Online Appendix for

Time is of the Essence: Climate Adaptation Induced by Existing Non-Climate Regulations

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This appendix provides details on the construction of the data, descriptive figures, and the tabular results of robustness tests and explorations of heterogeneity using alternate specifications. In Appendix A, we provide background information on the National Ambient Air Quality Standards for ozone, ozone formation, and further details on the sources of our data and construction of final variables. We additionally include maps of both weather and ozone monitoring station locations, illustrative figures of our decomposition of temperature and its relationship with ozone concentration, and tables of summary statistics. Appendix B includes additional discussion of alternate specifications, split between those investigating robustness in Subsection B.1, and those examining heterogeneity in Subsection B.2. Appendix C elaborates on the intuition behind regulation-induced adaptation and provides a formalization of our conceptual framework as discussed in Section II.

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Appendix A. The National Air Quality Standards, Ozone Formation, and Additional Data Discussion

This appendix section provides background information on the National Ambient Air Quality Standards in Section A.1 as well as background information on ozone pollution in Section A.2. Section A.3 then provides further details on the data sets discussed in Section III, as well as auxiliary data sets used in alternative specifications. It then includes relevant Figures and Tables as outlined below.

A.1. Background Details on the National Ambient Air Quality Standards

Ambient ozone is an important component of smog that is capable of damaging living cells, such as those present in the linings of the human lungs. With the Clean Air Act Amendments of 1970, EPA was authorized to set up and enforce a National Ambient Air Quality Standard (NAAQS) for ambient ozone. Since then, a nationwide network of air pollution monitors has allowed EPA to track ozone concentration, and a threshold is used to determine whether pollution levels are sufficiently dangerous to warrant regulatory action. Exposure to ambient ozone has been causally linked to increases in asthma hospitalization, medication expenditures, and mortality, and decreases in labor productivity (e.g., Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2012; Deschenes, Greenstone and Shapiro, 2017).

If any monitor within a county exceeds the NAAQS, EPA designates the county to be out of compliance or in "nonattainment" (USEPA, 1979, 1997, 2004, 2008, 2015). The corresponding state is required to submit a state implementation plan (SIP) outlining its strategy for the nonattainment county to reduce air pollution levels in order to comply with NAAQS.[1] Figure A5 depicts all counties monitored under the NAAQS for ozone during the period 1980-2013, noting the decade in which they were first designated as in "nonattainment," if ever. While the structure of enforcement is dictated by the CAA and the EPA, much of the actual enforcement activity is carried out by regional- and state-level environmental protection agencies. In particular, EPA divides the country into 10 geographic regions, and significant portions of the EPA's operations are conducted through these regional offices. For instance, regional EPA offices conduct inspections and/or issue sanctions when a state's enforcement

[1] In more details, the Clean Air Act defines air quality control regions (AQCRs) so that air quality is managed in a more localized manner (Section 107 of the CAA as codified in 40 CFR Part 81, Subpart B). Boundaries of AQCRs are usually based upon county lines or other political divisions, but it is important to highlight that each AQCR is a contiguous area where air quality is relatively uniform; where topography is a factor in air movement, AQCRs often correspond with airsheds. AQCRs may consist of two or more cities, counties or other governmental entities, and each region is required to adopt consistent pollution control measures across the political jurisdictions involved. Each AQCR is treated as a unit for the purposes of pollution reduction and achieving the NAAQS. They are designated on a pollutant-by-pollutant basis. For example, for nitrogen dioxide and sulfur dioxide, the AQCR for Nebraska is the entire state. For particulate matter, the state is divided into several AQCRs.

is below required levels, and assist states with major cases.

EPA allows counties with polluting firms from 3 to 20 years to adjust their production processes.[2] Specifically, the CAA mostly mandates command-and-control regulations, requiring that plants use the best available control technology (BACT) in their production processes. BACT requires that plants' pollution be at or below thresholds that could be achieved with best practices. However, if pollution levels continue to exceed the standards or if a county fails to abide by the approved plan, sanctions may be imposed on the county in violation. These sanctions may include the withholding of federal highway funds and the imposition of technological "emission offset requirements" on new or modified sources of emissions within the county (USCFR, 2005).

The first NAAQS for ambient ozone was established in 1979, when 120 parts per billion (ppb) was defined as the maximum 1-hour concentration that could not be violated more than once a year for a county to be designated as in attainment (USEPA, 1979).[3] The CAA requires periodic review and, if appropriate, revision of existing air quality criteria to reflect advances in scientific knowledge on the effects of the pollutant on public health and welfare. So, in 1997, the standards were strengthened to 80ppb, but with a different form for the threshold: annual fourth-highest daily maximum 8-hour concentration averaged over 3 years (USEPA, 1997).[4] The 1997 NAAQS were challenged in court, and not enforced until 2004 (USEPA, 2004). In 2008, the standards were revised downward to 75ppb (USEPA, 2008). The latest revision happened in 2015, and the current 8-hour threshold is 70ppb (USEPA, 2015). The EPA is currently conducting a review of the air quality criteria and the

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

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

[4] 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"* (USEPA, 1997, p.38868).

NAAQS for photochemical oxidants including ozone (USEPA, 2019).[5] In accordance with the prevailing regulatory standard for the majority of our sample period – 1980-2004 – we use the 1-hour maximum ozone concentration level (ppb) for our empirical analysis.

A.2. Background Details on Ozone

Background on Ozone — The ozone the U.S. EPA regulates as an air pollutant is mainly produced close to the ground (tropospheric ozone).[6] It results from complex chemical reactions between pollutants directly emitted from vehicles, factories and other industrial sources, fossil fuel combustion, consumer products, evaporation of paints, and many other sources. These highly nonlinear Leontief-like reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NOx) in the presence of sunlight. In "VOC-limited" locations, the VOC/NOx ratio in the ambient air is low (NOx is plentiful relative to VOC), and NOx tends to inhibit ozone accumulation. In "NOx-limited" locations, the VOC/NOx ratio is high (VOC is plentiful relative to NOx), and NOx tends to generate ozone.

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

[5] A summary of the changes in the form and levels of the NAAQS for ambient ozone is provided in Appendix Table A1. Additionally, during our period of analysis (1980-2013), nitrogen dioxide (NO2) also had its own NAAQS, but there were no changes from 1971 to 2010. Furthermore, from 2003 to 2008, there was a cap-and-trade program created to reduce the regional transport of NOx emissions from power plants and other large combustion sources in the eastern United States – the NOx Budget Trading Program (NBP), which was shown to be effective in reducing ozone concentrations (Deschenes, Greenstone and Shapiro, 2017). There were also regulations targeting VOCs: restrictions on the chemical composition of gasoline that are primarily intended to reduce VOC emissions from mobile sources. Apart from the more stringent regulations in California, these regulations have been shown to be ineffective in reducing ambient ozone concentrations (Auffhammer and Kellogg, 2011).

[6] 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.

of sunlight. Modeling studies point to temperature as the most important weather variable affecting ozone concentrations.[7]

Ambient ozone concentrations increase during the day when formation rates exceed destruction rates, and decline at night when formation processes are inactive.[8] Ozone concentrations also vary seasonally. They tend to be highest during the late spring, summer and early fall months.[9] The EPA has established "ozone seasons" for the required monitoring of ambient ozone concentrations for different locations within the U.S.[10] Recently, there is growing concern that the ozone season may prolong with climate change (e.g., Zhang and Wang, 2016).

A.3. Further Details on the Construction of the Data

Weather Data — Meteorological data was obtained from the National Oceanic and Atmospheric Administration's Global Historical Climatology Network database (NOAA, 2014). This dataset provides detailed weather measurements at over 20,000 weather stations across the country, for which we use the period April-September, 1950-2013, for the contiguous 48 states. In constructing our complete, unbalanced panel of weather stations we make only one restriction: for each weather station in each year, we include only those stations for which valid measurements of maximum and minimum temperature, as well as precipitation, exist for at least 75 percent of the days in the ozone monitoring season (April-September). Figure A2 plots annual deviations of temperature from the 1950-1979 baseline average. These

[7] 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.

[8] 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.

[9] 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.

[10] Appendix Table A2 shows the ozone season for each state during which continuous, hourly averaged ozone concentrations must be monitored.

are the thin solid, dotted, and dashed lines, representing average, maximum, and minimum temperature, respectively. The baseline represents both the pre-ozone regulation era as well as, generally speaking, the pre-climate change awareness era. The climate trend relative to this baseline – the smoothed thick solid line in the figure – has been slowly but steadily increasing since the mid-1970s, with an increase in the average temperature of approximately 0.5 degrees Celsius by 2010. This is consistent with findings from the U.S. Fourth National Climate Assessment, which indicate an increase in average temperature of 0.7 degrees Celsius for the period 1986-2016 relative to 1901-1960 (Vose et al., 2017).

We decompose average temperature into a *climate norm* (30 year monthly moving average, lagged by 1 year) and a *temperature shock* (deviation of daily temperature from the climate norm). Figure A6 depicts similar variation in both the climate norm and temperature shock as Figure 3, but using only the temperature assigned to each ozone monitor in our final sample. Notice that there seems to be more variation in the 30-year MA in the latter figure because it includes cross-sectional variation as well. Also, the 30-year MA trends down towards the end of the period of our study due to changes in ozone monitor location over time, as shown in Figure A1. Table A4 reports summary statistics for maximum temperature and our decomposed measures of climate norm and temperature shock, averaged across our entire sample for each year 1980-2013. Figures A8 and A9 provide illustrative examples of this decomposition for Los Angeles county for a single year – 2013 – and for the entire period 1980-2013, respectively.

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

We have valid ozone measurements for a total of 5,638,273 monitor-days.[11] The number of total valid monitors increased from 1,361 in the 1980s to 1,851 in the 2000s, indicating a growth of 16.6 percent of the ozone monitoring network per decade.[12] The number of monitored counties in our main estimating sample also grew from 585 in the 1980s to 840 in the 2000s. Figure A1 depicts the evolution of our sample monitors over the three decades in our data, and illustrates the expansion of the network over time. Table A3 provides some summary statistics regarding the increase in the number of monitors over time.[13]

Figure A4 depicts the daily maximum 1-hour ambient ozone concentrations from 1980-2013, split by counties in and out of attainment of the ozone NAAQS. In this figure we compare the trends in ozone concentrations with the updated 1997, 2008 and 2015 NAAQS. These standards were based on the observed 4th Highest 8-hour average ambient ozone concentration of 80, 75 or 70 ppb respectively. Figure A4 contrasts these attainment cut-offs with the maximum yearly ozone concentrations in attainment and nonattainment counties. Table A1 clearly illustrates the evolution of the National Ambient Air Quality Standards for ozone over the years. Alternatively, Figure A10 compares the trends in ozone concentrations from 1980-2013 for counties with low- median- and high-belief in climate change. Notably, the concentrations appear to be converging over time – high-belief counties started out with

[11]Note that this value refers to *all* valid ozone measurements, the final samples used in estimation will be smaller due to, e.g., instances where an ozone monitor is not paired with any weather stations under our matching algorithm. For instance, our main estimating sample contains 5,139,529 valid monitor-day observations.

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

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

higher baseline ozone levels, but over time reduced them to almost be in-line with low- and median-belief counties.

Matching Ozone and Weather Data — These weather stations are typically not located adjacent to the ozone monitors. Hence, we develop an algorithm to obtain a weather observation at each ozone monitor in our sample. Using information on the geographical location of ozone monitors and weather stations, we calculate the distance between each pair of ozone monitor and weather station using the Haversine formula. Then, for every ozone monitor we exclude weather stations that lie beyond a 30 km radius of that monitor. Moreover, for every ozone monitor we use weather information from only the closest two weather stations within the 30 km radius. Once we apply this algorithm, we exclude ozone monitors that do not have any weather stations within 30km. We calculate weather at each ozone monitor location as the weighted average of these two weather stations using the inverse of the squared distance between them. Figure A3 illustrates the proximity of our final sample of ozone monitors to these matched weather stations. We additionally assess the robustness of our results to changes in this algorithm by increasing the radius to 80 km and using the 5 closest weather stations, and by varying the weights used – unweighted arithmetic mean and simple inverse distance weighting – in calculating the approximate daily weather at each ozone monitoring location. The results of our model under these alternative specifications is discussed further in Appendix B.1.

After matching ozone monitors with weather stations, we have valid ozone and temperature measurements for a total of 5,139,529 monitor-days. Figure A7 illustrates the close association between ambient ozone concentrations and both components of temperature. Notice that the relationship between ozone and the climate norm, depicted in Panel A of Figure A7 appears to be weaker than that with the temperature shock, in Panel B. This suggests that economic agents undertake adaptive behavior, after having observed the historical climate norm.

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

In column (3) of Table B2 we include a monitor-day level interaction term for whether the local air quality authority had issued an ozone "action day" alert for the respective county. These "action day" alerts are often made day-of, or a few days in advance of, days in which the relevant air quality authority observes, or expects to observe, unhealthy levels of pollution on the Air Quality Index and releases a public service announcement to this effect. Individuals and firms are urged to take *voluntary* action to reduce the emissions of pollutants that are conducive to ozone formation. Note that although action day policies first began in the 1990's, EPA only provides data beginning in 2004, leading to a restricted overall sample (approximately 36% of our full sample).

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

Additionally, it has been shown that, e.g., manufacturing plants have relocated in response to ozone nonattainment designations (Henderson, 1996; Becker and Henderson, 2000). In Table B6 we replace our daily ozone dependent variable with measures of (logged) monthly employment or quarterly wages at the county level obtained from the Quarterly Census of Employment and Wages.

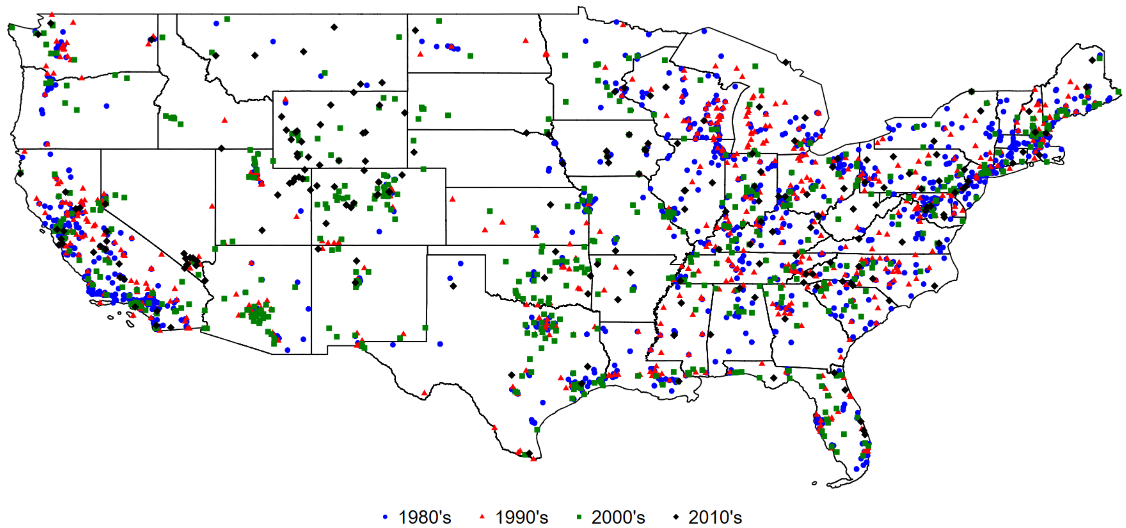
In Table B8 we examine heterogeneity in our results when separating counties into low- median- and high-levels of belief regarding the existence of climate change. These measures were constructed using county level survey data collected by Howe et al. (2015) in 2013 which estimate the percentage of each county's respective population that hold such beliefs.

Notably, we do not rely on the explicitly stated aggregate level of belief, but rather the relative level of belief compared to the rest of our sample. Specifically, we separate counties into low- median- or high-belief terciles based on their stated level of belief in the existence of climate change. In this way we arrive at three equally sized groups for which we are able examine heterogeneity in climate impacts and adaptive response. For reference, Table B9 provides summary statistics of basic demographic characteristics across these three county groupings using data from the 2006-2010 5-year American Community Survey.

As a placebo check we also examine the heterogeneity in our results when separating counties into low- median- and high-belief regarding "preferences" for single-parenthood in Table B10. Similar to our construction of "climate beliefs," we begin with a measure of the fraction of single-parent households at the county level from the Opportunity Atlas (Chetty et al., 2018). We then again separate counties into low- median- or high-belief terciles based on their relative level of "preference" for single-parenthood. In this way we arrive at three equally sized groups for which we are able examine heterogeneity in climate impacts and adaptive response.

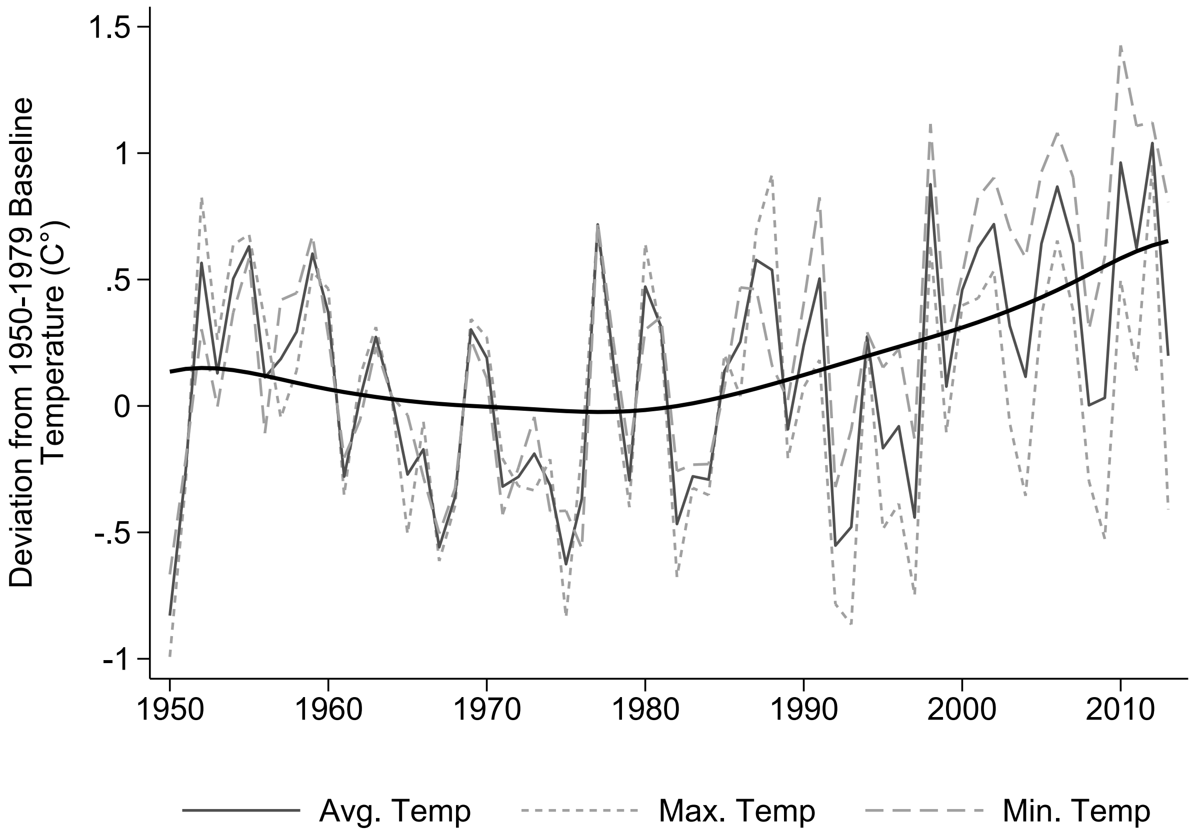
In Table B11 we use measures of whether a county is "VOC-limited" or "NOx-limited." These measures were constructed using data collected by the EPA's network of respective monitoring stations. Note, however, that these are often separate pollution monitors from our main sample of ozone monitors. Additionally, data – especially for VOCs – is relatively sparse compared to ozone data. Due to these data constraints, we construct measures of whether a county is, in general, VOC-limited or NOx-limited for each 5-year period in our sample, e.g. 1980-1984, which we then match with our sample of ozone monitors at the county level. To construct these measures we first combine the EPA's VOC and NOx data at the county-day level and generate a daily ratio of VOCs to NOx for each county. Following the scientific literature, observations with a ratio less than or equal to 4 are coded as VOC-limited, while those greater than 15 are coded NOx-limited, and the remainder are coded as non-limited. We then sum these three measures by county across each 5-year interval and denote a county as VOC-limited, NOx-limited, or non-limited for that interval based on whichever measure was the most prevalent. For example, a county with 50 VOC-limited day, 20 NOx-limited days, and 30 non-limited days would be marked as VOC-limited for this 5-year window. Admittedly, this creates a somewhat coarse measure of whether a county is VOC- or NOx-limited. Given the available data, however, this appears to be the furthest this question can be investigated, and, if anything, should be expected to bias the observed effect from this heterogeneity towards zero.

Figure A1: Ozone Monitor Location by Decade of First Appearance



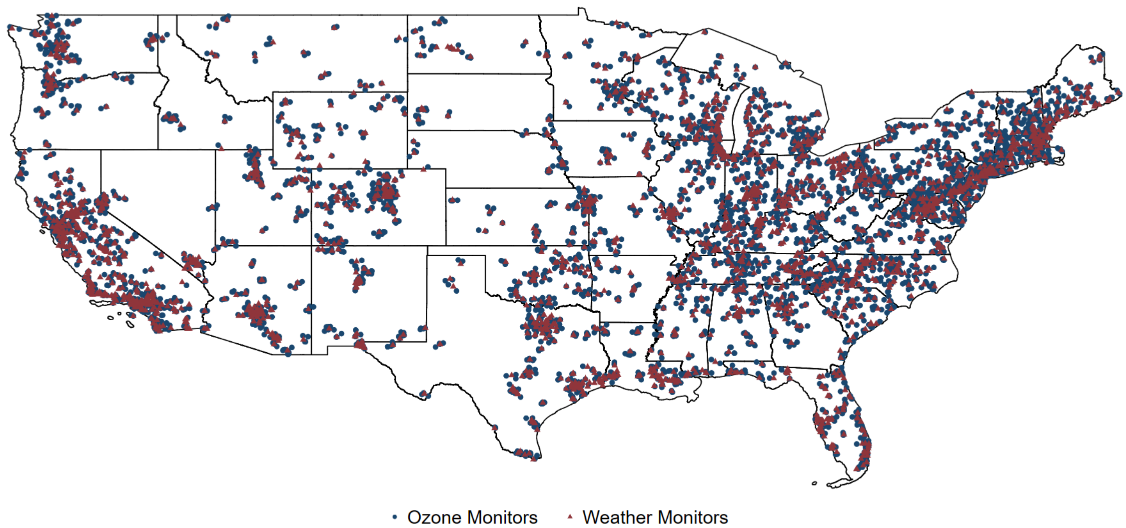
Notes: This figure depicts the evolution of ozone monitors in our sample over three decades and illustrates the expansion of the monitoring network. We use an unbalanced panel of ozone monitors, after making the following two restrictions. Firstly, we only include monitors if 8-hour averages are available for at least 75 percent of the possible hours of the day, or (ii) daily maximum concentration is higher than the standard. Secondly, as a minimum data completeness requirement, for each ozone monitor we include only years for which least 75 percent of the days in the typical ozone monitoring season (April-September) are valid; years having concentrations above the standard are included even if they have incomplete data. We have valid ozone measurements for a total of 5,139,529 monitor-days after matching monitors with weather stations. The number of unique valid monitors increased from 1,285 in 1980 to over 1,850 in the 2000's.

Figure A2: Temperature Relative to Baseline (1950-1979)



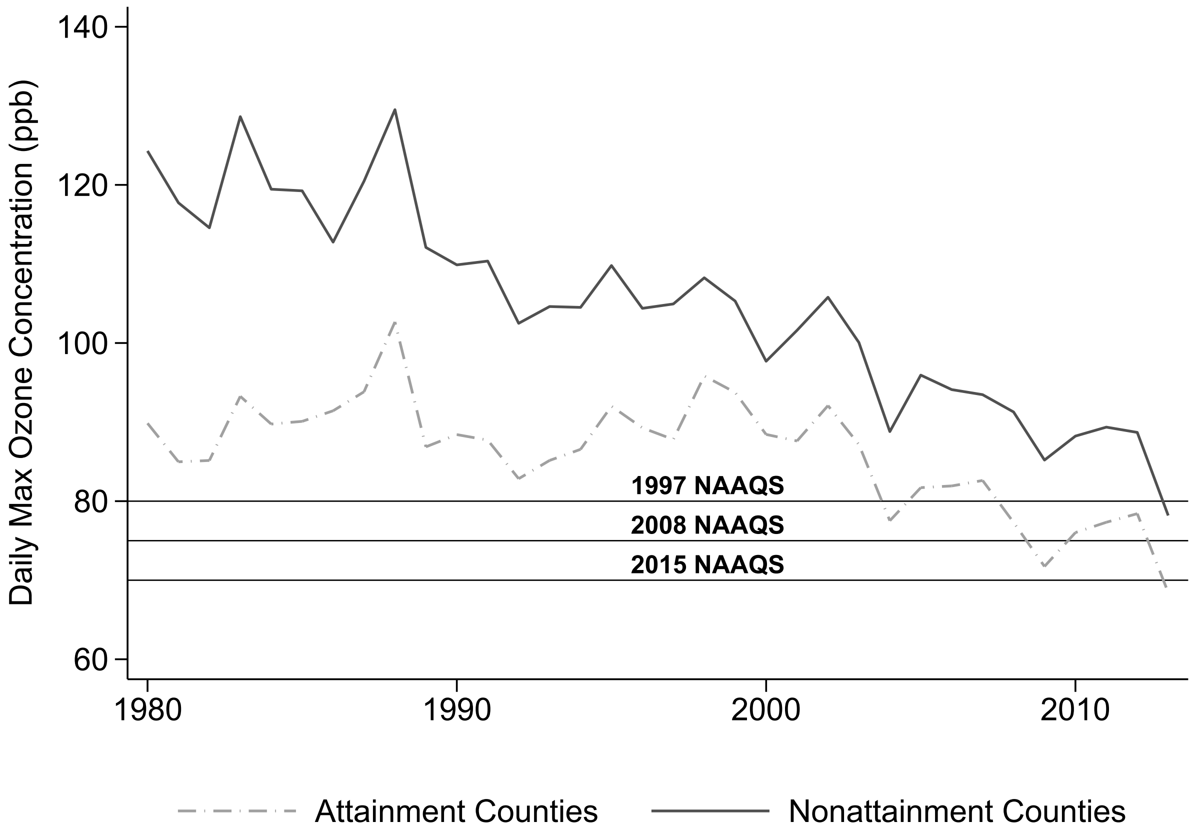
Notes: This figure depicts annual temperature fluctuations and the overall climatic trend for the ozone season in the US relative to a 1950-1979 baseline average. The baseline and the yearly deviations from it are constructed from the comprehensive sample of weather stations across the US from 1950 to 2013 following the data construction steps detailed in Appendix A.3. The 1950-1979 baseline represents, generally speaking, the pre-climate change awareness era. The average temperature, relative to this baseline, has been slowly but steadily increasing since 1980, with an increase in the average temperature of approximately 0.5 degree Celsius (°C) by 2010. For clarity, the thin solid line, the short-dashed line, and long-dashed line refer to annual averages for daily average, maximum, and minimum temperature, respectively, as coded in the legend. The thick solid line smooths out the annual observations for average temperature over the period covered in the graph.

Figure A3: Ozone Monitors and their Matched Weather Monitors



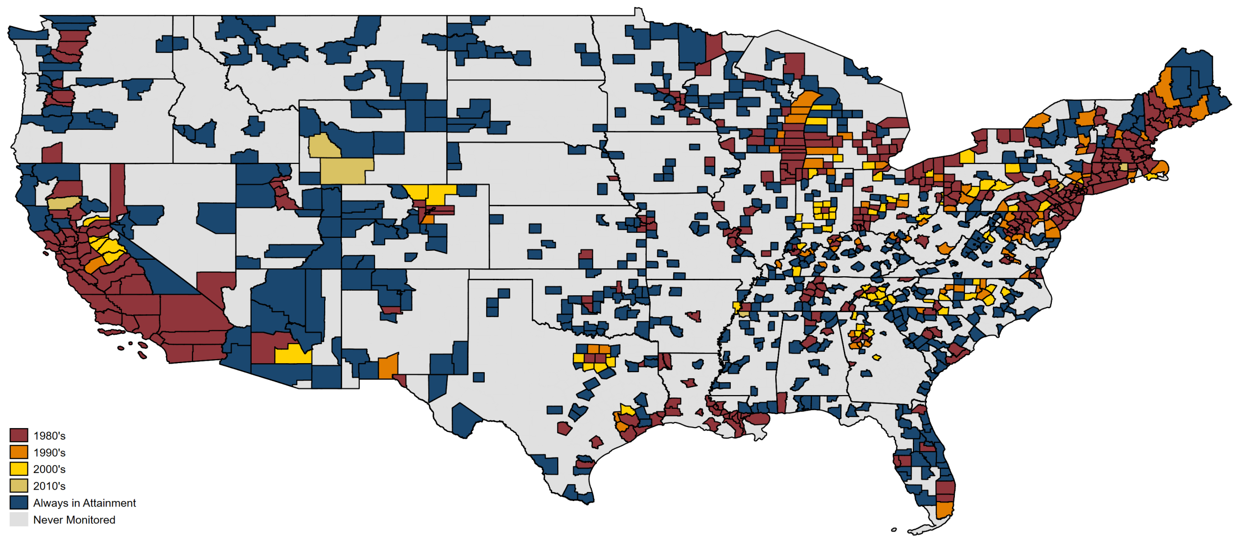
Notes: This figure illustrates the proximity of our final sample of ambient ozone monitors to the matched weather stations. Using information on the geographical location of pollution monitors and weather stations we calculate the Haversine distance between each pair of ozone monitor and weather station. 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.

Figure A4: Evolution of the 4th Highest Ambient Ozone Concentration



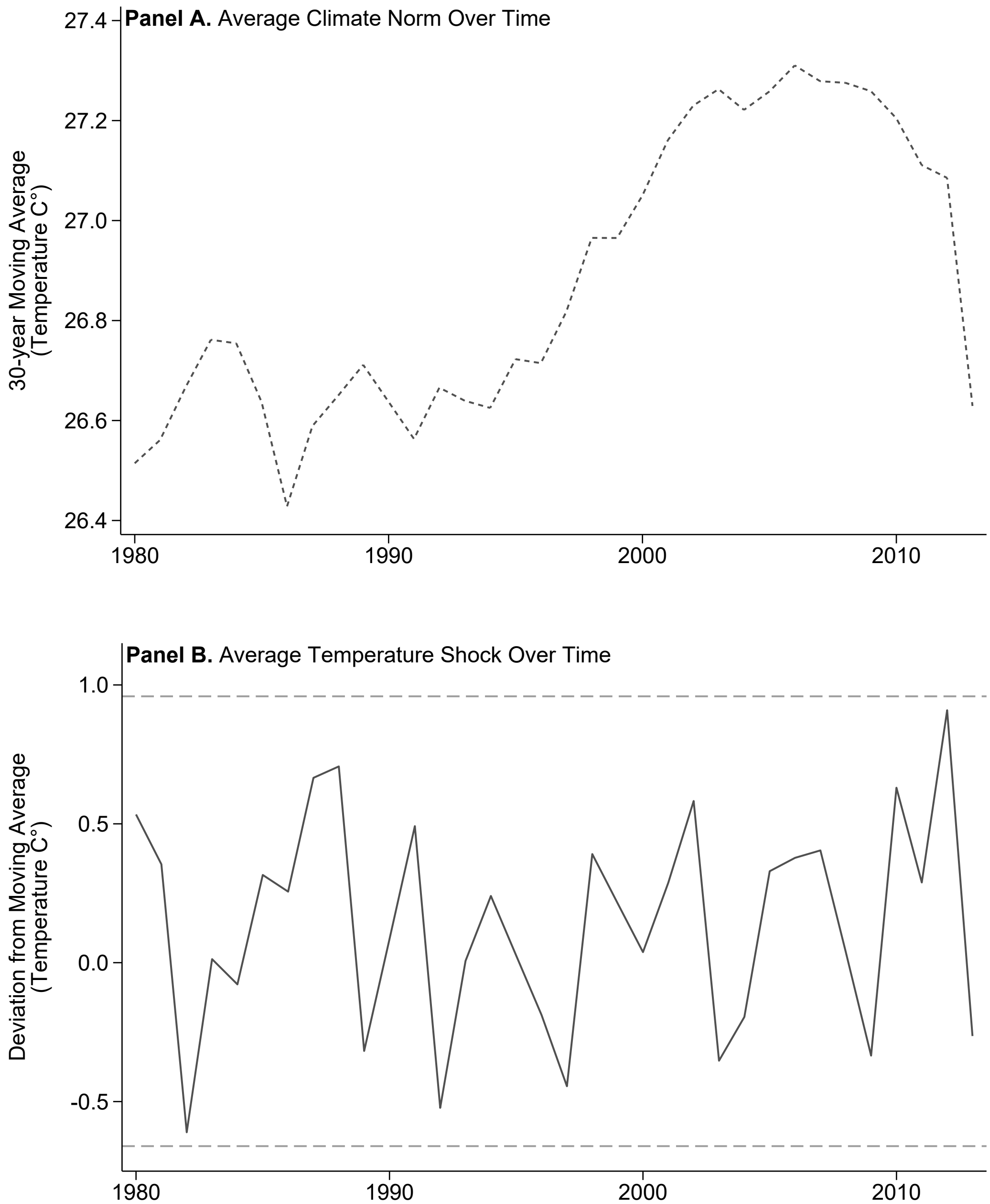
Notes: This figure depicts the national average of the annual 4th highest daily maximum 1-hour ambient ozone concentration over time in the US, split by counties designated as in- or out- of attainment under the National Ambient Air Quality Standards (NAAQS). The 1997, 2008, and 2015 NAAQS updates for designating a county's attainment status were based on the observed 4th highest 8-hour average ambient ozone concentration of 80, 75, and 70 ppb or higher, respectively. Here we contrast these attainment status cutoffs with the yearly ozone concentrations in Attainment and Nonattainment counties.

Figure A5: Map of Monitored Counties - by First Decade Designated in Nonattainment



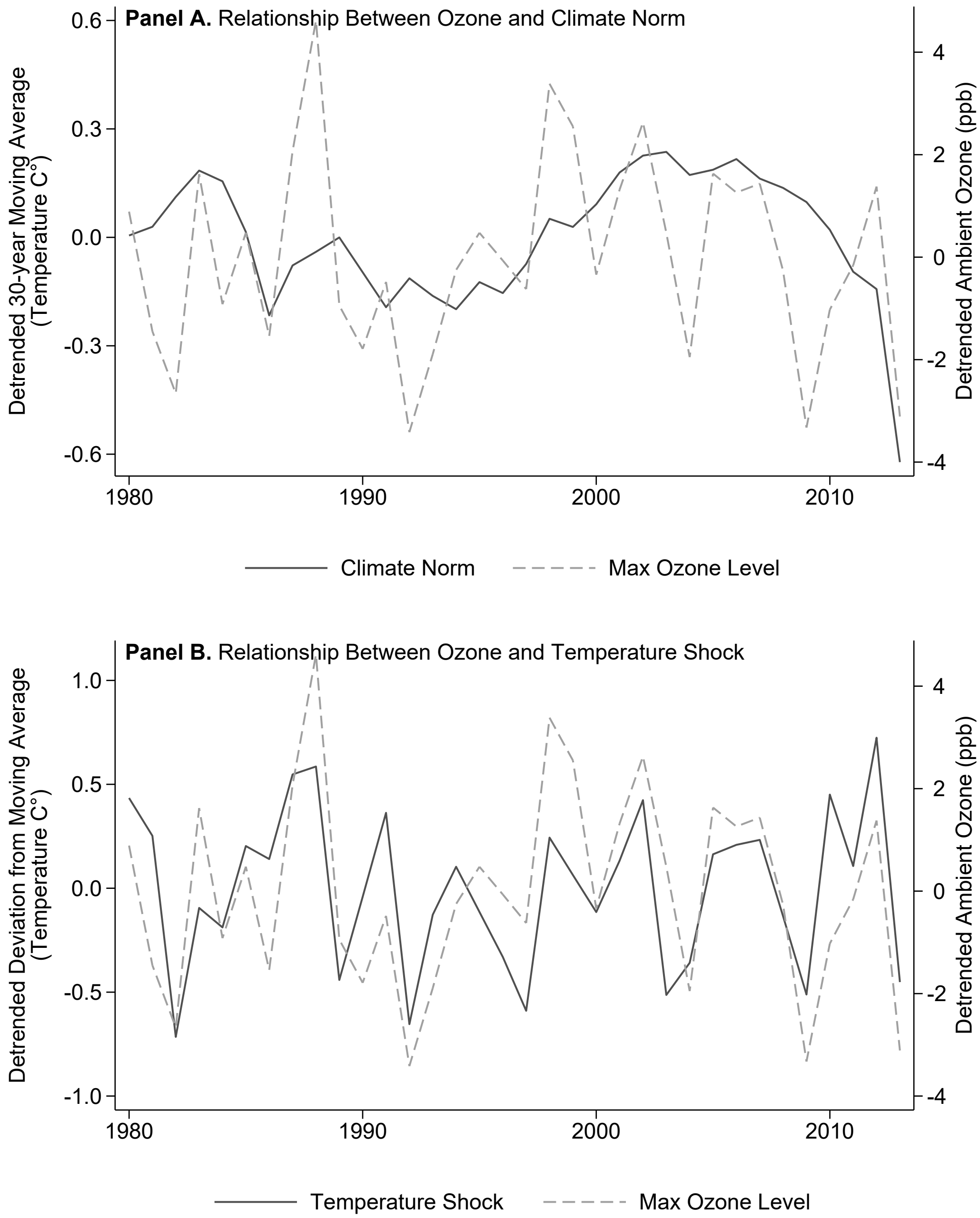
Notes: This figure illustrates all counties monitored under the NAAQS for ozone during the period 1980-2013, noting the decade in which they were first designated as in "nonattainment," if ever. While the structure of enforcement is dictated by the CAA and the EPA, much of the actual enforcement activity is carried out by regional- and state-level environmental protection agencies. Most counties out of attainment were first designated in nonattainment in the 1980s. The map displays concentrations of those counties in California, the Midwest, and in the Northeast. Nevertheless, a nontrivial number of counties went out of attainment for the first time in the 1990s and 2000s.

Figure A6: Climate Norms and Shocks (Final Sample)



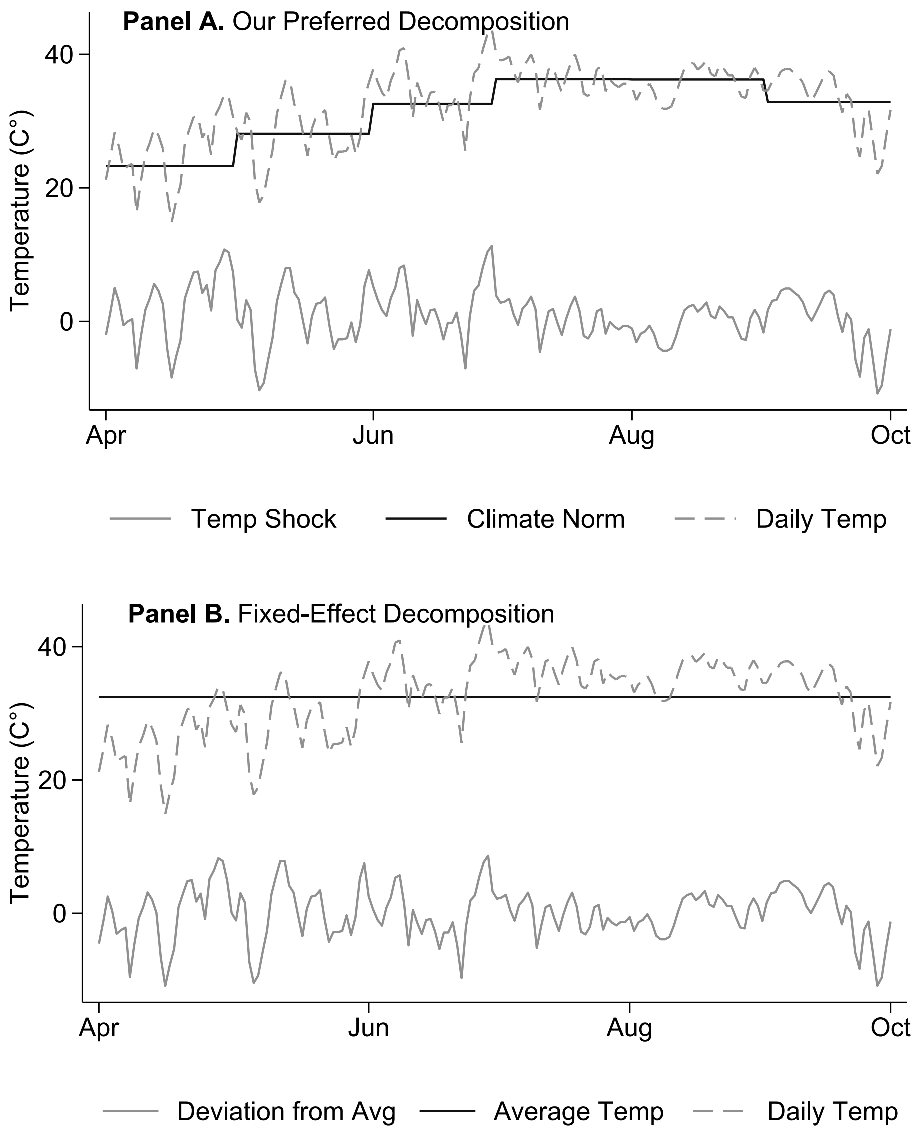
Notes: This figure depicts US temperature over the years in our sample (1980-2013), decomposed into their climate norm and temperature shock components. The climate norm (Panel A) and temperature shocks (Panel B) are constructed from the panel of weather stations included in our main model sample across the US from 1950 to 2013, restricting the months over which measurements were gathered to specifically match the ozone season of April–September, the typical ozone season in the US (see Appendix Table A2 for a complete list of ozone seasons by state). The unbalanced feature of our main sample, with ambient ozone monitors moving north over time (see Figure A1), is the likely driving force behind the downward pattern of the average climate norm at the end of our sample period in Panel (A). Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature. The horizontal dashed lines in Panel (B) highlights that temperature shocks are bounded in our period of analysis.

Figure A7: Relationship between Ambient Ozone and Temperature



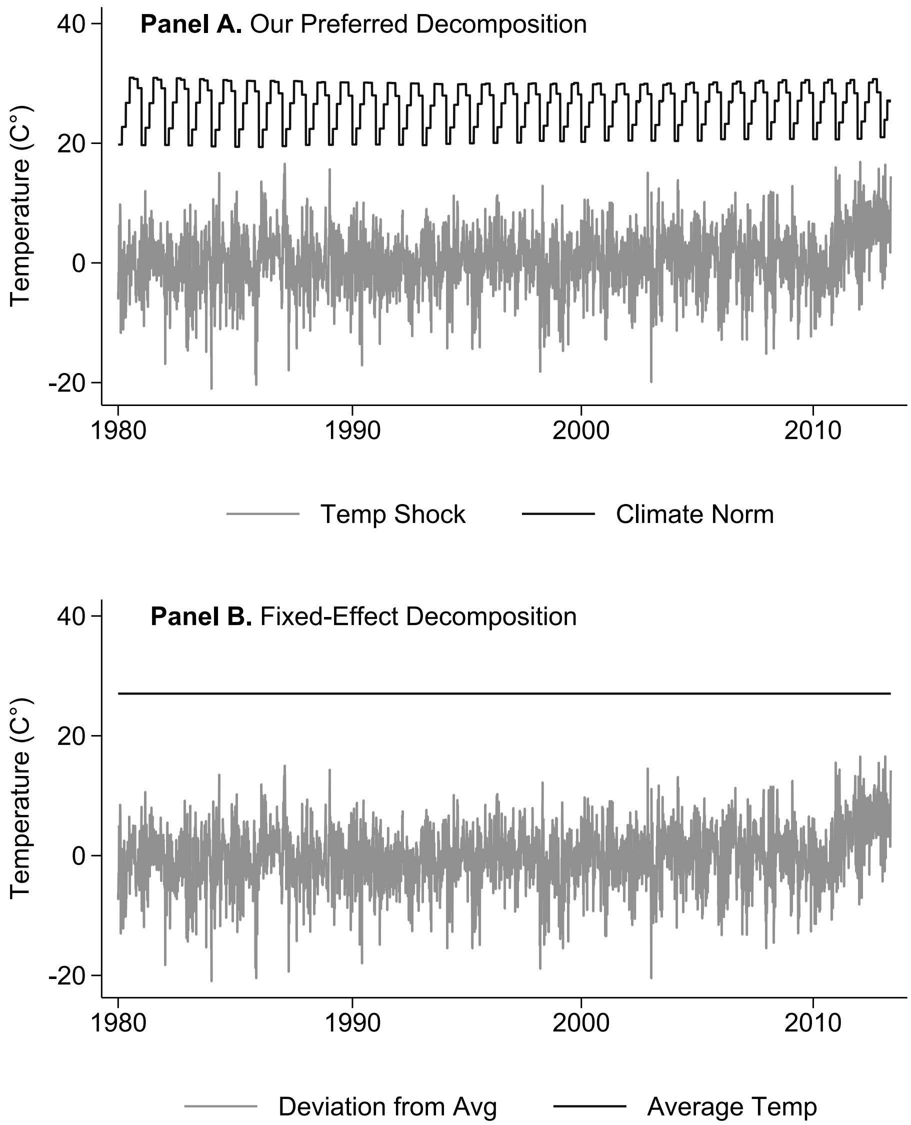
Notes: This figure depicts the general relationship between daily maximum ozone concentrations and temperature over the years in our sample (1980-2013) after decomposing temperature into our measure of climate norm and temperature shock and de-trending the data. Both the climate norm (Panel A) and the temperature shock (Panel B) appear to have a close correlation with ozone concentrations, although the relationship in Panel (A) appears weaker than that in Panel (B), providing suggestive evidence of adaptative behavior. Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

Figure A8: Decomposition of Temp. Norms & Shocks – Illustration (Los Angeles, 2013)



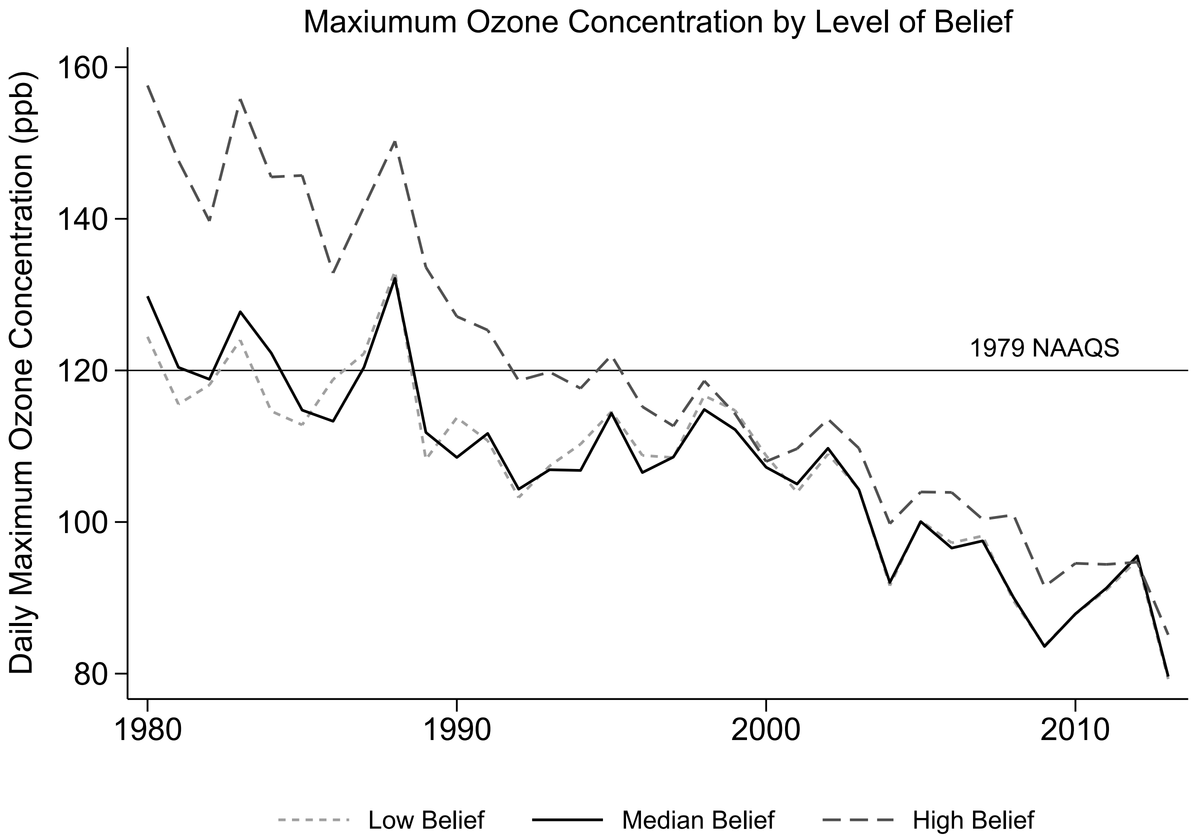
Notes: This figure compares our preferred temperature decomposition method with a standard fixed-effects approach using data from the 2013 Los Angeles ozone season, illustrating the benefit of this approach relative to the standard fixed-effects model. Specifically, Panel (A) depicts the daily measure of temperature, as well as its decomposition into climate norm and temperature shock. By contrast, Panel (B) depicts the same daily measure of temperature, but instead decomposed into a typical fixed-effect average temperature and the deviations from this constant value after additionally controlling for month-by-year fixed effects. The dashed line at the top of each panel indicates observed daily maximum temperature while the black solid line represents long-run norms. The gray solid line at the bottom of each panel indicates temperature shocks. Notice that the temperature shocks in our preferred decomposition are nearly identical to the deviations in the fixed-effects decomposition, as would be expected from the Frisch-Waugh-Lovell theorem, and illustrate the source of variation used for identifying β_W. Additionally, Panel (A) highlights the source of variation in climate used to identify β_C, while the fixed-effects decomposition lacks any such variation in the measure of climate, as the LA fixed effect is collinear with average temperature. Recall that for our proposed approach the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

Figure A9: Decomposition of Temp. Norms & Shocks – Illustration (Los Angeles, All Years)



Notes: This figure illustrates the same comparison as in Figure A8 for Los Angeles, but now using the entire sample period, 1980-2013. Specifically, Panel (A) depicts the decomposition of daily temperature into its climate norm and temperature shock. By contrast, Panel (B) depicts the same daily temperature, but instead decomposed into a typical fixed-effect average temperature and the deviations from this constant value after additionally controlling for month-by-year fixed-effects. The black solid line at the top of each panel indicates long-run norms. The gray solid line at the bottom of each panel indicates temperature shocks. Notice that the temperature shocks in our preferred decomposition are nearly identical to the deviations in the fixed-effects decomposition, as would be expected from the Frisch-Waugh-Lovell theorem, and illustrate the source of variation used for identifying β_W. Additionally, Panel (A) highlights the source of variation in climate used to identify β_C, while the fixed-effects decomposition lacks any such variation in the measure of climate, as the LA fixed effect is collinear with average temperature. Recall that for our proposed approach the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

Figure A10: Evolution of Ozone Concentration by Belief in Climate Change



Notes: This figure depicts the national average of the highest daily maximum 1-hour ambient ozone concentration over time in the US, split by counties with low- median- and high-belief in climate change. Notably, the concentrations appear to be converging over time – high-belief counties started out with higher baseline ozone levels, but over time reduced them to almost be in-line with low- and median-belief counties. Here we contrast these concentrations with the 1980's attainment status cutoff of 120ppb threshold.

Table A1: History of Ambient Ozone NAAQS

Enacted	Primary/ Secondary	Indicator	Averaging Time	Level	Form
1971	Primary and Secondary	Total photo-chemical oxidants	1-hour	80 ppb	Hourly concentration not to be exceeded more than one hour per year
1979	Primary and Secondary	Ozone	1-hour	120 ppb	Hourly concentration not to be exceeded more than one day per year
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

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

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

† The 1997 NAAQS was challenged in courts, and not implemented until 2004.

Table A2: Ozone Monitoring Season by State

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

Notes: This table shows, for each state, the season when ambient ozone concentration is required to be measured and reported to the U.S. EPA. The ozone season is defined differently in different parts of Texas.

Source: USEPA (2006, p.AX3-3).

Table A3: Yearly Summary Statistics for Ozone Monitoring Network

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

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

Table A4: Yearly Summary Statistics for Daily Maximum Temperature

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

Notes: This table outlines the evolution of maximum temperature in our sample from the years 1980–2013 in column (2). Columns (3) and (4) decompose this into our respective measures of climate norm and temperature shock. Recall that the climate norm represents the 30-year monthly moving average of the maximum temperature, lagged by one year, while the temperature shock represents the difference between this value and the contemporaneous maximum temperature.

Appendix B. Further Robustness Checks and Heterogeneity

This appendix provides further elaboration of the alternative specifications used for robustness checks and examinations of heterogeneity as discussed in Section V. It then includes relevant Tables as outlined below.

Table B1. Alternative Lengths of Climate Norms

Table B2. Adaptation Responses

Table B3. Alternative Specifications and Sample Restrictions

Table B4. Further Sample Restrictions: Historical NAAQS Designations

Table B5. Alternative Criteria for Selection of Weather Stations

Table B6. Alternative Outcome Variables

Table B7. Bootstrapped Standard Errors

Table B8. Adaptation by Local Beliefs in Climate Change

Table B9. Beliefs in Climate Change: Summary Stats

Table B10. Placebo: Preferences for Single Parenting

Table B11. Adaptation by VOC- or NOx-limited Atmosphere

Table B12. Results by Decade

Tables B13a & B13b. Non-Linear Effects of Temperature

B.1. Further Robustness Checks

Alternative Lengths of Climate Norms — A potential concern with our primary estimates reported in Table 1 might be the way in which we define our climate norm. Recall that we define the climate norm as the 30-year monthly moving average of temperature, lagged by one year. Although this is the usual definition of climate used in the literature by climatologists, in Table B1, we address any possible concerns about measurement error impacting our results. In this table, we vary the length of time that we use in constructing the climate norms. In going from column (1) to (4), we report estimates using a 3-year, 5-year, 10-year and 20-year moving average as our climate norm. If we observe the coefficients of the climate norm, we see a slight increase in the magnitude as we move to longer-run averages. However, if we compare effect of the climate norm in column (4) of Table B1 (20-year average) to column (2) of Table 1 (30-year average), we see a decline in magnitude. This latter result suggests that the widely used climate normals are close to the "optimal" long-run norms. The improvements from reducing measurement error might be offset by the panel-driven attenuation bias between 20- and 30-year time windows.

Adaptation Responses — Given that in this paper, we speak at length about adaptation to climate change, and in particular, regulation-induced adaptation, another major concern might be the time given to economic agents to adapt. Recall that in our preferred specification, we define climate norm as the 30-year monthly moving average of temperature, lagged by one year (e.g., the 30-year moving average associated with May 1982 is the average May temperatures over the years 1952-1981). Thus, economic agents will have had at least one year to respond and adapt to unexpected changes in the climate normal temperature. One might wonder whether one year is enough time for agents to adapt and adjust their behavior. To alleviate such concerns, we check the sensitivity of our results when agents have 10 or 20 years to adapt, instead of just one. In Table B1 column (1), we define climate norm as a 20-year monthly moving average of temperature, lagged by 10 years such that economic agents have a decade to make adjustments in response to unexpected changes in the climate norm (e.g., the climate norm associated with May 1982 would now instead be the average of May temperatures over the years 1952-1971). Similarly, in column (2), we report estimates using a 10-year moving average as our climate norm, lagged by 20 years, giving even more time to economic agents to adapt. The estimated impacts are remarkably similar to our main findings, suggesting that economic agents react as soon as information becomes available to them and that those effects are persistent. In column (3) we turn to possibility of agents responding rapidly to weather shocks. Were this to be the case, such short-run adaptive behaviors would affect our benchmark impacts of temperature shocks and hence bias our estimates of regulation-induced adaptation downwards. To investigate this possibility, we make use of a widespread policy of "Ozone Action Day" (OAD) alerts, where a local air pollution authority would issue an alert, usually a day in advance, that meteorological conditions are expected to be more conducive to forming potentially hazardous levels of ambient ozone in the following day. As a result, individuals and firms are urged to *voluntarily* take actions that would reduce emissions of ozone precursors. Thus, if agents are adapting to contemporaneous weather shocks, these "action days" would be the days we would be most likely to observe an adaptive response. Interacting an indicator variable for days in which OAD alerts were issued for a given county with our other covariates, we find that such alerts have a negligible and statistically insignificant impact on the effect of a 1°C change in the contemporaneous temperature shock in both attainment and nonattainment counties – signifying limited opportunities, or willingness, to adapt in the short term.[14]

Alternative Specifications and Sample Restrictions — In Table B3 we further explore the sensitivity of our results to changes in the primary econometric specification and additional sample restrictions. First, it may be a concern that our climate norm variable structures the

[14] Although the recovered coefficients of temperature shocks, climate norms, and implied adaptation levels are quantitatively different for column (3) than columns (1) and (2), this is likely due to a difference in the underlying sample. EPA data on "action day" alerts were only provided from 2004 onwards, leading to a restricted overall sample (approximately 36% of our full sample).

long-run climate normal temperature as the 30-year *monthly* moving average, despite the fact that seasonal – or within-season – shifts in temperature are unlikely to exactly follow the calendar at a monthly level. We examine the sensitivity of our results to this decision by alternatively constructing this variable as a 30-year *daily* moving average, allowing it to vary arbitrarily within each month. Results of our main specification, substituting daily moving averages for the standard monthly ones, are presented in column (1). The impacts of both components of temperature in attainment as well as nonattainment counties are nearly identical to our original findings. Ultimately, we prefer the monthly moving average because it is likely that individuals recall climate patterns by month, not by day of the year, making the interpretation of adaptation more intuitive. Indeed, as mentioned before, broadcast meteorologists often talk about how a month has been the coldest or warmest in the past 10, 20, or 30 years, but not how a particular day of the year has deviated from the norm.

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

Following those authors' results, we can expect that ozone monitors that have consistently been in our sample across all years must be located in areas having very high pollution levels, thus commanding constant monitoring and regulation by the EPA. To check if this claim is accurate, we run our analysis using a *balanced* sample of ozone monitors. Starting from our original sample, and using only monitors that have been in the data for every year from 1980-

2013, we are left with 92 pollution monitors. The results are reported in column (2) of Table B3. As expected, the temperature effects obtained from the balanced panel are *larger* than those in our main results, although the level of adaptation remains largely unchanged. Our preferred, unbalanced sample of monitors includes areas with different levels of air pollution, and thus estimates should be more representative of the entire country.

Lastly, although temperature is the primary meteorological factor affecting tropospheric ozone concentrations, other factors such as wind speed and sunlight have also been noted as potential contributors. High wind speed may prevent the build-up of ozone precursors locally, and dilute ozone concentrations. Ultraviolet solar radiation should trigger chemical reactions leading to the formation of ground-level ozone. To test whether our main estimates are capturing part of the effects of wind speed and sunlight, we control for these variables in an alternative specification using a smaller sample containing those variables. Column (3) of Table B3 presents our main results from estimating Equation (2) plus controls for average daily wind speed (meters/second) and total daily sunlight (minutes). As expected, higher wind speeds lead to lower ozone concentrations, and more sunlight leads to higher concentrations. We find that a 1 meter/second increase in average daily wind speed would decrease ozone concentrations by 2.2 ppb, whereas a 1 minute increase in daily sunlight leads to 0.01 ppb increase in ozone concentrations. Including these additional variables does not significantly change our primary estimates of interest, however, which remain statistically indistinguishable from our preferred model.

Further Sample Restrictions: NAAQS Designations — As our primary estimate of interest, regulation-induced adaptation, reflects the difference between adaptation in nonattainment and attainment counties, there may be concern that a specific subset of counties, with distinct NAAQS designations over the sample period, heavily influence the full sample estimate. For example, counties always in nonattainment may make more of an effort to adapt and work towards achieving attainment status than counties that are only occasionally designated as in nonattainment. Specifically, our full sample consists of 497 counties always in attainment, 51 counties always in nonattainment, and 458 counties that switched their attainment status at least once between 1980 and 2013. To investigate this potential concern, we create two sub-samples: one including only the first two sets of counties – those that never changed attainment status, and another including only the last set of counties – those with variation in their attainment status. The first sub-sample consists of 1,122,101 observations, roughly 20% of our full sample, while the second sub-sample contains the other 80%, at 4,017,428 observations. The results of estimating our preferred specification, given by Equation (2), using each of these sub-samples are shown in Table B4. Across both sample restrictions, our estimated coefficients are relatively similar to our full-sample results and, while it does appear that counties which have always been in nonattainment engage in slightly more adaptation than nonattainment counties that have switched their status at least once, the magnitudes of adaptation are not statistically distinguishable between these two sets of counties. Furthermore, in both cases we are unable to rule out that the recovered estimate of regulation-induced adaptation is statistically the same as our main estimate.

Alternative Criteria for Selection of Weather Stations — An additional concern arises from the fact that weather stations are not necessarily sited next to ozone monitors. Because of this, we do not have an exact measure of temperature at the same geographic point as our measure of ozone. As discussed in our data section, we define temperature at an ozone monitoring station as the mean of the reported daily maximum temperatures at the two closest weather stations within 30 kilometers, weighted by the inverse squared distance to the ozone monitor. In doing so, we are likely to approximate a good measure of the daily maximum temperature for the local region as a whole, while also maintaining a close geographic boundary around the ozone monitoring station so as not to influence this approximation with temperature readings from a weather station further away that may be subject to a different set of meteorological conditions. It's possible, however, that a less strongly distance weighted mean would provide a more accurate measure of temperature for the overall local region – although likely less accurate at the ozone monitoring station itself – or that the

2-station and 30-kilometer cutoffs are too restrictive. We investigate the effects of lessening the distance weighting in the calculation of expected temperature at the ozone monitoring station, as well as relaxing the constraints on both the number of included weather stations and distance from the ozone monitor in Table B5. Specifically, columns (1) and (2) report results of our main specification when we maintain the 2-station/30-kilometer restriction, but decrease the weighting scheme to either the simple arithmetic mean in column (1), or a non-squared inverse distance weight in column (2). Columns (3) and (4) use the same weighting schemes as in columns (1) and (2), but now include temperature readings from the 5 closest weather monitoring stations within 80 kilometers. Results in all four columns are relatively stable and consistent with our main specification.

B.2. Heterogeneity

Results by Local Climate Beliefs — Here we examine whether climate change beliefs may alter the effectiveness of existing government regulations and policy in inducing climate adaptation. On the one hand, the enormous heterogeneity in economic and environmental preferences/beliefs across local jurisdictions (e.g., Howe et al., 2015) makes the enactment of comprehensive climate policy difficult (Goulder, 2020). On the other hand, the same heterogeneity in local beliefs may be able to be leveraged to push forward local actions supporting climate adaptation. Using the results of a relatively recent county-level survey regarding residents' beliefs in climate change (Howe et al., 2015), we split the set of counties in our sample into terciles of high, median, and low belief, and interact indicators for high- and low-belief counties with our temperature and control variables.[15] Appendix Table B9 shows that low-belief counties are, on average, less populous, poorer, and more politically conservative than mid-belief counties, while high-belief counties skew more towards the political left, are richer and more populous.

[15] Appendix Figure A10 depicts the evolution of ozone concentration for these three sets of counties from 1980-2013. While the pattern for low- and median-belief counties track quite similarly, high-belief counties began with higher ozone concentrations, on average, but have now mostly converged with the other counties.

Table B8 reports the results. The main temperature effects represent the mid-belief tercile, whose interactions are omitted, and the coefficients of the interactions with low- and high-belief terciles are relative to the omitted category. In column (1) we can see that the ozone response to temperature is consistently larger in high-belief counties relative to the middle tercile, while for low-belief counties the evidence is mixed. This pattern is consistent with more economic activity in the more urban and richer high-belief counties.

In column (2), the adaptation estimates for the mid-belief tercile are qualitatively similar to our main estimates for nonattainment and attainment counties, although the implied level of adaptation is somewhat muted for nonattainment counties and somewhat larger for attainment counties. Comparatively, adaptation in low-belief counties is statistically indistinguishable from the middle-tercile when in nonattainment, but 44 percent lower when in attainment. This pattern is reversed for high-belief counties, with statistically indifferent adaptation relative to the middle-tercile when in attainment, but 45 percent higher when out of attainment. These results translate into positive measures of regulation-induced adaptation across all three sets of counties, as seen in column (3) – although critically arising from different channels. Low-belief counties, bound by the NAAQS when in nonattainment, are constrained to meet at least the minimum level of ozone reduction, inducing adaptation levels similar to the middle-tercile. When in attainment, however, low-belief counties make much less effort than other counties to adapt – this is reasonable because they do not face stringent regulation, are generally poorer, and do not believe in climate change. In this case, the NAAQS induces adaptation by enforcing a required level of action. Conversely, high-belief counties engage in normal levels of adaptation when in attainment, but increase their adaptive behavior when in nonattainment. This, too, seems reasonable, as this set of counties is probably the most affected by the NAAQS, are generally richer – thus more able to afford the adjustments implied by the NAAQS – and are more believing in climate change – thus more willing to adjust behaviors or make investments in response to a changing climate.

Because local beliefs in climate change are closely related to income, education, and political affiliation, one may wonder whether the heterogeneity in the response to environmental policy is not driven by other local unobserved factors. To provide evidence corroborating the role of environmentally-related local preferences, we investigate whether local views on single parenthood, as proxied by the county fraction of children growing up in single-parent families in 2012-16 (Chetty et al., 2018), affect climate adaptation induced by the NAAQS for ambient ozone. For ease of comparison, we once again split counties into low- median- and high-"belief" counties based on this measure and interact the indicators for low- and high-belief with our other variables, taking the median as the baseline. Table B10 reports the results in the same format as Table B8. In column (1), the interactions of temperature shocks and norms in nonattainment and attainment counties are by and large not statistically significant. The implied adaptation estimates presented in column (2) show no meaningful changes for counties in the low- or high-belief terciles. More importantly, the estimates for regulation-induced adaptation displayed in column (3) are statistically indistinguishable across all terciles of local preferences for single parenthood. Thus, the local unobserved factors that may shape responses to environmental policy seem to be the ones related to local preferences for environmental amenities, as we have hypothesized.

Ozone Formation in VOC- and NOx-limited Areas: Implications for Local Adaptation — As shown above, local climate change beliefs may effect the level of adaptation induced by the CAA. At the same time, the underlying composition of precursor emissions in the local atmosphere may also play an important role. Due to the Leontief-like production function of ozone, counties may find themselves with a baseline atmospheric composition that is "limited" in one precursor component – VOC or NOx. Urban areas are more prone to being VOC-limited, due to high levels of NOx pollution from production facilities and transportation, while rural areas are more prone to being NOx-limited due to the lack of such facilities and proximity to more VOC-rich undeveloped land. Counties with such a "limited" atmosphere may find it easier to adapt to climate change because even a small reduction in the limiting precursor's emissions could lead to meaningful reductions in ozone. Nonattainment counties in particular may exploit this option in an attempt to bring themselves back into attainment, amplifying regulation-induced adaptation in precursor-limited areas. We explore this important feature of the production function of ozone in Table B11 by interacting our main specification with indicators for whether a county is, in general, VOC- or NOx- limited – taking counties with non-limited atmosphere as the baseline. Unfortunately, data on VOC and NOx emissions are less available than for ozone,[16] and thus our estimating sample is restricted to approximately 20 percent of our main sample. For reference, we thus first estimate our main specification on this reduced sample, finding results strikingly similar to Table 1, reported here in column (1), and in column (2) for the implied measures of adaptation. Columns (3) and (4) report estimated impacts and implied adaptation, respectively, once interacting our measures of VOC- and NOx-limited atmosphere. Our results suggest that while counties without a precursor-limited atmosphere still observe regulation-induced adaptation, the effect is almost quadrupled in VOC-limited counties. NOx-limited counties similarly see a large increase, approximately doubling the effect in non-limited counties, but the estimate is statistically imprecise – likely due to the smaller number counties that fall into this sub-group.[17]

Results by Decade — To examine temporal heterogeneity, Table B12 reports our results by decade. We split our sample into three "decades" – 1980-90, 1991-2001, and 2002-2013 – so that we have roughly the same number of years in each. We find that the effects of both the climate norm and temperature shock in attainment as well as nonattainment counties, are decreasing over time, as shown in column (1). In column (2), we report the implied measures of adaptation in nonattainment and attainment counties, for each of the three decades. By comparing these differential magnitudes of adaptation in nonattainment

[16]See Appendix A.3 for further details of this data and our construction of the "limited" indicator variables.

[17]Specifically, observations in non-limited counties account for just under 60 percent of the estimating sample, while just over 36 percent are VOC-limited observations and the remainder, approximately 4 percent, are NOx-limited.

vs attainment counties, we can get our regulation-induced adaptation measures in each decade. The estimates suggest that regulation-induced adaptation was 0.39 ppb in the 1980's, 0.28 ppb in the 1990's, and 0.22 ppb in the 2000's. While seeming to decrease over time, potentially driven by technological innovation and market forces in attainment counties, we cannot rule out that they are statistically indifferent from our primary estimates in Table 1.

Nonlinear Effects of Temperature — Because ozone formation may be intensified with higher temperatures, we also examine the heterogeneous nonlinear effects of daily maximum temperature on ambient ozone concentrations. Similar to our previous investigations we start by creating indicator variables denoting whether the contemporaneous daily maximum temperature at a given ozone monitor falls within a certain 5°C temperature bin. In this way, the marginal effect of a 1°C change in either component of temperature is allowed to vary across each 5°C temperature bin. As expected, we find that higher temperatures generally lead to higher ozone concentrations. The lowest bin is below 20°C (just over the 10th percentile of our temperature distribution), and the highest bin is above 35°C (90th percentile of our temperature distribution). Tables B13a and B13b present the results of our preferred specification when interacting each of these temperature bin indicators with our other covariates in column (1). The implied measures of adaptation for both nonattainment and attainment counties are presented in column (2). By comparing the adaptation estimates for nonattainment vs attainment counties we arrive at our measure of regulation-induced adaptation for each temperature bin.

Below 20°C, temperature impacts are much lower, as we would expect, although adaptation estimates are in line with our main specification. Between 20-25°C and 25-30°C, temperature impacts steadily increase, while adaptation estimates are lower and statistically distinguishable from our main specification. Once the temperature increases above 30°C, however, the impact of the climate norm begins to attenuate – especially in nonattainment counties – and the estimate of regulation-induced adaptation increases substantially. Between 30-35°C, the magnitude of regulation-induced adaptation is 50% larger than our main specification, and above 35°C it is more than double, although we cannot rule out that they are statistically indifferent from our main specification. Notably, in nonattainment counties, adaptation reduces the effect of a 1°C increase in temperature by over 60 percent when temperatures are above 35°C, which is all the more relevant given the prospects of ever increasing temperatures in the coming decades.

This relatively high level of adaptation above 35°C – especially in nonattainment counties – can be plausibly explained by at least two reasons. First, regions having temperatures above 35°C might have higher incidence of sunlight which might lead to more extensive use of solar panels to generate electricity. Higher temperatures might be creating an environment that is more suited to shifts away from conventional and dirtier sources of power generation, thus leading to higher levels of adaptation. Second, and more specific to regulation-induced adaptation, days that are exceptionally hot are more likely to cause exceptionally high levels of ozone, which could trigger additional regulatory oversight. In order to avoid this, firms would be most likely to concentrate adaptation efforts on days where the "climate normal" temperature is itself the hottest.

Table B1: Alternative Lengths of Climate Norm

	Daily Max Ozone Levels (ppb)			
	3-yr MA	5-yr MA	10-yr MA	20-yr MA
	(1)	(2)	(3)	(4)
Nonattainment x Shock	1.992***	1.991***	1.986***	1.987***
	(0.082)	(0.081)	(0.080)	(0.079)
Nonattainment x Norm	1.346***	1.350***	1.362***	1.360***
	(0.064)	(0.065)	(0.067)	(0.067)
Attainment x Shock	1.266***	1.262***	1.260***	1.261***
	(0.027)	(0.027)	(0.027)	(0.027)
Attainment x Norm	0.922***	0.938***	0.956***	0.961***
	(0.033)	(0.033)	(0.034)	(0.035)
Implied Adaptation:				
Nonattainment Counties	0.646***	0.641***	0.625***	0.627***
	(0.055)	(0.056)	(0.056)	(0.055)
Attainment Counties	0.344***	0.323***	0.304***	0.300***
	(0.028)	(0.028)	(0.028)	(0.029)
Regulation Induced	0.302***	0.317***	0.321***	0.328***
	(0.056)	(0.056)	(0.056)	(0.056)
All Controls	Yes	Yes	Yes	Yes
Observations	5,139,529	5,139,529	5,139,529	5,139,529
R^2	0.434	0.434	0.434	0.434

Notes: This table addresses the potential concerns with the measurement of the climate norm as a 30-year monthly moving average of temperature, lagged by 1 year. To explore whether measurement error is a cause of concern in our analysis, we estimate Equation (2) using alternative definitions for the climate norm. From column (1) through column (4), we report the estimates using a 3-, 5-, 10- and 20-year moving average of temperature as the climate norm. Recall that all moving averages are lagged by one year to allow for the potential adaptation responses by individuals and firms. As argued seminally by Solon (1992), as we increase the time window of a moving average, the permanent component of a variable that also includes a transitory component will be less mismeasured. Our estimates remain remarkably stable over the different lengths of the moving averages, but if anything, they get slightly larger until the 20-year moving average. There is a slight decline in the coefficient of the climate norm as we move from the 20-year to 30-year moving average (as reported in Table 1), which suggests that the widely used three-decade averages of meteorological variables including temperature are close to the long-run norms. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B2: Adaptation Responses

	Daily Max Ozone Levels (ppb)		
	Long-Run 10-year Lag	Long-Run 20-year Lag	Short-Run *2004-2013 only*
	(1)	(2)	(3)
Nonattainment x Shock	1.987***	1.987***	1.406***
	(0.078)	(0.078)	(0.047)
Nonattainment x Norm	1.353***	1.351***	0.715***
	(0.067)	(0.067)	(0.056)
Shock x Action Day			−0.147
			(0.224)
Attainment x Shock	1.265***	1.267***	0.995***
	(0.028)	(0.028)	(0.020)
Attainment x Norm	0.947***	0.935***	0.484***
	(0.035)	(0.034)	(0.028)
Shock x Action Day			−0.056
			(0.150)
Implied Adaptation:			
Nonattainment Counties	0.634***	0.636***	0.691***
	(0.052)	(0.050)	(0.044)
Attainment Counties	0.318***	0.333***	0.511***
	(0.029)	(0.030)	(0.029)
Regulation Induced	0.316***	0.303***	0.179***
	(0.054)	(0.053)	(0.041)
Induced x Action Day			−0.091
			(0.256)
All Controls	Yes	Yes	Yes
Observations	5,131,949	5,127,892	1,879,044
R^2	0.434	0.434	0.422

Notes: This table reports estimates when allowing more or less time for economic agents to engage in adaptive behavior. The estimates in columns (1) and (2) are obtained by Equation (2), but using 10- and 20-year lags between the moving average and contemporaneous temperature, rather than the usual 1-year lag. By doing so, agents are provided with more time to potentially adjust to climate change. Even though we would expect that the effects of the weather shocks to be similar, one might expect the effects of the climate norm to be smaller than before, as agents might be more able to adapt when given more time. Yet, our estimates are remarkably similar to our main results in Table 1. Column (3) continues using the 1-year lag of the main specification, but adds an interaction term for "ozone action day" announcements at the county-level to estimate short-run adaptive behavior. These are days in which the relevant air quality authority expects to observe unhealthy levels of pollution. Individuals and firms are urged to take *voluntary* action to reduce precursor emissions. The estimate for the interaction between temperature shocks and action days is economically and statistically insignificant, pointing to limited opportunities for economic agents to adjust in the short run. Note that although action day policies first began in the 1990's, EPA only provided data beginning in 2004, leading to a restricted overall sample (approximately 36% of our full sample). Additionally, recall that the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B3: Further Robustness Checks

	Daily Max Ozone Levels (ppb)		
	Daily Moving Average	Semi-Balanced Panel	Meteorological Controls
	(1)	(2)	(3)
Nonattainment x Shock	1.997***	2.177***	2.056***
	(0.080)	(0.107)	(0.082)
Nonattainment x Norm	1.419***	1.582***	1.351***
	(0.068)	(0.085)	(0.065)
Attainment x Shock	1.265***	1.562***	1.228***
	(0.028)	(0.084)	(0.083)
Attainment x Norm	0.973***	1.286***	0.775***
	(0.032)	(0.102)	(0.089)
Average Wind Speed			−2.204***
			(0.284)
Total Daily Sunlight			0.015
			(0.015)
Implied Adaptation:			
Nonattainment Counties	0.578***	0.595***	0.705***
	(0.053)	(0.088)	(0.086)
Attainment Counties	0.292***	0.276***	0.453***
	(0.028)	(0.076)	(0.074)
Regulation Induced	0.286***	0.319***	0.251**
	(0.054)	(0.093)	(0.108)
All Controls	Yes	Yes	Yes
Observations	5,139,460	520,670	453,859
R^2	0.433	0.408	0.441

Notes: This table checks the sensitivity of our main results in Table 1 to changes in the primary econometric specification given by Equation (2) and sample restrictions. Column (1) replaces the monthly moving average with a daily moving average of temperature as the climate norm. Although the results are almost identical to our main estimates in Table 1, we prefer to use the monthly moving averages in our main specification because it is likely that individuals recall climate patterns by the month and not the day of the year. Column (2) reports estimates from a semi-balanced panel of 92 ozone monitors that form around 11% of our complete sample. Muller and Ruud (2018) have argued that the location of pollution monitors is not necessarily random and in most cases monitors are placed in areas where pollution is high and compliance with the regulation is a question. As expected, the impacts of both components of temperature are elevated, as compared to column (2) of Table 1, where we use our preferred unbalanced panel of monitors that is likely more nationally representative, though notably the adaptation estimates are largely unchanged. Column (3) provides estimates based on the reduced sample for which we have information on additional meteorological variables- average wind speed and total daily sunlight. High wind speeds prevent the build-up of ozone precursors and ultra-violet solar radiation triggers chemical reactions leading to the formation of ground-level ozone. Having controlled for these additional parameters as well, which have statistically significant impacts on ozone, our primary estimates remain indistinguishable from our results in Table 1. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B4: Further Sample Restrictions: Historical NAAQS Designations

	Same NAAQS Designation Over Sample Period		Switching NAAQS Designation Over Sample Period	
	Ozone (ppb)	Adaptation	Ozone (ppb)	Adaptation
	(1)	(2)	(3)	(4)
Nonattainment x Shock	1.948***		1.996***	
	(0.115)		(0.083)	
Nonattainment x Norm	1.270***	0.678***	1.404***	0.593***
	(0.137)	(0.098)	(0.071)	(0.056)
Attainment x Shock	0.970***		1.444***	
	(0.027)		(0.042)	
Attainment x Norm	0.489***	0.480***	1.168***	0.276***
	(0.034)	(0.034)	(0.046)	(0.037)
Regulation Induced		0.198*		0.317***
		(0.104)		(0.058)
All Controls	Yes		Yes	
Observations	1,122,101		4,017,428	
R^2	0.352		0.445	

Notes: This table checks the sensitivity of our main results in Table 1 to alternative restrictions in the sample used to estimate the primary econometric specification given by Equation (2). Column (1) reports results when restricting the sample to only those counties that were either consistently designated as in attainment or designated as in nonattainment across the entire sample period, excluding all counties with variation in their attainment status. Conversely, column (3) reports results when restricting the sample to include only those counties with variation in their attainment status across the sample period. Columns (2) and (4) report the respective levels of implied adaptation in attainment and nonattainment counties, as well as the resulting measure of regulation-induced adaptation. In both cases our estimate of regulation-induced adaptation remains statistically indistinguishable from our full sample estimate, indicating that our primary results are not being driven by a sub-set of counties with specific NAAQS designations. The full list of controls are the same as in the main model, depicted in column (2) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B5: Alternative Criteria for Selection of Weather Stations

	Daily Max Ozone Levels (ppb)			
	(1)	(2)	(3)	(4)
Nonattainment x Shock	2.043***	2.019***	2.149***	2.135***
	(0.080)	(0.080)	(0.094)	(0.091)
Nonattainment x Norm	1.353***	1.352***	1.344***	1.343***
	(0.067)	(0.067)	(0.066)	(0.065)
Attainment x Shock	1.298***	1.281***	1.345***	1.334***
	(0.027)	(0.027)	(0.028)	(0.028)
Attainment x Norm	0.957***	0.957***	0.946***	0.946***
	(0.036)	(0.035)	(0.036)	(0.035)
Implied Adaptation:				
Nonattainment Counties	0.690***	0.667***	0.805***	0.792***
	(0.052)	(0.053)	(0.064)	(0.063)
Attainment Counties	0.341***	0.325***	0.399***	0.388***
	(0.030)	(0.029)	(0.029)	(0.029)
Regulation Induced	0.348***	0.342***	0.406***	0.404***
	(0.055)	(0.056)	(0.066)	(0.064)
Distance Cut-off	30 km	30 km	80 km	80 km
Stations Included	2	2	5	5
Weighting Scheme	Simple Avg	1/Dist	Simple Avg	1/Dist
All Controls	Yes	Yes	Yes	Yes
Observations	5,139,529	5,139,529	5,284,426	5,284,426
R^2	0.437	0.436	0.439	0.440

Notes: This table reports estimates from models using alternative criteria to match weather stations to ozone monitors. These estimates are from Equation (2), but we have varied the distance cut-off, the number of monitors in the matching as well as the averaging strategy to match the weather stations with the ozone monitors. Recall that in our main estimates in Table 1, we arrive at our sample by matching each ozone monitor to the closest two weather stations within a 30 km radius and we get the weather realization at each ozone monitor by averaging our weather variables over these closest two weather stations, weighted by their inverse squared distance from the monitor. In columns (1) and (2), we continue to use the closest two weather stations whereas in columns (3) and (4) we use the closest 5 weather stations within a 80 km radius of the ozone monitor. We also vary the weighting scheme: in columns (1) and (3), instead of a weighted average we just use a simple average across all matched weather stations; whereas in columns (2) and (4) we average the weather variables weighted by the inverse of the distance from the monitor. Our estimates are stable across the four columns and very similar to our main results in Table 1. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B6: Alternative Outcomes: Employment and Wages

	Log Employment	Log Wages
	(1)	(2)
Nonattainment x Shock	−0.002	0.004*
	(0.001)	(0.002)
Nonattainment x Norm	0.002***	−0.002
	(0.000)	(0.001)
Attainment x Shock	0.000	−0.001
	(0.001)	(0.001)
Attainment x Norm	0.001***	0.000
	(0.000)	(0.001)
Nonattainment Adaptation	0.000	0.000
	(0.001)	(0.002)
Attainment Adaptation	−0.001	−0.001
	(0.001)	(0.002)
Regulation Induced Adaptation	0.001	0.001
	(0.001)	(0.001)
All Controls	Yes	Yes
Observations	84,423	28,390
R^2	0.996	0.972

Notes: This table reports the effects of temperature shocks and changes in the climate norm on monthly log employment and quarterly log wages at the county level for all counties in our main estimating sample, years 1990-2013. As shown by, e.g., Henderson (1996) and Becker and Henderson (2000), manufacturing plants have relocated in response to ozone nonattainment designations. Critically, however, the lack of any response in employment or wages to climate variables, in both attainment and nonattainment counties, suggests that firms are not adapting to climatic changes when making such relocation decisions. This lack of relocation response implies that the main channel for our central estimates of regulation-induced adaptation, and adaptation in general, from Table 1 is more likely stemming from "in-place" behavioral or production adjustments, rather than permanent or transitory shifts in production location. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B7: Alternative Clustering and Bootstrapped Standard Errors

	Daily Max Ozone Levels (ppb)	Implied Adaptation
	(1)	(2)
Nonattainment x Shock	1.990***	
(County Cluster)	(0.079)	
(State Cluster)	(0.126)	
(Bootstrapped)	(0.081)	
Nonattainment x Norm	1.351***	0.639***
(County Cluster)	(0.067)	(0.054)
(State Cluster)	(0.103)	(0.104)
(Bootstrapped)	(0.065)	(0.055)
Attainment x Shock	1.263***	
(County Cluster)	(0.027)	
(State Cluster)	(0.060)	
(Bootstrapped)	(0.028)	
Attainment x Norm	0.956***	0.308***
(County Cluster)	(0.035)	(0.029)
(State Cluster)	(0.076)	(0.058)
(Bootstrapped)	(0.037)	(0.029)
Regulation Induced		0.332***
(County Cluster)		(0.056)
(State Cluster)		(0.078)
(Bootstrapped)		(0.056)
All Controls	Yes	
Observations	5,139,529	
R^2	0.434	

Notes: This table compares the standard errors of our main estimates with ones obtained by clustering at the state- rather than county-level, and by bootstrap (block method clustered at the county level, 250 iterations). The latter addresses the potential concern that because our temperature shocks and norm are constructed, they could be seen as generated regressors. Bootstrapped standard errors are all within 6% of those estimated via clustering at the county level, and across all three estimation methods recovered coefficients remain statistically significant at the 1% level. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B8: Adaptation by Local Beliefs in Climate Change

	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	(1)	(2)	(3)
Nonattainment x Shock	1.698***		
	(0.060)		
x Low Belief	0.020		
	(0.087)		
x High Belief	0.388***		
	(0.108)		
Nonattainment x Norm	1.171***	0.527***	
	(0.085)	(0.087)	
x Low Belief	−0.040	0.060	
	(0.086)	(0.094)	
x High Belief	0.152	0.236**	
	(0.103)	(0.107)	
Attainment x Shock	1.268***		
	(0.033)		
x Low Belief	−0.093*		
	(0.049)		
x High Belief	0.057		
	(0.069)		
Attainment x Norm	0.874***	0.394***	0.133*
	(0.043)	(0.037)	(0.074)
x Low Belief	0.081	−0.173***	0.234**
	(0.062)	(0.051)	(0.107)
x High Belief	0.139*	−0.082	0.318**
	(0.081)	(0.071)	(0.144)
All Controls	Yes		
Observations	5,139,529		
R^2	0.435		

Notes: This table reports differential climate and adaptation estimates according to local beliefs on the existence of climate change. All counties in the sample were split into terciles based on the results of a survey conducted on climate change beliefs (Howe et al., 2015), and those terciles were then interacted with the main variables in Equation (2). In column (1), the main impacts of the climate norm and temperature shock represent the effects in counties having beliefs in the middle tercile (for which the interactions have been omitted). The coefficients on the interaction terms reveal the incremental effects of the climate norm and temperature shock in low- and high-belief terciles. Column (2) reports our implied measures of adaptation. By comparing the main estimates of the climate norm and shock in column (1), we obtain adaptation in mid-belief counties. Using the coefficients on the interaction terms, we obtain the incremental adaptation in low- and high-belief counties in comparison to the mid-belief counties. Column (3) displays the measure of regulation-induced adaptation for the mid-belief tercile, followed by the incremental induced adaptation in low- and high-belief terciles. Each estimate represents the difference of adaptation in nonattainment and attainment counties reported in column (2). The full list of controls are the same as in the main model, depicted in column (2) of Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B9: County Summary Statistics by Belief in Climate Change

	Count	Mean	Std. Dev.	Minimum	Maximum
	Panel A. Low Belief Counties				
Population (1000's)	334	80.8	107.3	0.8	837.5
Average Education (Years)	334	12.7	0.6	11.0	14.3
Median Income ($1000/year)	334	48.5	10.4	21.9	83.3
Average Income ($1000/year)	334	61.5	11.3	36.9	111.9
Voted Democrat in 2008 (%)	334	37.2	10.4	6.6	64.8
	Panel B. Median Belief Counties				
Population (1000's)	335	162.7	213.3	1.9	1,870.4
Average Education (Years)	335	13.2	0.6	11.8	15.1
Median Income ($1000/year)	335	53.9	12.4	26.3	109.8
Average Income ($1000/year)	335	68.3	14.6	39.2	142.2
Voted Democrat in 2008 (%)	335	45.6	10.7	17.0	74.9
	Panel C. High Belief Counties				
Population (1000's)	336	478.5	803.3	1.3	9,758.3
Average Education (Years)	336	13.6	0.7	11.5	16.1
Median Income ($1000/year)	336	60.5	16.8	30.4	125.7
Average Income ($1000/year)	336	79.5	21.3	41.1	146.0
Voted Democrat in 2008 (%)	336	56.8	11.6	16.0	92.5

Notes: This table reports summary statistics of underlying demographics for each of the terciles of counties used in Table B8. Demographic data were obtained from the 2006-2010 5-year American Community Survey, with income reported in 2015 dollars, and average years of education based on a population weighted average of educational attainment status for the county population over 25 years of age. Voting data is obtained at the county level from the MIT Election Lab, and refers specifically to votes cast in the 2008 presidential election.

Table B10: Adaptation by Local 'Preferences' for Single Parenting

	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	(1)	(2)	(3)
Nonattainment x Shock	2.147***		
	(0.167)		
x Low Tercile	−0.159		
	(0.170)		
x High Tercile	−0.216		
	(0.164)		
Nonattainment x Norm	1.431***	0.716***	
	(0.142)	(0.100)	
x Low Tercile	0.039	−0.198	
	(0.115)	(0.127)	
x High Tercile	−0.068	−0.147	
	(0.117)	(0.123)	
Attainment x Shock	1.311***		
	(0.049)		
x Low Tercile	−0.123**		
	(0.062)		
x High Tercile	−0.021		
	(0.068)		
Attainment x Norm	1.009***	0.302***	0.414***
	(0.068)	(0.044)	(0.102)
x Low Tercile	−0.096	−0.027	−0.170
	(0.077)	(0.062)	(0.151)
x High Tercile	−0.082	0.061	−0.209
	(0.089)	(0.069)	(0.158)
All Controls	Yes		
Observations	5,139,529		
R^2	0.435		

Notes: This table reports differential climate and adaptation estimates according to local beliefs unrelated to environmental amenities – the 'preference' for single parenting. All counties in the sample were split into terciles based on the fraction of single-parent households from the Opportunity Atlas (Chetty et al., 2018), and those terciles were then interacted with the main variables in Equation (2). In column (1), the main impacts of the climate norm and temperature shock represent the effects in counties classified in the middle tercile (for which the interactions have been omitted). The coefficients on the interaction terms reveal the incremental effects of the climate norm and temperature shock in low- and high-fraction terciles. Column (2) reports our implied measures of adaptation. By comparing the main estimates of the climate norm and shock in column (1), we obtain adaptation in mid-fraction counties. Using the coefficients on the interaction terms, we obtain the incremental adaptation in low- and high-fraction counties in comparison to the mid-fraction counties. Column (3) displays the measure of regulation-induced adaptation for the mid-fraction tercile, followed by the incremental induced adaptation in low- and high-fraction terciles. Each estimate represents the difference of adaptation in nonattainment and attainment counties reported in column (2). Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B11: Adaptation by VOC- or NOx-limited Atmosphere

	Main Specification		VOC/NOx-Limited	
	Ozone(ppb)	Adaptation	Ozone(ppb)	Adaptation
	(1)	(2)	(3)	(4)
Nonattainment x Shock	2.097***		2.139***	
	(0.136)		(0.176)	
x VOC-limited			0.439*	
			(0.225)	
x NOx-limited			−0.134	
			(0.273)	
Nonattainment x Norm	1.398***	0.699***	1.406***	0.733***
	(0.149)	(0.107)	(0.159)	(0.118)
x VOC-limited			0.126	0.313*
			(0.142)	(0.176)
x NOx-limited			−0.235	0.101
			(0.239)	(0.328)
Attainment x Shock	1.707***		1.872***	
	(0.182)		(0.245)	
x VOC-limited			−0.513*	
			(0.262)	
x NOx-limited			−0.421	
			(0.342)	
Attainment x Norm	1.326***	0.381***	1.385***	0.487***
	(0.133)	(0.112)	(0.159)	(0.135)
x VOC-limited			−0.106	−0.407**
			(0.125)	(0.182)
x NOx-limited			−0.288**	−0.133
			(0.125)	(0.307)
Regulation Induced		0.318***		0.246**
		(0.104)		(0.117)
x VOC-limited				0.720**
				(0.346)
x NOx-limited				0.233
				(0.592)
All Controls	Yes		Yes	
Observations	1,007,563		1,007,563	
R^2	0.459		0.460	

Notes: This table reports estimates of temperature shock and climate norm interacted with an indicator of whether a county was VOC- or NOx-limited over a 5-year interval (1980-1984, 1985-1989, etc.). For comparison, columns (1) and (2) depict the results of our main specification under the restricted sample (about 20% of our full sample) for which precursor pollutant data is available. In columns (3), main impacts, and (4), implied adaptation, results reflect the effect for non-limited counties, while the interaction terms depict the differential effect in precursor limited counties. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B12: Results by Decade

	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	(1)	(2)	(3)
	Panel A. 1980's		
Nonattainment x Shock	2.496***		
	(0.165)		
Nonattainment x Norm	1.746***	0.750***	
	(0.115)	(0.119)	
Attainment x Shock	1.715***		
	(0.078)		
Attainment x Norm	1.356***	0.359***	0.391***
	(0.064)	(0.052)	(0.106)
	Panel B. 1990's		
Nonattainment x Shock	2.042***		
	(0.068)		
Nonattainment x Norm	1.470***	0.571***	
	(0.057)	(0.056)	
Attainment x Shock	1.360***		
	(0.034)		
Attainment x Norm	1.068***	0.292***	0.279***
	(0.037)	(0.039)	(0.064)
	Panel C. 2000's		
Nonattainment x Shock	1.506***		
	(0.042)		
Nonattainment x Norm	0.959***	0.547***	
	(0.061)	(0.061)	
Attainment x Shock	1.054***		
	(0.022)		
Attainment x Norm	0.729***	0.324***	0.223***
	(0.034)	(0.033)	(0.054)
All Controls	Yes		
Observations	5,139,529		
R^2	0.441		

Notes: This table reports our main estimates disaggregated by the three "decades" in our sample: 1980-1990; 1991-2001 and 2002-2013. Estimates in column (1) correspond to Equation (2), while estimates in column (2) report the implied measure of adaptation. The effects of the climate norm and temperature shock are decreasing over time in both attainment and nonattainment counties. Similarly, the measure of regulation-induced adaptation, column (3), appears to be somewhat decreasing across the three decades, although still statistically indistinguishable from our full sample results in Table 1. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B13a: Nonlinear Effects of Temperature

	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	Panel A. Below 20°C		
	(1)	(2)	(3)
Nonattainment x Shock	0.795***		
	(0.023)		
Nonattainment x Norm	0.124***	0.670***	
	(0.039)	(0.036)	
Attainment x Shock	0.594***		
	(0.021)		
Attainment x Norm	0.192***	0.403***	0.268***
	(0.036)	(0.032)	(0.047)
	Panel B. 20-25°C		
Nonattainment x Shock	1.900***		
	(0.120)		
Nonattainment x Norm	1.438***	0.462***	
	(0.114)	(0.040)	
Attainment x Shock	1.361***		
	(0.042)		
Attainment x Norm	1.081***	0.280***	0.182***
	(0.053)	(0.031)	(0.048)
All Controls	Yes		
Observations	5,139,529		
R^2	0.447		

Notes: This table explores the non-linear effects of the climate norm and temperature shock on ambient ozone concentrations. Specifically, we consider five bins of daily temperature: below 20°C, 20-25°C, 25-30°C, 30-35°C and above 35°C. Estimates in column (1) correspond to Equation (2) after interacting indicator variables for each of these temperature bins, while estimates in column (2) report the implied measure of adaptation. Although regulation-induced adaptation on days between 20-25°C and 25-30°C appears to be lower than in our full-sample model, above 35°C the magnitude of regulation-induced adaptation more than doubles, which is encouraging, given the prospects of ever increasing temperatures over the next decades. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table B13b: Nonlinear Effects of Temperature

	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	(1)	(2)	(3)
	Panel C. 25-30°C		
Nonattainment x Shock	2.488***		
	(0.118)		
Nonattainment x Norm	2.241***	0.246***	
	(0.131)	(0.053)	
Attainment x Shock	1.407***		
	(0.049)		
Attainment x Norm	1.365***	0.042	0.204***
	(0.060)	(0.033)	(0.051)
	Panel D. 30-35°C		
Nonattainment x Shock	2.509***		
	(0.132)		
Nonattainment x Norm	1.678***	0.831***	
	(0.193)	(0.104)	
Attainment x Shock	1.772***		
	(0.079)		
Attainment x Norm	1.394***	0.379***	0.452***
	(0.099)	(0.055)	(0.092)
	Panel E. Above 35°C		
Nonattainment x Shock	2.134***		
	(0.148)		
Nonattainment x Norm	0.809***	1.325***	
	(0.206)	(0.185)	
Attainment x Shock	1.642***		
	(0.114)		
Attainment x Norm	1.007***	0.635***	0.689***
	(0.150)	(0.153)	(0.225)
All Controls	Yes		
Observations	5,139,529		
R^2	0.447		

Notes: This table continues the results from Table B13a for the temperature bins 25-30°C, 30-35°C and above 35°C in panels (C), (D), and (E), respectively. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is lagged by 3 years. The full list of controls are the same as in the main model, depicted in Table 1. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Appendix C. Formalization of Conceptual Framework

This appendix provides further elaboration of the conceptual framework and formalization of regulation-induced adaptation as discussed in Section II.

C.1. New vs. Existing Regulations to Address Climate Change

Global warming is the most significant of all environmental externalities (Nordhaus, 2019). Nevertheless, because of free-riding, it has been proven difficult to induce countries to join in an international agreement with significant reductions in emissions. In fact, countries have an incentive to rely on the emissions reductions of others without taking proportionate domestic abatement. Moreover, even nationally, there may be temporal free-riding: present generations may choose to enjoy the consumption benefits of high carbon emissions, while future generations pay for those emissions in lower consumption or a degraded environment.

Since it has been politically infeasible to reach worldwide agreements to reduce carbon emissions, Nordhaus (2015) has proposed the establishment of "climate clubs" to overcome free-riding in international climate policy. Because without sanctions against non-participants there are no stable coalitions other than those with minimal abatement, he argues that a regime with small trade penalties on non-participants can induce a large stable coalition with high levels of abatement. An important question is how a top-down "climate club" would get started, and how it would evolve from a small number of countries who see the logic, and define a regime, to then invite other countries to join. Nordhaus (2015) acknowledges that "[i]nternational organizations evolve in unpredictable ways. Sometimes, it takes repeated failures before a successful model is developed. (...) The destination of a Climate Club is clear, but there are many roads that will get there" (p.1352).

Recognizing the difficulty in establishing new regulations and policies such as "climate clubs" in the international stage, and carbon pricing (the first-best climate policy) in the domestic stage, and the urgency in tackling the challenges of climate change, Goulder (2020) advocates for considerations of political feasibility and costs of delayed implementation in the choice of potential climate policy. Second-best policies are, by definition, socially inefficient, but if they are politically feasible for near-term implementation, they might move up in the ordering of the policies considered by the federal government (Goulder, 2020). In this study, we demonstrate that existing government regulations and policy are already inducing adaptation to climate change, and argue that policymakers should take these co-benefits into account when enforcing or revising them. Furthermore, we find suggestive evidence that local beliefs might also be effective in shaping the responses to climate change.[18]

C.2. The Nature of Existing Regulations Inducing Adaptation

The potential for government regulations and policy to induce or inhibit adaptation to climate change relies on how the outcomes targeted by those policies interact with climate. When climate is an input in production, and the output is a marketable good or service, policies considering output and/or input levels may not only distort economic agents' behavior and generate deadweight loss, but also potentially affect adaptive behavior. On the one hand, Annan and Schlenker (2015) provide an illustration for the case of policies precluding adaptation by examining the impact of the federal crop insurance program on crop production. Insured farmers may not engage in the optimal protection against harmful extreme heat because the resulting crop losses are covered by the insurance program. On the other hand, policies such as the federal air conditioning subsidies for low-income families would also generate deadweight loss, but could induce adaptation to climate change (Barreca et al., 2016). In this case, policymakers could weigh these costs and benefits in their

[18]This result is consistent with the well-known heterogeneity in climate beliefs across local jurisdictions, and from previous findings highlighting the role of social norms in shaping responses to public policies. A strand of the literature has documented that environmental ideology is an important determinant of producer and consumer choices (e.g., Henderson, 1996; Kahn, 2007; Kotchen and Moore, 2008). Another strand of the literature provides evidence that "nudges" based on social norms can substantially and cost-effectively change consumer behavior towards environmentally-friendly outcomes (e.g., Allcott, 2011; Ferraro and Price, 2013). In this study, we explore how heterogeneity in local beliefs about climate change strongly associate with adaptation induced by existing government regulations and policy. Our prior is that local social norms and beliefs may play a key role in determining the success of policies addressing environmental externalities.

decision process, in addition to equity considerations. Notice that this last example refers to consumption of goods and services, not production as above, pointing to the generality of the concept.

In contrast, and absent direct climate policy, when climate is an input in the production of economic outcomes that arise from market failures, corrective policies targeting those outcomes may not only address market failures but might also lead to climate adaptation. In fact, in this second-best setting, policies correcting pre-existing market distortions may also address the externality of climate change (e.g., Goulder and Parry, 2008; Bento et al., 2014; Jacobsen et al., 2020). This is the case we are examining in this study: the NAAQS for ambient ozone not only deal with the externality of local air pollution, but also generate regulation-induced adaptation. As economic agents reoptimize the level of NOx and VOCs to comply with NAAQS regulations, taking changes in climate as given, they are actually coping not with uncontrolled emissions of those ozone precursors, but rather with climate change.[19] However, if inputs other than climate are also the result of externalities, and corrective policies target them instead, then there may be no incentives to adapt to climate change: economic agents might be able to change the levels of those inputs regardless of climate considerations. For the case of ambient ozone, two prominent corrective policies targeting its precursors – regulations restricting the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources, and the NOx Budget Trading Program – did reduce the undesirable output (Auffhammer and Kellogg, 2011; Deschenes, Greenstone and Shapiro, 2017), but did not create incentives to cope with climatic changes.

To make the concept of regulation-induced adaptation as clear as possible in the context we are studying, we use the schematic representation depicted in Figure 1. In this figure, the y-axis represents the output – ozone formation – and the x-axis represents one of the

[19]Ironically, another EPA regulation fostering adaptation to climate change in terms of ambient ozone concentration relates to cooling water systems and thermal discharges under the Clean Water Act (e.g., McCall, Macknick and Hillman, 2016). Power plants cannot withdraw water from rivers to cool boilers if the water temperature rises; the discharge of hot water would endanger aquatic wildlife. Thus, with global warming, plants may be forced to curtail operations. This would decrease emissions of ozone precursors, and ultimately reduce ambient ozone concentration. Hence, regulation-induced adaptation.

inputs – the ratio of NOx and VOCs, whose levels move along the linear production function $F(I(\text{VOC/NOx}), \text{Climate})$ represented by the upward-sloping black curve. The blue horizontal line represents the maximum ambient ozone concentration a county may reach while still complying with the NAAQS for ozone. Above that threshold, a county would be deemed out of compliance with the standards, or in "nonattainment." Assume that an ozone monitor is sited in a county that is initially complying with the standards, as in point A. Moreover, suppose for simplicity that emissions of ozone precursors are initially under control, but then temperature rises. Because this is a bidimensional diagram representing ozone as a function of VOC/NOx – taking climate as given – an increase in temperature shifts the production function upward and to the left. This new production function under climate change is represented by the red upward-sloping curve. Because we assumed emissions of ozone precursors were initially under control, an increase in temperature raises ozone concentration for the same level of the VOC/NOx ratio, reaching point B. Since the ozone concentration is now above the NAAQS threshold, the county goes out of attainment, and firms are mandated to make adjustments in their production process to comply with the air quality standards in the near future, usually three years after a county receives the nonattainment designation. Notice that firms need to respond to the regulation not because they were not careful in controlling emissions in the baseline, but rather because climate has changed. As they take steps to reduce emissions to reach attainment, moving along the new production function curve until point C, those economic agents are in fact adjusting to a changing climate. Thus, they are adapting to climate change because of the ozone NAAQS regulation, that is, they are engaging in regulation-induced adaptation.[20]

[20] Ambient ozone concentration is a negative externality. For completeness, public policy can also induce adaptation to climate change in addressing positive externalities. Besides the social desirability of increasing the equilibrium levels of those outcomes, such policies can create a co-benefit of adjusting to or coping with a changing climate. One example is the Medicaid-covered influenza vaccination. Severe influenza seasons are likely to emerge with global warming (Towers et al., 2013), but publicly-funded annual vaccination allows Medicaid beneficiaries to cope with climatic changes. This is in addition to the herd-immunity impact of influenza vaccination (White, forthcoming). Again, the concept of policy-induced adaptation is quite broad, and incentives affecting adaptive behavior are already in place in a variety of policies implemented around the world.

Despite the contribution of current government regulations and policy in promoting adaptation, we must recognize the second-best nature of these incentives. As discussed above, it is well-known that the first-best policy to tackle climate change is carbon pricing. Nevertheless, if the political economy of climate change policy is unfavorable to the first-best policy, then second-best solutions could be implemented (Goulder, 2020). One possibility is to impose or strengthen policies correcting market failures related to outcomes that depend on climate. The NAAQS for ambient ozone, for instance, is a regulation correcting a market failure – an air pollution externality – while fostering adaptation because ozone is formed in the presence of sunlight and warm temperatures.[21]

C.3. A Simple Formalization

To fix ideas, assume that firms produce X units of a consumption good. They use $G(X)$ units of the numeraire Z, and generate P units of pollution, assumed to be proportional to X. Since we are focusing on ozone pollution, and ozone formation depends on climate (C) as well, then inspired by Phaneuf and Requate (2017, Chapter 5) we define $P \equiv F(X, C) = \delta(C)X$, with $\delta_C(.) > 0$. Also, suppose that there is a continuum of consumers with wealth Y and quasilinear utility

$$U(X) + Z - r\delta(C)X, \tag{C.1}$$

where r is the marginal damage of ozone pollution.

Let p denote the market price of the consumption good X. Firms maximize profits,

$$max_X \; pX - G(X), \tag{C.2}$$

[21] Many other second-best policies have been implemented around the world. The economic rationale has been laid out many decades ago (Lipsey and Lancaster, 1956). In the context of climate change, a prominent example is the the corporate average fuel economy (CAFE) standards. A first-best policy would be taxing tailpipe emissions directly. Another incentive-based policy would be raising the gas tax. Either way, it would send a price signal to consumers, affecting which cars they purchase, and how much they drive. Besides reducing driving, a higher gas tax would have other important benefits that improving fuel economy does not, such as congestion relief and accident reduction.

and consumers maximize utility, taking pollution and climate as fixed:

$$max_X \, U(X) + Y - pX. \tag{C.3}$$

Demand (D) and supply (S) satisfy $U'(X^D) = p = G'(X^S)$. At the equilibrium price, private marginal benefit equals private marginal cost $U'(X) = G'(X)$, but this is not Pareto efficient because of the negative externality of ozone pollution imposed on consumers. It may be possible to improve welfare (W) by reducing production, perhaps through a regulation such as the NAAQS for ambient ozone. Using the perturbation argument, consider a small change in production $dX < 0$. By the envelope theorem,

$$dW = [p - G'(X)]dX + [U'(X) - p]dX - r\delta dX = -r\delta dX > 0. \tag{C.4}$$

Because $dW \equiv dW(C) = -r\delta(C)dX$, marginal reductions in X, e.g., to keep ozone concentrations below the NAAQS, would be welfare improving even in the case of a constant climate. In the case of climate change, however, the welfare gains from such reductions would be even greater, as the amount of pollution avoided by decreasing X would be proportionally larger. We refer to these further welfare gains as "regulation-induced adaptation," which can be interpreted as a *co-benefit* of the NAAQS for ambient ozone:

$$\frac{dW}{dC} = -r\delta_C dX > 0. \tag{C.5}$$

In the empirical analysis, we focus on estimating the extent to which ozone concentration is affected by climate change under the NAAQS regulation, relative to a benchmark without (or lower levels of) regulation, aiming at recovering δ_C. Thus, with an estimate of r from the literature (e.g., Deschenes, Greenstone and Shapiro, 2017), we should be able to provide some back-of-the-envelope calculations regarding changes in welfare.

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