

Supplementary Materials for  
**Climate Change Will Unravel Air Quality Regulations**

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## Supplementary Text

### **S1 Background on ozone formation and the Clean Air Act**

The ozone regulated by the U.S. Environmental Protection Agency (EPA) as a criteria air pollutant is mainly produced close to the ground (tropospheric ozone).<sup>1</sup> It forms through complex chemical reactions between pollutants directly emitted from vehicles, factories and other industrial sources, fossil fuel combustion, consumer products, evaporation of paints, and many other sources. These highly nonlinear Leontief-like reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NO<sub>x</sub>) in the presence of sunlight and warm temperatures (26). In “VOC-limited” locations, the VOC/NO<sub>x</sub> ratio in the ambient air is low (NO<sub>x</sub> is plentiful relative to VOC), and NO<sub>x</sub> tends to inhibit ozone accumulation. In “NO<sub>x</sub>-limited” locations, the VOC/NO<sub>x</sub> ratio is high (VOC is plentiful relative to NO<sub>x</sub>), and NO<sub>x</sub> tends to generate ozone. The relationship between ratios of NO<sub>x</sub> and VOCs in ozone formation is illustrated in Fig. S1.

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

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<sup>1</sup> It is not the stratospheric ozone of the ozone layer, which is high up in the atmosphere, and reduces the amount of ultraviolet light entering the earth’s atmosphere.

sunlight. Modeling studies point to temperature as the most important weather variable affecting ozone concentrations.<sup>2</sup>

Ambient ozone concentrations increase during the day when formation rates exceed destruction rates, and decline at night when formation processes are inactive.<sup>3</sup> Ozone concentrations also vary seasonally. They tend to be highest during the late spring, summer and early fall months.<sup>4</sup> The EPA has established “ozone seasons” for the required monitoring of ambient ozone concentrations for different locations within the U.S – which generally consist of April through September. Recently, there is growing concern that climate change may prolong the ozone season (25).

The Clean Air Act (CAA) has greatly improved air quality since it was first enacted in 1970. It included specific regulations on ozone precursor pollutants (3, 28), and from 1979 onward on ambient ozone itself (9, 29). Under the provisions of the CAA, EPA sets air quality standards for ozone, designates attainment status at the county level – whether a county is in attainment with the standards, or in violation, often termed “nonattainment” – and outlines the

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<sup>2</sup> Dawson et al. (27), 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.

<sup>3</sup> 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.

<sup>4</sup> 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.

steps states have to follow when their counties are out of attainment with the standard so that attainment is restored. Currently, the standard is 70 parts per billion (ppb), calculated as the average over three years of the annual fourth-highest daily maximum 8-hour average concentration. In order to determine attainment status, the EPA maintains a network of monitoring stations across counties deemed to be at risk of exceeding the standard. Since 1979 over 1,000 counties have been monitored by the EPA for ozone at some point.

## **Materials and Methods**

### Materials

#### **S2     Data**

For our econometric analysis, we combine data from two sources: ozone monitoring data from EPA's AirData database ([epa.gov/outdoor-air-quality-data](https://epa.gov/outdoor-air-quality-data)) during the typical ozone season (April-September) for 1980-2019, and daily meteorological data from NOAA's Global Historical Climatology Network database ([ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn](https://ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn)) for the same months for 1950-2019. Fig. S2 depicts the nine National Oceanic and Atmospheric Association (NOAA) climate regions overlaid with the location of all ozone monitors in our final sample. As will be made clear, we incorporate past meteorological information to construct key variables in the analysis.

##### ***S2.1   Data on ambient ozone & nonattainment status***

*Ozone data* — Data on ambient ozone concentrations were obtained from the EPA's publicly available Air Quality Systems (AQS) AirData database ([epa.gov/outdoor-air-quality-data](https://epa.gov/outdoor-air-quality-data)). We

use daily readings from the nationwide network of the EPA's air quality monitoring stations for the years 1980-2019. 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 ozone readings. According to the EPA, daily measurements are valid for regulation purposes only if (i) 8-hour averages are available for at least 75 percent of the possible hours of the day, or (ii) daily maximum 8-hour average concentration is higher than the standard. Second, as a minimum data completeness requirement, for each ozone monitor we include only years for which at least 75 percent of the days in the ozone monitoring season (April-September) are valid; years having concentrations above the standard are included even if they have incomplete data.

Our final sample consists of valid ozone measurements for a total of 6,562,554 monitor-days. The number of monitors increased from 1,314 in the 1980's to 1,539 in the 2010's, while the number of monitored counties in our sample grew from 590 in the 1980's to 826 in the 2010's. Table S4 provides some summary statistics regarding the increase in the number of monitors over time, disaggregated by NOAA climate region. The full sample of ozone monitors used in the analysis spans 1,051 counties across all states in the continental U.S. and consists of 2,956 unique monitors. Not all monitors are active simultaneously, as some were phased in to replace older monitors that were being retired while others were added over time as new counties required monitoring.

Since the EPA began regulating ozone, average concentrations in July – typically the worst month of the year for ozone – have fallen by approximately 18.5 ppb, or 26.5%, while average concentrations on the worst days of the year have fallen from approximately 147 ppb to 87 ppb. Fig. S3 depicts the average ozone concentration for the month of July, as well as yearly fourth highest

concentrations, for each climate region from 1980-2019, illustrating the reductions in ambient ozone achieved since the passage of the CAA.

*Nonattainment data* — For data on the Clean Air Act nonattainment designations associated with county violations of the National Ambient Air Quality Standards (NAAQS) for ambient ozone, we use the EPA Green Book of Nonattainment Areas for Criteria Pollutants ([epa.gov/green-book](https://epa.gov/green-book)). We generate an indicator for nonattainment status for each county-year in our sample. In our empirical analysis, we use the nonattainment status lagged by three years because EPA gives counties with heavy-emitters at least three years to comply with NAAQS for ambient ozone (30).<sup>5</sup> Specifically, with regards to nonattainment status, if any monitor within a county exceeds the NAAQS, EPA designates the county to be out of attainment (30). Fig. S4 denotes every county the EPA ever monitored for ozone – noting whether, and when, they were first designated as out of attainment with the ozone standard.

## ***S2.2 Weather data & temperature bins***

*Meteorological data* — Data for daily temperature and precipitation, as well as sunlight, were obtained from the National Oceanic and Atmospheric Administration’s Global Historical Climatology Network database ([ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn](https://ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn)) (31). This dataset provides detailed

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<sup>5</sup> EPA allows nonattainment counties with polluting firms between 3 to 20 years to adjust their production processes. Nonattainment counties are “classified as marginal, moderate, serious, severe or extreme (...) at the time of designation” (30). They must reach attainment in: “Marginal – 3 years, Moderate – 6 years, Serious – 9 years, Severe – 15 or 17 years, Extreme – 20 years” (30).

weather measurements at over 20,000 weather stations across the country, for which we use the ozone season (April-September) for the period 1950-2019.

These weather stations are typically not located adjacent to the ozone monitors. Hence, we develop an algorithm to obtain a weather observation at each ozone monitor in our sample. Using information on the geographical location of pollution monitors and weather stations, we calculate the distance between each pair of pollution monitor and weather station using the Haversine formula. Then, for every pollution monitor we exclude weather stations that lie beyond a 30 km radius of that monitor. Moreover, for every pollution monitor we use weather information from only the closest two weather stations within the 30 km radius. Once we apply this algorithm, we exclude ozone monitors that do not have any weather stations within 30km. We calculate weather at each ozone monitor location as the weighted average of these two weather stations using the inverse of the squared distance between them.

In the robustness checks shown in Table S1 we include total daily sunlight as an additional regressor within our main specification. These data, although less frequently available, are collected at the same weather monitoring stations as our main temperature and precipitation variables. Due to the sparseness of these data, we do not decompose them into a long-run climate component and transitory weather shock as we do with temperature and precipitation. This decomposition is discussed in detail in Section S3.1.

*Temperature Bins* — In general, areas with higher temperatures tend to have higher ozone concentrations, as seen in the two county-level maps in Fig. S6A and B, respectively. Furthermore, this relationship appears to be nonlinear in nature – illustrated in Fig. S7. Thus, for our analysis, we construct five distinct temperature bins to represent the underlying distribution of daily maximum temperature: below 15°C, 15-20°C, 20-25°C, 25-30°C, and above 30°C, as

shown in Fig. S8. Nationally, the historical distribution of temperature bins during the ozone season is approximately centered around 25-30°C, with less than 15% of days falling below 20°C. The analytical advantages of using these 5°C bins are discussed in Section S3.1 along with the empirical approach.

An analogous figure with panels for each climate region is presented in Fig. S9. We see that regions in the Southern U.S., the West, and the Ohio Valley have higher shares of days 25-30°C and above 30°C during the ozone season as compared to the Upper Midwest, Northeast, or Rockies. Additional summary statistics on the heterogeneity among climate regions can be found in Table S4, indicating that higher ozone concentrations are related to areas with a greater number of high temperature days. Some cooler regions however (Upper Midwest, Northeast), also see high levels of ozone, which suggests that their local conditions may be particularly susceptible to an increase in high temperature days in the future.

### ***S2.3 Climate projections***

Data on projected climate temperatures for mid-century come from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) of the Coupled Model Intercomparisons Project Phase 5 (CMIP5) ([nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp](https://nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp)), which were developed in part for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). There are 21 model runs and 2 representative control pathway scenarios: RCP 4.5 and RCP 8.5. For each, the dataset provides predictions of daily maximum temperatures through 2099 at the 0.25° by 0.25° resolution level globally. We map these projection points to i) the continental U.S. and ii) the nine U.S. climate regions for the



period 2030–2059. We then calculate the average maximum temperature for each day from April–September annually across all projection points within the specified region.

These averages for mid-century are compared to a baseline, the projected temperature by bin averaged across the 21 model runs for each scenario for 2015–2018. We calculate the *change* in the forecasted values from this historical period and apply this rate of change to the average from our historical temperature data for 1980–2019 (described in Section S2.2) to project the future number of days in each temperature bin by mid-century (32). Following the convention in the literature, we present a single data point for each temperature bin as the average across the 21 model runs in each scenario.

## Methods

### **S3      Methods**

#### ***S3.1   Econometrics***

*Decomposition of meteorological variables: norms vs. shocks* — Implementing our econometric approach requires that we first decompose daily temperature (as well as precipitation) into its long-run component, the “climate norm,” and its short-run deviation from this value, the “weather shock,” following the methodology developed by Bento et al. (22). Illustrating the decomposition with temperature ( $Temp$ ), we can express it as:

$$Temp = Temp^C + Temp^W, \tag{S1}$$

where  $Temp^C$  represents climate normal temperature, and  $Temp^W (\equiv Temp - Temp^C)$  deviations from the norm.  $Temp^C$  and  $Temp^W$  in the decomposition above are associated with different sets of

information. On the one hand,  $Temp^C$  includes climate patterns that economic agents can only gather by experiencing weather realizations over a long period of time. On the other hand,  $Temp^W$  represents weather shocks, which by definition are revealed to economic agents virtually at the time of the weather realization. Now, usually one adjusts to something they happen to know by experience. Therefore, the estimated effect of  $Temp^C$  on ozone concentration can be understood to include adaptive behavior, conditional on controlling for the effects of  $Temp^W$ .

It is important to emphasize that this decomposition does not make any assumption on how individuals and firms process and use the information from the past. Forward-looking agents will respond optimally to all information at hand when deciding the degree of adaptation. Myopic and inattentive agents, on the other hand, may find it costly to absorb and process all the information at all times, and may respond only to partial information or only sporadically (33–35). Our measure of the effects of changes in the temperature norm – inclusive of adaptation – is agnostic to either type of behavior; the goal of our approach is to empirically assess the magnitude and statistical significance of the effect itself, regardless of how economic agents make decisions on whether to adapt, or the extent of adaptation.

Building upon the decomposition method proposed by Bento et al. (22), we focus on temperature around the location of ozone monitor  $i$  in day  $t$  of month  $m$  and year  $y$ , and construct the 5°C temperature bins discussed previously before decomposing each bin into  $Temp^C$  and  $Temp^W$  by defining  $Temp^C$  as the 30-year monthly moving average (MA) of past temperatures.<sup>6</sup> Specifically, we first allocate each day to its respective temperature bin for each ozone monitoring

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<sup>6</sup> Our decomposition of meteorological variables into a 30-year moving average (norm) and deviations from it (shocks) is a data filtering technique to separate the “signal” from the “noise.” This should not be confused with a moving-average model of climate change.

location for all years 1950-2019. For example, a day with a maximum temperature of 27°C would be coded as 1 for the temperature bin 25°C-30°C, and a 0 for all other temperature bins. We then average each bin by month – in essence, these monthly averages now reflect the “share” of the month in which the daily temperature fell within the respective bin. Next, we create the 30-year monthly MA – “climate norms” – by taking the 30-year average of these monitor-level monthly averages for each bin, lagged by 1-year. For example, the 30-year monthly MA temperature bins associated with May 1982 would be the average of May temperature bins for all years in the period 1952- 1981. Therefore, economic agents should have had at least one year to respond to unexpected changes in climate normal temperature at the time ambient ozone is measured.

We average temperature over 30 years because it is how climatologists usually define climate normals (36), 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. We use monthly MAs because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed, meteorologists on TV and social media often talk about how a month has been the coldest or warmest in the past 10, 20, or 30 years, but not how a particular day of the year has deviated from the trend.<sup>7</sup> Finally, we construct the daily temperature shocks as the deviation of the contemporaneous daily temperature bins from the lagged 30-year monthly MA temperature bins. By definition, these shocks capture daily *weather* fluctuations, not changes in the underlying climate, and thus – although crucial to control for their effects on daily ozone concentration – do not capture the effect of *climate change* on ozone.

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<sup>7</sup> As a robustness check, we use daily instead of monthly moving averages, shown in Table S1. Economic agents, however, may still associate a day with its corresponding month when making adjustment decisions.

*Econometric Model* — Given the decomposition of meteorological variables, our parsimonious econometric specification to estimate the impact of climate norms on ambient ozone is:

$$\begin{aligned}
 Ozone_{it} = & \beta_{15}^C(Temp_{it}^C < 15) + \beta_{20}^C(20 \leq Temp_{it}^C < 25) \\
 & + \beta_{25}^C(25 \leq Temp_{it}^C < 30) + \beta_{30}^C(Temp_{it}^C \geq 30) \\
 & + X_{it}\delta + \phi_{isy} + \epsilon_{it}
 \end{aligned}
 \tag{S2}$$

Where  $i$  represents an ozone monitor,  $t$  denotes day,  $s$  season (Spring or Summer) and  $y$  year. As previously mentioned, our analysis focuses on the most common ozone season in the U.S. – April to September – in the period 1980-2019.<sup>8</sup> The dependent variable *Ozone* captures daily maximum ambient ozone concentration.  $Temp^C$  represents the climate norm component of daily temperature.<sup>9</sup> The only functional form restriction is that the impact of temperature on ozone is constant within 5°C intervals. The choice of five temperature bins represents an effort to allow the data, rather than parametric assumptions, to determine the ozone-temperature relationship, while also obtaining estimates that are precise enough to have empirical content. This degree of flexibility and freedom from parametric assumptions is only feasible because we are using 40 years of data from the entire United States. The matrix of additional control covariates  $X$  contains daily temperature shocks ( $Temp^W$ ) and a similar decomposition of precipitation norms and shocks;<sup>10</sup>

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<sup>8</sup> Specifically, April through June are taken as the Spring months, while July through September are taken as the Summer months.

<sup>9</sup> Note that while  $Temp^C$  in our main specification only varies at the monthly level by its construction, it represents the temperature norm associated with a particular day,  $t$ , hence we denote it  $Temp^C$ .

<sup>10</sup> Although Dawson et al. (27) find it to be less important than temperature, Jacob and Winner (14) point out that

while  $\phi$  reflects *monitor-by-season-by-year* fixed effects, and  $\epsilon$  an idiosyncratic term. In all estimations standard errors are clustered at the county level.

As should be clear by now, we exploit plausibly random, monthly variation in local climate normal temperature within a single season, controlling for daily variation in weather, to estimate the impact of climate change on ambient ozone concentration. That is, analogous to Isen et al. (37), by including fixed effects for monitor-by-season-by-year, it is as if we regressed our main specification monitor by monitor, individually, for each season of the sample, and then took the weighted average of all recovered coefficients. Conceptually, consider the following thought experiment that we observe in our data many thousands of times for monthly climate norms: take two months in the same location, same season, and same year. Now, suppose that one of the months experiences a hotter climate norm than the other. Our estimation strategy quantifies the extent to which this difference in climate norm affected the ozone concentration observed on the days in that month, after additionally controlling for precipitation and daily temperature shocks. Therefore, this approach controls for a number of potential time-invariant and time-varying confounding factors that one may be concerned with, such as the composition of the local atmosphere, regulatory burden, and technological progress.

### ***S3.2 Projections***

*Ozone Concentrations* — In Fig. 1, we saw that higher temperatures are associated with higher daily maximum ozone levels. Based on the results in Table S2 and the climate projections by

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higher water vapor in the future climate may decrease ambient ozone concentration. Our estimates are in line with those authors' assessment and are available upon request.

region shown in Fig. 2, we estimate the increase in average ozone concentrations and the number of counties that are projected to fall out of attainment. Table S5 presents the resulting ozone concentrations where we adjust the baseline daily maximum ozone for each county (average for 2016–2019) by a multiplication of the coefficients in Table S2 with the projected change in the share of days per month in the 25–30°C and above 30°C bins.

We use as a baseline the average number of days by temperature bin in the month of July from 2016 – 2019, normalized relative to the number of days 15–20°C. For each county in our sample reporting data throughout our baseline period from 2016–2019, we calculate the projected difference in the average number of days in each temperature bin during the month of July by mid-century. We then convert these differences into the share of days per month in each bin and multiply by the coefficients for the respective temperature bins at i) the national level based on the coefficients plotted in Fig. 1 and shown in Column (1) of Table S1 and ii) the climate region level based on Table S2. Finally, we calculate the projected change in ozone concentrations by averaging across these county-level estimated changes nationally in the first row or by climate region in the remainder of the table.

Column (1) of Table S5 presents the average daily maximum ozone for the month of July from 1980–1983 from our historical data. Column (2) displays the difference in ozone concentrations between July 2016–2019 and the baseline in column (1).<sup>11</sup> Following the methodology described above, the projected difference in ozone concentrations by mid-century for the RCP8.5 scenario at both the national and regional levels are given in column (3).

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<sup>11</sup> For this and the remaining columns in the Table, we include only those counties in our sample that reported data for each year from 2016–2019.

*Projecting Nonattainment Status* — Since nonattainment status is based on the highest readings, our baseline for projecting nonattainment status are the days with the 30-highest ozone readings in our sample for 2016–2019. Fig. 3 in the paper presents the change in the share of counties projected to be out of attainment relative to 2016–2019 based on increases in the share of days per month with daily maximum temperatures of 25–30°C and greater than 30°C by climate region.

As an example, suppose after demeaning by the days in the 15–20°C bin, county A in the Southwest had 20 days above 30°C in the historical period and is projected to have 50 days above 30°C under RCP 8.5 at mid-century (2030–2059, also demeaned). This would be a roughly one month increase in the projected days in the above 30°C bin relative to our omitted category of 15–20°C. Looking at Column (8) in Table S2, we see that this would correspond to an approximately  $13.5 \text{ ppb} \times 1 \text{ month}$  increase in the average daily maximum ozone level. We then add this to the baseline daily maximum ozone level in county A. If the county’s baseline daily maximum ozone level was 63 ppb, then adding one month’s worth of days with an expected average daily maximum of 76.5 ppb would put this county out of attainment. We would count this as a 1 county increase if county A had previously been in attainment or 0 if the county was already out of attainment as of 2019. Tallying up these 1’s and 0’s across each climate region gives us the projected increase in the counties out of attainment; we convert these totals to the increase in the share of counties out of attainment and present the results in Fig. 3.<sup>12</sup>

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<sup>12</sup> Some counties project to have more than 1 month worth of days greater than 30°C; we cap the multiplier for the share of days per month at 1 in our projection of counties’ new daily maximum ozone levels.

Finally, to approximate the current and projected number of individuals living in areas with unhealthy levels of ozone – those counties in violation of the CAA ozone NAAQS – we combine the two sets of data above, 2016-2019 baseline and mid-century projections, with current county population estimates using data from the 5-year American Community Survey (ACS) for 2018. 346 counties were monitored consistently throughout the 2016-2019 baseline period, of which 100 were in violation of the ozone standards for at least one year. These 100 counties currently account for 66.8 million U.S. residents according to the ACS. The mid-century projections described above increase this count to 289 counties – an increase of 189, and *by current population counts* account for just under 100 million residents – an increase of just over 33 million. These population estimates represent 20.48% (currently) and 30.61% (mid-century) of the entire U.S. population, respectively.

## **S4 Econometric results & robustness checks**

### ***S4.1 National***

*Main results* – As discussed above, our main specification following Equation (S2) recovers the estimated coefficients presented in column (1) of Table S1. As would be expected, when temperatures are below the reference bin (15-20°C), we estimate a 3 ppb average decrease in the daily maximum ozone concentration. Increasing the daily temperature to the 20-25°C bin flips this result, increasing the daily maximum ozone concentration by an average of 1.5 ppb. While both results are statistically significant at the 1% level, neither is particularly large in magnitude. The estimates for the 25-30°C and above 30°C bins, by contrast, are similarly significant at the 1% level, while also being of a meaningful magnitude. On days with temperatures in the 25-30°C bin, daily maximum ozone concentrations are increased by over 9 ppb on average, while



above 30°C this further increases to over 15 ppb. To put this in perspective, the current ozone NAAQS threshold is 70 ppb, and the average ozone concentration on a day in the 15-20°C reference bin is 49 ppb, while a day in the 75th percentile of this bin observes an ozone concentration of 57 ppb. This would imply that increasing the temperature to above 30°C may easily put a county above the 70 ppb threshold set by the NAAQS.

*Robustness checks* — There may be concern, however, that because sunlight also plays a role in ozone formation and is also correlated with temperature, the omission of a variable capturing sunlight may lead to bias in our estimates. In column (2) we present estimates from a specification that includes a contemporaneous measure of total daily sunlight. Although this reduces the number of total observations available due to data sparseness, the magnitudes of the recovered coefficients are qualitatively the same as our main specification across all temperature bins and are statistically indistinguishable at the 5% level except for the 25-30°C bin, in which the model including sunlight implies a stronger temperature/ozone relationship.

Alternatively, one may be concerned that our results could be driven by outlier regions, such as Los Angeles, which have traditionally faced both large numbers of high temperature days as well as some of the highest historical ozone concentrations. Column (3) re-estimates our main specification on a sub-sample that excludes all observations with ozone concentrations below the 5th percentile or above the 95th percentile of the sample distribution. As might be expected of an analysis that artificially excludes the observations at both tails of the outcome variable distribution, the estimates recovered by this analysis are statistically smaller than our full sample estimates – however they are qualitatively similar, at approximately two-thirds the magnitude.

Lastly, it may be a concern that our climate norm variable structures the long-run climate normal temperature as the 30-year *monthly* moving average, despite the fact that seasonal – or within-season – shifts in temperature are unlikely to exactly follow the calendar at a monthly level. We examine the sensitivity of our results to this decision by alternatively constructing this variable as a 30-year *daily* moving average, allowing it to vary arbitrarily within each season. In column (4) we present results of our main specification after re-constructing our norm and shock variables for temperature and precipitation using 30-year moving averages at the *daily*, rather than *monthly*, level. While this change appears to attenuate the results when temperatures are below 25°C, and amplify them above 25°C, they remain qualitatively similar. Furthermore, we note that economic agents likely recall their historical experiences with temperature at the monthly level (e.g., the average May temperature over the last 30 years), rather than at the daily level (e.g., the average May 15th temperature over the last 30 years).

*Accounting for nonlinearities and adaptation* – Table S3 illustrates two of the main advantages of our approach: accounting for the nonlinear relationship between temperature and ozone, and for agents’ adaptive behavioral responses to climatic changes. Column (3) presents results of our main specification, decomposing temperature and precipitation into their respective norms and shocks, and including monitor-by-season-by-year fixed effects.<sup>13</sup> By comparison, column (1) adopts the standard fixed-effects approach from the literature (19,20) using contemporaneous daily measures of temperature and precipitation along with monitor-by-

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<sup>13</sup> The keen reader may notice that the recovered estimates and number of observations in column (3) of Table S3 are slightly different from those presented in column (1) of Table S1. The results presented in Table S1 are recovered from our full sample, while those presented in S3 were slightly restricted in order to guarantee that columns (1), (2) and (3) were all estimated on the exact same sample for direct comparison.

month-by-year fixed effects to estimate the average *linear* effect of contemporaneous temperature – not temperature *norms* – on the daily maximum ozone concentration. This estimate, however, assumes that there’s a strict linear relationship between temperature increases and increases in the daily ozone concentration – which does not appear to be the case. The results presented in column (2) extend the standard specification from column (1) to account for nonlinearities in the temperature/ozone relationship using the same temperature bins as our preferred specification, while still using contemporaneous measures of daily temperature and precipitation. Notably, the recovered estimates are now qualitatively in line with our preferred specification, but are, on average, approximately 40% larger in magnitude and statistically different at greater than the 1% level. This difference in magnitude is driven by the fact that the coefficients in column (2) are *exclusive* of most forms of adaptation due to the use of contemporaneous temperature values in estimating the model, while estimates in column (3) are *inclusive* of most forms of adaptation due to the use of temperature norms when estimating the model (22).

#### ***S4.2 Climate regions***

There is substantial heterogeneity among the climate regions in the projected effects of temperatures on ozone, shown in Fig. 2. We see the steepest effects, or a more upright chair, for those regions with higher levels of baseline ozone (Northeast, Ohio Valley, West). These regions will all see significant increases in ozone concentrations by mid-century, due primarily to a steeper gradient on ozone for high temperature days (Northeast) or a large increase in the number of days during the ozone season above 30°C by mid-century (Ohio Valley, Midwest). In contrast, regions with lower average ozone concentrations (Northwest, Rockies) or those that have

consistently faced hot temperatures (South, Southwest) have a less steep relationship, or a significantly reclined beach chair. Thus, unlike the Northeast, the South may experience little change in future ozone concentrations despite an increase in days above 30°C, likely because they have frequently faced high temperatures in the past and may have adapted.

Due to the regional heterogeneity in both the temperature/ozone relationship and in the effects of climate change on the regional temperature distribution, the projected change in ozone concentrations will vary considerably by region: while some regions will see minimal impacts (South, Northwest), others will experience massive increases of over 6 ppb (Ohio Valley) or 8.5 ppb (West) by mid-century (RCP8.5).

Many of the climate regions follow the same “V”-shaped pattern as the national trend with respect to counties becoming out of attainment with the ozone NAAQS (Fig. 3B). In a few of these regions 100% of the monitored counties are projected to go out of attainment. By contrast, some climate regions – such as the South, and the three Western climate regions, (Fig. 3C) – deviate from the national trend. These alternative patterns are likely driven by differences in underlying temperature distributions and projected changes by mid-century, combined with the different temperature/ozone relationships of each region (Fig. 2). Projected changes in attainment status under the RCP4.5 climate scenario are qualitatively similar (Fig. S10).

## **S5 Back-of-the-Envelope Calculations using EPA’s 2015 Ozone NAAQS RIA**

Our back-of-the-envelope calculations of the compliance cost and benefits for the additional counties projected out of attainment by mid-century are presented in Tables S6 and S7 and are based on EPA’s 2015 Ozone NAAQS RIA (38). All costs and benefits are presented in 2011

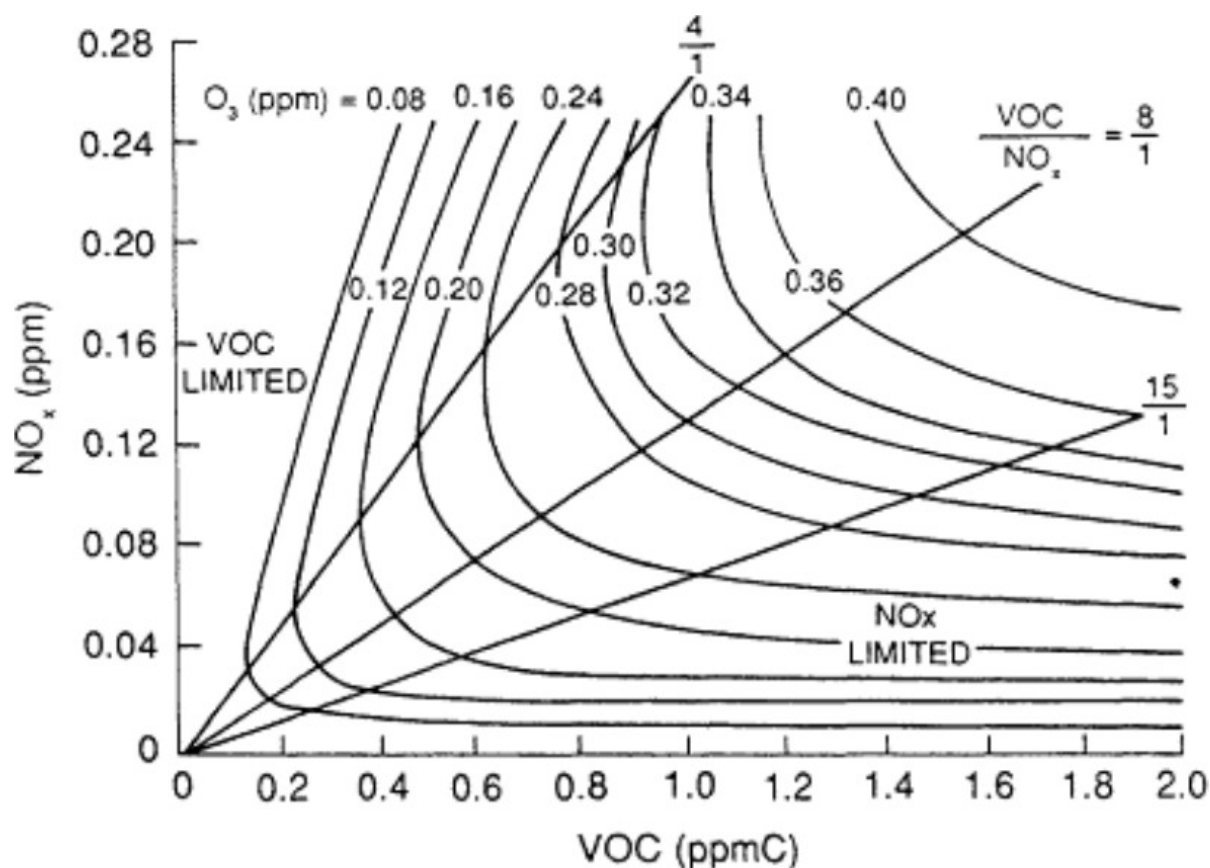
\$billions. EPA’s 2015 RIA presents estimates separately for California and the rest of the U.S., leading us to calculate the implicit costs and benefits separately for each and aggregate the two together for our totals.

Table S6 presents the breakdown for the calculation of the compliance costs. Row [1] presents the additional, incremental compliance cost at 65 ppb relative to the costs at 70 ppb – see Tables ES-5 and ES-9 from the 2015 RIA (38). This is based on the combination of our econometric estimates with climate projections that imply that ozone concentrations in July – typically the worst month of the year for ozone – would increase by 4 ppb by mid-century. In essence, for counties to remain in attainment with the current 70 ppb standards, it would be as if they had to meet a standard of at least 66 ppb. Row [2] shows the total number of counties projected in the 2015 RIA to exceed 65 ppb in 2025, calculated as the sum of the total counties projected to exceed 70 ppb and those projected to exceed 65 ppb – see Figures ES-2 and ES-3 in the 2015 RIA (38) – and row [3] calculates the implicit cost per county by dividing [1] by [2].

In row [4] of Table S6, we introduce our projection of the additional counties that would be out of attainment with a 70 ppb standard by mid-century under the RCP8.5 climate scenario. Finally, we multiply the implied cost per county in row [3] from EPA’s 2015 RIA with our nonattainment projections, suggesting up to a \$43.6 billion dollar increase in annual compliance costs.

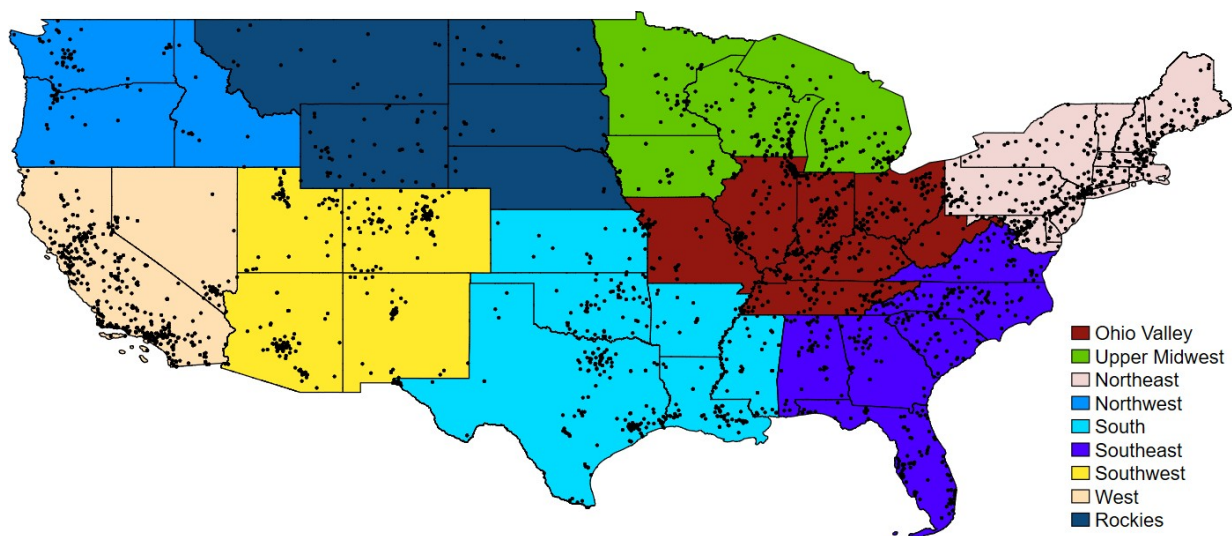
The benefit calculations in Table S7 follow a similar progression. One difference is that EPA’s 2015 RIA presents a range of possible health benefits based on various underlying studies estimating the relationship between ozone concentrations and health impacts. In Table S7, we thus present the back-of-the-envelope calculation for both the minimum and maximum benefits provided for a standard of 70 ppb – see Tables ES-2 and ES-9 of the 2015 RIA (38).

These implied annual health benefits range from \$38.9 – \$79.3 billion by mid-century, or an average benefit of \$59.1 billion. However, the majority of this benefit is derived from the co-benefits from reductions in particulate matter, as the EPA notes that “for a standard of 70 ppb the total health benefits are comprised of between 29 and 34 percent ozone benefits and between 66 and 71 percent PM<sub>2.5</sub> co-benefits” (38, *p.ES-14*). Thus, in the final row we remove the minimum 2/3 of the benefits from PM<sub>2.5</sub> co-benefits, resulting in an average ozone-only benefit of just under \$20 billion.



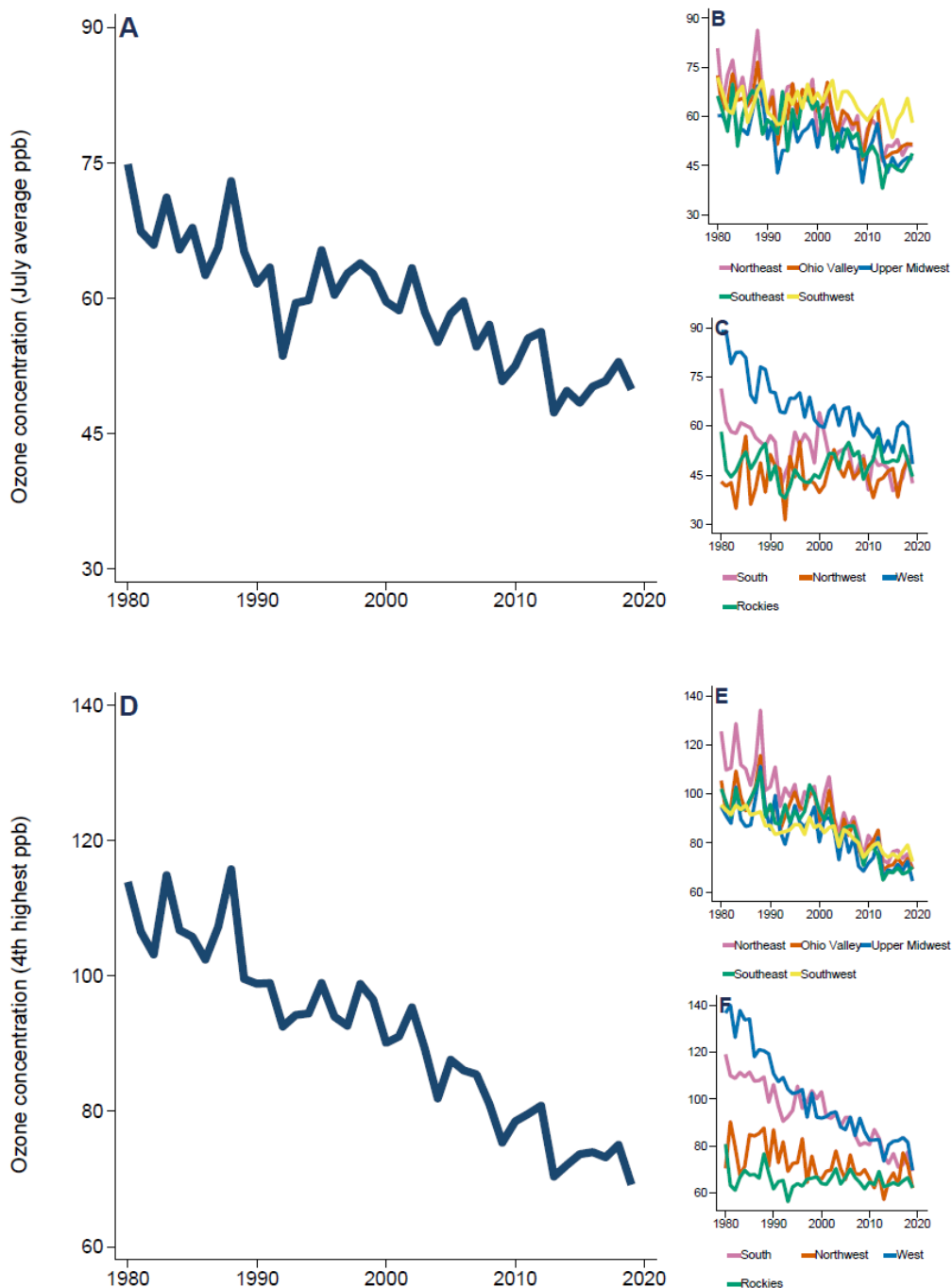
**Fig. S1. Production of ozone is a function of VOCs and NO<sub>x</sub> in the presence of sunlight and temperature.** Ozone forms most easily when the ratio of volatile organic compounds (VOCs) to nitrous oxides (NO<sub>x</sub>) is between 4/1 and 15/1. Below the 4/1 ratio, local air chemical composition is “VOC-limited” and additional NO<sub>x</sub> can actually inhibit ozone formation. Above the 15/1 ratio, local air chemical composition is “NO<sub>x</sub>-limited” and additional NO<sub>x</sub> can greatly increase ozone formation.

Source: *Rethinking the Ozone Problem in Urban and Regional Air Pollution*, National Academies Press, 1991.

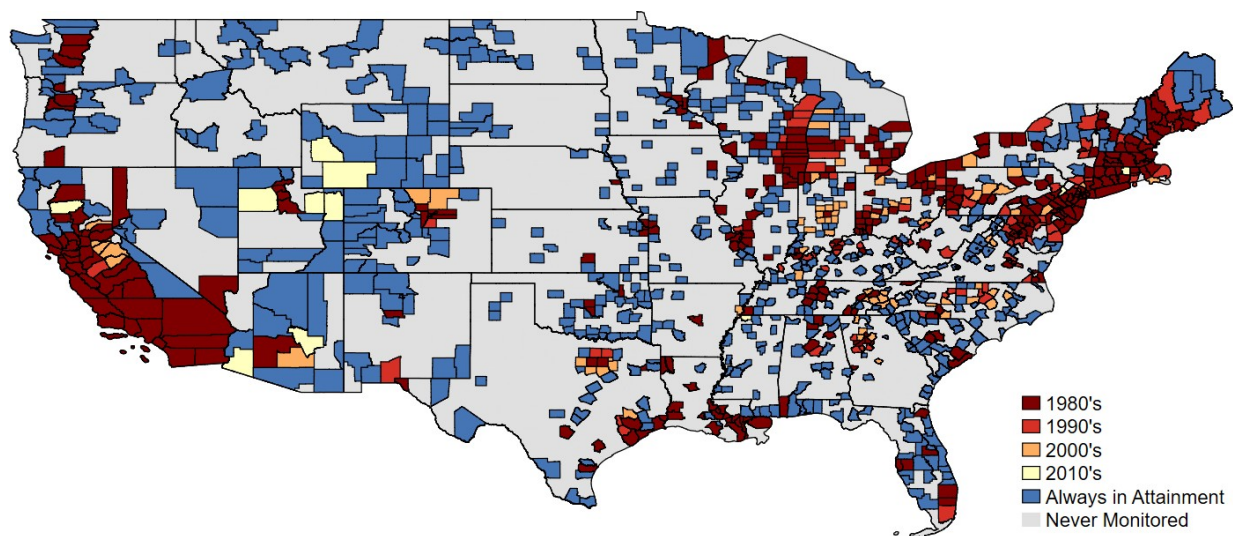


**Fig. S2. NOAA climate regions and EPA ozone monitor locations.** The National Oceanic and Atmospheric Administration (NOAA) identifies nine climatically consistent regions across the contiguous 48 states: the Northeast, Upper Midwest, Ohio Valley, Southeast, South, Southwest, Rockies, Northwest, and the West. The Environmental Protection Agency (EPA), under the provisions of the Clean Air Act (CAA), maintains a network of ozone monitoring stations across these states, often focused on urban areas and areas with potentially high ozone concentrations.

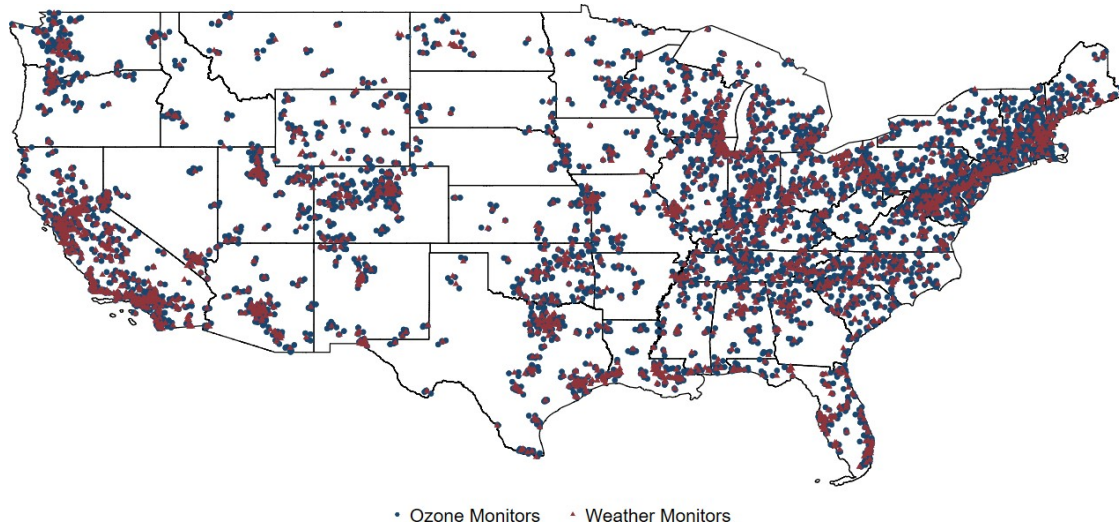




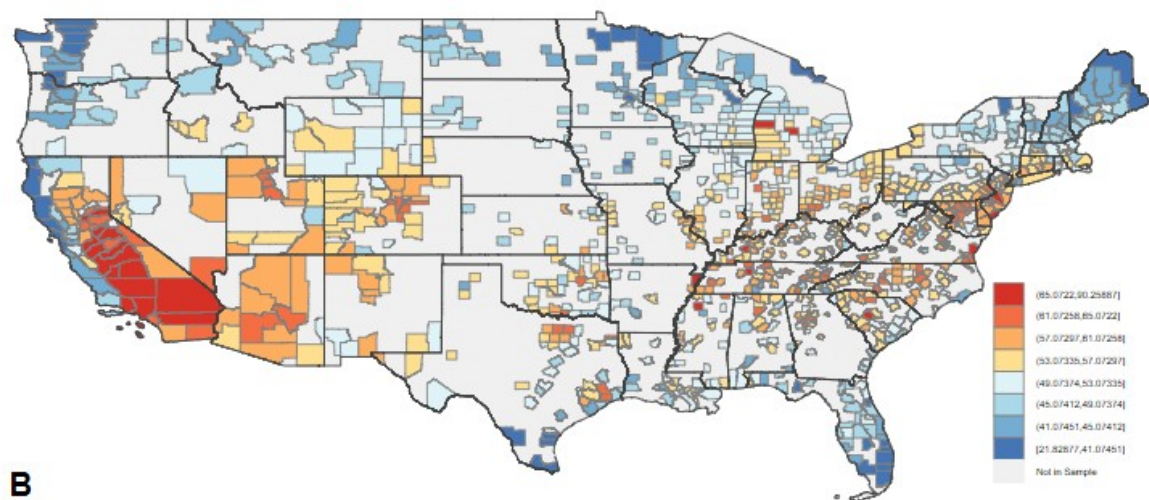
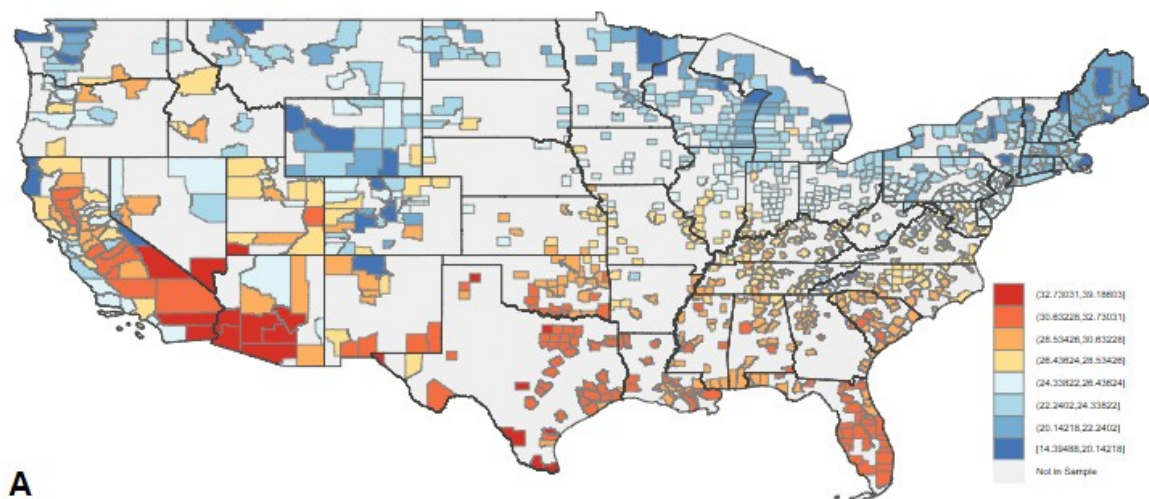
**Fig. S3. Nationally, the average fourth highest and July ozone concentrations have declined since the 1980's.** Nationally, both the average July (A) and 4th highest (D) annual ozone concentrations have declined since enforcement began under the CAA in 1980. (B) and (E) illustrate these trends for the same five regions as in Fig. 3B, while (C) and (F) do so for the four regions depicted in Fig. 3C.



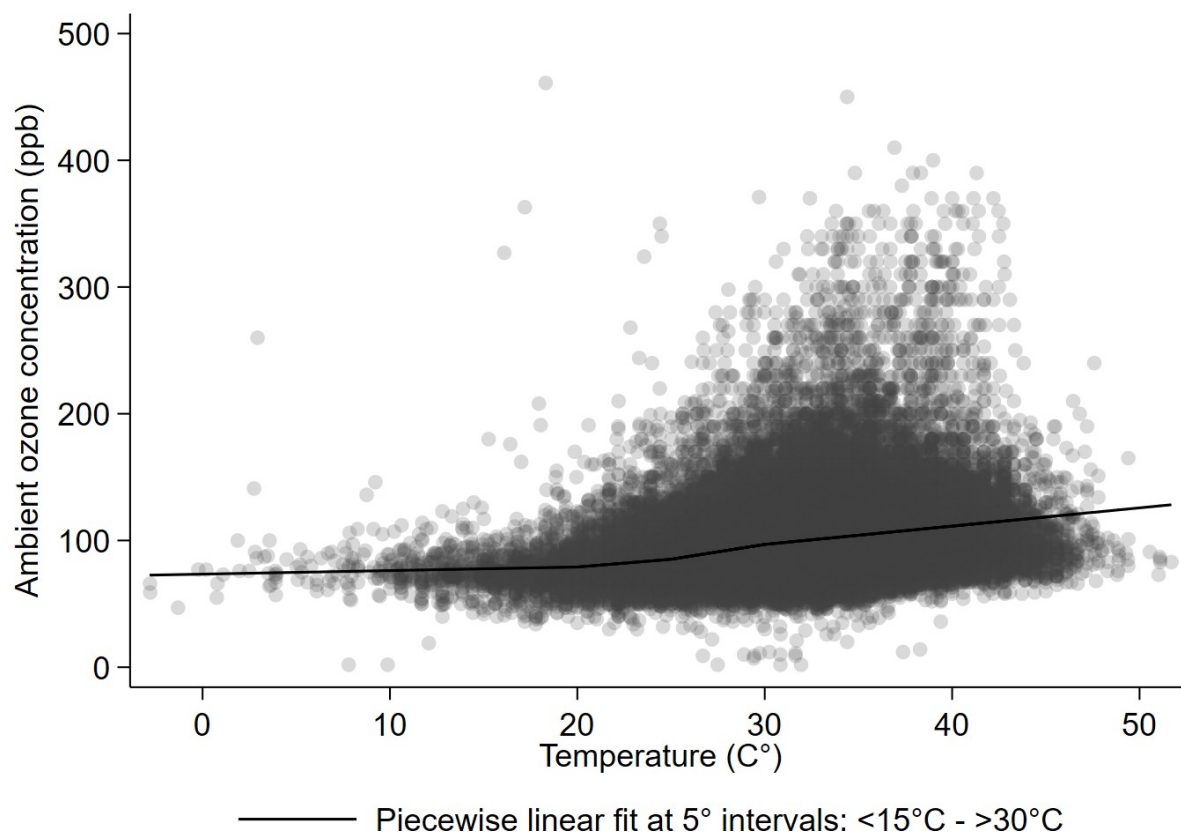
**Fig. S4. County monitoring and nonattainment designations over time.** In the 1980's it was predominantly California and the urban areas in the Upper Midwest and Northwest that were originally designated as out of attainment. In the 1990's, 2000's, and 2010's however additional counties were designated as out of attainment at least once – often those proximally close to the original set of nonattainment counties. Counties in dark red received their first nonattainment designation in the 1980's, light red in the 1990's, orange in the 2000's, yellow in the 2010's, and blue counties were monitored but never designated out of attainment.



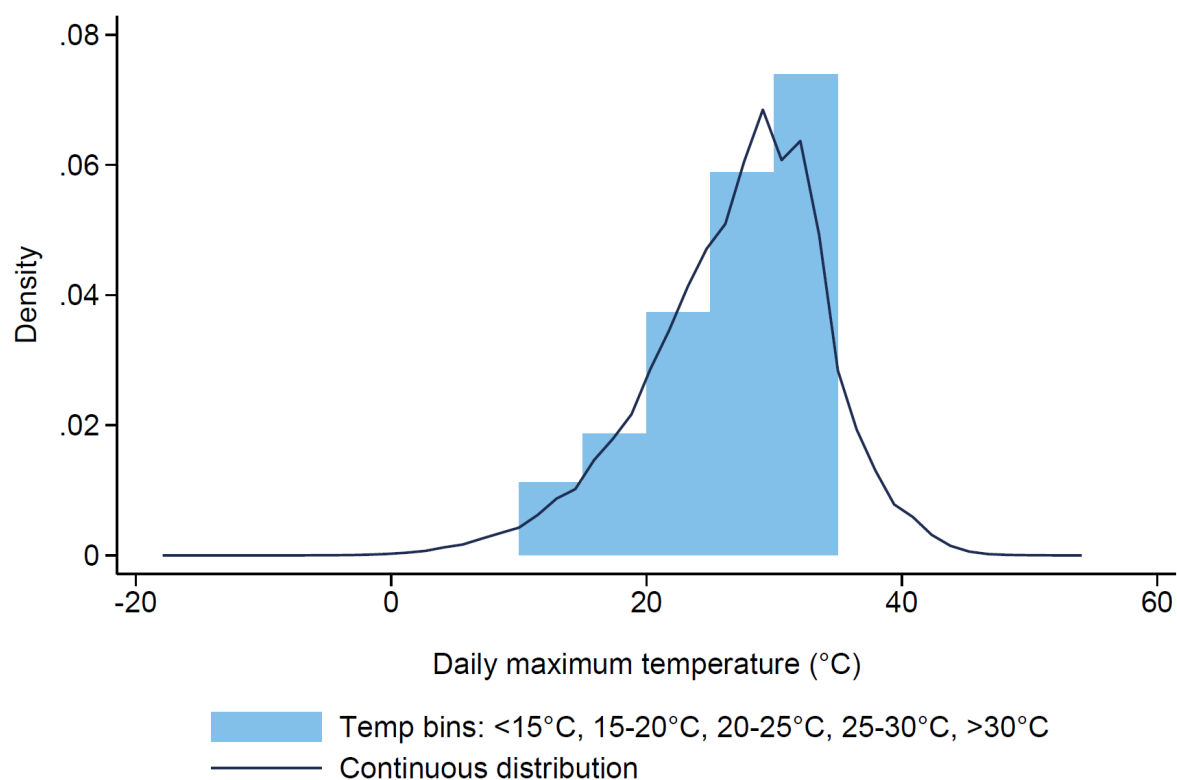
**Fig. S5. Matched EPA ozone monitor and NOAA weather station locations.** Using information on the geographical location of pollution monitors and weather stations we calculate the Haversine distance between each pair of ozone monitor and weather station. Then every ozone monitor is matched to the closest two weather stations within a 30 km radius of the monitor. We exclude ozone monitors that do not have any weather station within a 30 km radius. Once the monitors are matched to weather stations, we generate the approximate weather realizations at the ozone monitor by averaging the meteorological variables at the matched weather stations, weighted by their inverse squared distance from the monitor.



**Fig. S6. Geographic association of high temperatures and high ozone concentrations. (A)** Southern and western counties experience higher average temperatures. **(B)** Southwestern and eastern counties experience higher average ozone concentrations. In general, hotter counties observe higher ozone concentrations, although this is not always the case, as seen with southern Texas and Florida. Additionally, relatively cool regions may still observe high ozone concentrations, though these are often constrained to geographically small urban centers in the east.



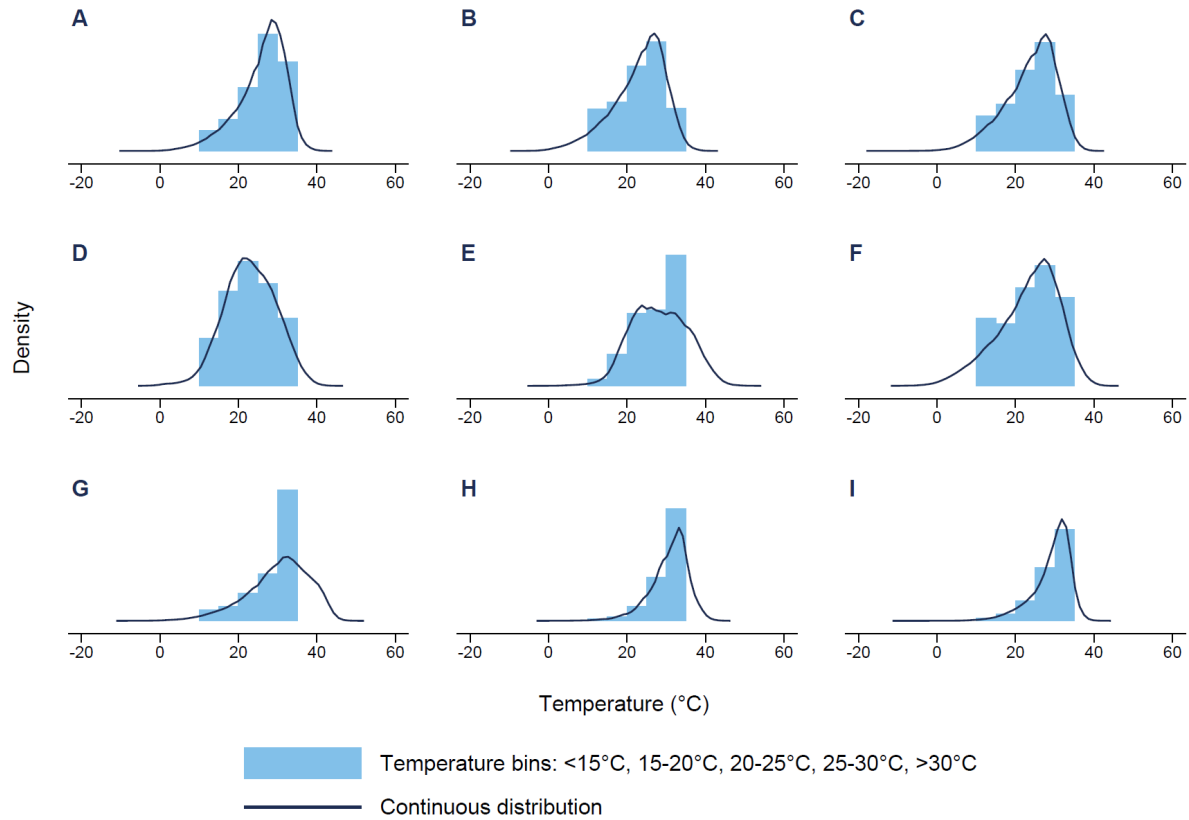
**Fig. S7. Temperature appears to have a nonlinear effect on ozone.** Comparing daily maximum temperatures with daily maximum ozone concentrations for the highest ozone concentration days at each monitor in each season of our sample illustrates a positive relationship between the two. Expressing this underlying data as a piecewise linear spline of 5°C temperature bins reveal a monotonic increasing nonlinear association.



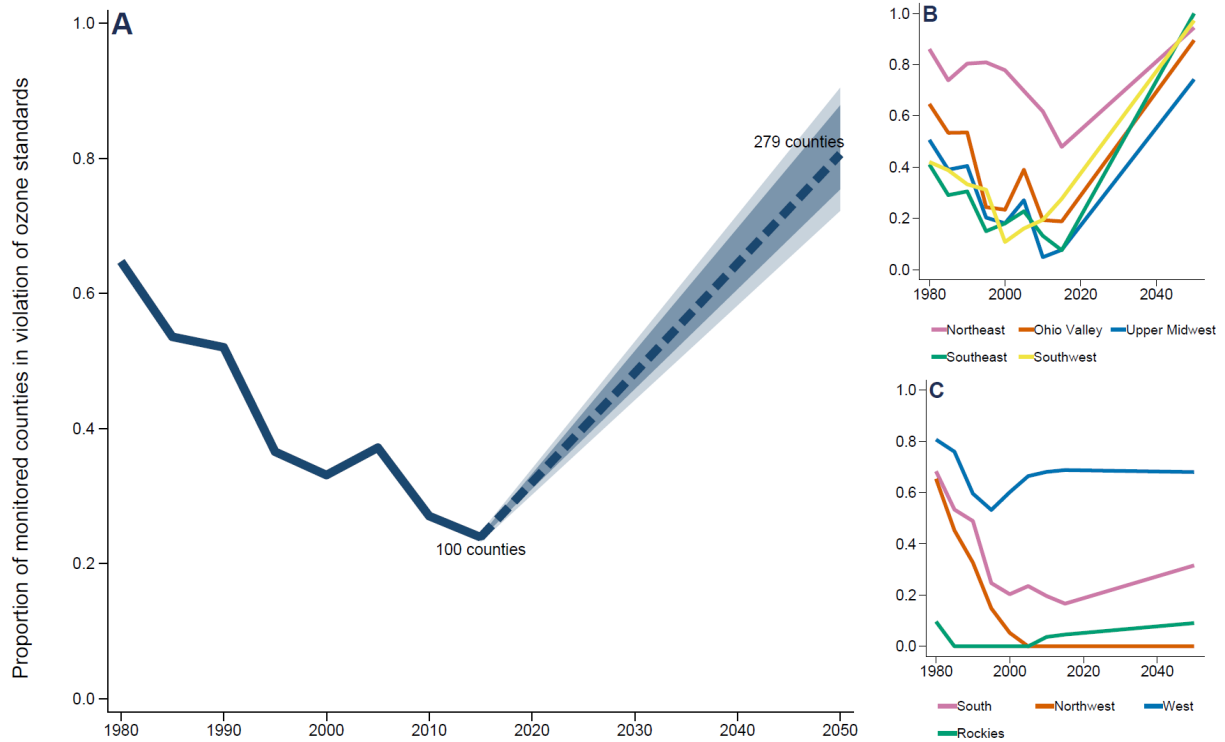
**Fig. S8. National temperature distribution from 1980-2019 by 5°C temperature bin.**

Nationally, the historical distribution of temperature bins during the ozone season is approximately centered around 25-30°C, with less than 15% of days falling below 20°C and 10% of days above 35°C. The selected 5°C temperature bins range from below 15°C, 15-20°C, 20-25°C, 25-30°C, to above 30°C and approximately match the underlying continuous distribution.





**Fig. S9. Regional temperature distribution from 1980-2019 by 5°C temperature bin.** The historical distribution of temperature bins during the ozone season varies by climate region, with some still centered around 25-30°C, as is the case nationally, while others are centered around 20-25°C or above 30°C. (A) Ohio Valley, (B) Upper Midwest, and (C) Northeast make up the three northern climate regions. (D) Northwest, (E) West, and (F) Rockies make up the three western climate regions. (G) Southwest, (H) South, and (I) Southeast make up the three southern climate regions. There is distinct heterogeneity in the climate distributions across the nine climate regions, however in most instances the selected 5°C temperature bins still approximate the continuous distribution.



**Fig. S10. Climate change will increase county violations of the ozone standards even under less severe warming scenarios (RCP4.5).** Although temperature increases – and resulting increases in ozone concentrations – are projected to be somewhat less severe by mid-century under the RCP 4.5 warming scenario compared to the RCP 8.5 scenario, both scenarios are projected to have similar impacts on county violations of the CAA ozone standards. Nationally (A), approximately 80% of currently monitored counties will be in violation of the ozone NAAQS by mid-century. (B) illustrates the historical and projected trends in county violations for the five climate regions that follow a similar “V”-shaped national trend. (C) does so for the four climate regions with flatter projections.



	Full Sample	Restricted Sample with Sunlight	Restricted Sample Trimmed Ozone	Full Sample Daily MA
	(1)	(2)	(3)	(4)
Below 15°Celsius	−2.906*** (0.512)	−2.113** (0.947)	−1.943*** (0.365)	−0.364 (0.729)
15-20°Celsius (baseline)	0	0	0	0
20-25°Celsius	1.521*** (0.330)	3.017*** (0.693)	1.569*** (0.234)	0.463 (0.727)
25-30°Celsius	9.896*** (0.369)	12.126*** (0.707)	6.660*** (0.238)	15.410*** (0.804)
Above 30°Celsius	15.519*** (0.825)	17.085*** (1.379)	10.535*** (0.399)	18.682*** (1.089)
<i>Controls:</i>				
Precipitation	Yes	Yes	Yes	Yes
Daily Sunlight		Yes		
<i>Fixed Effects:</i>				
Monitor-Season-Year	Yes	Yes	Yes	Yes
Observations	6,562,554	603,104	5,886,628	6,558,703
$R^2$	0.384	0.365	0.269	0.463

**Table S1. Non-linear effects of temperature on daily maximum ambient ozone (ppb).** This

table reports results of our main specification in column (1) with three alternative specifications in columns (2), (3) and (4) as robustness checks. Estimates in column (1) are recovered by

estimating Eq. (S2) on our full, national sample of monitors for the years 1980-2019

implementing the climate norm as the 30-year monthly moving-average (MA) of temperature.

Column (2) additionally controls for total minutes of daily sunlight. Column (3) excludes

potential outliers by excluding observations with daily ozone concentrations in the top and

bottom 5% of the distribution. Column (4) replaces the monthly MA with a daily one for the

purposes of decomposing the climate norm from the contemporaneous weather shock. Recall that

in all specifications the 30-year MA is lagged by 1 year, standard errors are clustered at the

county level, and \*\*\*, \*\*, and \* represent significance at 1%, 5% and 10%, respectively.

	Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Below 15°C	−11.517*** (0.749)	−5.228*** (0.447)	−0.285 (0.550)	1.316 (1.732)	2.667 (28.949)	3.758 (3.108)	−3.287*** (0.983)	−11.100*** (3.843)	−0.492 (0.974)
15-20°C (baseline)	0	0	0	0	0	0	0	0	0
20-25°C	−0.075 (0.583)	1.287** (0.510)	2.051*** (0.325)	−3.338*** (0.972)	2.464 (2.382)	6.817*** (1.504)	1.586* (0.911)	−2.845 (2.209)	−0.267 (1.051)
25-30°C	7.926*** (0.425)	10.796*** (0.584)	13.243*** (0.406)	3.789** (1.761)	5.375*** (2.059)	9.196*** (1.538)	7.009*** (1.085)	3.309** (1.638)	3.727*** (0.572)
Above 30°C	18.062*** (0.753)	19.753*** (1.598)	37.367*** (0.762)	11.001*** (1.948)	4.548* (2.483)	16.353*** (1.990)	13.738*** (1.520)	15.902*** (2.141)	12.775*** (1.110)
<i>Controls:</i>									
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed Effects:</i>									
Monitor-Season-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,562,554								
$R^2$	0.392								

**Table S2. Regional non-linear effects of temperature on daily maximum ambient ozone (ppb).** This table reports the estimation of our main specification, as in column (1) of Table S1, when disaggregated by climate region. Columns (1) – (9) present the estimates from a single estimating equation, where we interact the terms from our main specification with indicators for each of the nine NOAA climate regions. Recall that the 30-year MA is lagged by 1 year, standard errors are clustered at the county level, and \*\*\*, \*\*, and \* represent significance at 1%, 5% and 10%, respectively.

	Average Effect Model Without Adaptation	Nonlinear Model Without Adaptation	Nonlinear Model With Adaptation
	(1)	(2)	(3)
Max Temperature (°Celsius)	1.531*** (0.054)		
Below 15°Celsius		−3.949*** (0.095)	−2.911*** (0.513)
15-20°Celsius (baseline)		0	0
20-25°Celsius		5.356*** (0.152)	1.519*** (0.331)
25-30°Celsius		13.386*** (0.389)	9.899*** (0.370)
Above 30°Celsius		22.383*** (0.779)	15.518*** (0.824)
<i>Controls:</i>			
Precipitation	Yes	Yes	Yes
<i>Fixed Effects:</i>			
Monitor-Month-Year	Yes	Yes	
Monitor-Season-Year			Yes
Observations	6,543,713	6,543,713	6,543,713
$R^2$	0.541	0.527	0.385

**Table S3. Accounting for adaptation and nonlinear effects of temperature on daily maximum ambient ozone (ppb).** This table reports results of our main specification in column (3) compared with two alternative specifications in columns (1) and (2) that are based on the standard fixed-effects approach in the literature and thus overlook most opportunities for adaptive responses to changes in temperature. Column (1) presents a typical linear model that captures the average effect of a 1°C increase in the daily maximum temperature on the daily maximum ozone concentration. Column (2) extends this approach to include the estimation of nonlinear effects, yet still overlooks adaptation due to the structure of the data and the fixed-effects model. Column (3), our preferred specification, includes both nonlinear effects and incorporates adaptation by using the decomposed long-run climate normal temperature, rather than contemporaneous temperature, in estimating the effect on daily maximum ozone concentration. Recall that the 30-year MA is lagged by 1 year. Standard errors are clustered at the county level and \*\*\*, \*\*, and \* represent significance at 1%, 5% and 10%, respectively.

<b>Panel A: 1980 -- 1989</b>						
Region	# Observations	# Counties	# Ozone Monitors	Avg. Daily Max. Temp	Avg. 4th Highest Daily Max. Ozone	Avg. Daily Max. Ozone (July)
	(1)	(2)	(3)	(4)	(5)	(6)
Ohio Valley	22,408	88	139	26.2	108.8	67.1
Upper Midwest	9,439	44	60	23.4	104.3	60.0
Northeast	20,461	95	131	24.0	126.5	71.3
South	10,215	39	66	30.5	110.2	57.1
Southeast	12,790	59	81	28.9	105.0	63.3
Southwest	6,478	21	41	27.9	95.9	65.6
Northwest	2,209	9	15	22.8	86.3	43.3
West	23,060	42	138	27.7	103.2	65.6
Rockies	1,425	7	9	24.6	72.0	50.3
<i>National</i>	<i>108,484</i>	<i>403</i>	<i>680</i>	<i>26.4</i>	<i>109.1</i>	<i>64.7</i>
<b>Panel B: 2010 -- 2019</b>						
Region	# Observations	# Counties	# Ozone Monitors	Avg. Daily Max. Temp	Avg. 4th Highest Daily Max. Ozone	Avg. Daily Max. Ozone (July)
	(1)	(2)	(3)	(4)	(5)	(6)
Ohio Valley	35,509	144	205	26.2	78.0	52.3
Upper Midwest	15,631	67	91	22.7	76.0	48.2
Northeast	30,202	127	175	24.0	81.9	52.3
South	23,204	82	133	30.8	79.4	46.0
Southeast	29,621	129	172	29.2	74.8	46.3
Southwest	20,071	50	119	27.4	77.9	59.7
Northwest	3,449	16	23	23.2	72.4	44.0
West	29,094	50	171	28.1	80.3	54.0
Rockies	6,889	32	41	23.0	67.8	49.8
<i>National</i>	<i>193,668</i>	<i>694</i>	<i>1,128</i>	<i>26.6</i>	<i>77.6</i>	<i>50.4</i>

**Table S4. Summary Statistics by Climate Region (1980–1989; 2010–2019).** This Table presents counts of observation, counties, and monitors, as well as the average number of days with daily maximum temperatures in each 5°C bin and average 4th highest daily maximum ozone concentrations for each climate region in our main sample and average daily maximum ozone concentrations for the month of July from (A) 1980–1989 and (B) 2010–2019. Our main sample follows the EPA guidelines, which state that 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. Additionally, for each ozone monitor we include only years for which at least 75 percent of the days in the ozone monitoring season (April–September) are valid.

	Baseline (ppb)	Ambient Ozone (ppb)	
	(1) <i>1980</i>	(2) <i>Δ2019</i>	(3) <i>Δ2030-59</i>
Panel A. National Average			
Lower 48 States	69.7	-18.5	4.0
Panel B. By Climate Region			
Northeast	73.5	-22.8	5.0
Ohio Valley	67.9	-17.1	6.3
Upper Midwest	60.5	-14.3	2.7
South	61.4	-16.1	0.1
Southwest	65.0	-3.6	2.1
Southeast	63.2	-18.4	3.1
West	84.8	-25.6	7.3
Northwest	40.4	4.5	-1.9
Rockies	49.0	1.3	4.1

**Table S5. Projected Impacts of Climate Change on Ambient Ozone.** This Table presents our estimates of historical and projected ozone concentrations and their impacts on mortality costs. Ambient ozone is measured for the highest concentration in the month of July. Historical average daily maximum ozone based on average from (1) 1980–1983 and (2) difference between (1) and 2016–2019. For additional detail, see SI Section S3.2.

	All U.S. (except CA)	CA
Incremental Compliance Cost to get to 65ppb from 70ppb [1]	\$14.6	\$0.7
# of Counties in excess of 65ppb [2]	64	13
Implied Cost per County (\$ billion) [3]	\$0.23	\$0.05
# of Additional Counties Projected Out of Attainment (mid-century) [4]	192	-3
Implicit Compliance Cost [5]	\$43.8	-\$0.2
<b>Total Compliance Cost (\$ billions) [6]</b>	<b>\$43.6</b>	

**Table S6. Back-of-the-envelope cost calculations based on EPA’s 2015 regulatory impact analysis.**

[1]: Incremental compliance cost calculated as the cost of compliance for 65 ppb minus the cost for 70 ppb from Tables ES-5 and ES-9 of the 2015 EPA Ozone NAAQS Regulatory Impact Analysis (2015 RIA).

[2]: Total number of counties projected in excess of 65 ppb from the 2015 RIA, calculated as the sum of counties in excess of 70 ppb and the counties in excess of 65 ppb as shown in Figures ES-2 and ES-3.

[3]: [1] / [2].

[4]: Total number of additional counties we project to be out of attainment of the 70 ppb standard by mid-century under the RCP8.5 climate scenario.

[5]: [4] x [3].

[6]: Total of [5] for California and the rest of the U.S.

	All U.S. (except CA)	CA
Min. Benefits (70ppb, \$ billion) [1a]	\$2.9	\$1.2
Max Benefits (70ppb, \$ billion) [1b]	\$5.9	\$2.1
# of Counties [2]	14	4
Implied Min. Benefit per County (\$ billion) [3a]	\$0.21	\$0.30
Implied Max Benefit per County (\$ billion) [3b]	\$0.42	\$0.53
# of Additional Counties Projected Out of Attainment (mid-century) [4]	192	-3
Implicit Min. Compliance Benefit (\$ billion) [5a]	\$39.8	-\$0.9
Implicit Max Compliance Benefit (\$ billion) [5b]	\$80.9	-\$1.6
<b>Total Min. Benefit (\$ billions) [6a]</b>	<b>\$38.9</b>	
<b>Total Max Benefit (\$ billions) [6b]</b>	<b>\$79.3</b>	
<b>Avg. Benefit (\$ billions) [7]</b>	<b>\$59.1</b>	
<b>Avg. Benefit <i>excluding</i> PM2.5 co-benefits (\$ billions)</b>	<b>\$19.7</b>	

**Table S7. Back-of-the-envelope benefit calculations based on EPA’s 2015 regulatory impact analysis.**

[1]: Listed (a) minimum or (b) maximum benefits at 70 ppb from Tables ES-5 and ES-9 of the 2015 EPA Ozone NAAQS Regulatory Impact Analysis (2015 RIA).

[2]: Number of counties projected in excess of 70 ppb from Figures ES-2 and ES-3 of the 2015 RIA.

[3]: [1] / [2], calculated separately for (a) and (b).

[4]: Total number of additional counties we project to be out of attainment of the 70 ppb standard by mid-century under the RCP8.5 climate scenario.

[5]: [4] x [3], calculated separately for (a) and (b).

[6]: Total of [5] [(a) or (b)] for California and the rest of the U.S.

[7]: Average of [6a] and [6b].

[8]: 33% of [7]; “...for a standard of 70 ppb the total health benefits are comprised of between 29 and 34 percent ozone benefits and between 66 and 71 percent PM2.5 co-benefits (p. ES-14, 2015 RIA).”