).
[11] As it will be clear at the end of this section, although we focus on adaptation in our discussion, our approach can measure either adaptation or intensification.

long-run variables to recover climate impacts is an important innovation of our approach, as will be clear below.

To take advantage of variation in both components, we decompose meteorological variables into long-run trends and weather shocks[12]. A similar idea has been used in macroeconomics to measure business cycles since the seminal contribution of Burns 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. 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

$$Temp = Temp^{C} + Temp^{W}, \tag{1}$$

where $Temp^{C}$ represents climate patterns, and $Temp^{W}$ $(= Temp - Temp^{C})$ deviations from those long-run patterns. The decomposition highlights the two sources of variation that have been used in the climate-economy literature[14].

To understand why this decomposition allows us to exploit within-season variation to identify climate impacts in a regression framework conditioning on weather shocks, first notice the deviations attenuate the need to saturate the econometric model with high-frequency time fixed effects. In a panel data approach, we usually include time fixed effects at the level of temporal aggregation used in the 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 the deseasonalization embedded in the highly saturated model is equivalent to the use of deviations in the final regression model, and that we do not need to transform the outcome variable. Therefore, our decomposition allows us to exploit

[12] Again, a graphical representation of our decomposition has been illustrated for Los Angeles county over the entire sample period of 1980-2013 in Figures A1 and A2, and for 2013 only in Figures A3 and A4, in the appendix.
[13] See, for example, Hodrick and Prescott (1981,1997), Baxter and King (1999), and Christiano and Fitzgerald (2003).
[14] In related work, Kala (2016) studies adaptation under different learning models. Hence, variance of climatological variables is an important element of her framework. 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. In the data section, however, we provide evidence that the variance of our weather shocks seems roughly constant over time.

variation that evolves slowly over time by including only higher-frequency time fixed effects. In fact, 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. 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). We leverage this idea in our unifying approach.

*A Measure of Adaptation to Climate Change*

$Temp^C$ 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. It can be thought of as climate normals. 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, one can only adjust to something they know. Therefore, adaptation can be measured as the difference between responses to changes in $Temp^C$ relative to effects of weather shocks $Temp^W$.[15] 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 work less hard when facing a *permanent* increase in the output price, but works harder when the price increase is *transitory*.

As mentioned above, important contributions to the literature have already pointed out that the comparison between the "short-" and "long-run" effects provides evidence of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016). Unlike previous work, however, we are able to estimate and test the equality of those effects within the same econometric model using insights from Solon's (1992) seminal work on intergenerational mobility. Also, it is imperative to mention that we introduce our measure as adaptation, but this is without loss of generality. It is possible that the difference in responses to climate vis-à-vis weather reflects adaptation and/or intensification.

[15] In related work, Shrader (2016) introduces a method for identifying adaptation based on changes in expectations about a stochastic environmental process, and applies his method to estimate total adaptation by North Pacific albacore harvesters to ENSO-driven climate variation.

## 3. Background on Ambient Ozone Formation, Seasonality, and Federal Regulations

We apply our novel approach to measure climate impacts and adaptation in the context of the effects of climate change on ambient ozone concentration. This is an ideal application for four reasons. First, ozone is formed and destroyed rapidly, with processes directly tied to temperature and other meteorological conditions. Second, it is a seasonal pollutant, with temporal patterns that mimic climatic changes, which allow us to identify climate effects. Third, ambient ozone is a one of the six criteria pollutants regulated by the U.S. EPA, providing us with a unique opportunity to study whether existing regulatory frameworks would trigger adaptation. Four, from a public policy perspective, the application is also relevant as there are increasing concerns that climate may generate a "penalty" in terms of increased ambient ozone concentration, potentially undoing some of the benefits of the Clean Air Act regulations.

*Ozone Formation and Seasonality*

The ozone the U.S. EPA regulates as an air pollutant is mainly produced close to the ground (tropospheric ozone)[16]. It results from complex chemical reactions between pollutants directly emitted from vehicles, factories and other industrial sources, fossil fuel combustion, consumer products, evaporation of paints, and many other sources. These highly nonlinear Leontief-like reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NOx) in the presence of sunlight. In "VOC-limited" locations, the VOC/NOx ratio in the ambient air is low (NOx is plentiful relative to VOC), and NOx tends to inhibit ozone accumulation. In "NOx-limited" locations, the VOC/NOx ratio is high (VOC is plentiful relative to NOx), and NOx tends to generate ozone.

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

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

to temperature as the most important weather variable affecting ozone concentrations[17].

Ambient ozone concentrations increase during the day when formation rates exceed destruction rates, and decline at night when formation processes are inactive[18]. Ozone concentrations also vary seasonally. They tend to be highest during the summer and early fall months[19]. The EPA has established "ozone seasons" for the required monitoring of ambient ozone concentrations for different locations within the U.S. (CFR, 2000)[20]. Recently, there is growing concern that the ozone season may prolong with climate change (e.g. Zhang and Wang, 2016).

*Clean Air Act Regulations*

Ambient ozone is an important component of smog that is capable of damaging living cells, such as those present in the linings of the human lungs. With the Clean Air Act Amendments of 1970, the U.S. EPA was authorized to enforce a National Ambient Air Quality Standard (NAAQS) for ambient ozone[21]. A nationwide network of air pollution monitors allowed the EPA to track ozone concentration, and two types of standards were used to determine whether pollution levels were sufficiently dangerous to warrant regulatory action. As the EPA (2005) states, "primary standards set limits to protect public health, including the health of 'sensitive' populations such as asthmatics, children, and the elderly. Secondary standards set limits to protect public welfare, including protection against decreased visibility, damage to animals, crops, vegetation, and buildings."

If any monitor within a county exceeds these standards, the EPA can designate the county "non-attainment." As part of a state implementation plan (SIP), a non-attainment county is required to outline its strategy to reduce air pollution levels in order to be compliant with the NAAQS. As

[17] 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.

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

[19] 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.

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

[21] As shown in Table A1, the first standard put in place in 1971 was not focusing on ambient ozone, but rather all photochemical oxidants.

reported in Table A2, EPA allows emitters 3 to 20 years to adjust their production processes[22]. However, if pollution levels continue to exceed the standards or if a county fails to abide by an approved plan, the EPA can impose sanctions on the county in violation. These sanctions may include the withholding of federal highway funds and the imposition of technological "emission offset requirements" on new or modified sources of emissions within the county (National Archives and Records Administration, 2005).

The first NAAQS for ambient ozone was established in 1979, when 120ppb was defined as the maximum 1-hour concentration that could not be violated more than once a year for a county to be designed as in attainment. In 1997, the standards were strengthened to 80ppb, but with a different form for the threshold: annual fourth-highest daily maximum 8-hour concentration averaged over 3 years[23]. With the 2008 and 2015 revisions, the current 8-hour threshold is now 70ppb[24]. In the latest revision, EPA raised concerns about how climate change might affect air quality, indicating that this study may contribute to such an important policy debate[25].

## 4. Data Description

To examine the impact of climate change on ambient ozone concentrations, and ultimately measure adaptation, we utilize information from three major sources, as described below.

*Ozone Data*. For ground-level ozone concentrations, 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

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[22] "Non-attainment" counties are "*classified as marginal, moderate, serious, severe or extreme (...) at the time of designation*" (EPA, 2004, p.23954). The maximum period to reach attainment is: "*Marginal – 3 years, Moderate – 6 years, Serious – 9 years , Severe –15 or 17 years, Extreme – 20 years*" (EPA, 2004, p.23954).

[23] EPA justified the new form as equivalent to the empirical 1-hour maximum to not be exceeded more than once a year. "*The 1-expected-exceedance form essentially requires the fourth-highest air quality value in 3 years, based on adjustments for missing data, to be less than or equal to the level of the standard for the standard to be met at an air quality monitoring site.*" (U.S. EPA, 1997, p.38868) The new NAAQS was challenged in courts, and not implemented until 2004.

[24] Figures A8 and A9, in the appendix, show the trends in ozone concentration over time, as well as the several NAAQS for ozone over time. As we can see, on average the regulations seem to bring non-attainment counties to attainment.

[25] In the 2015 revision of the ozone NAAQS, EPA final rule mentions: "*In addition to being affected by changing emissions, future $O_3$ concentrations will also be affected by climate change. (...) If unchecked, climate change has the potential to offset some of the improvements in $O_3$ air quality (...) that are expected from reductions in emissions of $O_3$ precursors.*" (EPA, 2015, p.65300)

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.

Figure 2 depicts the evolution of our sample monitors over the three decades in our data, and illustrates the expansion of the network over time. Table 1 provides some summary statistics regarding the increase in the number of monitors, and the decrease in ozone concentration decade by decade. 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. Table A4, in the Appendix, describes the sample of ozone monitors used in our analysis, for every year between 1980 and 2013.

*Data on Non-Attainment Designations*. We use publicly available data on the Clean Air Act Non-Attainment Designations to generate our indicator of non-attainment status for each county in our sample. This data is available at the EPA website from the Green Book of Non-Attainment Areas for Criteria Pollutants. In our preferred specification we use the non-attainment status lagged by three years because EPA gives heavy-emitters at least three years to comply with ozone NAAQS (EPA, 2004, p.23954). This is a binary variable that takes the value of one for counties not complying with the NAAQS for ground level ozone.

*Weather Data*. For meteorological data, we use daily measurements of maximum and minimum temperature as well as total precipitation from the National Climatic Data Center's Cooperative Station Data (NOAA, 2008). This dataset provides detailed weather measurements at over 20,000 weather stations across the country. We have acquired information for the period 1950-2013. 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[26]. Figure A5, in the Appendix, illustrates the geographical location of the weather stations that we have used from 1950-2013, and Figure A6 illustrates the proximity of our final sample of ozone monitors to these matched weather stations.

Our methodology takes advantage of two components of high frequency meteorological data: climatological variation and weather shocks. For climatological variation, we construct long-term trends of daily maximum temperature and precipitation. Precisely, we first construct monthly means of daily weather measurements, and then construct 30-year moving averages of monthly means to generate our climate variables. We then construct weather shocks as deviations of meteorological variables from their 30-year moving averages. More details will be discussed in the following section.

Table 1 reports the summary statistics for ambient ozone and temperature, for each decade. Table A5, in the Appendix, presents this information at a more disaggregated level, for each year in our sample from 1980-2013. Figure 3 reports the variation we have in both components of the maximum temperature, namely, the shocks and the long-term trends[27].

Consolidating information from the above three sources, we reach our final unbalanced sample of ozone monitors over the period 1980-2013. In our application, we focus on the effect of daily maximum temperature on daily maximum ozone concentration since 1980. We choose this outcome because EPA's ambient ozone standards have been built around it. Likewise, increases in temperature are expected to be the principal factor in driving any ozone increases (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our sample, plotted in Figures 1 and 4, highlights the close relationship between these two variables. Interestingly, we see that not

[26] For robustness purposes, we have varied this radius to 80 km and used information from the closest 5 weather stations. We also try different weights and the results are summarized in Table A14.

[27] This figure shows the variation in both components of temperature using a balanced panel of weather stations over time. Figure A7, in the appendix, depicts similar variation, but using temperature assigned to each ozone monitor. 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 2.

only does contemporaneous temperature have an effect on ground level ozone, but the long-term temperature trend also seems to be affecting it very closely.

## 5. Empirical Strategy

In this section, we present our methodology to examine the impact of climate change on the economic outcome of interest in our application, ground-level ozone concentration. First, we provide an empirical counterpart for the decomposition of meteorological variables described in the conceptual framework section. Second, we introduce and discuss features of our econometric model to estimate the effects of the two components of weather on ambient ozone levels. Lastly, we use our novel way to measure adaptation to climate change to estimate behavioral responses in our application to air pollution.

*Decomposition of Meteorological Variables: An Empirical Counterpart*

Focusing on temperature (*Temp*), our primary variable of interest[28], we express it around ozone monitor *i* in day *d* of month *m* and year *y* as

$$Temp_{idmy} = Temp^{C}_{im,y-1} + Temp^{W}_{idmy}. \tag{2}$$

$Temp^C$ represents climate normals, and is defined as a 30-year monthly moving average (MA) of past temperatures. 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 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[29]. We use monthly MAs because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed, meteorologists on

[28] As emphasized before, among all meteorological variables, temperature is expected to be the main factor driving increases in ozone concentration as the climate changes (Jacob and Winner, 2009).
[29] In the robustness checks, we provide similar estimates using 10- or 20-year moving averages, and longer lags.

TV 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[30].

$Temp^W$ 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 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[31].

*Econometric Model*

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

$$\begin{aligned} Ozone_{icdmy} = \alpha + \beta_T^W Temp_{idmy}^W + \beta_T^C Temp_{im,y-1}^C + \gamma NonAttain_{c,y-3} \\ + Prcp_{icdmy}\delta + \lambda_{sy} Z_i + \eta_i + \phi_{rsy} + \varepsilon_{idmy}, \end{aligned} \tag{3}$$

where *i* represents an ozone monitor located in county *c* in NOAA climate region *r*, and *d* stands for day, *m* for month, *s* for season (Spring or Summer), and *y* for year. As mentioned in the data section, our analysis focuses on the most common ozone season in the U.S. – April to September – in the period 1980-2013. The dependent variable *Ozone* captures daily maximum ambient ozone concentration. *Temp*'s[32] account for the two components of the decomposition proposed above for meteorological variables. *NonAttain*, the Clean Air Act (CAA) non-attainment county designation, is a binary variable equals to one for counties not complying with the NAAQS for ground-level ozone – "non-attainment" designations followed regulation guidelines derived from the CAA Amendments. This variable is lagged by three years because EPA gives heavy-emitters

[30] As another robustness check, we use *daily* instead of *monthly* moving averages. Economic agents, however, may still associate a day with its corresponding month when making adjustment decisions.

[31] 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. An *Ozone Action Day* 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 only hours in advance. Nevertheless, unlike what happens in a few developing countries, neither production nor driving is forced to stop in those days, limiting the impact of short-run adjustments. In the robustness checks, we provide evidence that adaptation happens even counties facing the alerts. That is, short-run adjustments, if any, do not seem large enough to be comparable to what happens in the long run.

[32] We also add the two components of precipitation in our econometric analysis. Although less important than temperature, Jacob and Winner (2009) point out that higher water vapor in the future climate may decrease ground-level ozone concentration. The estimates are in line with those authors' assessment, and are available upon request.

at least three years to comply with ozone NAAQS (EPA, 2004, p.23954). *Z* represents time-invariant covariates (latitude and longitude of ozone monitors), which are interacted with season-by-year fixed effects in our econometric specification, $\eta$ represents monitor fixed effects, $\Phi$ region-by-season-by-year fixed effects, and ε an idiosyncratic term.

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.

Identification of the effect of climatic changes on ground-level 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 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. This is consistent with evidence that the ozone season could start earlier and/or last longer (e.g., Zhang and Wang 2016). In fact, when EPA strengthened the ozone standards in 2015, it extended the ozone monitoring season for 32 states and the District of Columbia. A review of all available monitoring data from 2010-2013 (including data from year-round air quality monitors) showed that ozone could be elevated earlier in the spring and last longer into the fall than some states previously were required to measure (EPA, 2015).

Our preferred econometric specification allows the effects of each component of our meteorological variables to differ according to the "attainment" or "non-attainment" designation of the county where each monitor is located. The estimating equation becomes

$$\begin{aligned} Ozone_{icdmy} = \alpha &+ \beta_{TA}^{W}(Temp_{idmy}^{W} \times Attain_{c,y-3}) + \beta_{TA}^{C}(Temp_{im,y-1}^{C} \times Attain_{c,y-3}) \\ &+ \beta_{TN}^{W}(Temp_{idmy}^{W} \times NonAttain_{c,y-3}) + \beta_{TN}^{C}(Temp_{im,y-1}^{C} \times NonAttain_{c,y-3}) \\ &+ \gamma NonAttain_{c,y-3} + Prcp_{icdmy}\delta + \lambda_{sy}Z_i + \eta_i + \phi_{rsy} + \varepsilon_{idmy}, \qquad (4) \end{aligned}$$

Because of the use of 30-year MAs and deviations from it to characterize climate – and ultimately uncover a measure of adaptation – it may be reasonable to focus on continuous temperature instead of more flexible temperature bins. We could, however, compute moving averages for the bins as averages of monthly bin dummies over the past 30 years, and deviations of values of each dummy variable associated with a bin in the contemporaneous period relative to the 30-year MA bin. Nevertheless, this procedure may decrease data variability by smoothing the temperature variables, and lead to a loss in statistical power when estimating the effect of each temperature bin. Indeed, deviations of a contemporaneous temperature measurement of 31°C relative to a 30-year MA of 23°C, for example, should be not as smooth as deviations of a contemporaneous 30°-35°C bin from a 30-year MA associated with the number of months in that bin. Despite these issues, we provide estimates of such nonlinear effects in the results section.

*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 $\beta_T^W$ and $\beta_T^C$ in equation (3). If economic agents engaged in full adaptive behavior, $\beta_T^C$ would be zero, and the magnitude of the average adaptation would be equal to the size of the weather shock effect on surface 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.

We can split our measure of average adaptation into two parts: regulation-induced and residual adaptation, as shown in Table 2. Regulation-induced adaptation reflects adjustments made by heavy emitters in "non-attainment" counties to comply with ozone NAAQS. EPA mandates those facilities to cut emissions by using the best pollution abatement technologies available. Because ozone formation depends on both emissions and meteorological conditions, by reducing emissions to abide by the CAA regulations, agents may be actually adapting to climatic changes[33]. Residual adaptation reflects adaptive responses by economic agents in counties under no pressure from stringent CAA regulations[34].

[33] Notice that, because those counties are also reducing emissions, some researchers might prefer using the term *mitigation*. Our argument is that those polluters would have not undertaken those costly investments if the climate had not changed, so we would rather call this a response to climate change or, in other words, regulation-induced adaptation. This is not a new use of the term adaptation. In the context of responses to natural disasters, Kousky (2012) explains that "*The negative impacts of disasters can be blunted by the adoption of risk reduction activities. (…) [T]he hazards literature (…) refers to these actions as mitigation, whereas in the climate literature, mitigation refers to reductions in greenhouse gas emissions. The already established mitigation measures for natural disasters can be seen as adaptation tools for adjusting to changes in the frequency, magnitude, timing, or duration of extreme events with climate change.*" (p.37, our highlights).

[34] If those counties are right below the ozone standards, it is possible that they take actions to avoid being out of attainment. If that is the case, then residual adaptation may include a component related to the threat of stringent

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 – 30 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. Because EPA may give heavy emitters up to two decades to comply with ozone NAAQS, adaptive responses many years after agents observe changes in temperature trends may be plausible.

Equations (3) and (4) are the econometric specifications used to estimate our main results. We can adjust them, however, to shed light on the impact of climate change on ambient ozone concentration for different decades. Indeed, in an additional specification, we interact the two components of meteorological variables and *Attain/NonAttain* county designations with each decade included in our sample – 1980s, 1990s, and 2000s. Once we have the estimates associated with weather shocks and lagged 30-year MAs in this case, we are able to provide measures of adaptation for each decade and each climate region in our sample. In all estimations, standard errors will be clustered at the monitor level[35].

## 6. Results

In this section we report our findings regarding (i) the impact of temperature on ambient ozone concentration, (ii) the extent to which economic agents adapt to climate change in the context of ozone pollution, and (iii) how those effects change by decade (1980s, 1990s, and 2000s). Then,

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regulations. In the robustness checks, we provide evidence that even counties far below the threshold of the standards engage in adaptive behavior. To provide an example of residual behavioral responses to climatic changes, we lean on Leard and Roth (2016). These authors find that mean temperatures above 80°F (relative to 50°-60°F) imply 5 percent fewer trips per household by light duty vehicles, which seems to be partially compensated by higher travel demand by ultralight duty vehicles. The overall decrease in travel demand and the change in vehicle composition induced by temperatures higher than expected can be seen as adaptive responses, and should imply less emissions of ozone precursors by vehicles.

[35] There may be a concern that our temperature shocks and trends are both constructed, so they could be considered generated regressors. In Table A16, we provide bootstrapped standard errors for our main estimates, and show that they vary from -5 percent to +11 percent, relative to the standard errors clustered at the monitor level. Given such a small variation, we opted to report the regular clustered standard errors.

we provide evidence of the robustness of our main results to alternative specifications and sampling strategies.

*Impact of Temperature on Ambient Ozone Concentration*

Table 3 presents the effects on ambient ozone of two components of observed temperature: climate, represented by the *lagged* 30-year monthly MA[36], and weather shock, represented by the deviation from that long-run trend. Although they are uncovered by estimating equation (3), 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 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 a 1.09ppb increase 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 region-by-month-by-year fixed effects. The coefficient indicates that a 1°C increase in maximum temperature leads to a 1.71ppb increase in maximum ground-level ozone concentration. When we decompose daily maximum temperature into our two components in column 3, as expected the effect on ambient ozone increases for the lagged 30-year MA, but is statistically the same for the weather shocks. A 1°C shock increases ozone concentration by 1.69ppb, and a 1°C change in trends in the same month of the previous year increases ozone concentration by 1.24ppb. 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 14 percent when compared to cross-sectional estimates.

[36] As mentioned before, even though we use monthly moving averages in our main estimates, as a robustness check we also estimate our preferred specifications using daily moving averages. The results are virtually identical, and are reported in Table A15.

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 methodology and our approach should be the same due to the properties of the Frisch-Waugh-Lovell theorem. The deseasonalization embedded in the panel-data model is equivalent to the use of deviations from 30-year trends in our regression model.

Even with larger estimates of the impact on ambient ozone concentrations of both unexpected spikes in temperature and rises in long-term temperature, our estimates imply a climate penalty on ozone – the sum of both effects – 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 can lead to a rise in summertime surface ozone concentrations by 1-10 ppb. The EPA, in its Interim Assessment (2009), claims that "*the amount of increase in summertime average ... O*3 *concentrations across all the modeling studies tends to fall in the range 2-8 ppb"*.

Column 4 shows that the estimates do not change when we include the CAA non-attainment county designation (*NonAttain*) in the regression, but column 5 indicates important heterogeneity in the effect of each component of temperature across counties in or out of attainment regarding the ozone NAAQS. A 1°C rise in the climate trend (as measured by the lagged 30-year MA of temperature) leads to a 0.98ppb rise in ozone concentrations in attainment counties, compared to 1.45ppb in non-attainment counties. Similarly, a 1°C increase in the weather shock increases ozone levels by 1.3ppb in attainment counties, whereas it leads to a 1.99ppb increase in non-attainment counties. It is imperative to note that the larger effects for non-attainment counties should not reflect higher levels of emissions of ozone precursors. In fact, we are controlling for emissions using the time-varying non-attainment status as a plausibly exogenous proxy in the econometric model. Therefore, we should interpret our estimates as the effects of the two components of temperature conditional on ozone precursor emissions. That is, even if emissions are stabilized in a particular location, climate change will induce higher concentrations of ambient ozone because it will lead to more suitable conditions for ozone formation.

*Measuring Adaptation to Climate Change*

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 3 with the effect of a temperature shock in column 2, adaptation would be overestimated – approximately 0.62ppb. 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 27 percent smaller: 0.45ppb.

Our results indicate that temperature shocks have a larger impact on ozone levels compared to long-term temperature trends. This suggests that economic agents might be *adapting* to climate trends. We summarize our measures of adaptation in Table 4. By comparing the coefficients of the temperature shock and the temperature trend in Column (4) of Table 3, we find that on average across all counties, *the level of adaptation is* 0.45ppb. This is roughly 37 percent of the direct effect of the Clean Air Act non-attainment designation (*NonAttain*), which means that our measure of adaptation is economically sizeable. If we ignore such adaptive responses by economic agents, then we would be overestimating the climate penalty on ozone by over 17 percent[37].

Using our estimates from Column (5) of Table 3, we can now disentangle the overall adaptation into *regulation-induced adaptation* and *residual adaptation*. The coefficients of the interaction terms with *Attain* gives us the impacts of weather shocks and climate trends in *attainment counties*, whereas the coefficients of the interactions with *NonAttain* gives us the same for *non-attainment counties.* From this specification, we find that the total adaptation in attainment counties is 0.33ppb whereas in non-attainment counties it is 0.55ppb. Hence, non-attainment counties adapt over 66 percent more than attainment counties in absolute terms. The incremental adaptation of 0.22ppb in non-attainment counties is our measure of *regulation-induced adaptation*. The remainder is *residual adaptation*. Therefore, 40 percent of the adaptation in non-attainment counties should be driven by the Clean Air Act regulations.

[37] In the absence of adaptation, the climate penalty would be twice the effect of weather shocks (i.e. 3.4 ppb) rather than the 2.9 ppb that we actually observe.

*Results by Decade*

In Tables 5 and 6, we report our results by decades. 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 decade. In Table 5, we present the main estimates, where we see the heterogeneity of our results across time. We find that the effects of contemporaneous daily maximum temperature, and its two components of our decomposition, are decreasing over time. Nevertheless, looking at columns (3) and (4) and Table 6, 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. Also, from column (4) and Table 6 we find that the regulation-induced adaptation in non-attainment counties decreases consistently from around 0.22ppb in the 1980s to about 0.09ppb in the 2000s. *Residual* adaptation varies from 0.42ppb in the 1980s to 0.27ppb in the 1990s and 0.38ppb in the 2000s. Therefore, the 1980s, which marked the initial phases of the regulation and when the average pollution levels were also higher, exhibit on one hand the largest impacts of the climate on ground-level ozone, and on the other hand also show the largest degree of adaptation over time.

## 7. Robustness Checks

### 7.1 Nonlinearities

Because ozone formation may be intensified with higher temperatures, we also look at the nonlinear effects of daily maximum temperature on ambient ozone concentrations. Instead of using daily maximum temperature continuously, we categorize contemporaneous daily maximum temperature and its monthly average into temperature bins of 5°C. The lowest bin is below 20°C (just over the $10^{th}$ percentile of our temperature distribution), and the highest bin is above 35°C ($90^{th}$ percentile of our temperature distribution). To get a measure of the long-term climate trend, we take the lagged 30-year MAs of these temperature bin dummies; the measure of our weather shock is constructed by taking the difference between the contemporaneous temperature bin dummies and the 30-year monthly MA of temperature bin dummies. In Table A6 in Appendix A, we report our estimates from this nonlinear specification.

By interacting our temperature bins with the regulatory variables *Attain* and *NonAttain*, as before, we can analyze the nature and degree of regulation-induced and residual adaptation at different points of the temperature distribution. From column (1), as expected, we find that higher temperatures increasingly lead to hike in ozone concentrations. As each bin is of 5°C, we can see that for temperatures between 20°C and 25°C, a 1°C increase would raise ozone levels by 1.22ppb on average; whereas for temperatures between 25-30°C, 30-35°C and above 35°C, the effects are 3.1ppb, 4.76ppb, and 6.54ppb, respectively. From our estimates in column (2), we have the following results about the degree of adaptation at different levels of temperature, which are summarized in Table A7.

*Average Adaptation (across all counties)*. From column (2) of Table A6, the average level of adaptation across all counties ranges from 0.51ppb (19.7%) for temperatures between 20-25°C, to 0.16ppb (2.65%) for temperatures between 25-30°C; 0.45ppb (4.66%) for temperatures between 30-35°C, and lastly almost 0.82ppb (6.12%) for temperatures in our highest bin[38]. So, by comparing the adaptation percentages, we see that a lot of it is driven by the 20-25°C bin.

Since the U.S. as a whole is predominantly NOx limited, we would expect that changes in electricity usage drastically affect ozone concentrations[39]. 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,

[38] 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.
[39] 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.

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 or heating. Thus, higher temperatures might be creating an environment that is more suited to shift away from conventional and dirtier sources of power generation, thus leading to higher levels of (residual) adaptation. Second, regions having higher temperatures have a larger climate penalty on ozone and, hence, might be more strongly regulated. This might determine larger levels of regulation-induced adaptation.

*Regulation-induced adaptation*. Like our main results, we find more adaptation in non-attainment counties at every level of temperature. However, out of the total adaptation in non-attainment counties, the proportion of regulation-induced adaptation varies from around 25 percent for temperatures between 20-25°C to around 62.5 percent for temperatures between 30-35°C.

### 7.2 Measurement Error

A concern regarding our decomposition of meteorological variables in equation (2) 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 equations (3) and (4) 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-, 20-, and 30-year MAs. 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 A8 remain remarkably stable over the different lengths of the moving averages, and if anything they get slightly larger until the 20-year moving average.

As pointed out by Angrist and Pischke (2015, p. 242-243), 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 A8 remain largely unchanged over the different lengths of the moving averages, with a slight attenuation of the coefficient of the weather shocks, and a slight reduction 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[40] – 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.

### 7.3 Lagged 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, so agents have only one year to adapt. Hence, we check the sensitivity of our results when agents get 10 or 20 years to adapt, instead of just one. In Table A9, we provide estimates from our preferred specification but using 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 adapt 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 A9, although the magnitude of the coefficients is close to that of our main results.

### 7.4 Non-Random Siting of Ozone Monitors

In recent work, Muller and Ruud (2017) 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

[40] "*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.*" (Wisconsin State Climatology Office, aos.wisc.edu/~sco/normals.html, 2003)

linking pollution to its varied impacts, and (ii) to check and enforce the NAAQS for 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 check for attainment status. 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 A10. We find that a 1°C increase in the daily maximum temperature leads to a rise in ozone concentrations by 1.88ppb. Average adaptation is 0.44ppb across all counties. We can further disentangle this to find that regulation-induced adaptation in non-attainment counties is 0.24ppb whereas residual adaptation is 0.25ppb. As expected, the effects obtained from the balanced panel are *larger* than those in our main results. 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.

### 7.5 Role of Wind Speed and Sunlight

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 our preferred specification using a smaller sample containing those variables. Table A11 reports these estimates. Columns (1) and (2) present our main results from estimating Equations (3) and (4), respectively. Next, we present estimates from Equation (4) plus controls for average daily wind speed (meters/sec) in Column (3), total daily sunlight (mins) in Column (4), and both in Column (5). As expected, higher wind speeds lead to lower ozone concentrations, and more sunlight leads to higher concentrations. From Column (5), 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 (2) with Column (5), 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, and *regulation-induced adaptation* is 0.17ppb in non-attainment counties. 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.

### 7.6 Adaptation and the Attainment Threshold

In our preferred specification given by Equation (4), we interact both our components of temperature – the climate trend and the weather shock – with the Clean Air Act attainment status (*Attain*) and Clean Air Act non-attainment status (*NonAttain*) to estimate the differential levels of adaptation in attainment versus non-attainment counties. However, within attainment group, some counties might have pollution levels very close to the federal threshold and some might be have levels much below it. A potential issue with our analysis is that most of the 0.33ppb of *residual adaptation* might still be driven by *attainment counties* that are on the margin of turning to non-attainment. If this is the case, then we would observe some degree of what would be *threat-of-regulation* adaptation.

To check if any intrinsic residual adaptation exists at all, we estimate our preferred specification by interacting both the climate trend and the weather shock with the different categories of the Air Quality Index (AQI). The AQI levels are categorized into *Good, Moderate, Unhealthy for Sensitive Groups*, and *Unhealthy*. Counties having Good or Moderate air quality are in attainment, with the ones having moderate AQI falling just below the federal pollution threshold. Similarly, counties having air quality worse than moderate are generally in non-attainment, and might have to disclose that information to the local media along with meteorology. Table A12, column (1), summarizes the results from the above specification. The estimates are consistent with our primary results. At each level of air quality, we find that a 1°C increase in the climate trend as well as a 1°C increase in the weather shock leads to an increase in ozone concentrations. Moreover, there is a positive and significant difference in these effects[41], indicating that there is indeed adaptation at every level of air quality. Finally, we find 0.36ppb of adaptation in counties that have good air quality whereas only 0.12ppb of adaptation in counties having moderate air quality. Hence, within all counties that are in attainment, counties that are just below the threshold are exhibiting lower levels of adaptation than counties that are not facing an immediate threat of regulation. This supports our argument that apart from regulation-induced or threat-of-regulation adaptation, there are other mechanisms through which economic agents might adapt, which we call residual adaptation[42].

## 8. Concluding Remarks

In this paper, we propose a novel methodology to study the effect of temperature on ambient ozone concentrations and measure adaptation to climate change. By decomposing high frequency daily data on meteorological variables since 1950, made available by the National Oceanic and Atmospheric Administration (NOAA), we are able to examine the impact on air quality of both long-term climatic trends and short-term deviations from such trends (i.e. weather shocks) in a single estimating equation. Using daily data on ambient ozone concentrations from EPA's Air Quality Systems (AQS) database, we find that unexpected spikes in temperature as well as increases in the long-term temperature trend have positive and significant impacts on ground-level ozone levels. A 1°C shock in temperature increases ozone levels by 1.7ppb on average, which is what would find in the standard fixed-effect approach. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.2ppb, which is 14 percent higher than what would have been found in the (biased) standard cross-section approach.

By comparing the long-term "climate effect" with the short-term "weather effect", we arrive at our measure of adaptation to climate change. We find an average adaptation of 0.45ppb across all counties in our sample. This measure captures the fact that the long-term effect of

[41] We have tested if the coefficients of the climate trend and the weather shock are significantly different from each other and the results are reported in Table A12, column (2).
[42] As reported in Table A13, qualitatively similar results are found when we restrict our sample to monitors with ozone concentrations just below and just above the NAAQS threshold. In that table, we see that there is almost no adaptation in counties with ozone concentrations around the threshold.

temperature, although positive, is smaller than the effect of a sudden shock, thus signifying potential changes in behavior of economic agents in response to a changing climate. In the absence of any adaptation, we would expect the impact of higher temperature to be twice as much as the effect of the temperature shock, i.e. a 3.4ppb increase in ozone levels. Thus, by ignoring adaptation, we would *overestimate* the climate penalty on ozone by over 17 percent.

Using data on Clean Air Act Attainment designations from the EPA's Green Book of Non-attainment Areas for Criteria Pollutants, we are also able to provide a measure *regulation-induced adaptation*, which is occurring in counties facing stringent regulations for being out of attainment of ozone NAAQS. That is above and beyond the measure of *residual adaptation*, which might be occurring in all counties. We find that non-attainment counties adapt over 66 percent more in terms of ozone concentrations. Comparing our estimates to the benefits from the CAA regulations, we find that adaptation in non-attainment counties represents almost 45 percent of the effect of being out of attainment. Finally, we break our analysis by decade to explore temporal heterogeneity of our estimates. We find that the 1980s, which marked the initial implementation phases of the Clean Air Act regulations and correspond to the highest pollution levels in our sample, had the largest impact of temperature on ambient ozone concentrations as well as the largest degree of adaptation to climate change.

By estimating the causal effect of temperature on ambient ozone, we have taken the first step towards calculating the costs of climate change in terms of higher air pollution. We have illustrated that in the presence of climate change, pollution levels are exacerbated, hence implying larger external costs of emissions. Thus, such estimates are crucial to guide more informed policymaking and reaching the socially desirable level of emissions. This also provides scope for further research along similar lines, to estimate the climate penalty on other criteria air pollutants that have severe health effects. Another potential direction for further research might be to consider various adaptation mechanisms and behavioral adjustments made by economic agents, such as re-allocation of production across hours of the day or migration to less polluted regions.

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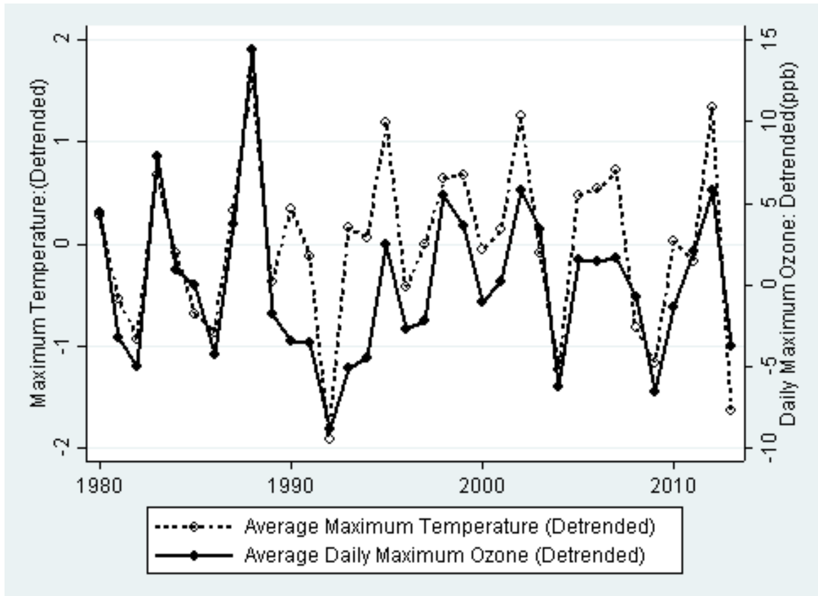
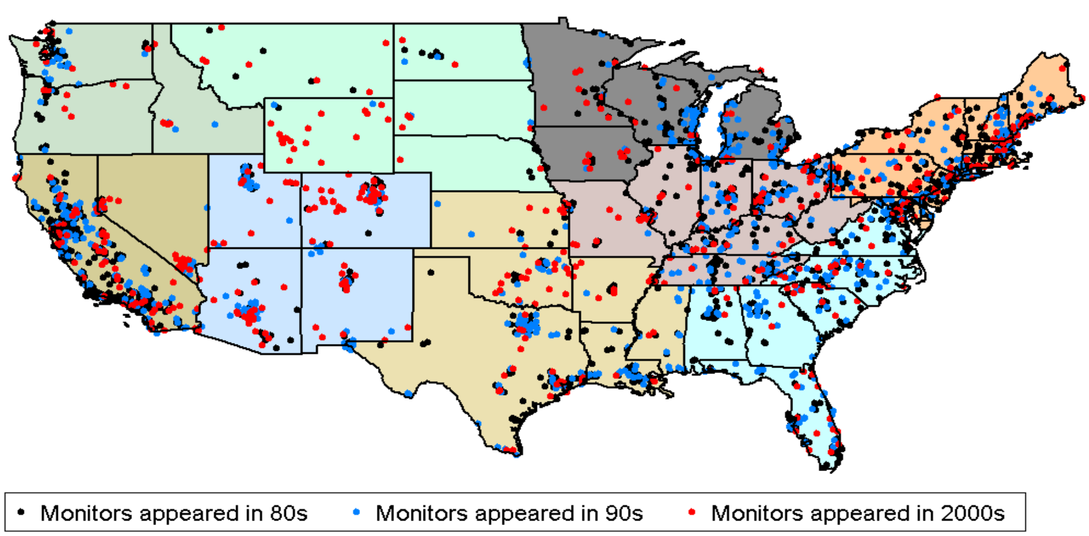
**Figures and Tables**

Figure 1: Relationship between Ozone and Contemporaneous Temperature



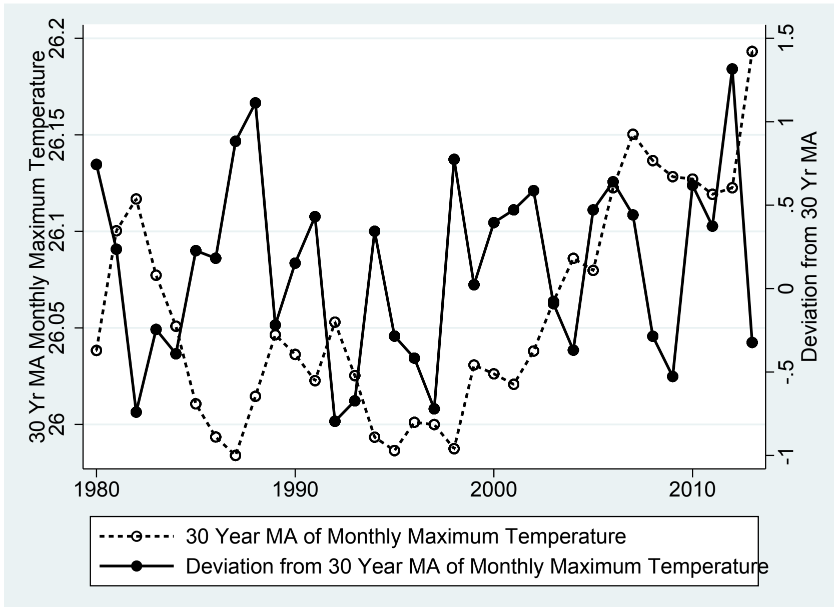

*Notes*: This figure reports the daily maximum temperature and ozone, averaged across all monitor-days, for each year. The variables have been detrended by eliminating a linear time trend.

Figure 2: Ozone Monitors by Decade of First Appearance



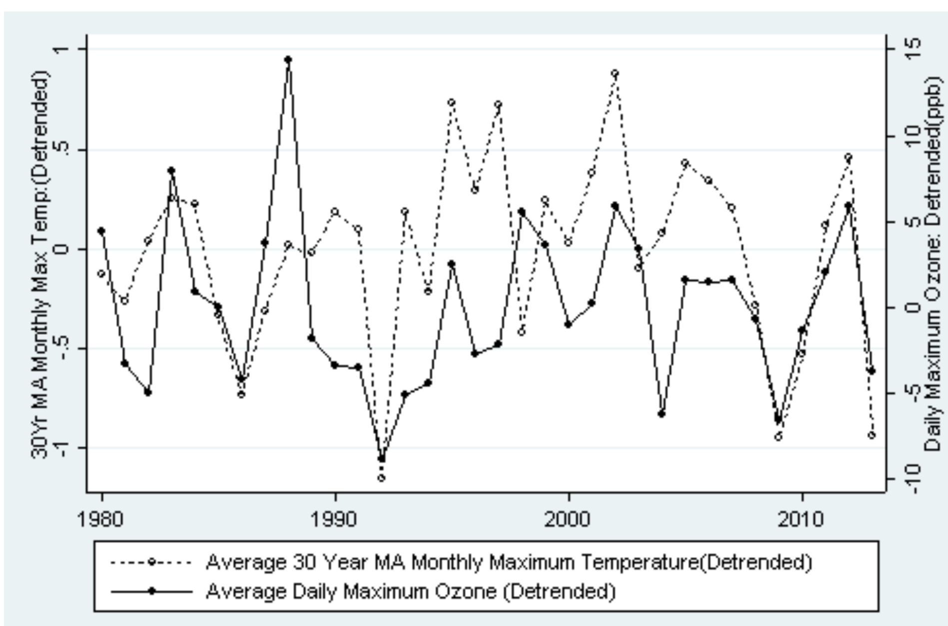

*Notes*: This figure maps the ozone monitors in our final sample, by decade of first appearance. Each shaded region represents a single climatic region as designated by the NOAA.

Figure 3: Temperature – Trends and Shocks




*Notes*: This figure reports the variation in both components of maximum temperature. The shock is a deviation of contemporaneous daily maximum temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year.

Figure 4: Relationship between Ozone and Moving Average of Temperature




*Notes*: This figure reports the 30-year monthly moving average of daily maximum temperature and ambient ozone concentration, averaged across all monitor-days, for each year. The variables have been detrended by eliminating a linear time trend.

Table 1: Summary Statistics by Decades

| ***Panel A. Ambient Ozone Monitoring Network*** | | | | | |
|---|---|---|---|---|---|
| **Decade** | **#Obs** | **#Counties** | **#Monitors** | **Daily Max Ozone Levels (ppb)** | |
| | | | | **Mean** | **Std. Dev.** |
| 1980s | 107,823 | 390 | 672 | 60.8 | 29.0 |
| 1990s | 153,858 | 509 | 888 | 57.6 | 21.1 |
| 2000s | 179,947 | 601 | 1026 | 54.3 | 16.7 |

| ***Panel B. Daily Temperature - Trends and Shocks*** | | | | | | |
|---|---|---|---|---|---|---|
| **Decade** | **Max Temp** | | **Max Temp 30-Yr MA** | | **Max Temp Shock** | |
| | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| 1980s | 26.8 | 6.7 | 26.6 | 5.3 | 0.2 | 4.3 |
| 1990s | 26.9 | 6.8 | 26.8 | 5.5 | 0.1 | 4.1 |
| 2000s | 27.4 | 7.0 | 27.2 | 5.7 | 0.2 | 4.1 |

*Notes*: This table reports some summary statistics. Data used in construction of Panel A uses monitor-days for which 8-hour averages were recorded for at least 18 hours of the day and monitor-years for which valid monitor-days were recorded for at least 75% of days between April 1st and September 30th. For Panel B, 30-year moving averages have been constructed at each pollution monitor, by using historical weather data from 1950-2013. Temperature deviations are defined as (Daily Max Temp – 30-Year monthly MA of Max Temp). Each pollution monitor has been matched to the closest two weather stations within a 30 km boundary. This table uses data for the months of April-September as that constitutes the typical ozone season. Decades are 1980-1990, 1991-2001 and 2002-2013 respectively.

Table 2: Measures of Adaptation

| Dependent Variable: Ambient Ozone | Average Adaptation [equation (3)] | Regulation-Induced Adaptation [equation (4)] | Residual Adaptation [equation (4)] |
|---|---|---|---|
| Marginal Effect of Weather Shocks | $\beta_T^W$ | $\beta_{TNA}^W \equiv (\beta_{TA}^W + \theta_T^W)$ | $\beta_{TA}^W$ |
| Marginal Effect of Climatic Changes | $\beta_T^C$ | $\beta_{TNA}^C \equiv (\beta_{TA}^C + \theta_T^C)$ | $\beta_{TA}^C$ |
| Measures of Adaptation | $(\beta_T^W - \beta_T^C)$ | $(\theta_T^W - \theta_T^C)$ | $(\beta_{TA}^W - \beta_{TA}^C)$ |

*Notes:* Estimates of Equation (3) gives us measures of average adaptation across all counties in our sample. The difference between the response to unexpected weather shocks, $\beta_T^W$, and observed climate trends, $\beta_T^C$, gives us a measure of adaptation by economic agents. In the absence of any adaptation, we would have $\beta_T^W = \beta_T^C$. Relative to this scenario, we find average adaptation to be $(\beta_T^W - \beta_T^C)$. Estimates from Equation (4) gives us levels of adaptation in attainment and non-attainment counties, using the interaction effects. Counties out of attainment have regulation-induced adaptation given by $(\theta_T^W - \theta_T^C)$. All counties exhibit residual adaptation, given by $(\beta_{TA}^W - \beta_{TA}^C)$.

Table 3: Main Estimates

| Dep. Var.: Daily Max Ozone Levels (ppb) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Max Temp | 1.0911*** | 1.7352*** | | | |
| | (0.0949) | (0.0240) | | | |
| Max Temp Shock | | | 1.6939*** | 1.6942*** | |
| | | | (0.0254) | (0.0254) | |
| Max Temp 30-Yr MA | | | 1.2424*** | 1.2423*** | |
| | | | (0.0239) | (0.0239) | |
| *Non*-Attainment County | | | | -1.2197*** | -14.0926*** |
| | | | | (0.1771) | (0.8447) |
| Attainment County | | | | | 1.3025*** |
| x Max Temp Shock | | | | | (0.0191) |
| Attainment County | | | | | 0.9767*** |
| x Max Temp 30-Yr MA | | | | | (0.0219) |
| *Non*-Attainment County | | | | | 1.9991*** |
| x Max Temp Shock | | | | | (0.0335) |
| *Non*-Attainment County | | | | | 1.4509*** |
| x Max Temp 30-Yr MA | | | | | (0.0283) |
| Observations | 2,535 | 4,974,322 | 4,974,155 | 4,974,155 | 4,974,155 |
| R-squared | 0.2521 | 0.4349 | 0.4223 | 0.4225 | 0.4286 |
| Precipitation Controls | Yes | Yes | Yes | Yes | Yes |
| Monitor FE | | Yes | Yes | Yes | Yes |
| Monitor Latitude & Longitude | Yes | | | | |
| Climate Region FE | Yes | | | | |
| Month-by-Year FE | | Yes | | | |
| Season-by-Year FE x Monitor Latitude | | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | | Yes | Yes | Yes | Yes |

*Notes:* This table reports our main climate impact results. Column (1) reports cross sectional estimates using *average* temperature and ozone concentrations at 2535 ozone monitors in sample. Having averaged the variables over all the years from 1980-2013, these estimates capture the effect of a change in the long-term *climate trend*. Column (2) reports the effect of daily temperature on ozone, exploiting day-to-day variation in maximum temperature and hence capturing the effect of a change in short term *weather*. In Column (3), we decompose daily temperature into *climate trends* and *weather shocks* in the same estimating equation, exploiting high frequency data. Recall that the 30-year MA is lagged by 1 year. In Column (4), we control for the Clean Air Act (CAA) non-attainment county designation, lagged by 3 years, and this is the specification expressed in Equation (3). In Column (5), we include interactions of weather shocks and climate trends with the CAA designation status to estimate heterogeneous effects across attainment and non-attainment counties, and this is the specification expressed in Equation (4). Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 4: Adaptation Main Estimates

| | **Total Adaptation (ppb)** | **Overestimation of Climate Penalty (%)** | **Relative to CAA Benefits (%)** | **Regulation Induced Adaptation (ppb)** | **Residual Adaptation (ppb)** | **% Regulation Induced** |
|---|---|---|---|---|---|---|
| All Counties | 0.45*** | 17.2 | 37.05 | 0.12 | 0.33 | 26.6 |
| | (0.021) | | | | | |
| *Non*-Attainment Counties | 0.55*** | 16.2 | 44.95 | 0.22*** | 0.33 | 40 |
| | (0.029) | | | (0.031) | | |
| Attainment Counties | 0.33*** | 14.5 | 26.71 | -- | 0.33 | -- |
| | (0.02) | | | | | |

*Notes*: This table reports our main adaptation results. For non-attainment counties, Level of adaptation (ppb) = Residual $(\beta_{TA}^{W} - \beta_{TA}^{C})$ + Regulation-induced $(\theta_{T}^{W} - \theta_{T}^{C})$, from column (5) of Table 3. For attainment counties, Level of adaptation (ppb) = $(\beta_{TA}^{W} - \beta_{TA}^{C})$, from column (5) of Table 3. Overestimation of climate penalty for non-attainment counties = $(\frac{\beta_{TNA}^{W}-\beta_{TNA}^{C}}{\beta_{TNA}^{W}+\beta_{TNA}^{C}})$*100; for attainment counties = $(\frac{\beta_{TA}^{W}-\beta_{TA}^{C}}{\beta_{TA}^{W}+\beta_{TA}^{C}})$*100. Average Level of adaptation (ppb) for all counties = $(\beta_{T}^{W} - \beta_{T}^{C})$, from column (4) of Table 3. Note that in all calculations, the effect of the CAA regulation is given by $\gamma$ as estimated by Equation (3), and reported in column (4) of Table 3. Proportion of counties in non-attainment in the entire sample is 0.54. Adaptation estimates for all counties are averages for estimates for attainment and non-attainment counties, weighted by the proportion of counties in non-attainment. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 5: Results by Decades

| Dep. Var.: Daily Max Ozone Levels (ppb) | (1) | (2) |
|---|---|---|
| ***Panel A. 1980s*** | | |
| Max Temp Shock | 2.2841*** | |
| | (0.0520) | |
| Max Temp 30-Yr MA | 1.7046*** | |
| | (0.0536) | |
| *Non*-Attainment County | 0.1004 | -11.7159*** |
| | (0.3952) | (1.5323) |
| Attainment County | | 1.7829*** |
| x Max Temp Shock | | (0.0448) |
| Attainment County | | 1.3614*** |
| x Max Temp 30-Yr MA | | (0.0474) |
| *Non*-Attainment County | | 2.5061*** |
| x Max Temp Shock | | (0.0613) |
| *Non*-Attainment County | | 1.8630*** |
| x Max Temp 30-Yr MA | | (0.0628) |
| ***Panel B. 1990s*** | | |
| Max Temp Shock | 1.7605*** | |
| | (0.0266) | |
| Max Temp 30-Yr MA | 1.3720*** | |
| | (0.0263) | |
| *Non*-Attainment County | -1.0401*** | -13.6521*** |
| | (0.2105) | (0.9892) |
| Attainment County | | 1.3650*** |
| x Max Temp Shock | | (0.0259) |
| Attainment County | | 1.0952*** |
| x Max Temp 30-Yr MA | | (0.0285) |
| *Non*-Attainment County | | 2.0390*** |
| x Max Temp Shock | | (0.0348) |
| *Non*-Attainment County | | 1.5760*** |
| x Max Temp 30-Yr MA | | (0.0299) |
| ***Panel C. 2000s*** | | |
| Max Temp Shock | 1.2897*** | |
| | (0.0182) | |
| Max Temp 30-Yr MA | 0.8793*** | |
| | (0.0257) | |
| *Non*-Attainment County | -1.5564*** | -11.0023*** |
| | (0.2374) | (1.0497) |
| Attainment County | | 1.0918*** |
| x Max Temp Shock | | (0.0184) |
| Attainment County | | 0.7136*** |
| x Max Temp 30-Yr MA | | (0.0240) |
| *Non*-Attainment County | | 1.5178*** |
| x Max Temp Shock | | (0.0266) |
| *Non*-Attainment County | | 1.0508*** |
| x Max Temp 30-Yr MA | | (0.0342) |
| Observations | 4,974,155 | 4,974,155 |
| R-squared | 0.4309 | 0.4354 |
| Precipitation Controls | Yes | Yes |
| Monitor FE | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes |

*Notes:* This table reports our main estimates by the three decades in our sample: 1980-1990; 1991-2001 and 2002-2013. Columns (1) and (2) show estimates obtained by Equations (3) and (4), respectively, but interacting our main variables with dummies for decades. Recall that the 30-yr MA is lagged by 1 year, and the CAA attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 6: Adaptation Estimates by Decades

| | Average Adaptation (ppb) | Regulation Induced Adaptation (ppb) | Residual Adaptation (ppb) | % Regulation Induced | Proportion in *Non*-Attainment |
|---|---|---|---|---|---|
| ***Panel A. 1980s*** | | | | | 0.71 |
| *Non*-Attainment Counties | 0.64 | 0.22 | 0.42 | 34.38 | |
| Attainment Counties | 0.42 | -- | 0.42 | -- | |
| All Counties | 0.58 | 0.16 | 0.42 | 27.59 | |
| ***Panel B. 1990s*** | | | | | 0.54 |
| *Non*-Attainment Counties | 0.46 | 0.19 | 0.27 | 41.3 | |
| Attainment Counties | 0.27 | -- | 0.27 | -- | |
| All Counties | 0.39 | 0.12 | 0.27 | 30.77 | |
| ***Panel C. 2000s*** | | | | | 0.45 |
| *Non*-Attainment Counties | 0.47 | 0.09 | 0.38 | 19.15 | |
| Attainment Counties | 0.38 | -- | 0.38 | -- | |
| All Counties | 0.41 | 0.03 | 0.38 | 7.32 | |

*Notes*: This table reports our adaptation results for the three decades in our sample: 1980-1990; 1991-2001 and 2002-2013. The adaptation measures have been calculated using estimates from Table 5, and the calculations follow the methodology explained in Table 4.

**(For Online Publication)**

**Appendix**

Figure A1: Our Decomposition of Temperature Trends and Shocks (Los Angeles)

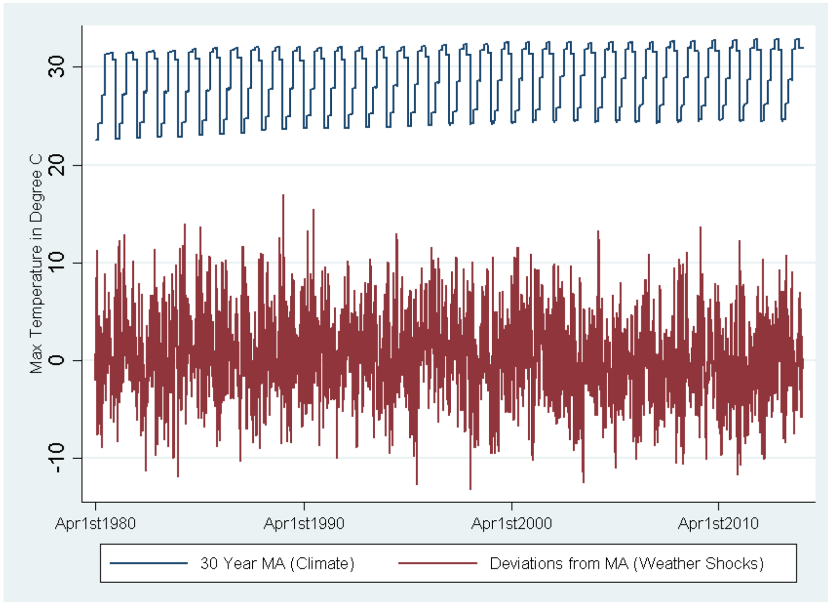



Figure A2: Fixed-Effect Decomposition of Temperature Trends and Shocks (Los Angeles)

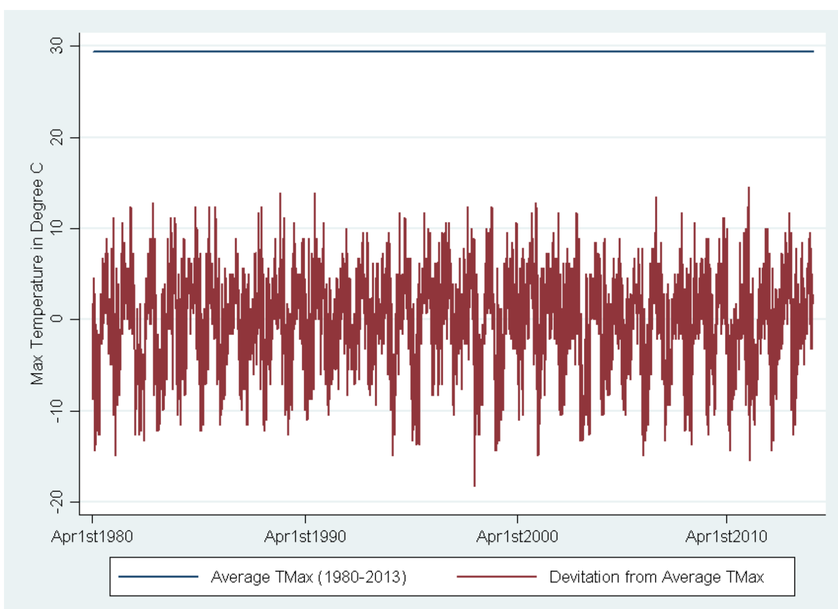


Figure A3: Our Decomposition of 2013 Temperature Trends and Shocks (Los Angeles)

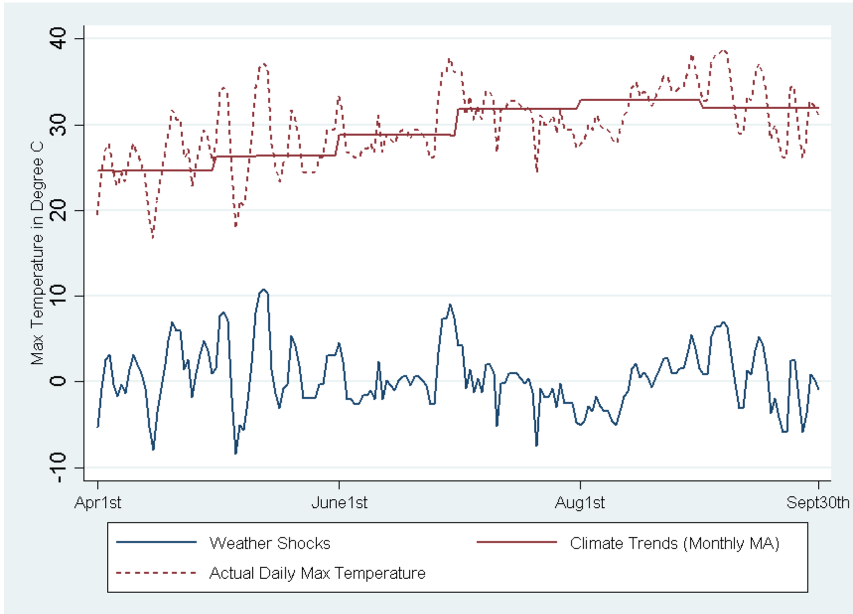



Figure A4: Fixed-Effect Decomposition of 2013 Temperature Trends and Shocks (Los Angeles)

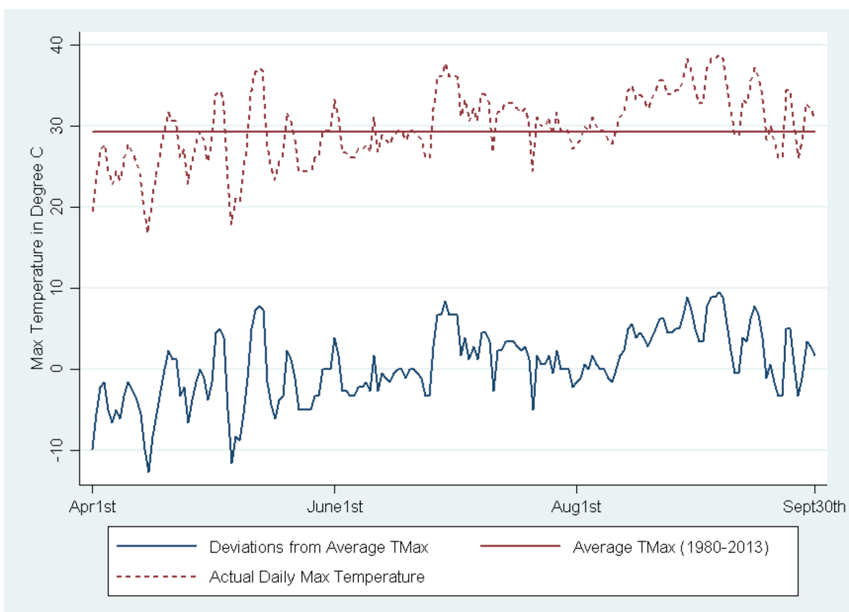
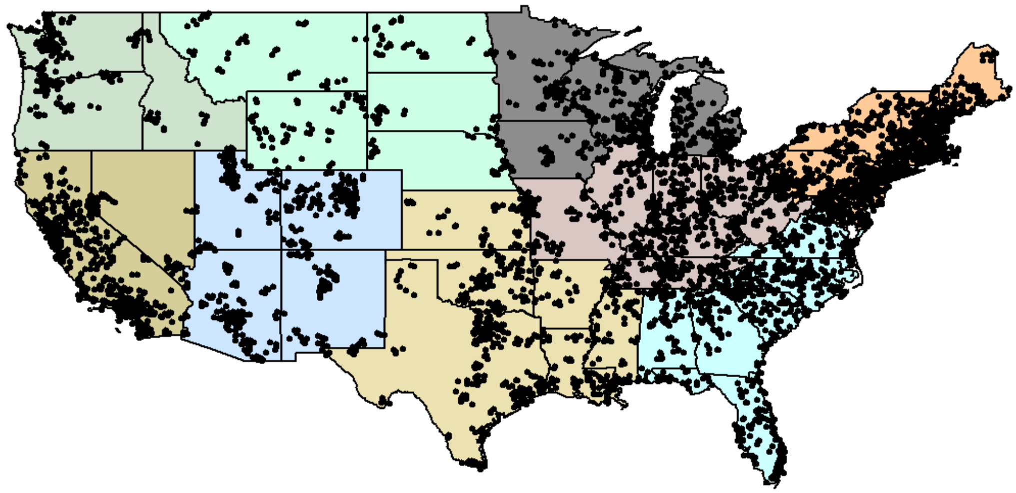
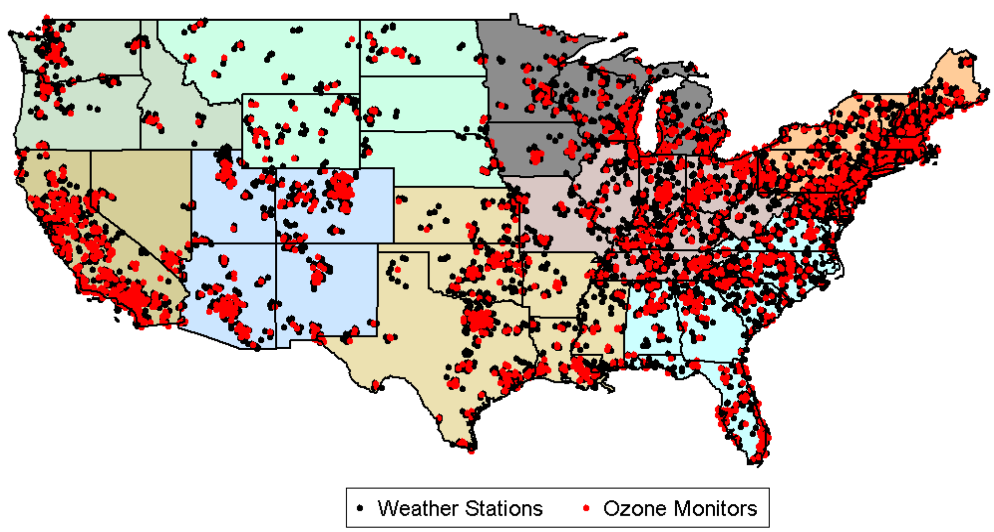


Figure A5: Weather Stations from 1950-2013



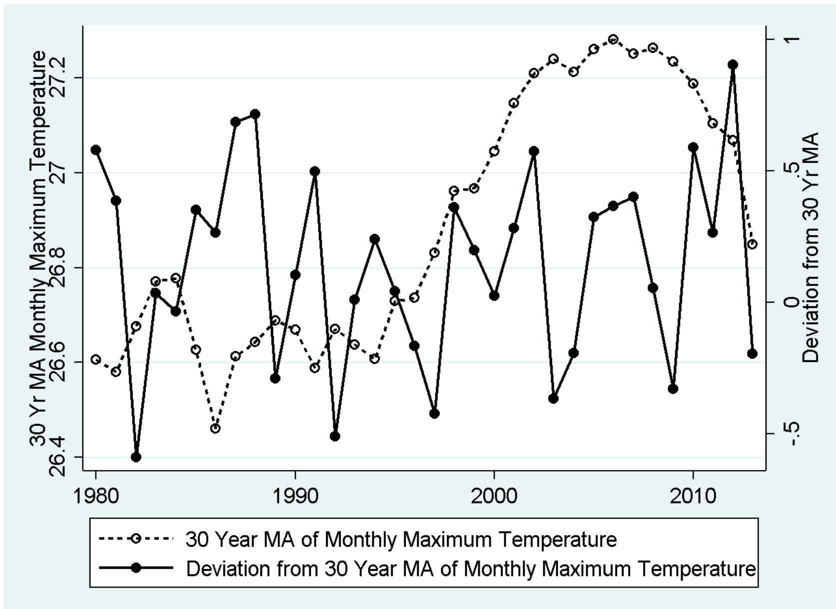
*Notes*: This figure maps the weather stations from 1950-2013 used in our analysis. For every ozone monitor in our final sample, we keep the closest two weather stations within a radius of 30 km. Each shaded region represents a single climatic region as designated by the NOAA.

Figure A6: Matched Ozone Monitors and Weather Stations



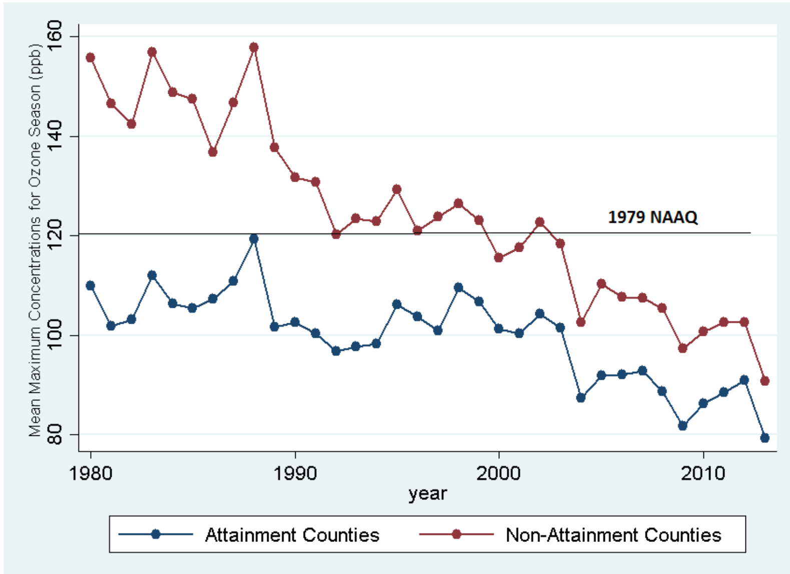

*Notes*: This figure maps the ozone monitors from 1980-2013 in our sample, and the matched weather stations. For each ozone monitor, the closest 2 stations within a 30 km radius have been used in the matching. Each shaded region represents a single climatic region as designated by the NOAA.

Figure A7: Temperature – Trends and Shocks (Matching Weather to Ozone Monitors)




*Notes*: This figure reports the variation in both components of temperature. The shock is a deviation of contemporaneous daily maximum temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year. This figure is analogous to Figure 3, but notice that there seems to be more variation in the 30-year MA here because it includes cross-sectional variation as well. Also, notice 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 2.

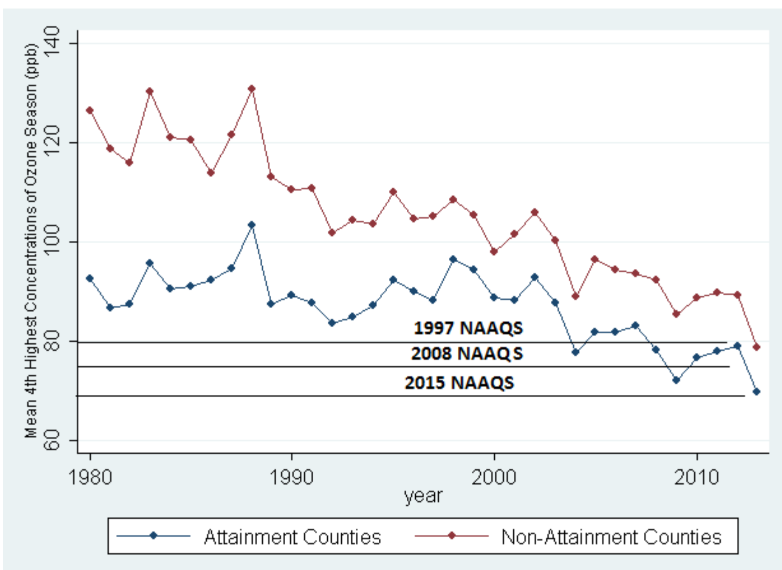
Figure A8: Evolution of Maximum Ambient Ozone Concentration




*Source*: Authors' compilation based on EPA data.

*Notes*: The 1979 NAAQS was built around the maximum ozone concentration, as explained in Table A1.

Figure A9: Evolution of the 4$^{th}$ Highest Ambient Ozone Concentration




*Source*: Authors' compilation based on EPA data.

*Notes*: Starting with the 1987 NAAQS, the target of the regulation became the 4$^{th}$ highest ozone concentration, as explained in Table A1.

Table A1: History of Ozone NAAQS

| Final Rule/ Decision | Primary/ Secondary | Indicator | Averaging Time | Level | Form |
|---|---|---|---|---|---|
| 1971 | Primary and Secondary | Total photochemical oxidants | 1-hour | 80 ppb | Not to be exceeded more than one hour per year |
| 1979 | Primary and Secondary | Ozone | 1-hour | 120 ppb | Attainment is defined when the expected number of days per calendar year, with maximum hourly average concentration greater than 120 ppb, is equal to or less than 1 |
| 1997 | Primary and Secondary | Ozone | 8-hour | 80 ppb | Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years |
| 2008 | Primary and Secondary | Ozone | 8-hour | 75 ppb | Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years |
| 2015 | Primary and Secondary | Ozone | 8-hour | 70 ppb | Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years |

*Source*: epa.gov/ozone-pollution/table-historical-ozone-national-ambient-air-quality-standards-naaqs.

*Notes*: This table shows the history of ambient ozone regulations in the U.S. The first standard was put in place in 1971, but targeted all photochemical oxidants. The first NAAQS for ambient ozone was established in 1979, when 120ppb was defined as the maximum 1-hour concentration that could not be violated more than once a year for a county to be designed as in attainment. In 1997, the standards were strengthened to 80ppb, but with a different form for the threshold: annual fourth-highest daily maximum 8-hour concentration averaged over 3 years. With the 2008 and 2015 revisions, the current 8-hour threshold is now 70ppb. EPA justified the new form in 1997 as equivalent to the empirical 1-hour maximum to not be exceeded more than once a year. "*The 1-expected-exceedance form essentially requires the fourth-highest air quality value in 3 years, based on adjustments for missing data, to be less than or equal to the level of the standard for the standard to be met at an air quality monitoring site.*" (U.S. EPA, 1997, p.38868) The 1997 NAAQS was challenged in courts, and not implemented until 2004. Lastly, as the EPA (2005) states, "primary standards set limits to protect public health, including the health of 'sensitive' populations such as asthmatics, children, and the elderly. Secondary standards set limits to protect public welfare, including protection against decreased visibility, damage to animals, crops, vegetation, and buildings."

Table A2: Period to Comply with NAAQS 1979

| Area Class | Design Value | Adjustment Period |
|---|---|---|
| Marginal | 121 to 138ppb | 3 years |
| Moderate | 138 to 160ppb | 6 years |
| Serious | 160 to 180ppb | 9 years |
| Severe | 180 to 280ppb | 15 years |
| Extreme | 280 and above | 20 years |

*Source*: U.S. Code (2011).

Table A3: Ozone Monitoring Seasons 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 |
| District of Columbia | 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 |

*Source*: U.S. EPA (2006, p. AX3-3).

*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. The ozone season is defined differently in different parts of Texas.

Table A4: Summary Statistics for the Ambient Ozone Monitoring Network by Year

| Year | #Obs | #Counties | #Ozone Monitors |
|---|---|---|---|
| 1980 | 91543 | 368 | 663 |
| 1981 | 102211 | 394 | 684 |
| 1982 | 102168 | 383 | 651 |
| 1983 | 102513 | 393 | 651 |
| 1984 | 104705 | 382 | 649 |
| 1985 | 106550 | 382 | 653 |
| 1986 | 104889 | 367 | 635 |
| 1987 | 110838 | 378 | 663 |
| 1988 | 114510 | 405 | 693 |
| 1989 | 119972 | 406 | 712 |
| 1990 | 126149 | 427 | 742 |
| 1991 | 131638 | 446 | 778 |
| 1992 | 136747 | 458 | 804 |
| 1993 | 144870 | 485 | 844 |
| 1994 | 147629 | 490 | 853 |
| 1995 | 151553 | 495 | 872 |
| 1996 | 150585 | 500 | 867 |
| 1997 | 157337 | 518 | 901 |
| 1998 | 160401 | 535 | 927 |
| 1999 | 165718 | 546 | 948 |
| 2000 | 168893 | 551 | 965 |
| 2001 | 177068 | 572 | 1014 |
| 2002 | 180316 | 579 | 1023 |
| 2003 | 182313 | 588 | 1036 |
| 2004 | 182229 | 596 | 1023 |
| 2005 | 180238 | 594 | 1019 |
| 2006 | 181903 | 598 | 1025 |
| 2007 | 183971 | 605 | 1036 |
| 2008 | 184197 | 607 | 1041 |
| 2009 | 186610 | 616 | 1048 |
| 2010 | 187713 | 623 | 1058 |
| 2011 | 190351 | 642 | 1076 |
| 2012 | 191206 | 637 | 1076 |
| 2013 | 128317 | 523 | 852 |

*Notes*: Decades are 1980-1990, 1991-2001 and 2002-2013 respectively. Data used in construction of this table uses monitor-days for which 8-hour averages were recorded for at least 18 hours of the day and monitor-years for which valid monitor-days were recorded for at least 75% of days between April 1st and September 30th. This table uses data for the months of April-September, as that constitutes the typical ozone season.

Table A5: Summary Statistics for Daily Maximum Temperature by Year

| Year | Max Temp | Max Temp 30-Yr MA | Max Temp Shock |
|---|---|---|---|
| 1980 | 27.2 | 26.6 | 0.6 |
| 1981 | 27.0 | 26.6 | 0.4 |
| 1982 | 26.1 | 26.7 | -0.6 |
| 1983 | 26.8 | 26.8 | 0.0 |
| 1984 | 26.7 | 26.8 | 0.0 |
| 1985 | 27.0 | 26.6 | 0.3 |
| 1986 | 26.7 | 26.5 | 0.3 |
| 1987 | 27.3 | 26.6 | 0.7 |
| 1988 | 27.4 | 26.6 | 0.7 |
| 1989 | 26.4 | 26.7 | -0.3 |
| 1990 | 26.8 | 26.7 | 0.1 |
| 1991 | 27.1 | 26.6 | 0.5 |
| 1992 | 26.2 | 26.7 | -0.5 |
| 1993 | 26.7 | 26.6 | 0.0 |
| 1994 | 26.8 | 26.6 | 0.2 |
| 1995 | 26.8 | 26.7 | 0.0 |
| 1996 | 26.6 | 26.7 | -0.2 |
| 1997 | 26.4 | 26.8 | -0.4 |
| 1998 | 27.3 | 27.0 | 0.4 |
| 1999 | 27.2 | 27.0 | 0.2 |
| 2000 | 27.1 | 27.0 | 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 | 27.3 | 0.3 |
| 2006 | 27.6 | 27.3 | 0.4 |
| 2007 | 27.6 | 27.3 | 0.4 |
| 2008 | 27.3 | 27.3 | 0.1 |
| 2009 | 26.9 | 27.2 | -0.3 |
| 2010 | 27.8 | 27.2 | 0.6 |
| 2011 | 27.4 | 27.1 | 0.3 |
| 2012 | 28.0 | 27.1 | 0.9 |
| 2013 | 26.7 | 26.8 | -0.2 |

*Notes*: Decades are 1980-1990, 1991-2001 and 2002-2013 respectively. 30-year moving averages have been constructed at each ozone monitor, by using historical weather data from 1950-2013. Temperature deviations are defined as (Daily Max Temp – 30-Year monthly MA of Max Temp). Each pollution monitor has been matched to the closest two weather stations within a 30 km boundary.

Table A6: Non-Linear Effects of Temperature

| Dep. Var.: Daily Max Ozone Levels (ppb) | (1) | (2) |
|---|---|---|
| *Non*-Attainment County | -1.1952*** | -6.0965*** |
| | (0.1739) | (0.4821) |
| ***Panel A. 20-25°C*** | | |
| Max Temp Shock | 6.4201*** | |
| | (0.1274) | |
| Max Temp 30-Yr MA | 3.8932*** | |
| | (0.2600) | |
| Attainment County | | 5.6972*** |
| x Max Temp Shock | | (0.1294) |
| Attainment County | | 3.5288*** |
| x Max Temp 30-Yr MA | | (0.3031) |
| *Non*-Attainment County | | 7.0937*** |
| x Max Temp Shock | | (0.1718) |
| *Non*-Attainment County | | 4.2572*** |
| x Max Temp 30-Yr MA | | (0.3228) |
| ***Panel B. 25-30°C*** | | |
| Max Temp Shock | 15.4827*** | |
| | (0.2313) | |
| Max Temp 30-Yr MA | 14.6562*** | |
| | (0.3063) | |
| Attainment County | | 12.7890*** |
| x Max Temp Shock | | (0.2226) |
| Attainment County | | 12.1578*** |
| x Max Temp 30-Yr MA | | (0.3177) |
| *Non*-Attainment County | | 17.5361*** |
| x Max Temp Shock | | (0.3015) |
| *Non*-Attainment County | | 16.4758*** |
| x Max Temp 30-Yr MA | | (0.3584) |
| ***Panel C. 30-35°C*** | | |
| Max Temp Shock | 24.2475*** | |
| | (0.3686) | |
| Max Temp 30-Yr MA | 21.9899*** | |
| | (0.5097) | |
| Attainment County | | 18.9043*** |
| x Max Temp Shock | | (0.3166) |
| Attainment County | | 17.8664*** |
| x Max Temp 30-Yr MA | | (0.4555) |
| *Non*-Attainment County | | 28.4692*** |
| x Max Temp Shock | | (0.4749) |
| *Non*-Attainment County | | 25.6477*** |
| x Max Temp 30-Yr MA | | (0.6285) |
| ***Panel D. Above 35°C*** | | |
| Max Temp Shock | 33.4858*** | |
| | (0.5398) | |
| Max Temp 30-Yr MA | 29.3890*** | |
| | (0.8011) | |
| Attainment County | | 25.7193*** |
| x Max Temp Shock | | (0.4259) |
| Attainment County | | 22.3466*** |
| x Max Temp 30-Yr MA | | (0.7879) |
| *Non*-Attainment County | | 39.3769*** |
| x Max Temp Shock | | (0.6946) |
| *Non*-Attainment County | | 34.2748*** |
| x Max Temp 30-Yr MA | | (0.9196) |
| Observations | 4,986,685 | 4,986,685 |
| R-squared | 0.4158 | 0.4221 |
| Precipitation Controls | Yes | Yes |
| Monitor FE | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes |

*Notes*: This table reports the non-linear effects of daily maximum temperature on ambient ozone levels. We categorize daily maximum temperature into 5 bins from <25°C to >35°C with 5°C intervals in between. In column (1), we decompose daily temperature into *climate trends* and *weather shocks* in the same estimating equation, exploiting high frequency data, as in Equation (3). In column (2), we include interactions of weather shocks and climate trends with the Clean Air Act (CAA) designation status to estimate heterogeneous effects across attainment and non-attainment counties, as in Equation (4). Recall that the 30-yr MA is lagged by 1 year, and the CAA attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A7: Adaptation Estimates for Nonlinearities

| | Average Adaptation (ppb) | Regulation Induced Adaptation (ppb) | Residual Adaptation (ppb) | % Regulation Induced |
|---|---|---|---|---|
| ***Panel A. 20-25°C*** | | | | |
| *Non*-Attainment Counties | 0.57 | 0.14 | 0.43 | 24.6 |
| Attainment Counties | 0.43 | -- | 0.43 | -- |
| All Counties | 0.51 | 0.08 | 0.43 | 15.7 |
| ***Panel B. 25-30°C*** | | | | |
| *Non*-Attainment Counties | 0.21 | 0.08 | 0.13 | 38.1 |
| Attainment Counties | 0.13 | -- | 0.13 | -- |
| All Counties | 0.16 | 0.03 | 0.13 | 18.75 |
| ***Panel C. 30-35°C*** | | | | |
| *Non*-Attainment Counties | 0.56 | 0.35 | 0.21 | 62.5 |
| Attainment Counties | 0.21 | -- | 0.21 | -- |
| All Counties | 0.45 | 0.24 | 0.21 | 53.3 |
| ***Panel D. Above 35°C*** | | | | |
| *Non*-Attainment Counties | 1.02 | 0.35 | 0.67 | 34.3 |
| Attainment Counties | 0.67 | -- | 0.67 | -- |
| All Counties | 0.82 | 0.15 | 0.67 | 18.3 |

*Notes*: This table reports our adaptation results for each 5$^{o}$C bin of temperature. The adaptation measures have been calculated using estimates from Table A6, and the calculations follow the methodology explained in Table 4.

Table A8: Alternative Definitions of Climate Trend

| Dep. Var.: Daily Max Ozone Levels (ppb) | 3-yr MA | 5-yr MA | 10-yr MA | 20-yr MA | Main Results: 30-yr MA |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Non*-Attainment County | -15.3900*** | -15.0266*** | -14.5932*** | -14.2359*** | -14.0926*** |
| | (0.7978) | (0.8119) | (0.8274) | (0.8445) | (0.8447) |
| Attainment County | 1.3068*** | 1.3020*** | 1.3001*** | 1.2994*** | 1.3025*** |
| x Max Temp Shock | (0.0187) | (0.0188) | (0.0189) | (0.0191) | (0.0191) |
| Attainment County | 0.9440*** | 0.9609*** | 0.9776*** | 0.9834*** | 0.9767*** |
| x Max Temp 3to30-Yr MA | (0.0211) | (0.0213) | (0.0218) | (0.0220) | (0.0219) |
| *Non*-Attainment County | 2.0003*** | 1.9979*** | 1.9935*** | 1.9954*** | 1.9991*** |
| x Max Temp Shock | (0.0333) | (0.0334) | (0.0334) | (0.0334) | (0.0335) |
| *Non*-Attainment County | 1.4495*** | 1.4558*** | 1.4644*** | 1.4603*** | 1.4509*** |
| x Max Temp 3to30-Yr MA | (0.0276) | (0.0280) | (0.0284) | (0.0285) | (0.0283) |
| Observations | 4,974,155 | 4,974,155 | 4,974,155 | 4,974,155 | 4,974,155 |
| R-squared | 0.4282 | 0.4282 | 0.4284 | 0.4286 | 0.4286 |
| Precipitation Controls | Yes | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table reports the results for alternative definitions for the climate trend. Columns (1)-(4) show estimates obtained by Equation (4), but using moving averages of temperature for different time windows. For comparison purposes, our main results are reported in column (5). Recall that the 3to30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table A9: Lagged Responses

| Dep. Var.: Daily Max Ozone Levels (ppb) | Main Results: 30-Yr MA Lagged by 1 year | | 20-Yr MA Lagged by 10 years | | 10-Yr MA Lagged by 20 years | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Max Temp Shock | 1.6942*** | | 1.6941*** | | 1.6962*** | |
| | (0.0254) | | (0.0255) | | (0.0256) | |
| Max Temp 30(20)(10)-Yr MA | 1.2423*** | | 1.2376*** | | 1.2290*** | |
| | (0.0239) | | (0.0239) | | (0.0237) | |
| *Non*-Attainment County | -1.2197*** | -14.0926*** | -1.2125*** | -14.2923*** | -1.2261*** | -14.5336*** |
| | (0.1771) | (0.8447) | (0.1777) | (0.8512) | (0.1790) | (0.8361) |
| Attainment County | | 1.3025*** | | 1.3028*** | | 1.3065*** |
| x Max Temp Shock | | (0.0191) | | (0.0193) | | (0.0194) |
| Attainment County | | 0.9767*** | | 0.9693*** | | 0.9559*** |
| x Max Temp 30(20)(10)-Yr MA | | (0.0219) | | (0.0216) | | (0.0211) |
| *Non*-Attainment County | | 1.9991*** | | 1.9976*** | | 1.9980*** |
| x Max Temp Shock | | (0.0335) | | (0.0336) | | (0.0337) |
| *Non*-Attainment County | | 1.4509*** | | 1.4508*** | | 1.4478*** |
| x Max Temp 30(20)(10)-Yr MA | | (0.0283) | | (0.0286) | | (0.0286) |
| Observations | 4,974,155 | 4,974,155 | 4,967,557 | 4,967,557 | 4,964,220 | 4,964,220 |
| R-squared | 0.4225 | 0.4286 | 0.4222 | 0.4284 | 0.4221 | 0.4283 |
| Precipitation Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table reports estimates allowing more time for economic agents to engage in adaptive behavior. The estimates in columns (3) through (6) are obtained by Equations (3) and (4), but using 10 and 20 year moving averages of maximum temperature. For comparison purposes, our main results are reported in columns (1) and (2). Recall that the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

Table A10: Balanced Panel of Ozone Monitors

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **Main Results: Unbalanced Panel of Ozone Monitors** | | **Balanced Panel of Ozone Monitors** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Max Temp Shock | 1.6942*** | | 2.0480*** | |
| | (0.0254) | | (0.0838) | |
| Max Temp 30-Yr MA | 1.2423*** | | 1.6113*** | |
| | (0.0239) | | (0.0697) | |
| *Non*-Attainment County | -1.2197*** | -14.0926*** | -1.8371** | -10.2361*** |
| | (0.1771) | (0.8447) | (0.7918) | (2.2352) |
| Attainment County | | 1.3025*** | | 1.6644*** |
| x Max Temp Shock | | (0.0191) | | (0.0783) |
| Attainment County | | 0.9767*** | | 1.4114*** |
| x Max Temp 30-Yr MA | | (0.0219) | | (0.0935) |
| *Non*-Attainment County | | 1.9991*** | | 2.1740*** |
| x Max Temp Shock | | (0.0335) | | (0.0910) |
| *Non*-Attainment County | | 1.4509*** | | 1.6806*** |
| x Max Temp 30-Yr MA | | (0.0283) | | (0.0689) |
| Observations | 4,974,155 | 4,974,155 | 543,971 | 543,971 |
| R-squared | 0.4225 | 0.4286 | 0.4126 | 0.4149 |
| Precipitation Controls | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes |

*Notes*: This table reports estimates from a balanced panel of ozone monitors over the period 1980-2013. Columns (3) and (4) show estimates obtained by Equations (3) and (4), respectively, but using a balanced panel of 92 ozone monitors. For comparison purposes, our main results are presented in columns (1) and (2). Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A11: Adding Wind Speed and Sunlight Irradiance

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **Main Results** | **Adding Other Meteorological Vars.** | | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| *Non*-Attainment County | -14.0926*** | -13.7245*** | -16.1596*** | -16.7932*** |
| | (0.8447) | (1.1532) | (2.0324) | (2.1615) |
| Attainment County | 1.3025*** | 1.4105*** | 1.3461*** | 1.2365*** |
| x Max Temp Shock | (0.0191) | (0.0263) | (0.0593) | (0.0621) |
| Attainment County | 0.9767*** | 0.7663*** | 0.9240*** | 0.7247*** |
| x Max Temp 30-Yr MA | (0.0219) | (0.0313) | (0.0577) | (0.0621) |
| *Non*-Attainment County | 1.9991*** | 2.0559*** | 2.0580*** | 2.0611*** |
| x Max Temp Shock | (0.0335) | (0.0332) | (0.0536) | (0.0515) |
| *Non*-Attainment County | 1.4509*** | 1.2339*** | 1.4730*** | 1.3723*** |
| x Max Temp 30-Yr MA | (0.0283) | (0.0324) | (0.0426) | (0.0465) |
| Average Wind Speed | | -2.1792*** | | -2.2289*** |
| | | (0.0931) | | (0.2098) |
| Total Daily Sunlight | | | 0.0150*** | 0.0144*** |
| | | | (0.0006) | (0.0006) |
| Observations | 4,974,155 | 2,019,634 | 581,465 | 455,533 |
| R-squared | 0.4286 | 0.4183 | 0.4049 | 0.4366 |
| Precipitation Controls | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes |

*Notes*: This table reports estimates controlled for additional meteorological variables for a subset of our main sample. These estimates are obtained by Equation (4), but in column (2) we control for average daily wind speed (meters/sec); in column (3) we control for total daily sunlight (mins), and in column (4) we control for both. For comparison purposes, our main results are presented in column (1). Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A12: Climate Impacts and Adaptation Based on AQI Category

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **(1)** | **(2)** |
|---|---|---|
| *Non*-Attainment County | -0.7472*** | |
| | (0.1618) | |
| AQI Good | | |
| x Max Temp Shock | 0.6481*** | *Adaptation:* |
| | (0.0105) | |
| x Max Temp 30-Yr MA | 0.2912*** | 0.357*** |
| | (0.0140) | (0.015) |
| AQI Moderate | | |
| x Max Temp Shock | 0.8400*** | *Adaptation:* |
| | (0.0171) | |
| x Max Temp 30-Yr MA | 0.7244*** | 0.116*** |
| | (0.0135) | (0.014) |
| AQI Unhealthy for Sensitive Groups | | |
| x Max Temp Shock | 1.2885*** | *Adaptation:* |
| | (0.0278) | |
| x Max Temp 30-Yr MA | 1.0578*** | 0.231*** |
| | (0.0153) | (0.026) |
| AQI Unhealthy | | |
| x Max Temp Shock | 2.3474*** | *Adaptation:* |
| | (0.0996) | |
| x Max Temp 30-Yr MA | 1.6493*** | 0.698*** |
| | (0.0473) | (0.095) |
| Observations | 4,974,155 | |
| R-squared | 0.6590 | |
| Precipitation Controls | Yes | |
| Monitor FE | Yes | |
| Season-by-Year FE x Monitor Latitude | Yes | |
| Season-by-Year FE x Monitor Longitude | Yes | |
| Season-by-Year-by-Climate-Region FE | Yes | |

*Notes:* This table reports estimates of temperature shocks and trends, but interacted with an Air Quality Index (AQI) category. Here, we replace the CAA *Attain* and *NonAttain* dummy variables in Equation (4) with AQI levels categorized as *Good, Moderate, Unhealthy for Sensitive Groups*, and *Unhealthy*. Counties with *Good* or *Moderate* air quality are both in attainment, with the ones having *Moderate* AQI falling just below the ozone NAAQS threshold. Similarly, counties having air quality worse than moderate are generally in non-attainment, and might have to disclose that information to the local media along with meteorology. In column (1), we report the main estimates, and in column (2), the implied adaptation measures. Recall that the 30-yr MA is lagged by 1 year. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A13: Sample of Ozone Monitors with Readings around Ozone NAAQS

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **Main Results** (1) | **Observations *Just Below* & *Just Above* Ozone NAAQS** (2) |
|---|---|---|
| *Non*-Attainment County | -14.0926*** | -5.2284*** |
| | (0.8447) | (0.4874) |
| Attainment County | 1.3025*** | 0.3876*** |
| x Max Temp Shock | (0.0191) | (0.0100) |
| Attainment County | 0.9767*** | 0.3970*** |
| x Max Temp 30-Yr MA | (0.0219) | (0.0108) |
| *Non*-Attainment County | 1.9991*** | 0.6069*** |
| x Max Temp Shock | (0.0335) | (0.0145) |
| *Non*-Attainment County | 1.4509*** | 0.5757*** |
| x Max Temp 30-Yr MA | (0.0283) | (0.0132) |
| Observations | 4,974,155 | 670,122 |
| R-squared | 0.4286 | 0.8260 |
| Precipitation Controls | Yes | Yes |
| Monitor FE | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes |
| Season-by-Year-by-Climate-Region FE | Yes | Yes |

*Notes*: This table reports estimates with a sample of ozone monitors with concentrations falling just below and above the ozone NAAQS threshold. The estimates in column (2) are obtained by Equation (4), but with this restricted sample. For comparison purposes, our main results are presented in column (1). Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A14: Alternative Criteria for Selection of Weather Stations

| Dep. Var.: Daily Max Ozone Levels (ppb) | Main Results: 30 km 2 stations; Weight=1/dist$^2$ (1) | Alternative Weighting of Weather Stations: 30 km 2 stations; Simple Avg (2) | 30 km 2 stations; Weight=1/dist (3) | 80 km 5 stations; Simple Avg (4) | 80 km 5 stations; Weight=1/dist (5) |
|---|---|---|---|---|---|
| *Non*-Attainment County | -14.0926*** | -14.3669*** | -14.1701*** | -14.3410*** | -14.2474*** |
| | (0.8447) | (0.8561) | (0.8473) | (0.8429) | (0.8316) |
| Attainment County | 1.3025*** | 1.3418*** | 1.3222*** | 1.3881*** | 1.3762*** |
| x Max Temp Shock | (0.0191) | (0.0188) | (0.0190) | (0.0184) | (0.0191) |
| Attainment County | 0.9767*** | 0.9765*** | 0.9776*** | 0.9649*** | 0.9688*** |
| x Max Temp 30-Yr MA | (0.0219) | (0.0221) | (0.0219) | (0.0216) | (0.0215) |
| *Non*-Attainment County | 1.9991*** | 2.0493*** | 2.0272*** | 2.1508*** | 2.1369*** |
| x Max Temp Shock | (0.0335) | (0.0341) | (0.0338) | (0.0365) | (0.0358) |
| *Non*-Attainment County | 1.4509*** | 1.4541*** | 1.4528*** | 1.4440*** | 1.4450*** |
| x Max Temp 30-Yr MA | (0.0283) | (0.0285) | (0.0284) | (0.0277) | (0.0277) |
| Observations | 4,974,155 | 4,974,155 | 4,974,155 | 5,100,445 | 5,100,445 |
| R-squared | 0.4286 | 0.4317 | 0.4303 | 0.4334 | 0.4338 |
| Precipitation Controls | Yes | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table reports estimates from alternative criteria to match weather stations to ozone monitors. These estimates are obtained by Equation (4), but using different radius, number of weather stations, and weights. In our main analysis, reported again in column (1) for comparison purposes, we use a radius of 30 km, the 2 closest stations, and the inverse squared distance as the weight. In the following columns, we give the same weight (simple average), or use the inverse distance as an alternative weight. We also vary the radius to 80 km, and use the information from the closest 5 weather stations. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A15: Daily Moving Averages

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **Main Results: 30-Yr *Monthly* MA** | | **30-Yr *Daily* MA** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Max Temp Shock | 1.6942*** | | 1.6993*** | |
| | (0.0254) | | (0.0259) | |
| Max Temp 30-Yr MA | 1.2423*** | | 1.2793*** | |
| | (0.0239) | | (0.0233) | |
| *Non*-Attainment County | -1.2197*** | -14.0926*** | -1.2095*** | -15.1605*** |
| | (0.1771) | (0.8447) | (0.1769) | (0.7952) |
| Attainment County | | 1.3025*** | | 1.3029*** |
| x Max Temp Shock | | (0.0191) | | (0.0195) |
| Attainment County | | 0.9767*** | | 0.9959*** |
| x Max Temp 30-Yr MA | | (0.0219) | | (0.0207) |
| *Non*-Attainment County | | 1.9991*** | | 2.0082*** |
| x Max Temp Shock | | (0.0335) | | (0.0344) |
| *Non*-Attainment County | | 1.4509*** | | 1.5058*** |
| x Max Temp 30-Yr MA | | (0.0283) | | (0.0279) |
| Observations | 4,974,155 | 4,974,155 | 4,974,117 | 4,974,117 |
| R-squared | 0.4225 | 0.4286 | 0.4211 | 0.4275 |
| Precipitation Controls | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes |

*Notes*: This table compares our main estimates in columns (1) and (2) with the ones in columns (3) and (4), which are obtained by replacing monthly moving averages of temperature with daily moving averages. These estimates are obtained by Equations (3) and (4), respectively. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A16: Bootstrapped Standard Errors

| **Dep. Var.: Daily Max Ozone Levels (ppb)** | **Main Results: Clustered SEs** | | **Bootstrapped SEs** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Max Temp Shock | 1.6942*** | | 1.6942*** | |
| | (0.0254) | | (0.0282) | |
| Max Temp 30-Yr MA | 1.2423*** | | 1.2423*** | |
| | (0.0239) | | (0.0255) | |
| *Non*-Attainment County | -1.2197*** | -14.0926*** | -1.2197*** | -14.0926*** |
| | (0.1771) | (0.8447) | (0.1856) | (0.8909) |
| Attainment County | | 1.3025*** | | 1.3025*** |
| x Max Temp Shock | | (0.0191) | | (0.0203) |
| Attainment County | | 0.9767*** | | 0.9767*** |
| x Max Temp 30-Yr MA | | (0.0219) | | (0.0209) |
| *Non*-Attainment County | | 1.9991*** | | 1.9991*** |
| x Max Temp Shock | | (0.0335) | | (0.0404) |
| *Non*-Attainment County | | 1.4509*** | | 1.4509*** |
| x Max Temp 30-Yr MA | | (0.0283) | | (0.0306) |
| Observations | 4,974,155 | 4,974,155 | 4,974,155 | 4,974,155 |
| R-squared | 0.4225 | 0.4286 | 0.4225 | 0.4286 |
| Precipitation Controls | Yes | Yes | Yes | Yes |
| Monitor FE | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Latitude | Yes | Yes | Yes | Yes |
| Season-by-Year FE x Monitor Longitude | Yes | Yes | Yes | Yes |
| Season-by-Year-by-Climate Region FE | Yes | Yes | Yes | Yes |

*Notes*: This table compares the standard errors of our main estimates in columns (1) and (2) with the ones in columns (3) and (4), which are obtained by bootstrap. The issue is that our temperature shocks and trends are constructed, so they could be seen as generated regressors. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/non-attainment county designation is lagged by 3 years. Standard errors in columns (1) and (2) are clustered at the monitor level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.