A New Approach to Measuring Climate Change Impacts and Adaptation

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March 2017

Abstract

We propose a novel approach to estimate adaptation to climate change based on a decomposition of meteorological variables into long-run trends and deviations from those trends (weather shocks). Our estimating equation simultaneously exploits weather variation to identify the impact of weather shocks, and climatic variation to identify the effect of longer-run observed changes. We then compare the simultaneously estimated short- and long-run effects to provide a measure of adaptation. We apply our methodology to study the impact of climate change on air quality, and estimate the so-called climate penalty on ozone. This penalty means that climate change might offset some of the improvements in air quality expected from reductions in ozone precursors. We have three main findings. First, a changing climate appears to be affecting ground-level ozone concentrations in two ways. A shock in temperature of one degree Celsius increases ozone levels by 1.7 ppb on average, which is 11 percent higher than 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 1.2 ppb, 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 change of 1^{o}C in temperature, our measure of adaptation in terms of ozone concentration is 0.45 ppb. If adaptive responses were not taken into account, 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 appears to be over 66 percent larger than adaptation in counties in "attainment". This difference is what we call regulation-induced adaptation. The remainder is our measure of residual adaptation.

1. Introduction

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 degrees Celsius over the 21st century, depending on the emissions scenario. Measuring climate impacts and potential adaptation to climate change is crucial to decide whether and how to design policies and technologies to smooth out the transition to a warmer world. Because by definition economic agents are unable to offset the impacts of weather shocks, but can make adjustments to cope with changes in long-run climatic trends (e.g., Barreca et al., 2015, 2016), the estimation of climate impacts must disentangle these two dimensions of changes in meteorological variables. Due to data limitations, influential cross-section and fixed-effect approaches have estimated either of those effects separately, not controlling for the other in the estimating equation. Standard econometrics therefore suggests the presence of omitted variable bias in both approaches. Since adaptation measures are often derived from those short- and long-run estimates, they are likely to be biased as well.

In this paper, we propose a novel approach to estimate climate impacts and adaptation, and provide an application using high-frequency data in the context of the impact of climate change on ground-level ozone concentration (Jacob and Winner, 2009). As explained below, ozone is not emitted but rather formed in the presence of sunlight and warm temperatures. Our approach to estimate climate impacts and adaptation bridges two strands of the climate-economy literature. In the same estimating equation, we exploit meteorological variation to identify the impact of weather shocks on surface ozone levels (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), and climatological variation to identify the causal effect of longer-run observed climatic changes (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005). We then compare the simultaneously estimated short- and long-run effects to provide a measure of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016).

A key element of our approach is the decomposition of meteorological variables into two components: long-run trends and shocks, the latter defined as deviations from those trends. Taking advantage of high-frequency data, we decompose daily maximum temperature into a monthly moving average incorporating information from the past three decades, and a

deviation from that lagged 30-year average often referred to as climate normal[1]. This decomposition is meant to have economic content. Agents can only respond to climatic variables 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 ozone levels, our main outcome in our application. In contrast, agents cannot respond to weather shocks by definition. Our measure of adaptation is the difference between simultaneously estimated responses to weather shocks and responses to changes in lagged 30-year moving averages[2]. If policymaking can influence adaptive behavior, then variables representing governmental policies or regulations can be interacted with those two components of our decomposition to uncover measures of regulation-induced adaptation and residual adaptation.

For an example of regulation-induced adaptation, 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 the violation of EPA's ozone standards, that county may be forced to install scrubbers 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. For an example of residual adaptation, consider a county where ozone levels are below the EPA's standards in the baseline, and most of the residents have installed rooftop solar panels. Because those panels would generate electricity more intensively when ozone formation would be the highest, that county would reduce emissions of ozone precursors from coal-fired power plants at that critical time. The resulting decline in ozone concentration would be achieved regardless of ozone regulations. It would be a consequence of exploiting a technology that coincidently would be more effective at higher temperatures. That would be an unintended adaptation to climate change. Hence, we call it residual adaptation.

We apply our methodology to study the impact of climate change on air quality. We tackle an issue that is of interest per se: the so-called climate penalty on ozone. Ground-level or "bad" ozone is not emitted directly into the air, but rather created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC) in the presence of sunlight

[1] Climate normals are three-decade averages of climatological variables including temperature and precipitation.

[2] Although we present our methodology focusing on adaptation, we are agnostic about the true effects. They can 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.

and warm temperatures. Hence, meteorological conditions do matter in determining surface ozone levels, and climate change may increase ozone concentration in the near future. While the projected impact is not uniform, modeling studies have shown that climate change has the potential to increase average summertime ozone concentrations in the contiguous U.S. by as much as 1-5 ppb by 2030, if greenhouse gas emissions are not mitigated (EPA 2009; Jacob and Winner, 2009)[3]. This 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[4]. Thus, stronger emission controls may be needed to meet a given air quality standard. In fact, when strengthening the standards for ground-level ozone from 75 to 70 ppb recently, the U.S. Environmental Protection Agency (EPA) has recognized the role climate change may play in driving air pollution in coming decades[5].

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 Figure 1, highlights the close relationship between these two variables.

We identify the impacts of climate change on ozone concentration by taking advantage of (i) daily measurements of ambient ozone levels from hundreds of air quality monitors across the U.S. during 1980-2013; and (ii) the rich spatial and temporal variation with which Clean Air Act regulations were rolled out. Through a Freedom of Information Act request, we obtained daily air pollution concentrations for each monitor based on the universe of the state and national pollution monitoring network. 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

[3] These modeling studies are based on coupled global climate and regional air quality models, and are designed to assess the sensitivity of U.S. air quality to climate change. A wide range of future climate scenarios and future years has been modeled.

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

[5] "*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)

designates that county as “nonattainment”. Heavy emitters in nonattainment counties face far more stringent regulations than their counterparts in attainment counties. We therefore seek to identify changes in ozone concentrations due to observed changes in temperature at the times and locations in which the CAAA designations were in effect vis-à-vis places that were not facing the constraints associated with being out of attainment. We use a standard fixed-effects 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 CAAA “nonattainment” designations.

We have three main findings. First, a changing climate appears to be affecting ground-level ozone concentrations in two ways. A shock in temperature of one degree Celsius increases ozone levels by 1.7 ppb on average, which is 11 percent higher than 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 1.2 ppb, 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 change of one degree Celsius in temperature, our measure of adaptation in terms of ozone concentration is 0.45 ppb. When we compare our estimate of adaptation to the direct effect of the CAAA “nonattainment” designations, it is equivalent to over one third of that effect. Also, if adaptive responses were not taken into account in the measurement of adaptation, 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 adaptation in counties in “attainment”, and is equivalent to about 45 percent of the direct effect of the CAAA “nonattainment” designations. Counties out of attainment must reduce ozone concentration by making costly adjustments in their production processes (Greenstone, List, and Syverson, 2012). Thus, part of our measure of adaptation for these counties is regulation-induced adaptation. Nevertheless, counties complying with EPA’s ozone standards might still adapt by exploiting technological advances such as photovoltaic panels, as explained before, or by unconscious behavioral responses. Therefore, part of our measure of adaptation is residual adaptation. For nonattainment counties, regulation-induced adaptation represents 40 percent of the total adaptation. For completeness, we have also found (i) a higher degree of adaptation in the 1980s relative to the following decades, (ii) a

similar magnitude for the estimates of adaptation in the 1990s and 2000s, and (iii) a remarkable heterogeneity across the nine NOAA climate regions in the U.S.

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 the history of ozone regulations. Section 4 describes our 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 exhibits the spatial and temporal heterogeneity of our results. Lastly, Section 9 concludes.

2. Conceptual Framework

The Fifth Assessment Report from the Intergovernmental Panel on Climate Change alerts that by late 21st century it is virtually certain that (i) average temperature will rise, and (ii) heat waves will become more frequent (IPCC, 2013). Implicit in this assertion is the dual manner climate change is supposed to affect society. It should alter not only averages, but also the dispersion of climatological variables.

We propose a unifying approach to identifying the impact of both components of climate change, and ultimately measuring adaptation. In empirical work aiming at identifying the effects of climate change, researchers have used either long- or short-term variation in meteorological conditions. These different research designs, however, usually trade off key assumptions. As pointed out by Hsiang (2016), only in certain conditions weather variation exactly identifies the effects of climate. Our methodology bridges those two strands of the climate-economy literature. In the end, because estimates associated with different time-horizon variables have distinct informational content, the comparison between them allows us to uncover a measure of adaptation to climate change.

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

In order to estimate the impact of climate change on ozone concentration, and ultimately uncover our measure of adaptation, we exploit both climatological and meteorological variation. The same estimating equation uses climatological variation to identify the causal

effect of longer-run observed climatic changes (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005), and meteorological variation to identify the impact of weather shocks (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). Afterwards, the comparison between simultaneously estimated trend and shock effects should provide a measure of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016).

To take advantage of variation in both components, we decompose meteorological variables into long-run trends and weather shocks. A similar idea has been used in the literature of intergenerational mobility following Solon's seminal work. Observed income is noisy: it includes a permanent and a transitory component. To establish a relationship between permanent income of sons and fathers, Solon (1992) suggests 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 ozone levels, our outcome variable. Illustrating the decomposition with temperature (*Temp*), we can express it as

$$Temp = Temp^{C} + Temp^{W}, \quad (1)$$

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[6].

A Measure of Adaptation to Climate Change

$Temp^{C}$ and $Temp^{W}$ in the decomposition above are associated with different sets of information. On 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 only at the time of the weather realization. Now, one can only

[6] 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.

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 $Temp^W$.[7]

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.

3. Ambient Ozone, Weather and Environmental Regulations

Ambient ozone, an important component of smog, is a highly reactive and unstable gas capable of damaging living cells, such as those present in the linings of the human lungs. It has a very characteristic pungent odor. Humans vary in their ability to smell ozone, but some can smell it at levels as low as 5 ppb. Ozone is a powerful oxidant – its actions can be compared to household bleach, which can kill living cells such as germs or human skin cells upon contact. Exposure has been associated with several adverse health effects, such as aggravation of asthma and decreased lung function.

Most of the ozone in the air 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 reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NOx) in the presence of sunlight. As a photochemical pollutant, ozone is formed only during daylight hours under appropriate conditions, but is destroyed throughout the day and night. It is formed in greater quantities on hot, sunny, calm days. Therefore, ozone concentrations vary depending upon both the time of day and the location.

The ozone that the EPA regulates as an air pollutant is mainly produced close to ground (tropospheric ozone). A layer of ozone high up in the atmosphere, called stratospheric ozone,

[7] 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.

reduces the amount of ultraviolet light entering the earth's atmosphere. Without the protection of the stratospheric ozone layer, plant and animal life would be seriously harmed. Here, 'ozone' refers to tropospheric ozone.

This section presents the processes by which ozone is formed and depleted, the role of weather, and spatial and temporal variations in ozone concentrations. In addition, it discusses the National Ambient Air Quality Standards (NAAQS) for ground-level ozone.

3.1 Formation and Depletion of Tropospheric Ozone

Ozone is formed in the troposphere when an atom of oxygen (O) associates with a molecule of oxygen (O2) in the presence of a third body. Key reactions happen in the NOx cycle and the VOC oxidation cycle (see more details in the appendix).

In the NOx cycle, the ultraviolet portion of solar radiation triggers the photolysis of nitrogen dioxide (NO2). As a result, NO2 is broken into an atom of oxygen and nitrogen monoxide (NO). The oxygen atom reacts with O2 to form ozone again, but NO reacts with ozone to destroy it. Therefore, the NOx cycle maintains a photostationary equilibrium. Consequently, for ozone to accumulate, an additional pathway is needed to convert NO to NO2; one that will not destroy ozone. The photochemical oxidation of VOCs, such as hydrocarbons and aldehydes, provides that pathway.

In the VOC oxidation cycle, hydroxyl radical initially attacks a parent hydrocarbon. The hydroxyl radical is ever-present in the ambient air, and is formed by photolysis of ozone in the presence of water vapor, nitrous acid, hydrogen peroxide, or other sources. After the attack, hydrogen or other organic fragments emerge, and react with oxygen to generate the peroxy radical. Here is the most important part of this cycle: through a fast radical transfer reaction with NO, peroxy radical converts NO to NO2. Thus, the NO that would be used to destroy ozone is transformed in NO2. Consequently, ozone formation might increase, ozone depletion might decrease, and ozone accumulation may occur. These reactions should explain the typical pattern of ozone concentrations found in the urban atmosphere.

Although VOCs are necessary to generate high concentrations of ozone, NOx emissions can

be the determining factor in the peak ozone concentrations observed in many places. The relative balance of VOCs and NOx at a particular location determines whether the NOx behaves as a net ozone generator or a net ozone inhibitor. When the VOC/NOx ratio in the ambient air is low (NOx is plentiful relative to VOC), NOx tends to inhibit ozone accumulation. These locations are called "VOC-limited". When the VOC/NOx ratio is high (VOC is plentiful relative to NOx), NOx tends to generate ozone. Those are "NOx-limited" locations. Importantly, the VOC/NOx ratio can differ substantially by location and time-of-day within a geographic area.

3.2 Role of Weather in Ozone Air Quality

The local rate of ozone formation depends on atmospheric conditions such as the availability of solar ultraviolet radiation capable of initiating photolysis reactions, air temperatures and the concentrations of chemical precursors.

Our basic understanding of meteorological processes associated with summertime ozone episodes has not changed over recent years. Major episodes of high ozone concentrations in the eastern U.S. and in Europe are associated with slow moving, high pressure systems. High pressure systems are associated with the sinking of air, resulting in warm, generally cloudless skies, with light winds. The sinking of air results in the development of stable conditions near the surface that inhibit or reduce the vertical mixing of ozone precursors. The combination of inhibited vertical mixing and light winds minimizes 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 indeed point to temperature as the most important weather variable affecting ozone concentrations. 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.

An association between ambient ozone concentrations and temperature has also been demonstrated from measurements in outdoor smog chambers and from measurements in ambient air. Some possible explanations for such a correlation include (EPA, 2006):

(1) increased photolysis rates under meteorological conditions associated with higher temperatures;
(2) increased H2O concentrations with higher temperatures as this will lead to greater OH (hydroxyl; hydroxy) production;
(3) increase of anthropogenic hydrocarbon (e.g., evaporative losses) emissions or NOx emissions with temperature or both;
(4) increase of natural hydrocarbon emissions (e.g., isoprene) with temperature;
(5) relationships between high temperatures and stagnant circulation patterns;
(6) advection of warm air enriched with O3.

It should be noted, however, that a high correlation of ozone with temperature does not necessarily imply a causal relation. Extreme episodes of high temperatures (a heat wave) are often multiday events, high ozone episodes are also multiday events, concentrations build, temperatures rise, but both are being influenced by larger-scale regional or synoptic meteorological conditions. We will be investigating this relationship using longitudinal variation from U.S. counties since the 1980s.

3.3 Spatial and Temporal Variations of Ozone Concentrations

Ambient ozone concentrations can vary from non-detectable near combustion sources, where nitric oxide (NO) is emitted into the air, to several hundreds ppb of air in areas downwind of VOC and NOx emissions. In continental areas far removed from direct anthropogenic effects, ozone concentrations are generally 20-40 ppb. In rural areas downwind of urban centers, ozone concentrations are higher, typically 50-80 ppb, but occasionally 100-200 ppb. In urban and suburban areas, ozone concentrations can be high (well over 100 ppb), but peak for at most a few hours before deposition and reaction with NO emissions cause ozone concentrations to decline (Chameides et al. 1992, Smith et al. 1997, Seinfeld and Pandis 1998,

Finlayson-Pitts and Pitts 2000). Due to the lack of ozone-destroying NO, ozone in rural areas tends to persist at night, rather than declining to the low concentrations (<30 ppb) typical in urban areas and areas downwind of major urban areas that have plenty of fresh NO emissions.

With respect to temporal variation, ozone concentrations tend to vary in phase with human activity patterns, magnifying the resulting adverse health and welfare effects. Ambient ozone concentrations increase during the day when formation rates exceed destruction rates, and decline at night when formation processes are inactive. This diurnal variation in ozone depends on location, with the peaks being very high for relatively brief periods of time (an hour or two duration) in urban areas, and being low with relatively little diurnal variation in remote regions. 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. Thus, the peak urban ozone period of the day can correspond with the time of day when people, especially children, tend to be active outdoors.

Ozone concentrations also vary seasonally. Ozone concentrations tend to be highest during the summer and early fall months. 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. The EPA has established "ozone seasons" for the required monitoring of ambient ozone concentrations for different locations within the United States and U.S. territories (CFR, 2000). Table 1 shows the ozone seasons during which continuous, hourly averaged ozone concentrations must be monitored. Note that ozone monitoring is optional outside of the "ozone season" and is monitored in many locations throughout the year.

3.4 National Ambient Air Quality Standards (NAAQS) for Ambient Ozone

The Clean Air Act requires EPA to set national ambient air quality standards (NAAQS) for ozone and other pollutants considered harmful to public health and the environment (the other pollutants are particulate matter, nitrogen oxides, carbon monoxide, sulfur dioxide and lead). The law also requires EPA to periodically review the standards to ensure that they provide adequate health and environmental protection, and to update those standards as necessary.

As shown in Table 2, the first standard was put in place in 1971, following the Clean Air Act Amendments of 1970. It was not focusing on ozone, however, but rather all photochemical oxidants. The first NAAQS for 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 revised to be 80ppb, but with a different form for the threshold: annual fourth-highest daily maximum concentration averaged over 3 years. 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) Another reason was *"the inherent lack of year-to-year stability in the measure of air quality on which the 1-expected-exceedance form is based. ... [A] more robust, concentration-based form would minimize such instability and provide some insulation from the impacts of extreme meteorological events that are conducive to O3 formation. Such instability can have the effect of reducing public health protection by disrupting ongoing implementation plans and associated control programs.*" (U.S. EPA, 1997, p.38868) The new NAAQS was challenged in courts, and not implemented until 2004.

The NAAQS for ozone were revised again in 2008 and 2015, and the current 8-hour threshold is 70ppb. In the last revision, EPA raised concerns about how climate change might affect air quality. "*In addition to being affected by changing emissions, future O3 concentrations may also be affected by climate change. Modeling studies in the EPA's Interim Assessment (U.S. EPA, 2009a) … as well as a recent assessment of potential climate change impacts (Fann et al., 2015) project that climate change may lead to future increases in summer O3 concentrations across the contiguous U.S. While the projected impact is not uniform, climate change has the potential to increase average summertime O3 concentrations by as much as 1-5 ppb by 2030, if greenhouse gas emissions are not mitigated. Increases in temperature are expected to be the principal factor in driving any O3 increases, although increases in stagnation frequency may also contribute (Jacob and Winner, 2009). If unchecked, climate change has the potential to offset some of the improvements in O3 air quality, and therefore some of the improvements in public health, that are expected from reductions in emissions of*

O3 precursors." (U.S. EPA, 2015, p. 65300) This suggests that the present study may contribute to such an important policy debate.

Regarding the patterns of ozone concentration over time, Figures 2 and 3 depict how much maximum and fourth-highest ozone levels have declined with the establishment of the NAAQS. As we can see in Figure 2, maximum concentrations decreased sharply in the late 1980s for the counties designated to be out of attainment. The same is not true for NAAQS 1997 and 2008. As Figure 3 shows, counties in non-attainment seem to be adjusting slowly to the new standards.

It is important to mention that the observed delay in complying with the NAAQS is expected. As reported in Table 3, for example, EPA allows heavy emitters up to 20 years to adjust their production processes. "*Each area designated nonattainment for ozone … shall be classified at the time of such designation … as a Marginal Area, a Moderate Area, a Serious Area, a Severe Area, or an Extreme Area based on the design value for the area. … For each area …, the primary standard attainment date for ozone shall be as expeditiously as practicable but not later than the date provided.*" (U.S. Code, 2011, p.6325)

4. Data

To examine the impact of climate change on surface ozone concentrations, and ultimately estimate our measure of 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 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 4 shows the geographical location of our final sample of ozone monitors and highlights the spatial heterogeneity of our sample. Figure 5 depicts the evolution of our sample monitors over the three decades in our data, and illustrates the expansion of the network over time. Table 4 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 A1, 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[8]. Figure A1, in the Appendix, illustrates the geographical location of the weather stations that we have used from 1950-2013, and Figure A2 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 5 reports the summary statistics for our main meteorological variables, for each decade. Table A2, in the Appendix, presents this information at a more disaggregated level, for each year in our sample from 1980-2013. Figure 6 illustrates the variation we have in both components of the meteorological variables, namely, the weather shocks and the long-term climate trends. Figure 7 depicts this variation for each of the nine different NOAA climate regions.

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 8, highlights the close relationship between these two variables. Interestingly, we see that not 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. Figures 9 and 10 illustrate the spatial heterogeneity of this close relationship between ground level ozone

[8] For robustness purposes, we have also used 80 km, 100 km and 150 km radii around ozone monitors.

and these two different components of the meteorological variables for the nine NOAA climate regions.

5. Empirical Strategy

In this section, we present our methodology to examine the impact of climate change on ambient ozone concentration. First, we provide an empirical counterpart for the decomposition of meteorological variables described previously. Second, we introduce and discuss features of our econometric model to estimate the effects of the two components of weather on 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[9], we express it around ozone monitor *i* in day *d* of month *m* and year *y* as

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

$Temp^{C}$ 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 ground-level ozone 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 have had 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[10]. We use monthly MAs because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed,

[9] As emphasized before, among all meteorological variables, temperature is expected to be the principal factor driving increases in ozone concentration as the climate changes (Jacob and Winner, 2009).

[10] In the robustness checks, we provide estimates based on alternative 10- or 20-year moving averages.

meteorologists on TV often talk about how a month has been the coldest or warmest in the past 10, 30, or 50 years, but not how a particular day of the year has deviated from the trend[11].

$Temp^W$ 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 that 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[12].

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:

$$Ozone_{icdmy} = \alpha + \beta_T^W Temp_{idmy}^W + \beta_T^C Temp_{im,y-1}^C + \beta_P^W Prcp_{idmy}^W + \beta_P^C Prcp_{im,y-1}^C + \delta CAANAS_{c,y-3} + \lambda_{sy} Z_i + \eta_i + \phi_{rsy} + \varepsilon_{idmy}, \quad (3)$$

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 and *Prcp*'s[13] account for the two components of the decomposition proposed above for both meteorological variables[14]. *CAANAS* (Clean Air Act Non-Attainment Status) is a binary variable equals to one for counties not complying with the NAAQS for ground-level ozone – counties designated as "nonattainment" following regulations derived from the Clean Air Act (CAA) Amendments. This variable is lagged by three years

[11] 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.

[12] 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.

[13] We also add 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.

[14] In the robustness checks, we also include weather shocks lagged by a few days to evaluate the extent to which coefficients associated 30-year MAs capture those lagged effects. Because ozone formed in one day may affect ground-level ozone concentration in the next few days, weather shocks might have a delayed effect.

because EPA gives heavy-emitters 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, η represents monitor fixed effects, Φ 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 one degree Celsius 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 one degree Celsius 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.

Our preferred econometric specification allows the effects of each component of our meteorological variables to differ according to the "nonattainment" status of the county where each monitor is located. The estimating equation becomes

$$\begin{aligned} Ozone_{icdmy} = \alpha + \gamma_T^W Temp_{idmy}^W + \gamma_T^C Temp_{im,y-1}^C \\ + \delta_T^W \left(CAANAS_{c,y-3} * Temp_{idmy}^W\right) + \delta_T^C \left(CAANAS_{c,y-3} * Temp_{im,y-1}^C\right) \\ + \gamma_P^W Prcp_{idmy}^W + \gamma_P^C Prcp_{im,y-1}^C + \delta_P^W \left(CAANAS_{c,y-3} * Prcp_{idmy}^W\right) \\ + \delta_P^C \left(CAANAS_{c,y-3} * Prcp_{im,y-1}^C\right) + \delta CAANAS_{c,y-3} + \lambda_{sy} Z_i + \eta_i + \phi_{rsy} \\ + \varepsilon_{idmy}. \end{aligned} \quad (4)$$

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 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 β_T^W and β_T^C in equation (3). If economic agents engaged in full adaptive behavior, β_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 versus residual adaptation, as shown in Table 6. Regulation-induced adaptation reflects adjustments made by heavy emitters in “nonattainment” 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[15]. Residual adaptation reflects adaptive responses by economic agents in counties under no pressure from stringent CAA regulations. They react unintentionally to climatic changes by changing electricity production and consumption patterns or driving behavior, for example.

To provide examples of residual behavioral responses to climatic changes, we lean on two papers. First, Deschenes and Greenstone (2011) estimate a U-shape relationship between residential energy consumption and bins of temperature relative to the 50°-60°F range. Temperature-days in the highest two categories (80-90°F and >90°F) and the lowest four categories (30°-40°F and the three categories below) are associated with statistically significant increases in residential energy consumption. In terms of magnitude, temperature-days below 10°F and above 90°F are associated with 0.3 percent-0.4 percent increases in annual residential energy consumption. This overall increase in consumption should be related to heating or air conditioning. Thus, it might lead to more ozone precursor emissions by fossil fuel power plants, making reductions in ozone concentration more difficult.

Second, Leard and Roth (2016) 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

[15] EPA already recognizes the role of climate change on future ground-level ozone concentration. In the 2015 revision of the ozone NAAQS, the 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)

precursors by vehicles. Therefore, places with a monthly 30-year MA temperature higher than average in the previous year may observe an effect on ozone that is less than the impact of weather shocks because households might have already adjusted their travel behavior. They may have already acquired bikes and motorcycles, and planned outdoor activities not involving too much driving in that particular month[16].

Regarding regulation-induced adaptation, it refers to behavioral responses to climatic changes driven by regulations arising from the CAA Amendments. Polluters in counties designated as "nonattainment" face far more stringent regulations than their counterparts in "attainment" counties. "Nonattainment" counties may not be complying with ozone NAAQS because of climatological changes conditional on particular levels of emissions rather than emissions surges arising from changes in production processes. Therefore, when heavy emitters are mandated to adopt costly pollution abatement technologies, they are implicitly coping with a warmer climate – an implicit adaptive behavior.

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).

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

[16] Graff Zivin, Hsiang, and Neidell (2015) provide another example of unconscious adaptive response to climate change. They find that short-run changes in temperature beyond 26^{o}C lead to statistically significant decreases math performance. In contrast, their long-run analysis reveals no effect of climate on human capital, consistent with the notion that adaptation, particularly unconscious compensatory behavior, plays a significant role in limiting the long-run impacts from short-run weather shocks.

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[17], adaptive responses many years after agents observe changes in temperature trends may be plausible. As Kousky (2012) points out in her review on the costs of natural disasters, "*(…) end-of-the-pipe adjustments, like shutters or increasing the market penetration of air conditioning, will underestimate how fully communities are adapted to their present disaster risk: infrastructure, building architecture, street geometries, and even institutions such as emergency response are all adapted to a current climate, and changing these to fit with a new risk profile, if sufficiently different, could be a very long-term process (…).*" (p.39).

Heterogeneity of Temperature Effects and Measures of Adaptation

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, and for different NOAA climate regions.

In an additional specification, we basically interact the two components of meteorological variables and the *CAANAS* with each decade included in our sample – 1980s, 1990s, and 2000s. In another specification, we interact those same variables with each climate region as defined by NOAA – Ohio Valley, Upper Midwest, Northeast, Northwest, South, Southeast, Southwest, West, and Rockies, as shown in the data section. Once we have the estimates associated with weather shocks and lagged 30-year MAs in these two cases, we are able to provide measures of adaptation for each decade and each climate region in our sample.

6. Results

In this section we report our findings regarding (i) the impact of temperature on ambient ozone concentration, and (ii) the extent to which economic agents adapt to climate change in the

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

context of ozone pollution[18]. Then, we provide evidence of the robustness of our main results to alternative specifications and sampling strategies. Lastly, we explore heterogeneity of our estimates by decade (1980s, 1990s, and 2000s) and by NOAA climate region.

Impact of Temperature on Ambient Ozone Concentration

Table 7 presents the effects on ambient ozone of two components of observed temperature: climate, represented by the *lagged* 30-year monthly MA[19], 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 and total precipitation 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 at each monitor. The estimate suggests that a 1°C increase in average maximum temperature is associated with a 1.10ppb increase in ozone concentration, approximately. Column 2 reports the effect of temperature on ozone identified by exploiting day-to-day variation in maximum temperature. The coefficient indicates that a 1°C increase in maximum temperature leads to a 1.53ppb increase in maximum ground-level ozone concentration. When we decompose daily maximum temperature into those two components in column 3, the overall effect on ozone concentration goes to 2.9ppb. A 1°C shock increases ozone concentration by 1.7ppb, and a 1°C change in trends in the same month of the previous year increases ozone concentration by 1.2ppb. Therefore, by including the two components of temperature – the lagged 30-year

[18] We report the estimates for precipitation in the tables as well, but do not discuss them in the paper. As mentioned before, previous evidence has shown that temperature is the primary factor influencing ozone concentration (Jacob and Winner, 2009).

[19] 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 almost the same and are reported in Table A3 in the Appendix.

MA and deviations from it – the impact of changes in observed maximum temperature doubles or triples when compared to the panel or cross-sectional approaches, respectively.

To emphasize, both unexpected spikes in temperature and rises in long-term temperature trend have a positive and significant effect on ozone concentrations. The total effect of a higher temperature is almost 2.9 ppb, which is in line with previous studies in the literature. 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 their Interim Assessment (2009) also claim 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 Clean Air Act Non-Attainment Status (CAANAS) 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. We find that in non-attainment counties, daily maximum ozone concentrations are around 1.22 ppb lesser as compared to counties in attainment. A 1-degree Celsius rise in the climate trend (as measured by the lagged 30-year MA of temperature) also has differential impacts in attainment and non-attainment counties. In attainment counties it leads to around 0.98 ppb rise in ozone concentrations, whereas in non-attainment counties we find an additional increase of around 0.47 ppb, which implies a cumulative increase of 1.45 ppb of summertime surface ozone levels. Similarly, we find heterogeneity in the effect of the weather shock; a 1-degree Celsius increase in the weather realization increases ozone levels by 1.3 ppb in attainment counties, whereas it leads to an additional 0.69 ppb increase in non-attainment counties.

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). When we compare the impact of long-run temperature on ozone concentration in column 1 of Table 7 with the effect of a temperature shock in column 2, the measure of adaptation is approximately 0.44ppb. Interestingly, 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 very similar: 0.45ppb.

Our results indicate that temperature shocks have a larger impact on ozone levels compared to long-term temperature trends. This points to the fact that economic agents may potentially *adapt* to climate trends. We summarize our measures of adaptation in Table 8. By comparing the coefficients of the temperature shock and the temperature trend in Column (4) of Table 7, we find that on average across all counties, *the level of adaptation is* 0.45 ppb. If we ignore such adaptive responses by economic agents, then we would be overestimating the climate penalty on ozone by over 17 percent[20]. We find that the level of adaptation is roughly 37 percent of the direct effect of the Clean Air Act regulation, which means that our measure of adaptation is economically sizeable.

Using our estimates from Column (5) of Table 7, we can now disentangle the overall adaptation into *regulation-induced adaptation* and *residual adaptation*. The coefficients of the interaction terms now give us the *incremental* impacts of weather shocks and climate change in *non-attainment counties.* From this specification, we find that the *regulation-induced adaptation* (in non-attainment counties) is 0.22 ppb, whereas the *residual level of adaptation*[21] (both, in attainment and non-attainment counties) is 0.33 ppb, as shown in Table 8. Thus, in non-attainment counties we find a total adaptation of 0.55 ppb. More than 40 percent of this cumulative level of adaptation in non-attainment counties should be driven by the Clean Air Act regulations.

Non-attainment counties adapt over 66 percent more than attainment counties in absolute terms. To give a sense of the magnitude of our adaptation estimates by attainment status, we can compare them to the impact of the CAA regulations. As we found in Column (3) of Table 7, the CAA regulations reduce ozone levels by around 1.22 ppb. Hence, in *attainment counties* it represents 26.7 percent of the effect of being out of attainment and in *non-attainment counties* almost 45 percent. Therefore, our estimates of adaptation seem sizeable. By ignoring such adaptive measures, we would be overestimating the climate penalty in attainment counties by 14.5 percent, and by over 16 percent in non-attainment counties.

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[20] 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.

[21] Again, regulation-induced adaptation is defined as $(\delta_T^W - \delta_T^C)$. It reflects adjustments made by heavy emitters in non-attainment counties to comply with the ozone NAAQS. Residual adaptation is defined as $(\gamma_T^W - \gamma_T^C)$. It is a measure of adaptive responses by economic agents in counties under no pressure of stringent CAA regulations..

7. Robustness Checks

7.1 Nonlinearities

Because ozone formation may be intensified with higher temperatures, we also look at the non-linear effects of daily maximum temperature on surface ozone concentrations. Instead of using daily maximum temperature continuously, we have categorized the contemporaneous daily maximum temperature and also its monthly average into temperature bins of 5□C. We have put temperatures below 20□C (just over the 10^{th} percentile of our temperature distribution) into our lowest bin and those above 35□C (90^{th} percentile of our temperature distribution) into our highest bin. We have then taken the lagged 30 year moving averages of these temperature bin dummies, to get a measure of the long term climate trend; the measure of our weather shock has been constructed by taking the difference between the contemporaneous temperature bins and the 30 year monthly moving average of temperature bins. In Table 9, we have reported our estimates from this non-linear specification.

By interacting our temperature bins, with the regulatory variable, as before, we can analyze the nature and degree of regulation induced and residual adaptation at different points of the temperature distribution. From column (2), 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 degree C increase would raise ozone levels by 1.22 ppb on average; whereas for temperatures between 25-30□C, 30-35□C and above 35□C, the effects are 3.1 ppb, 4.76 ppb and 6.54 ppb respectively. From our estimates in columns (3) and (4), we have the following results about the degree of adaptation at different levels of temperature, which are summarized in Table 10.

Average Adaptation (across all counties). From column (4) of Table 9, like we had for our main results, we find that the average level of adaptation across all counties ranges from 0.51 ppb for temperatures between 20-25□C, to 0.16 ppb for temperatures between 25-30□C; 0.45 ppb for temperatures between 30-35□C, and lastly almost 0.82 ppb for temperatures in our highest bin. So we see that a lot of the adaptation is driven by the 20-25C bin. As the USA as a whole is predominantly NO_x limited, we would expect that changes in electricity usage might drastically reduce ozone concentrations (since electricity use is a major source of NO_x, also, since ozone formation has a Leontief like production function in terms of NO_x and VOCs, reduction in electricity use in a NO_x limited region would imply large changes in ozone

formation.) 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.

However, temperatures between 20-25□C represent very pleasant weather which might potentially induce people to cut down on electricity demand and hence cut down on NO_x which might be driving the high degrees of adaptation in this bin. This again points to the fact that most of this adaptation is driven by the lower temperature bins, where adapting to a warming climate is relatively easier. In a recent paper (Deschenes and Greenstone, 2011), the authors analyze the non-linear effects of daily average temperature on residential energy consumption and quite interestingly, they 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 degrees Fahrenheit (comparable to our intermediate temperature bin of 20-25□C), is the lowest. This also justifies our estimates of adaptation at different levels of temperature. At intermediate levels of daily temperature, economic agents can adjust and bring down their energy consumption, hence leading to large decreases in ozone concentrations. Interestingly, we also see a relatively high level of adaptation above 35□C. This can be plausibly explained by the following reasons. As discussed in Leard and Roth (2016), higher temperatures signify more pleasant weather and can lead to changes in transportation patterns in a way that people might prefer walking or biking rather than driving. Such behavioral changes might be driving the higher levels of residual adaptation that we see across all counties. Also, in regions having temperatures above 35□C, we would expect higher incidence of sunlight which might be leading 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 power generation, thus leading to higher levels of adaptation. Lastly, regions having higher temperatures have a larger climate penalty on ozone and hence are more strongly regulated. This might be driving the larger levels of regulation induced adaptation that we see in the higher temperature bins.

Regulation-induced adaptation + *Residual Adaptation (in non-attainment counties)*. Similar to our main results, we find a higher degree of 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.

Residual Adaptation (in attainment and non-attainment counties). From column (5) of Table 9, we find that the residual adaptation, ranges from 0.13 ppb for temperatures between 25-30□C, to around 0.67 ppb, for temperatures above 35□C.

7.2 Lagged Responses

Another potential concern with our preferred specification might be the fact that we have used the lagged 30 year moving average to capture the long term climate trend; hence to avoid such concerns, we test the sensitivity of our estimates using the lagged 20 years and lagged 10 years monthly moving averages of temperature and precipitation. The results which have in reported in Table A4 in the Appendix, prove to be quite robust and the magnitudes are very similar to our main results in Table 7. This is potentially being caused because the 30 year monthly moving average that we use in our preferred specification, already has all the information that is present in the 20 year, or the 10 year moving average. In all the three kinds of moving average used, agents are getting just one year to adapt. Hence, a more interesting robustness check could be to look at the effects, when agents get 10 years and 20 years to adapt, instead of just one. In Table 11, we provide estimates from our preferred specification; however, by using 20 year moving averages of temperature and precipitation (*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 expect that the effects of the weather shocks would 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 11.

7.3 Non-Random Citing of Ozone Monitors

In a recent working paper (Muller & Ruud, 2016), the authors argue that the location of pollution monitors are not necessarily random. They claim that the U.S. Environmental Protection Agency (EPA) maintains a dense network of pollution monitors in the country for two major reasons. Firstly, it wishes to check and enforce the National Ambient Air Quality

Standards (NAAQs) for the criteria pollutants; and secondly, it wants to provide useful data for the analysis of important questions linking pollution with its varied impacts. The authors claim that these are conflicting interests, because to check attainment status, the monitors are generally placed in areas where pollution levels are the highest, whereas in terms of providing good quality representative data, monitors must be placed in regions having different levels of pollution.

The authors further assert that if the most important objective of the EPA was to provide an unbiased estimate of the level of criteria pollutants across the nation, then the monitors must be placed more densely, where surface variation is the largest. However, since the monitors also serve the EPA's purpose of enforcing the NAAQs, they are not randomly placed. Most of the monitors tend to be in areas where pollution levels have been high and compliance with the regulation is a question. Following the argument of the paper and relying on their results, we might believe that monitor location is essentially endogenous and hence using an unbalanced panel of monitors over time might be giving us incorrect estimates as we are only observing ozone concentrations at monitors which have high pollution levels.

To nullify such threats to identification, we can check the sensitivity of our main estimates reported in Table 7, by using a balanced panel of ozone monitors. Starting from our original sample, we only use observations from monitors that have been in the data for every year from 1980-2013 and we are left with 92 pollution monitors. By doing so we eliminate the various possible confounding factors that might drive the positioning of monitors and their subsequent selection into the sample. The results from this estimation have been reported in Table 12. We find that a 1-degree Celsius increase in the daily maximum temperature leads to a rise in ozone concentrations by 1.88 ppb. Average adaptation is 0.44 ppb across all counties. We can further disentangle this to find that regulation induced adaptation in non-attainment counties is 0.24 ppb whereas residual adaptation in attainment as well as non-attainment counties is 0.25 ppb. The effects using a balanced panel are actually even larger than those in our main results reported in Table 7. This ensures that our central estimates are robust to any sort of errors potentially caused by the endogenous placement of ozone monitors, because had such claims been true, the effects should have been smaller when we use a balanced sample. As explained before, if monitors are expected to be placed endogenously in areas having high pollution levels, then when we use an unbalanced panel in our preferred sample, we should be

overestimating the effect of temperature on ozone concentrations, which does not seem to be true.

7.4 Dependence on 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. Firstly, high wind speeds can dilute ozone concentrations locally and also potentially lead to the transportation of ozone to neighboring regions. Strong ventilation with high wind speeds prevents the build-up of high local pollutant concentrations. Ozone precursors, namely, NOx and VOCs can also be transported significant distances from their point of origin and hence can lead to elevated ozone levels in other areas. Secondly, ultraviolet solar radiation initiates the photolysis of NO_2 to nitric oxide and a free oxygen atom which can then react with molecular oxygen to form ozone. In order to test if our main estimates are actually capturing the effects of wind speed and sunlight, we control for these variables in our preferred specification. Table 13 reports these estimates. Columns (1) and (2) present our main results from estimating Equations (3) and (4) respectively. Next we present results from estimating Equation (4), however, having additionally controlled for average daily wind speed (meters/sec) in Column (3), total daily sunlight (mins) in Column (4) and both in Column (5). As expected, we find that 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 2.2 ppb, whereas a 1 min increase in daily sunlight leads to 0.02 ppb increase in ozone concentrations. More importantly, by comparing Column (2) with Column (5), we find that our main results do not change dramatically, either in direction or magnitude, after the inclusion of these other meteorological variables. We still find that a shock in daily maximum temperature of 1□C leads to a 1.24 ppb increase in daily maximum ozone whereas a 1□C increase in the climate trend leads to a 0.72 ppb increase in ozone. Our estimates of the interaction terms suggest a *regulation-induced adaptation* of 0.17 ppb in non-attainment counties. Also, we still find a *residual adaptation* of 0.52 ppb, across all counties. This ensures that our primary estimates of the impact of temperature on ozone concentrations, and hence, our measures of adaptation, are not being driven by the dependence on other potentially important meteorological factors.

8. Heterogeneity

8.1 Results by Decade

In the following tables, we present our results from estimating equation (4) by decades. We split our sample into three decades, 1980-90, 1991-2001 and 2002-2013 respectively, so that we have roughly the same number of years in each decade. In Table 14, we present the main results, where we see the heterogeneity of our results across time. All the effects discussed in the Main Results are present in each decade; however, we find that the effect of contemporaneous daily maximum temperature is decreasing over time. Also, looking at columns (3) and (4), we find evidence of adaptation by economic agents, in every decade. The average adaptation across all counties in our sample ranges from 0.58 ppb in the 1980s to 0.39 ppb in the 1990s and 0.41 ppb in the 2000s. Also, from column (4) we find that the regulation-induced adaptation in non-attainment counties decreases consistently from around 0.22ppb in the 1980s to about 0.09 ppb in the 2000s. *Residual* adaptation in attainment and non-attainment counties varied from 0.42 ppb in the 1980s to 0.27 ppb in the 1990s and 0.38 ppb in the 2000s. Hence, 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. The temporal heterogeneity of our adaptation estimates, has been illustrated in Table 15.

8.2 Results by Climate Region

Next we aim to establish the spatial heterogeneity of our results. We have estimated our main specification by the nine different climate regions as defined by the National Oceanic and Atmospheric Association (NOAA), through detailed climate analysis. Each of these regions have very similar climatic conditions and hence, very comparable baselines of temperature, precipitation and other important meteorological variables, thus providing a reliable criterion for breaking up our main estimates to analyze heterogeneity across space. In Tables 16 and 17 we provide our main estimates from the regional regressions and also the heterogeneity of our adaptation estimates. In Table 16, the main estimates for each region have been reported. To avoid confusion, we have just presented the results from the 3rd and 4th specification, for each region. We find that even though the overall direction of effects of weather shocks as well as

long term climate trends are consistent, their magnitudes are extremely varied across space. To make things clearer, Table 17 reports the adaptation estimates for each climate region; here, as before, using column (3) we have first calculated estimates on average level and percentage of adaptation across all counties in each region. Then, using column (4), we disentangle this into regulation-induced and residual adaptation. In this table we also provide the mean daily maximum temperature (climatic baseline) and the average proportion of counties in non-attainment in each region, using which we can try to interpret the results in an improved manner.

As we can observe from Table 17, almost all the regions exhibit adaptation to climate change, as we have discussed before. However, their magnitudes are quite different, and since we also have the baseline climate for each region, we can link these estimates to our estimates for non-linear temperature effects, reported in Table 9. As we can see here, most of the adaptation is driven by the Upper Midwest, Northeast and Northwest, where average daily maximum temperatures fall in the range 20-25□C. This is consistent with our finding in Table 10, where we claimed that a major portion of adaptation happens at such lower temperatures. Regions having average temperatures in the range 25-30□C, namely the Ohio Valley, Southeast, Southwest and West, exhibit lower degrees of adaptation, which is also consistent with our results on non-linear effects of temperature. If we analyze the estimates of residual and regulation-induced adaptation, we find that the West and the Northwest have 0.526 ppb and 0.724 ppb regulation induced adaptation, which is huge compared to most other regions. On the other hand, in the Northeast, we actually find evidence of *intensification*, rather than adaptation. To understand this further, we can compare the Northeast and the Northwest, both having a climatic baseline between 20-25□C, hence implying feasible conditions for adaptation. However, we find that even though there is a high level of residual adaptation in both regions, the regulation induced adaptation is a huge 0.724 ppb in the Northwest, whereas it is -0.151 ppb in the Northeast. This can potentially be explained by the fact that regulation in this states, has already reached the limit of effectiveness. This can be observed from the fact that in the Northeast, more than three-fourths of the counties are already being regulated as compared to the Northwest, where this proportion is only about 0.2. Northeast officials have stressed that they have done everything in their capacity to bring down emissions. However, a huge proportion of the ozone air pollution in these states are driven by cross border pollutants from upwind Southern and Midwestern states. Officials have mentioned on multiple occasions

that installing pollution abatement technology would be far less costly for Midwestern states, than it would be for the Northeast. It has been estimated that the marginal cost of regulation in the Northeast is a whopping $10000 whereas in the Midwest, it is only about $200. Hence, we find that regulation has no further effect in these states. Looking at the other climatic extreme, we can compare the Southwest and the West, both having average temperatures close to 30□C. Even though the West has a reasonably high proportion of counties in non-attainment, we find evidence that there is still some scope of regulation induced adaptation. However, in both regions, we find evidence of residual intensification, which is probably driven by the fact that temperatures are too high and hence unfeasible for economic agents to adjust their behavior patterns.

9. 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 over the past 64 years, 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 surface ozone levels. A shock in daily maximum temperature of one degree Celsius increases ozone levels by 1.7 ppb, whereas a similar increase in the 30-year monthly moving average of temperature leads to a further 1.2 ppb increase in ozone, implying a total impact of 2.9 ppb. Hence, by ignoring the climate normal, we would *underestimate* the total effect – or the so-called climate penalty on ozone – by over 40 percent.

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 0.45 ppb across all counties in our sample. This measure captures the fact that the long-term effect of 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 3.4 ppb 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 Nonattainment Areas for Criteria Pollutants, we are also able to disentangle our measure of adaptation into *regulation-induced adaptation*, occurring in counties facing stringent regulations for being out of attainment of ozone NAAQS, and *residual adaptation* occurring in all counties. We find that, in both attainment and non-attainment counties, the residual level of adaptation is 0.33 ppb. However, there is an additional 0.22 ppb regulation-induced adaptation in non-attainment counties. Hence, in comparison to attainment counties, non-attainment counties are adapting over 66 percent more in terms of ozone concentrations. Comparing our estimates to the benefits coming out of CAA regulations, we find that in attainment counties, adaptation represents 26.7 percent of the effect of being out of attainment, whereas in non-attainment counties, its almost 45 percent.

Categorizing temperature into multiple bins, we have also explored the non-linear effects of temperature on ambient ozone levels. Subsequently, we also get adaptation estimates for each of these temperature bins. In line with existing literature, we find that higher temperatures have larger impacts on ozone levels, with the largest effect of 6.54 ppb being driven by temperatures above 35 degrees Celsius. Finally, we also analyze the spatial as well as temporal heterogeneity of our estimates. We find that the 1980s, which marked the initial implementation phases of the Clean Air Act regulations and also correspond to the highest pollution levels in our sample, had the largest impact of temperature on surface ozone concentrations as well as the largest degree of adaptation to climate change. Having estimated our preferred specification by the nine climate regions, as defined by the NOAA, we find that most of the adaptation is driven by the Upper Midwest, Northeast and Northwest, where average temperatures lie between 20-25 degrees Celsius, which is in line with our non-linear estimates.

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 policy making 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 look into 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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10. Tables and Figures

Table 1: 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). [1]The ozone season is defined differently in different parts of Texas.

Table 2: 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.

Table 3: 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 4: Summary Statistics for Monitoring Network by Decades

Decade	Observations	Counties	Monitors	Daily Maximum Ozone	
				Mean	Std. Dev
1980s	107823	390	672	60.8	29.0
1990s	153858	509	888	57.6	21.1
2000s	179947	601	1026	54.3	16.7

Note: 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 ozone season.

Table 5: Summary Statistics for Meteorological Variables

Decade	Max Temperature		30 Yr MA of Max Temperature		Temp Deviations	
	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

Note: Decades are 1980-1990, 1991-2001 and 2002-2013 respectively. 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.

Table 6: 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	β_T^W	δ_T^W	γ_T^W
Marginal Effect of Climatic Changes	β_T^C	δ_T^C	γ_T^C
Measures of Adaptation	$\beta_T^W - \beta_T^C$	$(\delta_T^W - \delta_T^C)$	$(\gamma_T^W - \gamma_T^C)$

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, β_T^W, and observed climate trends, β_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 $(\delta_T^W - \delta_T^C)$. All counties exhibit residual adaptation, given by $(\gamma_T^W - \gamma_T^C)$. For more details, please refer to Table 8.

Table 7: Main Estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)
A. Temperature Variables					
Maximum Temperature	1.0911***	1.5274***			
	(0.0949)	(0.0231)			
Dev from 30 Yr MA of Max Temp (Weather Shock)			1.6939***	1.6942***	1.3025***
			(0.0254)	(0.0254)	(0.0191)
30 Yr MA of Max Temp (Climate Trend)			1.2424***	1.2423***	0.9767***
			(0.0239)	(0.0239)	(0.0219)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp					0.6967***
					(0.0345)
Lag 3 CAANAS x 30 Yr MA of Max Temp					0.4743***
					(0.0273)
B. Clean Air Act Non-Attainment Status					
Lag 3 CAANAS				-1.2197***	-14.0926***
				(0.1771)	(0.8447)
C. Precipitation Variables					
Total Precipitation	-2.5974***	-0.2434***			
	(0.3326)	(0.0036)			
Dev from 30 Yr MA of Prcp (Weather Shock)			-0.2263***	-0.2263***	-0.2201***
			(0.0040)	(0.0040)	(0.0049)
30 Yr MA of Prcp (Climate Trend)			-1.8023***	-1.8042***	-1.6627***
			(0.1218)	(0.1219)	(0.1194)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp					-0.0144**
					(0.0066)
Lag 3 CAANAS x 30 Yr MA of Prcp					0.0630
					(0.1269)
Observations	2,535	4,974,322	4,974,155	4,974,155	4,974,155
R-squared	0.2521	0.4183	0.4223	0.4225	0.4286

Notes: 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. In Column (4), we control for the lagged Clean Air Act Non-Attainment Status and in Column (5) we include interactions of weather shocks and climate trends with the CAANAS to estimate heterogeneous effects across attainment and non-attainment counties. Column (1) has fixed effects for climate region, monitor latitude and monitor longitude. Columns (2)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 8: Adaptation Main Estimates

	Average Adaptation (ppb)	Overestimation of Climate Penalty (%)	Relative to CAA Benefits (%)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	% Regulation Induced
Non-Attainment Counties	0.55	16.2	44.95	0.22	0.33	40
Attainment Counties	0.33	14.5	--	--	0.33	--
All Counties	0.45	17.2	37.05	0.12	0.33	26.6

Notes: For Non-Attainment counties: Level of adaptation (ppb) = Residual ($\gamma^{W}_{T} - \gamma^{C}_{T}$) + Regulation-induced ($\delta^{W}_{T} - \delta^{C}_{T}$) from column (5). Attainment Counties: Level of adaptation (ppb) = ($\gamma^{W}_{T} - \gamma^{C}_{T}$) from column (5) based on equation (4). Overestimation of Climate Penalty for Non-attainment counties= (2*($\gamma^{W}_{T} + \delta^{W}_{T}$)*100)/($\gamma^{W}_{T} + \delta^{W}_{T} + \gamma^{C}_{T} + \delta^{C}_{T}$); for Attainment Counties: (2*γ^{W}_{T}*100)/($\gamma^{W}_{T} + \gamma^{C}_{T}$). Estimates for attainment and non-attainment counties are derived from column (5) of Table 7 and estimates for all counties are derived from Column (4) in Table 7; Average Level of adaptation (ppb) for All Counties = $\beta^{W}_{T} - \beta^{C}_{T}$ from column (4), based in equation (3). Note that in all above calculations, the effect of the CAA regulation is given by δ as estimated by equation (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.

Table 9: Non-Linear Effects of Temperature

VARIABLES		(1)	(2)	(3)	(4)	(5)
Maximum Temperature	20< Max Temp< 25	1.8883	6.1273***			
		(1.4378)	(0.1361)			
	25 < Max Temp <30	10.4610***	15.3174***			
		(1.5004)	(0.2367)			
	30 < Max Temp <35	13.6329***	23.8054***			
		(1.7991)	(0.3720)			
	Max Temp >35	10.2964***	32.7301***			
		(1.9574)	(0.5376)			
Dev from 30 Yr MA of Max Temp	20< Max Temp< 25			6.4159***	6.4201***	5.6972***
				(0.1276)	(0.1274)	(0.1294)
	25 < Max Temp <30			15.4782***	15.4827***	12.7890***
				(0.2315)	(0.2313)	(0.2226)
	30 < Max Temp <35			24.2426***	24.2475***	18.9043***
				(0.3687)	(0.3686)	(0.3166)
	Max Temp >35			33.4807***	33.4858***	25.7193***
				(0.5399)	(0.5398)	(0.4259)
30 Yr MA of Max Temp	20< Max Temp< 25			3.8945***	3.8932***	3.5288***
				(0.2600)	(0.2600)	(0.3031)
	25 < Max Temp <30			14.6576***	14.6562***	12.1577***
				(0.3062)	(0.3063)	(0.3177)
	30 < Max Temp <35			21.9923***	21.9899***	17.8664***
				(0.5099)	(0.5097)	(0.4555)
	Max Temp >35			29.3915***	29.3890***	22.3465***
				(0.8014)	(0.8011)	(0.7880)
Lag 3 of CAANAS					-1.1952***	-6.0965***
					(0.1739)	(0.4821)
Lag 3 CAANAS x Deviation from 30 Yr MA of Max	20< Max Temp< 25					1.3965***
						(0.1882)
	25 < Max Temp <30					4.7471***
						(0.3251)
	30 < Max Temp <35					9.5649***
						(0.4952)
	Max Temp >35					13.6576***
						(0.7146)
Lag 3 CAANAS x 30 Yr MA of Max Temp	20< Max Temp< 25					0.7283*
						(0.3918)
	25 < Max Temp <30					4.3180***
						(0.3928)
	30 < Max Temp <35					7.7813***
						(0.5388)
	Max Temp >35					11.9282***
						(0.9746)
Total Precipitation & Interactions		Yes	Yes	Yes	Yes	Yes
Observations		2,535	4,986,863	4,986,685	4,986,685	4,986,685
R-squared		0.2723	0.4137	0.4157	0.4158	0.4221

Notes: In Columns (1)-(5) we report non-linear effects of daily maximum temperature on surface ozone levels. We categorize daily maximum temperature into 5 bins from <25□C to >35□C with 5□C intervals in between. 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. In Column (4), we control for the lagged Clean Air Act Non-Attainment Status and in Column (5) we include interactions of weather shocks and climate trends with the CAANAS to estimate heterogeneous effects across attainment and non-attainment counties. Column (1) has fixed effects for climate region, monitor latitude and monitor longitude. Columns (2)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 10: Adaptation Estimates for Nonlinearities

	Average Adaptation (ppb)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	% Regulation Induced
A. 20-25 Celsius				
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
B. 25-30 Celsius				
Non-Attainment Counties	0.21	0.08	0.13	38.10
Attainment Counties	0.13	--	0.13	--
All Counties	0.16	0.03	0.13	18.75
C. 30-35 Celsius				
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
D. Above 35 Celsius				
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: Adaptation estimates have been calculated using estimates from Table 9, and dividing that by 5 to get adaptation in response to a 1□C change in temperature. Adaptation measures are calculated, as explained in Table 8.

Table 11: Lagged Responses

VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	20Yr MA: lagged by 10 years				**10Yr MA: lagged by 20 years**			
Max Temp	1.5274***				1.5274***			
	(0.0231)				(0.0231)			
Total Precipitation	-0.2434***				-0.2434***			
	(0.0036)				(0.0036)			
Dev from MA of Max Temp (Weather Shock)		1.6938***	1.6941***	1.3028***		1.6959***	1.6962***	1.3065***
		(0.0255)	(0.0255)	(0.0193)		(0.0256)	(0.0256)	(0.0194)
MA of Max Temp (Climate Trend)		1.2378***	1.2376***	0.9693***		1.2291***	1.2290***	0.9559***
		(0.0239)	(0.0239)	(0.0216)		(0.0237)	(0.0237)	(0.0211)
Lag 3 CAANAS			-1.2125***	-14.2923***			-1.2261***	-14.5335***
			(0.1777)	(0.8512)			(0.1790)	(0.8361)
Lag 3 CAANAS x Dev from MA of Max Temp				0.6948***				0.6914***
				(0.0345)				(0.0346)
Lag 3 CAANAS x MA of Max Temp				0.4815***				0.4919***
				(0.0276)				(0.0277)
Dev from MA of Prcp (Weather Shock)		-0.2273***	-0.2273***	-0.2216***		-0.2284***	-0.2284***	-0.2231***
		(0.0040)	(0.0040)	(0.0049)		(0.0040)	(0.0040)	(0.0048)
MA of Prcp (Climate Trend)		-1.4908***	-1.4898***	-1.3726***		-1.1104***	-1.1132***	-1.0281***
		(0.1153)	(0.1152)	(0.1145)		(0.0913)	(0.0913)	(0.0938)
Lag 3 CAANAS x Dev from MA of Prcp				-0.0136**				-0.0125*
				(0.0066)				(0.0065)
Lag 3 CAANAS x MA of Prcp				0.0678				0.0500
				(0.1261)				(0.1117)
Observations	4,974,322	4,967,557	4,967,557	4,967,557	4,974,322	4,964,220	4,964,220	4,964,220
R-squared	0.4183	0.4221	0.4222	0.4284	0.4183	0.4219	0.4221	0.4283

Notes: Columns (1)-(4) and Columns (5)-(8) are analogous to Columns (2)-(5) in Table 7. Here, we report similar estimates, however, by using 10 and 20 year lagged moving averages of temperature and precipitation. Columns (1)-(8) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. *Standard errors are clustered at the monitor level. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.*

Table 12: Balanced Panel of Monitors

VARIABLES	(1)	(2)	(3)	(4)
Max Temp	1.8878***			
	(0.0726)			
Total Precipitation	-0.2833***			
	(0.0121)			
Dev from 30 Yr MA of Max Temp (Weather Shock)		2.0483***	2.0480***	1.6644***
		(0.0839)	(0.0838)	(0.0783)
30 Yr MA of Max Temp (Climate Trend)		1.6106***	1.6113***	1.4114***
		(0.0696)	(0.0697)	(0.0935)
Lag 3 CAANAS			-1.8371**	-10.2362***
			(0.7918)	(2.2352)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp				0.5096***
				(0.0909)
Lag 3 CAANAS x 30 Yr MA of Max Temp				0.2693***
				(0.0876)
Dev from 30 Yr MA of Prcp (Weather Shock)		-0.2674***	-0.2674***	-0.2285***
		(0.0140)	(0.0139)	(0.0180)
30 Yr MA of Prcp (Climate Trend)		-2.0297***	-2.0296***	-2.1647***
		(0.5377)	(0.5382)	(0.5498)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp				-0.0606***
				(0.0185)
Lag 3 CAANAS x 30 Yr MA of Prcp				0.3789
				(0.4251)
Observations	543,971	543,971	543,971	543,971
R-squared	0.4085	0.4123	0.4126	0.4149

Notes: Columns (1)-(4) are analogous to Columns (2)-(5) in Table 7. Here, we report similar estimates, however, by using a balanced panel of 92 ozone monitors. Columns (1)-(4) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 13: Wind Speed and Sunlight

VARIABLES	(1)	(2)	(3)	(4)	(5)
Dev from 30 Yr MA of Max Temp (Weather Shock)	1.6942***	1.3025***	1.4105***	1.3461***	1.2365***
	(0.0254)	(0.0191)	(0.0263)	(0.0593)	(0.0621)
30 Yr MA of Max Temp (Climate Trend)	1.2423***	0.9767***	0.7663***	0.9240***	0.7247***
	(0.0239)	(0.0219)	(0.0313)	(0.0577)	(0.0621)
Lag 3 CAANAS	-1.2197***	-14.0926***	-13.7245***	-16.1596***	-16.7932***
	(0.1771)	(0.8447)	(1.1532)	(2.0324)	(2.1615)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp		0.6967***	0.6454***	0.7119***	0.8247***
		(0.0345)	(0.0393)	(0.0708)	(0.0770)
Lag 3 CAANAS x 30 Yr MA of Max Temp		0.4743***	0.4676***	0.5491***	0.6477***
		(0.0273)	(0.0353)	(0.0592)	(0.0622)
Dev from 30 Yr MA of Prcp (Weather Shock)	-0.2263***	-0.2201***	-0.1679***	-0.0849***	-0.0615***
	(0.0040)	(0.0049)	(0.0063)	(0.0140)	(0.0125)
30 Yr MA of Prcp (Climate Trend)	-1.8042***	-1.6627***	-1.8777***	-0.9536**	-1.0373***
	(0.1219)	(0.1194)	(0.1239)	(0.4057)	(0.3841)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp		-0.0144**	-0.0261***	-0.0484***	-0.0399**
		(0.0066)	(0.0089)	(0.0187)	(0.0188)
Lag 3 CAANAS x 30 Yr MA of Prcp		0.0630	0.1175	-0.0372	-0.4943
		(0.1269)	(0.1561)	(0.3447)	(0.3448)
Average Daily 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	4,974,155	2,019,634	581,465	455,533
R-squared	0.4225	0.4286	0.4183	0.4049	0.4366

Notes: Columns (1) and (2) are analogous to Columns (4) and (5) in Table 7. In Column (3) we control for average daily wind speed (meters/sec); in Column (4) we control for total daily sunlight (mins) and in Column (5) we control for both. Columns (1)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 14: Results by Decades

VARIABLES	(1)	(2)	(3)	(4)
Max Temperature 80s	2.0763***			
	(0.0465)			
Max Temperature 90s	1.6198***			
	(0.0236)			
Max Temperature 2000s	1.1342***			
	(0.0178)			
Dev from 30 Yr MA of Max Temp; 80s		2.284***	2.2841***	1.7829***
		(0.0521)	(0.0520)	(0.0448)
Dev from 30 Yr MA of Max Temp; 90s		1.760***	1.7605***	1.3650***
		(0.0266)	(0.0266)	(0.0259)
Dev from 30 Yr MA of Max Temp; 2000s		1.290***	1.2897***	1.0918***
		(0.0182)	(0.0182)	(0.0184)
30 Yr MA of Max Temp; 80s		1.710***	1.7046***	1.3614***
		(0.0540)	(0.0536)	(0.0474)
30 Yr MA of Max Temp; 90s		1.375***	1.3720***	1.0952***
		(0.0263)	(0.0263)	(0.0285)
30 Yr MA of Max Temp; 2000s		0.873***	0.8793***	0.7136***
		(0.0255)	(0.0257)	(0.0240)
Lag 3 of CAANAS; 80s			0.1004	-11.7159***
			(0.3952)	(1.5323)
Lag 3 of CAANAS; 90s			-1.0401***	-13.6521***
			(0.2105)	(0.9892)
Lag 3 of CAANAS; 2000s			-1.5564***	-11.0023***
			(0.2374)	(1.0497)
Lag 3 CAANAS x Dev from MA Temp; 80s				0.7232***
				(0.0596)
Lag 3 CAANAS x Dev from MA Temp; 90s				0.6740***
				(0.0417)
Lag 3 CAANAS x Dev from MA Temp; 2000s				0.4260***
				(0.0307)
Lag 3 CAANAS x 30 Yr MA Temp; 80s				0.5016***
				(0.0535)
Lag 3 CAANAS x 30 Yr MA Temp; 90s				0.4807***
				(0.0333)
Lag 3 CAANAS x 30 Yr MA Temp; 2000s				0.3372***
				(0.0312)
Precipitation Controls	Yes	Yes	Yes	Yes
Observations	4,974,322	4,974,155	4,974,155	4,974,155
R-squared	0.4268	0.431	0.4309	0.4354

Notes: Columns (1)-(4) are analogous to Columns (2)-(5) in Table 7. We report our main estimates by the three decades in our sample: 1980-1990; 1991-2001 and 2002-2013. Columns (1)-(4) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 15: Adaptation Estimates by Decades

	Average Adaptation (ppb)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	% Regulation Induced	Proportion in Non-Attainment
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	
B. 1990s					0.54
Non-Attainment Counties	0.46	0.19	0.27	41.30	
Attainment Counties	0.27	--	0.27	--	
All Counties	0.39	0.12	0.27	30.77	
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: Adaptation estimates have been calculated using estimates from Table 14. Adaptation measures are calculated, as explained in Table 8.

Table 16: Results by Climate Regions

	Ohio Valley		Upper Midwest		Northeast	
VARIABLES	**3**	**4**	**3**	**4**	**3**	**4**
Dev from 30 Yr MA of Max Temp (Weather Shock)	1.5875***	1.4750***	1.7020***	1.5259***	2.1127***	1.6690***
	(0.0331)	(0.0357)	(0.0499)	(0.0456)	(0.0438)	(0.0552)
30 Yr MA of Max Temp (Climate Trend)	1.4832***	1.3735***	1.2826***	1.1359***	1.4621***	0.9069***
	(0.0235)	(0.0266)	(0.0386)	(0.0430)	(0.0442)	(0.0606)
Lag 3 CAANAS	-0.8725***	-6.8064***	-1.2307***	-16.2031***	-0.6237**	-25.1981***
	(0.3020)	(1.2124)	(0.3962)	(2.0401)	(0.2466)	(2.6634)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp		0.2226***		0.4104***		0.5697***
		(0.0440)		(0.0755)		(0.0646)
Lag 3 CAANAS x 30 Yr MA of Max Temp		0.2069***		0.3320***		0.7207***
		(0.0344)		(0.0497)		(0.0665)
	Northwest		**South**		**Southeast**	
VARIABLES	**3**	**4**	**3**	**4**	**3**	**4**
Dev from 30 Yr MA of Max Temp (Weather Shock)	1.5975***	1.4400***	1.1127***	1.0039***	1.5608***	1.3586***
	(0.0995)	(0.0991)	(0.0397)	(0.0437)	(0.0529)	(0.0425)
30 Yr MA of Max Temp (Climate Trend)	0.4911***	0.5141***	0.2555***	0.1861**	1.3326***	1.0773***
	(0.0926)	(0.0946)	(0.0631)	(0.0759)	(0.0656)	(0.0521)
Lag 3 CAANAS	-1.0722	4.7527	-1.6304***	-4.1519	-1.5514***	-16.3115***
	(0.8256)	(7.2386)	(0.5678)	(2.6146)	(0.3563)	(2.4084)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp		0.6341***		0.2646***		0.6051***
		(0.1033)		(0.0611)		(0.0879)
Lag 3 CAANAS x 30 Yr MA of Max Temp		-0.0903		0.1639**		0.6025***
		(0.2555)		(0.0787)		(0.0891)
	Southwest		**West**		**Rockies**	
VARIABLES	**3**	**4**	**3**	**4**	**3**	**4**
Dev from 30 Yr MA of Max Temp (Weather Shock)	0.7684***	0.6339***	2.1279***	1.3735***	0.8612***	0.8449***
	(0.0324)	(0.0377)	(0.0827)	(0.0691)	(0.0684)	(0.0642)
30 Yr MA of Max Temp (Climate Trend)	0.8591***	0.7264***	1.8709***	1.5179***	0.5919***	0.5774***
	(0.0484)	(0.0483)	(0.1290)	(0.1061)	(0.0524)	(0.0517)
Lag 3 CAANAS	0.6729	-8.9720***	-2.1284***	-13.8761***	-7.7448***	1.9302
	(0.4118)	(1.8766)	(0.7019)	(2.7249)	(2.2525)	(6.6686)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp		0.3030***		0.9927***		0.4561***
		(0.0511)		(0.0878)		(0.1594)
Lag 3 CAANAS x 30 Yr MA of Max Temp		0.3148***		0.4659***		0.3944**
		(0.0595)		(0.0889)		(0.1583)
Precipitation Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,974,155	4,974,155	4,974,155	4,974,155	4,974,155	4,974,155
R-squared	0.4337	0.4382	0.4337	0.4382	0.4337	0.4382

Notes: Columns (1) and (2) for each climate region are analogous to Columns (4) and (5) in Table 7. We report our main estimates by the nine different NOAA climate regions in the United States. The climate regions are defined as follows: Ohio Valley: IL, IN, KY, MO, OH, TN and WV; Upper Midwest: IA, MI, MN and WI; Northeast: CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI and VT; Northwest: ID, OR and WA; South: AR, KS, LA, MS, OK and TX; Southeast: AL, FL, GA, NC, SC and VA; Southwest: AZ, CO, NM and UT; West: CA and NV; Rockies: MT, NE, ND, SD and WY. Columns (1) and (2) for each region have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-

monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

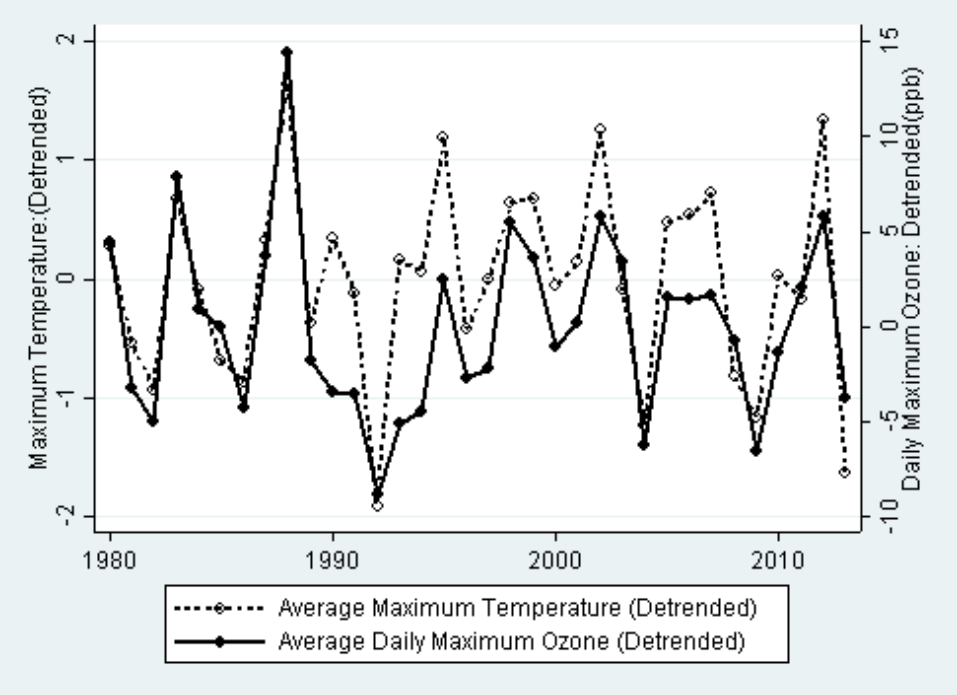
Table 17: Adaptation Estimates by Climate Regions

	Average Adaptation (ppb)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	Average Max Temp	Proportion in Non-Attainment
A. Ohio Valley				25.99	0.453
Non-Attainment Counties	0.117	0.015	0.102		
Attainment Counties	0.102	--	0.102		
All Counties	0.104	0.002	0.102		
B. Upper Midwest				23.05	0.396
Non-Attainment Counties	0.468	0.078	0.390		
Attainment Counties	0.390	--	0.390		
All Counties	0.419	0.029	0.390		
C. Northeast				23.79	0.784
Non-Attainment Counties	0.611	-0.151	0.762		
Attainment Counties	0.762	--	0.762		
All Counties	0.651	-0.111	0.762		
D. Northwest				22.87	0.208
Non-Attainment Counties	1.650	0.724	0.926		
Attainment Counties	0.926	--	0.926		
All Counties	1.106	0.180	0.926		
E. South				30.92	0.485
Non-Attainment Counties	0.919	0.101	0.818		
Attainment Counties	0.818	--	0.818		
All Counties	0.857	0.039	0.818		
F. Southeast				29.06	0.287
Non-Attainment Counties	0.284	0.003	0.281		
Attainment Counties	0.281	--	0.281		
All Counties	0.228	-0.053	0.281		
G. Southwest				30.61	0.436
Non-Attainment Counties	-0.104	-0.011	-0.093		
Attainment Counties	-0.093	--	-0.093		
All Counties	-0.091	0.002	-0.093		
H. West				28.19	0.796
Non-Attainment Counties	0.382	0.526	-0.144		
Attainment Counties	-0.144	--	-0.144		
All Counties	0.257	0.401	-0.144		
I. Rockies				23.55	0.038
Non-Attainment Counties	0.329	0.061	0.268		
Attainment Counties	0.268	--	0.268		
All Counties	0.269	0.001	0.268		

Notes: Adaptation estimates have been calculated using estimates from Table 16. Adaptation measures are calculated, as explained in Table 8. The climate regions are defined as follows: Ohio Valley: IL, IN, KY, MO, OH, TN and WV; Upper Midwest: IA, MI, MN and WI; Northeast: CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI and VT;

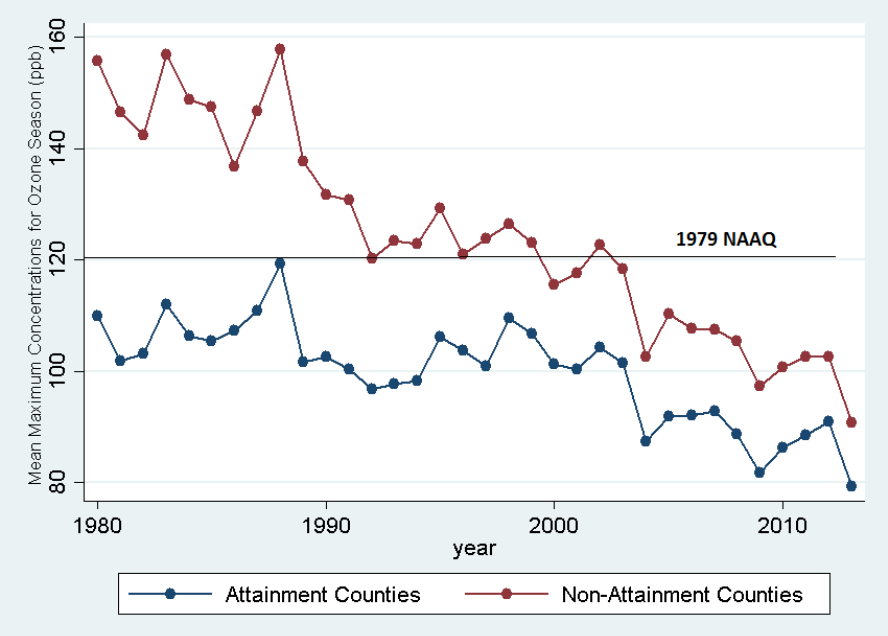
Northwest: ID, OR and WA; South: AR, KS, LA, MS, OK and TX; Southeast: AL, FL, GA, NC, SC and VA; Southwest: AZ, CO, NM and UT; West: CA and NV; Rockies: MT, NE, ND, SD and WY.

Figure 1: Relationship between Ozone and Contemporaneous Temperature



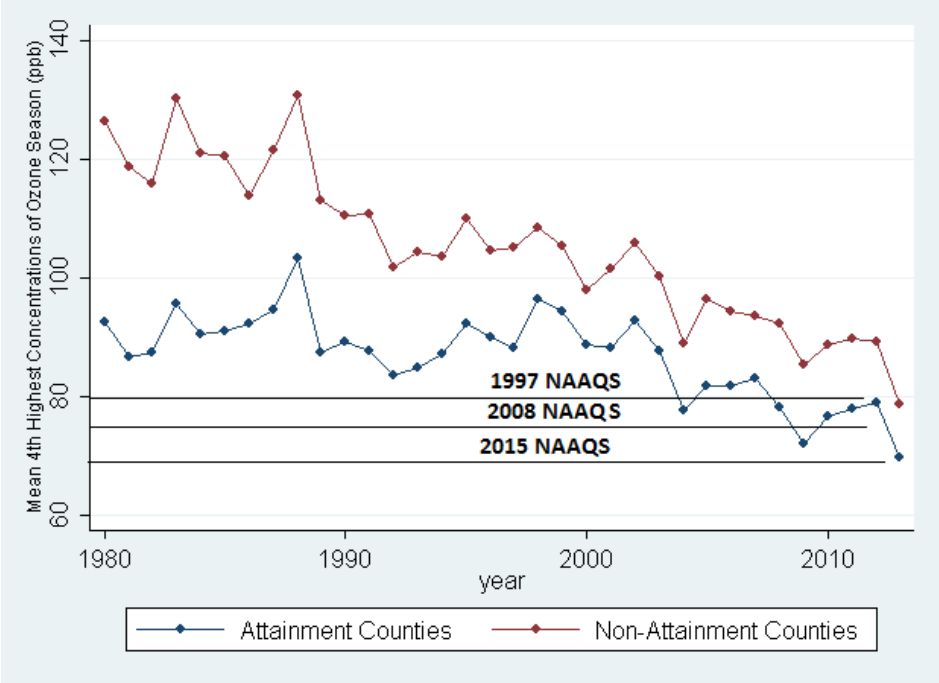
Note: Figure 1 illustrates the daily maximum temperature and ozone, averaged across all monitor-days, for each year. The variables have been detrended by eliminating the time trend.

Figure 2: Evolution of Maximum Ozone Concentration



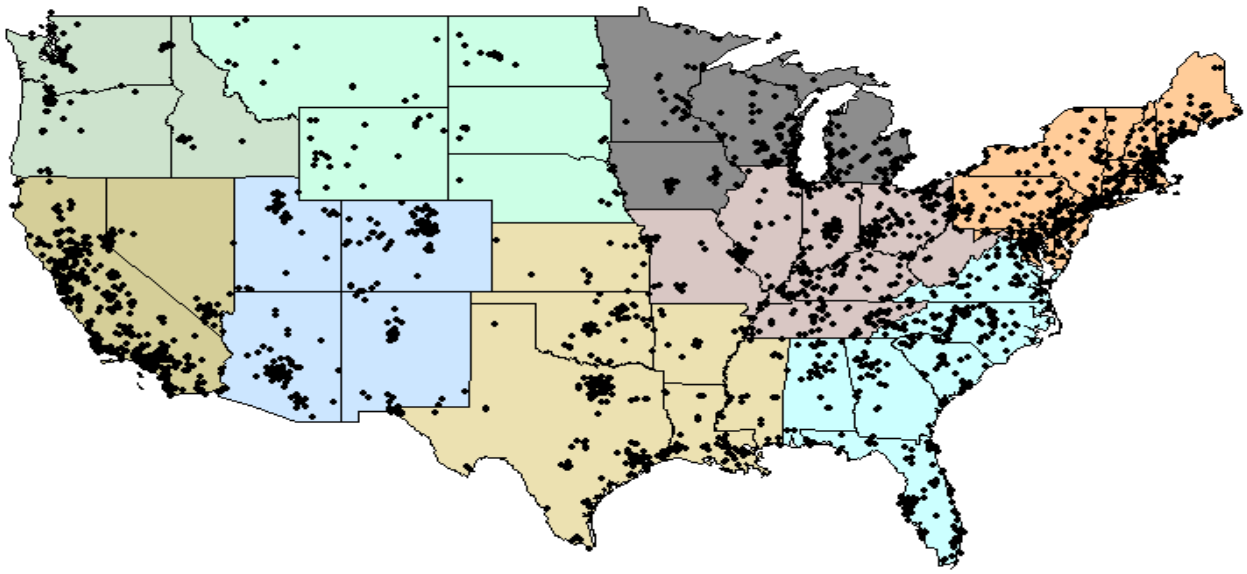
Source: Authors' compilation based on EPA data.

Figure 3: Evolution of Fourth-Highest Ozone Levels



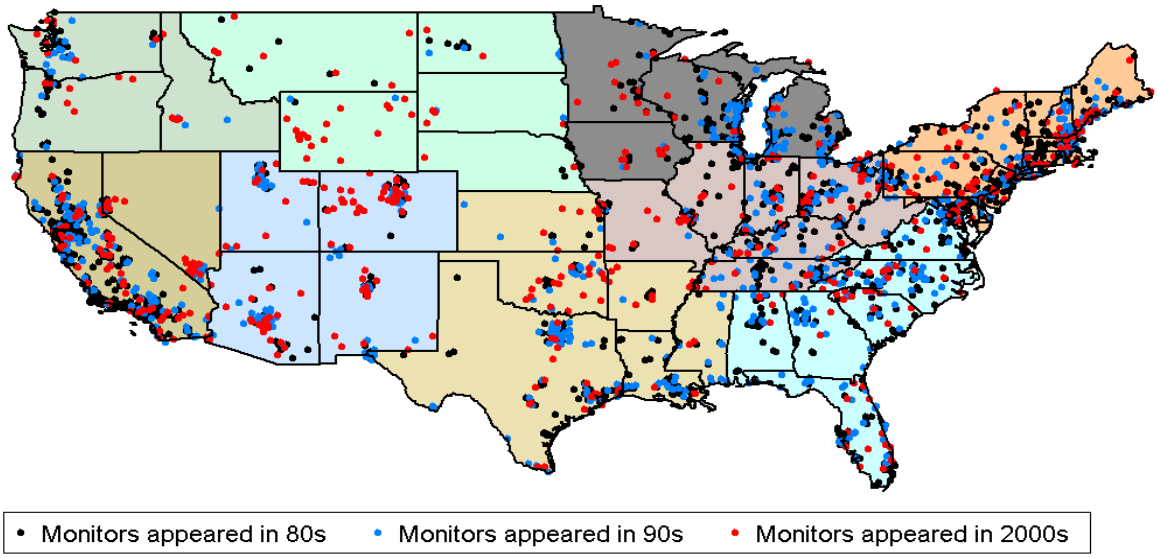
Source: Authors' compilation based on EPA data.

Figure 4: Ozone Monitors in Sample



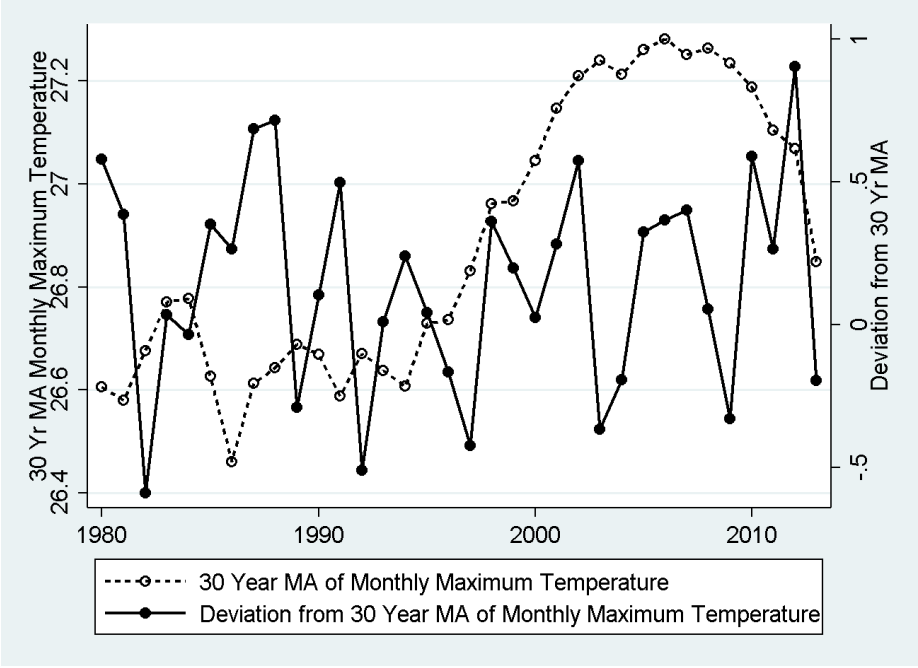
Note: Each shaded region represents a single climatic region as designated by the NOAA. According to the EPA, daily measurements are valid for regulation purposes only if (i) 8-hour averages are available for at least 75% of possible hours of the day, or (ii) the daily maximum 8-hour concentration is higher than the standard. Firstly, we only include monitors having valid daily information. Secondly, for every year between 1980-2013, we include monitors having valid monitor-days for at least 75% of the ozone season. Figure 4 illustrates our final sample of ozone monitors.

Figure 5: Ozone Monitors by Decade of First Appearance



Note: Each shaded region represents a single climatic region as designated by the NOAA. Figure 5 illustrates the ozone monitors in our final sample, by decade of first appearance.

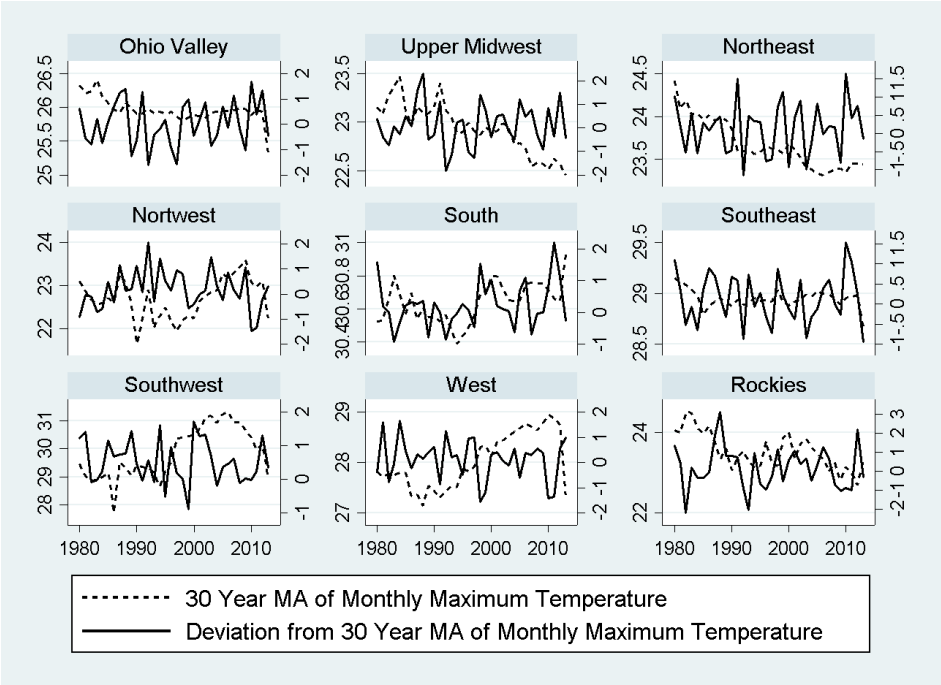
Figure 6: Meteorological Variables- Trends and Shocks



Note: Figure 6 illustrates the variation in both the components of the meteorological variables. The weather shock is a deviation of contemporaneous daily maximum

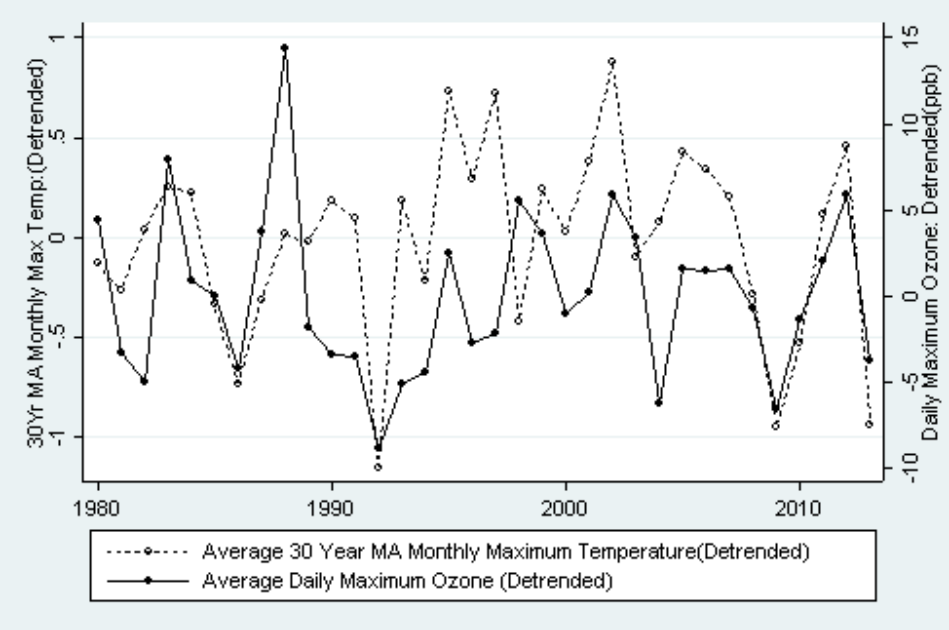
temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year.

Figure 7: Meteorological Variables- Trends and Shocks by Region



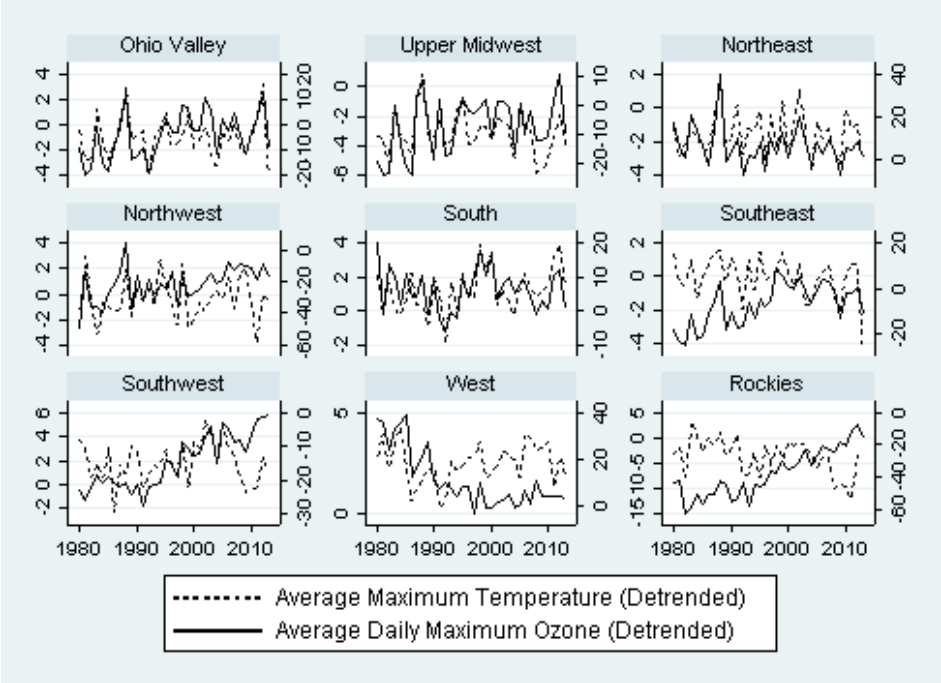
Note: Figure 7 illustrates the variation in both the components of the meteorological variables, by the climate regions. The weather shock is a deviation of contemporaneous daily maximum temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year.

Figure 8: Relationship between Ozone and Moving Average of Temperature



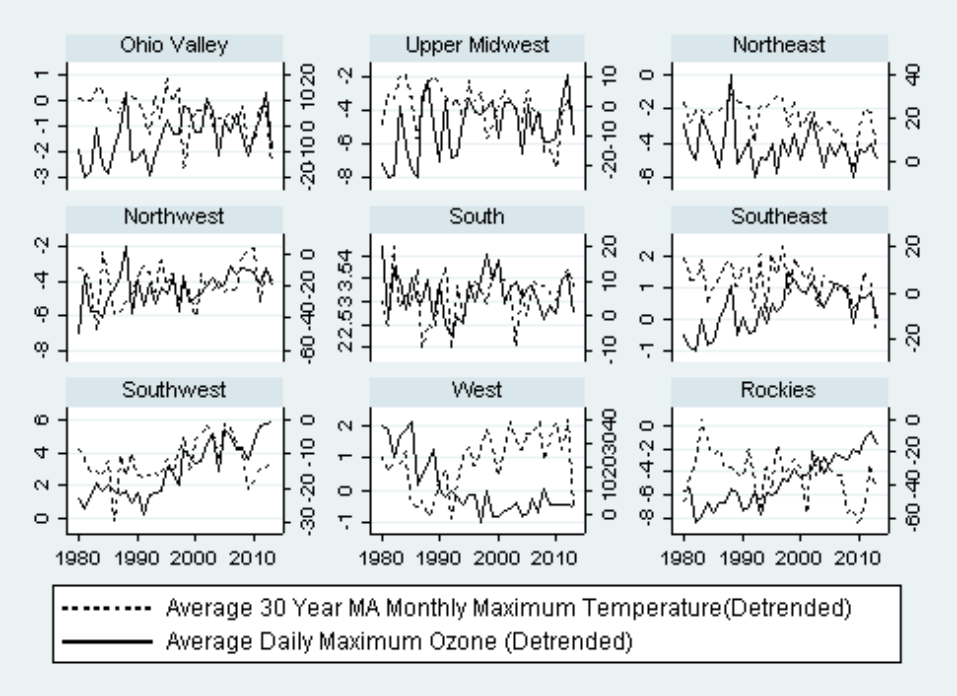
Note: Figure 8 illustrates the 30-year monthly moving average of daily maximum temperature and ozone, averaged across all monitor-days, for each year. The variables have been detrended by eliminating the time trend.

Figure 9: Relationship between Ozone and Contemporaneous Temperature by Regions



Note: Figure 9 illustrates the daily maximum temperature and ozone, averaged across all monitor-days, for each year and climate region. The variables have been detrended by eliminating the time trend.

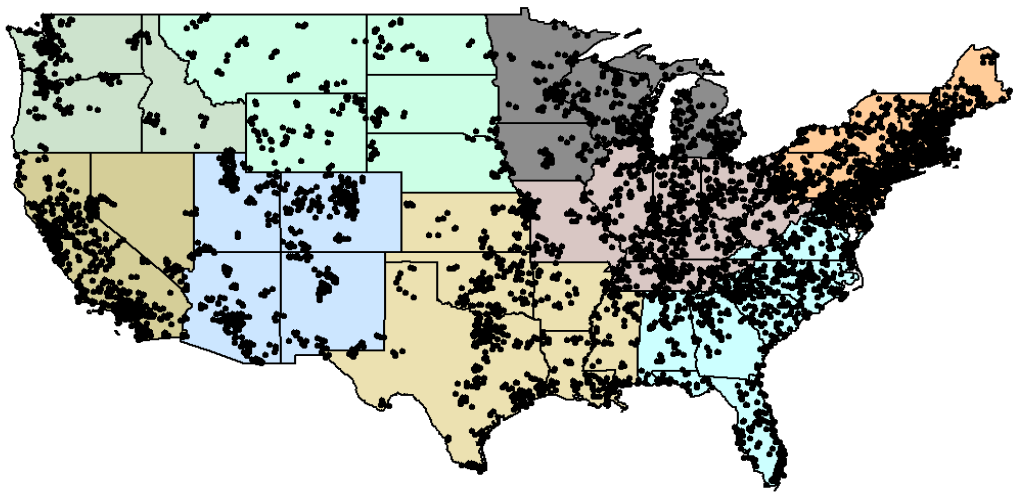
Figure 10: Relationship between Ozone and Moving Average of Temperature by Regions



Note: Figure 10 illustrates the 30-year monthly moving average of daily maximum temperature and ozone, averaged across all monitor-days, for each year and climate region. The variables have been detrended by eliminating the time trend.

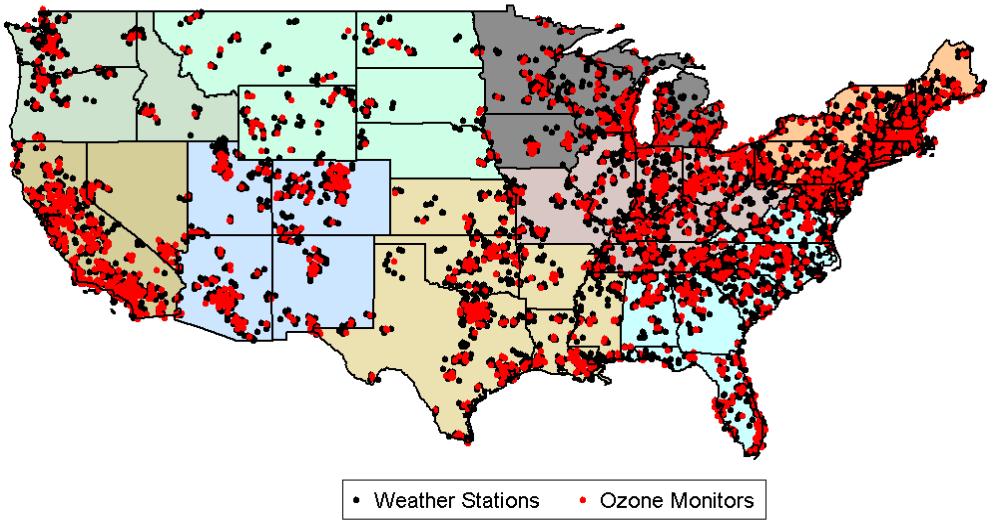
Appendix A

Figure A1: Weather Stations from 1950-2013



Note: Each shaded region represents a single climatic region as designated by the NOAA. Figure A1 illustrates the weather stations used from 1950-2013. For every ozone monitor in our final sample, we keep the closest two weather stations within a radius of 30 km.

Figure A2: Matched Ozone Monitors and Weather Stations



Note: Each shaded region represents a single climatic region as designated by the NOAA. Figure A2 illustrates the ozone monitors in sample from 1980-2013 and the matched weather stations. For each ozone monitor the closest 2 stations within a 30 km radius have been used.

Table A1: Summary Statistics for Monitoring Network by Year

Year	Observations	Counties	Monitors	Number of Monitors by Climate Regions								
				Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
1980	91543	368	663	132	67	149	12	51	72	36	134	10
1981	102211	394	684	137	65	137	15	66	77	45	133	9
1982	102168	383	651	129	54	131	16	62	75	44	132	8
1983	102513	393	651	127	52	135	12	74	80	42	123	6
1984	104705	382	649	118	51	129	15	76	78	41	134	7
1985	106550	382	653	127	53	134	17	67	75	39	133	8
1986	104889	367	635	114	52	127	17	70	73	33	142	7
1987	110838	378	663	116	56	129	14	70	81	41	147	9
1988	114510	405	693	123	56	130	12	71	94	46	150	11
1989	119972	406	712	126	58	129	12	71	91	46	168	11
1990	126149	427	742	129	60	134	13	73	97	52	175	9
1991	131638	446	778	135	74	141	13	80	100	54	171	10
1992	136747	458	804	144	66	144	11	85	108	53	183	10
1993	144870	485	844	151	69	145	15	83	124	66	180	11
1994	147629	490	853	153	65	146	16	84	125	62	193	9
1995	151553	495	872	154	67	153	17	86	127	60	199	9
1996	150585	500	867	152	66	158	21	86	129	66	179	10
1997	157337	518	901	158	66	163	23	91	135	75	180	10
1998	160401	535	927	160	66	165	26	98	140	77	187	8
1999	165718	546	948	161	68	169	25	98	149	75	192	11
2000	168893	551	965	166	68	159	24	111	154	79	192	12
2001	177068	572	1014	168	68	175	25	121	164	82	198	13
2002	180316	579	1023	160	67	174	27	127	167	87	199	15
2003	182313	588	1036	160	73	173	29	133	168	89	195	16
2004	182229	596	1023	159	71	173	29	131	166	92	187	15
2005	180238	594	1019	154	72	174	27	131	159	99	184	19
2006	181903	598	1025	154	71	177	26	129	159	101	187	21
2007	183971	605	1036	155	69	180	26	129	155	113	188	21
2008	184197	607	1041	154	70	176	25	132	154	114	194	22
2009	186610	616	1048	154	71	179	25	132	153	117	192	25
2010	187713	623	1058	154	71	178	29	132	152	120	193	29
2011	190351	642	1076	161	73	186	29	129	161	120	185	32
2012	191206	637	1076	155	72	190	27	128	165	115	189	35

2013	128317	523	852	129	38	176	8	120	149	89	119	24	

Note: 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 ozone season. The nine different climatic regions are as defined by the National Oceanic and Atmospheric Association (NOAA).

Table A2: Summary Statistics for Meteorological Variables by Year

Year	Max Temperature	30 Yr MA of Max Temp	Temp Deviations
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

Note: Decades are 1980-1990, 1991-2001 and 2002-2013 respectively. 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.

Table A3: Daily Moving Averages

VARIABLES	(1)	(2)	(3)	(4)
Max Temp	1.5274***			
	(0.0231)			
Total Precipitation	-0.2434***			
	(0.0036)			
Dev from 30 Yr MA of Max Temp (Weather Shock)		1.6991***	1.6993***	1.3029***
		(0.0260)	(0.0259)	(0.0195)
30 Yr MA of Max Temp (Climate Trend)		1.2794***	1.2793***	0.9959***
		(0.0233)	(0.0233)	(0.0207)
Lag 3 CAANAS			-1.2095***	-15.1604***
			(0.1769)	(0.7952)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp				0.7053***
				(0.0351)
Lag 3 CAANAS x 30 Yr MA of Max Temp				0.5099***
				(0.0278)
Dev from 30 Yr MA of Prcp (Weather Shock)		-0.2306***	-0.2306***	-0.2251***
		(0.0039)	(0.0039)	(0.0048)
30 Yr MA of Prcp (Climate Trend)		-0.4590***	-0.4593***	-0.4922***
		(0.0201)	(0.0201)	(0.0264)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp				-0.0120*

				(0.0065)
Lag 3 CAANAS x 30 Yr MA of Prcp				0.1112***
				(0.0386)
Observations	4,974,322	4,974,117	4,974,117	4,974,117
R-squared	0.4183	0.4209	0.4211	0.4275

Notes: This tables reports our main estimates, however, using daily moving averages of temperature and precipitation instead of monthly moving averages. Columns (1)-(4) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table A4: 20 Year and 10 Year Moving Averages

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	**20 Year Moving Averages**				**10 Year Moving Averages**			
Max Temp	1.5274***				1.5274***			
	(0.0231)				(0.0231)			
Total Precipitation	-0.2434***				-0.2434***			
	(0.0036)				(0.0036)			
Dev from MA of Max Temp (Weather Shock)		1.6902***	1.6904***	1.2994***		1.6889***	1.6890***	1.3001***
		(0.0253)	(0.0253)	(0.0191)		(0.0252)	(0.0252)	(0.0189)
MA of Max Temp (Climate Trend)		1.2511***	1.2509***	0.9834***		1.2509***	1.2509***	0.9776***
		(0.0241)	(0.0241)	(0.0220)		(0.0241)	(0.0240)	(0.0218)
Lag 3 CAANAS			-1.2124***	-14.2360***			-1.2328***	-14.5932***
			(0.1764)	(0.8445)			(0.1766)	(0.8274)
Lag 3 CAANAS x Dev from MA of Max Temp				0.6960***				0.6934***
				(0.0344)				(0.0343)
Lag 3 CAANAS x MA of Max Temp				0.4769***				0.4868***
				(0.0274)				(0.0274)

Dev from MA of Prcp (Weather Shock)		-0.2268***	-0.2268***	-0.2203***		-0.2280***	-0.2279***	-0.2212***
		(0.0040)	(0.0040)	(0.0049)		(0.0040)	(0.0040)	(0.0049)
MA of Prcp (Climate Trend)		-1.7213***	-1.7219***	-1.6083***		-1.4298***	-1.4345***	-1.3708***
		(0.1054)	(0.1055)	(0.1053)		(0.0784)	(0.0786)	(0.0817)
Lag 3 CAANAS x Dev from MA of Prcp				-0.0149**				-0.0149**
				(0.0066)				(0.0066)
Lag 3 CAANAS x MA of Prcp				0.0932				0.1244
				(0.1187)				(0.1002)
Observations	4,974,322	4,974,155	4,974,155	4,974,155	4,974,322	4,974,155	4,974,155	4,974,155
R-squared	0.4183	0.4222	0.4224	0.4286	0.4183	0.4220	0.4222	0.4284

Notes: This tables reports our main estimates, however, using 20 year and 10 year moving averages of temperature and precipitation instead of our preferred 30 year moving averages. Columns (1)-(8) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Appendix B

B. Formation and Depletion of Tropospheric Ozone

The formation of ozone in the troposphere is a complex process involving the reactions of hundreds of precursors. The key elements, as summarized in Finlayson-Pitts and Pitts (2000), and Seinfeld and Pandis (1998) are discussed below.

B.1 Nitrogen Cycle and the Photostationary-State Relationship for Ozone

The formation of ozone in the troposphere results from only one known reaction: addition of atomic oxygen (O) to molecular oxygen (O2) in the presence of a third "body" (M). M is any "body" with mass, primarily nitrogen or oxygen molecules, but also particles, trace gas molecules, and surfaces of large objects.

$$O + O2 + M \rightarrow O3 + M \qquad (B1)$$

The oxygen atoms are produced primarily from photolysis of NO2 by the ultraviolet portion of

solar radiation (hn).

$NO2 + hn \rightarrow NO + O$ (B2)

Reaction 3 converts ozone back to oxygen and NO back to NO2, completing the "nitrogen cycle."

$O3 + NO \rightarrow NO2 + O2$ (B3)

Reactions 1 and 3 are comparatively fast. Therefore, the slower photolysis reaction 2 is usually the rate-limiting reaction for the nitrogen cycle and the reason why ozone is not formed appreciably at night. It is also one of the reasons why ozone concentrations are high during the summer months, when temperatures are high and solar radiation is intense. The cycle time for the three reactions described above is only a few minutes. Ozone accumulates over several hours, depending on emission rates and meteorological conditions.

The nitrogen cycle operates fast enough to maintain a photostationary state. The net effect of this cycle is neither to generate nor destroy ozone molecules. Therefore, for ozone to accumulate, an additional pathway is needed to convert NO to NO2; one that will not destroy ozone. The photochemical oxidation of VOCs, such as hydrocarbons and aldehydes, provides that pathway.

B.2 The VOC Oxidation Cycle

Hydrocarbons and other VOCs are oxidized in the atmosphere by a series of reactions to form carbon monoxide (CO), carbon dioxide (CO2) and water (H2O). Intermediate steps in this overall oxidation process typically involve cyclic stages driven by hydroxyl radical (OH) attack on the parent hydrocarbon, on partially oxidized intermediate compounds, and on other VOCs. The hydroxyl radical is ever-present in the ambient air; it is formed by photolysis from ozone in the presence of water vapor, and also from nitrous acid, hydrogen peroxide, and other sources. In the sequence shown below, R can be hydrogen or virtually any organic fragment. The oxidation process usually starts with reaction 4, from OH attack on a hydrocarbon or other VOC:

$RH + OH \rightarrow H2O + R$ (B4)

This is followed by reaction with oxygen in the air to generate the peroxy radical (RO2).

$R + O2 + M \rightarrow RO2 + M$ (B5)

The key reaction in the VOC oxidation cycle is the conversion of NO to NO2. This takes place through the fast radical transfer reaction with NO.

$RO2 + NO \rightarrow NO2 + RO$ (B6)

R can also be generated by photolysis, which usually involves only VOCs with molecules containing the carbonyl (C=O) bond. The simplest VOC molecule that contains the carbonyl bond is formaldehyde (HCHO). Because formaldehyde enters into several types of reactions of importance for understanding ozone formation and depletion, we will use it to help illustrate these reactions. The oxidation cycle for formaldehyde can be written in the following sequence of reactions.

$OH + HCHO \rightarrow H2O + HCO$ (B7)
$HCO + O2 \rightarrow HO2 + CO$ (B8)
$HO2 + NO \rightarrow NO2 + OH$ (B9)

Hydroperoxyl radical (HO2) is generated by reaction 8, and the hydroxyl radical (consumed in reaction 7) returns in reaction 9 to complete the cycle. In addition, reaction 9 produces the NO2 required for ozone formation, as described above. Also, the carbon monoxide (CO) generated by reaction 8 can react like an organic molecule to yield another hydroperoxyl radical.

$OH + CO \rightarrow H + CO2$ (B10)
$H + O2 + M \rightarrow HO2 + M$ (B11)

Another component that formaldehyde provides for smog formation is a source of hydrogen radicals.

$HCHO + hn \rightarrow H + HCO$ (B12)

The hydrogen atom (H) and formyl radical (HCO) produced by this photolysis reaction yield

two hydroperoxyl radicals via reaction with oxygen, as shown in reactions 8 and 11.

The reactions above comprise the simplest VOC oxidation cycle. Actually, hundreds of VOC species participate in thousands of similar reactions. These reactions should explain the typical pattern of ozone concentrations found in the urban atmosphere.

B.3 Ratio of Volatile Organic Compounds to Nitrogen Oxides in Ambient Air

Although VOCs are necessary to generate high concentrations of ozone, NOx emissions can be the determining factor in the peak ozone concentrations observed in many locations (Chameides, 1992; National Research Council, 1991).

The relative balance of VOCs and NOx at a particular location helps to determine whether the NOx behaves as a net ozone generator or a net ozone inhibitor. When the VOC/NOx ratio in the ambient air is low (NOx is plentiful relative to VOC), NOx tends to inhibit ozone formation. In such cases, the amount of VOCs tends to limit the amount of ozone formed, and the ozone formation is called "VOC-limited". When the VOC/NOx ratio is high (VOC is plentiful relative to NOx), NOx tends to generate ozone. In such cases, the amount of NOx tends to limit the amount of ozone formed, and ozone formation is called "NOx -limited". The VOC/NOx ratio can differ substantially by location and time-of-day within a geographic area.