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ABSTRACT

Time is of the Essence: Climate Adaptation Induced by Existing Institutions*

In the absence of first-best climate policy, we demonstrate that existing government institutions and policy established for reasons unrelated to climate change may induce climate adaptation. We examine the impact of temperature on ambient ozone concentration in the United States from 1980-2013, and the role of institution-induced adaptation. Ozone is formed under warm temperatures, and regulated by the Clean Air Act institution. Adaptation in counties out of attainment with air quality standards is 107 percent larger than under attainment, implying substantial institution-induced adaptation. Furthermore, local beliefs about climate change appear to reinforce adaptive behavior, suggesting a nontrivial role in second-best climate policy.

JEL Classification: Q53, Q54, Q58, H23, K32, P48, D02

Keywords: climate change, government institutions and policy, Clean Air Act, institution-induced adaptation, ambient ozone concentration, climate change beliefs

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I. Introduction

Many government institutions and policy have been established to address the underprovision of public goods and externalities. A few examples are public health and welfare programs, transportation infrastructure, and environmental standards. Several of these institutions allow individuals and firms to smooth out the effects of shocks – such as access to medical care when sick, job training when unemployed, and roads when evacuating from a disaster area. Because negative shocks will become more frequent and/or more severe with climate change, *existing* institutions may *incidentally* attenuate the adverse impacts of those shocks by enabling adaptive behavior. Thus, institutions created for reasons unrelated to climatic changes may help society cope with such changes by inducing adaptation. This study conceptualizes and provides credible and emblematic evidence of what we refer to as *institution-induced adaptation*. The context is the impact of temperature changes on ambient "bad" ozone in the United States from 1980-2013. Ozone is formed by a Leontief-like production function of nitrogen oxides (NOx) and volatile organic compounds (VOCs) under sunlight and warm temperatures; hence, affected by climate change. Furthermore, ambient ozone is a pollution externality regulated by the existing institution of the Clean Air Act.[1]

To understand the mechanism behind institution-induced adaptation in our setting, consider a location where emissions of ozone precursors are under control in the baseline. If a rise in temperature leads to more intense ozone formation and the violation of the National Ambient Air Quality Standards (NAAQS), economic agents will be pressured by the U.S. Environmental Protection Agency (EPA) to adopt pollution abatement strategies to reduce emissions of NOx and VOCs, and ultimately ambient ozone concentration. Since those actions would have to be taken not because of higher ozone precursor emissions but rather higher temperatures, we refer to the resulting decline in ozone levels as adaptation to climate change induced by the ozone NAAQS regulations. At the end of the day, the pollution shocks triggered by climate change may be attenuated by adjustments induced by

[1] North (1991)'s classic definition of institutions includes "constitutions, laws, property rights" (p.97).

the existing institution of the Clean Air Act.[2]

The insight that *existing* institutions established for reasons unrelated to climate change may mimic key incentives of comprehensive climate policy goes to the heart of the second-best theory (Lipsey and Lancaster, 1956; Harberger, 1964, 1971, 1974; Hines, 1999; Goulder and Williams, 2003). When the outcome of interest arises from market failures, climate change may exacerbate those failures (e.g., Goulder and Parry, 2008; Bento et al., 2014), but existing institutions will be there to smooth out the climate impacts.[3] Indeed, when the outcome of interest is affected by climate change, those government programs might generate an added *co-benefit* by enabling beneficiaries to cope with climatic changes.[4] Ultimately, existing institutions may serve as a *de facto* "surrogate carbon tax" for currently inexistent or incomplete climate policy, providing incentives for producers and consumers to internalize at least part of the social costs of carbon emissions. In fact, although economic theory provides clear guidance on addressing externalities, it has proven difficult to create new institutions to combat climate change, the most significant of all environmental externalities (Aldy, Barrett and Stavins, 2003; Stavins, 2011, 2019; Nordhaus, 2019; Aldy and Zeckhauser, 2020; Goulder, 2020). Thus, until first-best climate policy is enacted, it may be relatively easier for existing government institutions to be modestly adjusted to maximize adaptation co-benefits.[5]

[2] This is not a new use of the term climate adaptation. In the context of responses to natural disasters, Kousky (2012) explains that "[t]he negative impacts of disasters can be blunted by the adoption of risk reduction activities. (...) [T]he hazards literature (...) refers to these actions as mitigation, whereas in the climate literature, mitigation refers to reductions in greenhouse gas emissions. The already established *mitigation measures* for natural disasters *can be seen as adaptation tools* for adjusting to changes in the frequency, magnitude, timing, or duration of extreme events with climate change." (p.37, our highlights).

[3] In contrast, and absent market failures, if government institutions and policy distort private behavior, then individuals and firms might abstain from adaptive behavior. Annan and Schlenker (2015), for example, show that insured farmers may not engage in the optimal protection against extreme heat because crop losses are covered by the federal crop insurance program. Similarly, Deryugina (2017) provides evidence suggesting that *non-disaster* government transfers to disaster-prone areas – such as unemployment benefits – "may counteract the natural tendencies for out-migration from those areas" (Dell, Jones and Olken, 2014).

[4] This is on top of the *direct* effects of the provision of public goods and other government programs facilitating adaptation to climate change. Dell, Jones and Olken (2014) note that snowfalls that once in a while disrupts Southern U.S. states have negligible effects in the Northeast, in part because of policy-induced investments in snow removal. Similarly, around the world, governments have incentivized the development of crop varieties that are better suited for a changing climate (e.g., Olmstead and Rhode, 2008, 2011*a*,*b*).

[5] At the same time, economic agents may continue to rely on market forces to adjust to climate change. Hornbeck (2012) and Hornbeck and Naidu (2014), for example, highlight migration out of affected areas; and Barreca et al. (2016) call attention to the diffusion of existing technologies, such as air conditioning.

Examining the degree of adaptation to climate change induced by existing air quality standards regarding ambient ozone is an ideal setting to study *institution-induced adaptation*. Ambient "bad" ozone is not emitted directly into the air, but rather formed rapidly by Leontief-like chemical reactions between NOx and VOCs in the presence of sunlight and warm temperatures. Therefore, climate change will increase ozone concentration in the near future (e.g., Jacob and Winner, 2009). Moreover, ambient ozone is regulated by the Clean Air Act due to its effects on human health and the environment (e.g., Neidell, 2009; Moretti and Neidell, 2011; Graff Zivin and Neidell, 2012; McGrath et al., 2015; Deschenes, Greenstone and Shapiro, 2017), and such regulations may be effective in reducing ambient ozone concentrations (e.g., Henderson, 1996; Auffhammer and Kellogg, 2011; Deschenes, Greenstone and Shapiro, 2017). Because ambient ozone concentration is the result of pollution externalities generated by economic agents, these corrective policies address a market failure, and indirectly also serve as a "surrogate carbon tax" inducing climate adaptation.

We leverage a unifying approach to estimate climate impacts, and infer the empirical importance of adaptation induced by existing institutions. We build on Bento et al. (2020), and use variation in both weather and climate to uncover the effects of both short- and long-run variation in the *same* estimating equation. Inspired by Dell, Jones and Olken (2009, 2012, 2014), adaptation is derived *directly* from the difference between the responses to weather shocks and climatic changes; hence, unlike previous approaches, assessing its statistical significance is straightforward. In addition, because those are responses by the *same* economic agents, our unifying approach does not require extrapolation of weather responses over time and space to infer adaptation. Indeed, analogous to the Lucas Critique (Lucas, 1976), preferences may not be constant across time and space. In the end, our measure of institution-induced adaptation is the difference between adaptation in counties in and out of attainment with the ozone NAAQS.[6] This strategy is only possible because

[6]Counties violating the air quality standards are required to take costly action to reduce emissions of ozone precursors to bring ozone levels below the standards, even when the violation may have been caused by rising average temperatures. Thus, there may be more climate adaptation in counties out of attainment.

once we recover a measure of adaptation from responses to weather shocks and longer-term climatic changes by the *same* economic agents, then we can compare the degree of adaptation across counties with different attainment status.

Our main results demonstrate that existing government institutions and policy unrelated to climate change can indeed facilitate adaptation. The estimate of adaptation in nonattainment counties is about 107 percent larger than in attainment counties.[7] This finding is robust to a wide variety of specification tests, such as accounting for alternative climate measurement, different periods of adjustment, and competing regulations for ozone precursors, among others. We also find suggestive evidence that institution-induced adaptation may be driven by adjustments in counties where residents generally believe in the existence of climate change. Thus, climate change beliefs could be leveraged to maximize adaptation co-benefits arising from existing institutions. These latter findings are of particular relevance given how institutional inertia, politics, and heterogeneity in local beliefs/preferences continue to delay the introduction of direct climate policy, especially at higher levels of government (Stavins, 2011, 2019; Goulder, 2020).

This study makes three main contributions to the literature. First, it provides the first credible evidence that existing government institutions and policy can be used as a buffer to climate shocks and still induce climate adaptation. Previous work has shown that although government programs may smooth out negative shocks associated with climate change, they might inadvertently inhibit adaptive behavior (e.g., Deryugina, 2017). Second, it demonstrates that existing government institutions may provide an alternative catalyst for adaptation to climate change beyond market forces and private responses. Prior literature has highlighted, for example, migration out of affected areas (e.g., Hornbeck, 2012; Hornbeck and Naidu, 2014; Deryugina and Molitor, 2020) and diffusion of existing technology (e.g., Barreca et al., 2016). Third, it suggests that given the urgency to address climate change,

[7] The magnitude of the institution-induced adaptation associated with a 1°C increase in temperature is roughly 0.33 parts per billion (ppb). Because the impact of a 1°C temperature shock on ambient ozone concentration is approximately 2ppb in nonattainment counties, institution-induced adaptation reduces that impact by about 17 percent.

existing institutions can be used as a means to reach that goal. Previous studies have examined the design and implementation of new institutions and policy, but have recognized their economic and political feasibility challenges (e.g., Aldy, Barrett and Stavins, 2003; Stavins, 2011; Nordhaus, 2019; Stavins, 2019; Aldy and Zeckhauser, 2020; Goulder, 2020).

The paper proceeds as follows. Section II presents a conceptual framework to understand how existing government institutions and policy may affect adaptation to climate change. Section III provides a background on the NAAQS for ambient ozone, ozone formation, and the data used in our analysis. Section IV introduces the empirical strategy; Section V reports and discusses the results; and Section VI concludes.

II. Conceptual Framework

A. Existing Institutions vs. New Institutions

The creation of new institutions can often prove politically or technologically infeasible, but existing institutions may mimic key incentives of a new institution. In the context of climate change, several global climate policy architectures – basically new institutions – have been proposed over the years (e.g., Aldy, Barrett and Stavins, 2003; Stavins, 2011, 2019; Nordhaus, 2019; Aldy and Zeckhauser, 2020). Nevertheless, because of free-riding and political polarization, it has been proven difficult to induce countries to join in an international agreement with significant emission reductions, or to enact federal legislation addressing climate change.

Recognizing the difficulty in implementing first-best climate policy, 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 climate policy. Second-best policies may be 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).[8] In this study, we demonstrate that existing government institutions are already providing incentives for producers and consumers to adapt to climate change – much like a second-best policy – and argue that policymakers should take these co-benefits into consideration when enforcing or revising them.

Our study focuses on the existing institution of the Clean Air Act (CAA) – specifically the National Ambient Air Quality Standard (NAAQS). With the CAA Amendments of 1970, the EPA was authorized to set up and enforce a NAAQS for ambient ozone.[9] Since then, a nationwide network of air pollution monitors has allowed EPA to track ozone concentrations, and a threshold is used to determine whether pollution levels are sufficiently dangerous to warrant regulatory action.[10] Counties with ozone levels exceeding the NAAQS threshold are designated as in "nonattainment" and 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 reach compliance.[11] In cases of persistent nonattainment the CAA mostly mandates command-and-control regulations, requiring that plants use the best available emission control technology (BACT) in their production processes. Furthermore, 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, such as retention of funding for transportation infrastructure.

B. The Nature of Existing Institutions Inducing Adaptation

To understand how existing institutions such as the Clean Air Act's NAAQS may induce climate adaptation, let us consider a simple formalization using the sufficient statistic ap-

[8]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 in the United States is the corporate average fuel economy (CAFE) standards. A first-best policy would be taxing tailpipe emissions directly.

[9]For further details of the ozone NAAQS see Appendix A.1.

[10]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).

[11]Appendix Table A1 details the current and historical thresholds used to determine "nonattainment" status under the prevailing NAAQS.

proach (Harberger, 1964; Chetty, 2009; Kleven, forthcoming). 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 for simplicity to be proportional to X. Since we are focusing on ozone pollution, and ozone formation depends on climate (C) as well, then we define $P \equiv F(X, C) = \delta(C)X$, with $\delta(.) > 0$ and $\delta_C(.) \equiv \delta'(.) > 0$.[12] Also, suppose that there is a continuum of consumers with wealth Y and quasilinear utility $U(X) + Z - r\delta(C)X$, where r is the marginal damage of ozone pollution.

Under profit and utility maximization, it can be shown (see Appendix C) that welfare (W) can be improved by reducing production.[13] This might be the case when the NAAQS for ambient ozone are binding. Because $dW \equiv dW(C) = -r\delta(C)dX > 0$, 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 "institution-induced adaptation," which can be interpreted as a *co-benefit* of the NAAQS for ambient ozone:

$$\frac{dW}{dC} = -r\delta_C dX > 0. \tag{1}$$

Therefore, absent direct first-best climate policy, when climate is an input in the production of economic outcomes that arise from market failures such as ozone pollution, corrective policies targeting those outcomes may 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). In the case of the NAAQS for ambient ozone, the standards not only deal with the externality of local air pollution, but also generate institution-induced adaptation.[14]

[12]See Appendix A.2 for more details on ozone formation, and the role of climate.

[13]Indeed, the private optimum is not Pareto efficient because of the negative externality ozone pollution imposes on consumers. Hence, this is clearly a second-best setting (Lipsey and Lancaster, 1956).

[14]In contrast, when climate is an input in production but the output is a marketable good or service,

To make the concept of institution-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 a composite index $I(.)$ of two inputs – NOx and VOCs – whose levels move along the production function $F(I(\text{NOx,VOCs}), \text{Climate})$ represented by the upward-sloping black line. $F(I(\text{NOx,VOCs}),$ Climate) is equivalent to the $F(\text{X,C})$ in the formalization above. 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 $I(\text{NOx,VOCs})$ – 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 line. Because we assumed emissions of ozone precursors were initially under control, an increase in average temperature raises ozone concentration for the same level of the index $I(\text{NOx,VOCs})$, reaching point B. Since the ozone concentration is now above the NAAQS threshold, the county is designated as out of attainment, and firms are pressured 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 careless in controlling emissions in the baseline, but rather because climate has changed. As they take

policies considering output and/or input levels may not only distort economic agents' behavior and generate deadweight loss, but also potentially affect adaptive behavior. Annan and Schlenker (2015) illustrate the case of policies precluding adaptation: farmers may not engage in the optimal protection against harmful extreme heat because the resulting crop losses are covered by the federal crop 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 decision process, in addition to equity considerations.

steps to reduce emissions to reach attainment, moving along the new production function 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 institution-induced adaptation.[15]

III. Data and Data Descriptions

Ambient ozone is one of the six criteria pollutants regulated under the existing Clean Air Act institution. However, unlike other pollutants, it is not emitted directly into the air. Rather, it is formed by Leontief-like chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs), under sunlight and warm temperatures. Because ambient ozone is affected by both climate and regulations, and high-frequency data are available since 1980, this is an ideal setting to study institution-induced adaptation. In Appendix A, we provide further details regarding the ozone standards, ozone formation and the data.

A. NAAQS, Ozone Pollution, and Climate: Background and Data

NAAQS Data. For data on the Clean Air Act nonattainment designations associated with exceeding the NAAQS for ambient ozone, we use the EPA Green Book of Nonattainment Areas for Criteria Pollutants. We generate an indicator for nonattainment status for each county-year in our sample. In our empirical analysis, we use the nonattainment status lagged by three years because EPA gives counties with heavy-emitters at least three years to comply with NAAQS for ambient ozone (USEPA, 2004, p.23954).[16]

[15]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 level of those outcomes, such policies can create a co-benefit of adjusting to 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). Thus, 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.

[16]EPA allows nonattainment counties with polluting firms between 3 to 20 years to adjust their production processes. Nonattainment counties are *"classified as marginal, moderate, serious, severe or extreme (...) at*

Specifically, with regards to nonattainment status, if any monitor within a county exceeds the NAAQS, EPA designates the county to be out of attainment (USEPA, 1979, 1997, 2004, 2008, 2015*a*). 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, with local agencies having discretion over enforcement as long as they are within attainment for the NAAQS. Regional EPA offices do, however, conduct inspections to confirm attainment status and/or issue sanctions when a state's enforcement is below required levels, and assist states with major cases. Thus, while there may be heterogeneity in local enforcement for nonattainment counties, we would expect that those counties achieve at least the minimum level of increased regulation mandated by the EPA.

Ozone Data. For ambient ozone concentrations, we use daily readings from the nationwide network of the EPA's air quality monitoring stations. Following Auffhammer and Kellogg (2011), in our preferred specification we use an unbalanced panel of ozone monitors, and make only two restrictions to construct our analysis 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 concentration is higher than the standard. Second, as a minimum data completeness requirement, for each ozone monitor we include only years for which at least 75 percent of the days in the typical ozone monitoring season (April-September) are valid; years having concentrations above the standard are included even if they have incomplete data.[17] Our final sample consists of valid ozone measurements for a total of 5,139,129 monitor-days.[18]

the time of designation" (USEPA, 2004, p.23954). They must reach attainment in: *"Marginal – 3 years, Moderate – 6 years, Serious – 9 years, Severe – 15 or 17 years, Extreme – 20 years"* (USEPA, 2004, p.23954).

[17] The typical ozone monitoring season around the country is April-September, but in fact it varies across states. Appendix Table A2 reports the season for each state.

[18] Appendix Figure A1 depicts the evolution of ambient ozone monitors over the three decades in our data, and illustrates the expansion of the network over time. Appendix Table A3 provides annual summary statistics on the ozone monitoring network. The number of monitors increased from 1,361 in the 1980s to over 1,851 in the 2000s. The number of monitored counties also grew from roughly 585 in the 1980s to over 840 in the 2000s. While Muller and Ruud (2018) find that compliance with the NAAQS for ambient ozone is not

Weather Data. For climatological data, we use daily measurements of maximum temperature as well as total precipitation from the National Oceanic and Atmospheric Administrations's Global Historical Climatology Network databse (NOAA, 2014). This dataset provides detailed weather measurements at over 20,000 weather stations across the country. We use information from 1950-2013, because we need 30 years of data prior to the period of analysis to construct a moving average series of climate.[19] The weather stations are typically not located adjacent to the ozone monitors. Hence, we match ozone monitors to nearby weather stations using a straightforward procedure.[20]

B. *Basic Trends in Pollution, Attainment Status, and Weather: Implications for the Importance of Institutions*

To give a sense of the data, Figure 2 illustrates the evolution of ozone concentrations and the proportion of counties in nonattainment over our sample period, while Figure 3 does the same for two components of temperature – moving averages and deviations from them.

Ozone Concentrations and Nonattainment Designations. Figure 2, Panel A, depicts the annual average of the highest daily maximum ambient ozone concentration recorded at each monitor from 1980-2013 in the United States. The sample is split according to whether counties were in or out of attainment with the NAAQS for ambient ozone, established in 1979. Counties out of compliance with the NAAQS experienced, on average, a steeper reduction in the daily maximum ozone levels than counties in compliance. We will argue that part of that reduction is associated with institution-induced adaptation.[21]

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consistently associated with network composition, Grainger, Schreiber and Chang (2019) provide evidence that local regulators do avoid pollution hotspots when siting new ozone monitors. Later, as a robustness check, we show qualitatively similar results for a semi-balanced panel of ozone monitors.

[19] Appendix Figure A2 presents the yearly temperature fluctuations and overall trend in climate for the contiguous US as measured by these monitors, relative to a 1950-1979 baseline average temperature.

[20] 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. Moreover, for every ozone monitor we use weather information from only the closest two weather stations within the 30-km radius. Appendix Figure A3 illustrates the proximity of our final sample of ozone monitors to these matched weather stations. Once we apply this procedure, we exclude ozone monitors that do not have any weather stations within 30km. As will be discussed later, our results do not seem sensitive to these choices.

[21] Appendix Figure A4 further compares similar trends in ozone levels with the updated 1997, 2008, and

Figure 2, Panel B, shows that as ambient ozone concentrations fell, the number of counties out of attainment also declined. Notice that when the 1997 NAAQS revisions were implemented in 2004 after litigation, the share of our sample counties out of attainment increased more than 50 percent. Such a jump is not observed in the implementation of the 2008 revision, however. In this case, the share of counties in nonattainment remained stable around 0.3. Appendix Figure A5 shows that most counties out of attainment were first designated in nonattainment in the 1980's. 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 1990's and 2000's.

Decomposing Temperature into long-run climate norms and short-run weather shocks. In order to disentangle variation in weather versus climate, we decompose average temperature into a climate norm – a 30-year monthly moving average (MA) following (WMO, 2017), and a weather shock – the daily deviation from the norm. Figure 3, Panel A, plots the annual average of the 30-year MA in the dotted line, as well as a smoothed version of it in the solid line; note that due to the nature of the MA, this takes into account information since 1950. Panel B plots the annual average of the shocks. Notice that the average deviations from the 30-year MA are bounded around zero, with bounds relatively stable over time, suggesting little changes in the variance of the climate distribution.[22] Using our final sample, not surprisingly Appendix Figure A7 shows that ambient ozone is closely related to both components of temperature, which we examine more formally in the empirical analysis.

2015 NAAQS levels which, while much lower, are based instead on the observed 4th highest 8-hour average ambient ozone concentration.

[22]Appendix Figure A6 presents a similar illustration to Figure 3 using our final sample of weather monitors once matched to ozone monitors. Appendix Table A4 reports the summary statistics for daily temperature and our decomposed variables, for each year in our sample from 1980-2013.

IV. Empirical Framework

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. The goal is to recover $\delta_C dX$ in Equation (1), the up-to-scale measure of institution-induced adaptation. Thus, with an estimate of r from the literature (e.g., Deschenes, Greenstone and Shapiro, 2017), we are able to provide some back-of-the-envelope calculations regarding welfare changes.

We build upon a unifying approach to estimating climate impacts (Bento et al., 2020) which bridges the two leading approaches of the climate-economy literature – the cross-sectional approach to estimate the impact of climate change on economic outcomes (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005), and the panel fixed-effects approach to estimate the impact of weather shocks (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) – identifying both weather and climate impacts in the same equation. Inspired by Dell, Jones and Olken (2009, 2012, 2014), our *direct* measure of adaptation is the difference between short-run weather responses, which are approximately exclusive of adaptation, and long-run climate responses, which are potentially inclusive of adaptation. Since they are estimated in the same equation, our method allows for a straightforward test of the statistical significance of our measure of adaptation.

Moreover, because our approach critically identifies adaptation by comparing how the *same* economic agents respond to both weather and climate variation, we are able to recover our measure of institution-induced adaptation by comparing heterogeneous adaptation from counties in and out of attainment with the NAAQS for ozone without needing to make assumptions over preferences. In contrast, previous studies have inferred adaptation *indirectly*, by flexibly estimating economic damages due to weather shocks – sometimes for different time periods and locations – then assessing climate damages by using shifts in the future weather distribution predicted by climate models (e.g., Deschenes and Greenstone, 2011; Barreca et al., 2016; Auffhammer, 2018; Carleton et al., 2019; Heutel, Miller and Molitor, forthcoming). That implies an extrapolation of weather responses over time and space, which requires preferences to be constant across those dimensions, an assumption that can be challenging for reasons similar to the Lucas Critique (Lucas, 1976).

Our approach has two key elements. The first is the decomposition of meteorological variables into two components: long-run climate norms and transitory weather shocks, the latter defined as deviations from those norms. This decomposition is meant to have economic content. It is likely that individuals and firms respond to information on climatic variation they have observed and processed over the years. In contrast, economic agents may be constrained to respond to weather shocks, by definition. As mentioned above, our measure of adaptation is the difference between those two responses by the *same* economic agents. In practice, we decompose temperature into a monthly moving average incorporating information from the past three decades, often referred to as climate normal, and a deviation from that 30-year average. This moving average is purposely lagged in the empirical analysis to reflect all the information available to individuals and firms up to the year prior to the measurement of the outcome variables.[23]

The second key element of our approach is identifying responses to weather shocks and longer-term climatic changes in the *same* estimating equation. We are able to leverage both sources of variation in the same estimating equation because of the properties of the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963). The deseasonalization embedded in the standard fixed-effects approach is approximately equivalent to the construction of weather shocks as deviations from long-run norms as a first step. Furthermore, there is no need to deseasonalize the outcome variable to identify the impact of those shocks (Lovell, 1963, Theorem 4.1, p.1001). As a result, we do not need to saturate the econometric model with highly disaggregated time fixed effects; thus, we are able to also exploit variation that evolves slowly over time to identify the impacts of longer-term climatic changes.

[23] A graphical representation of our decomposition has been illustrated for Los Angeles county in 2013 in Appendix A.3 Figure A8, and over the entire sample period of 1980-2013 in Figure A9.

Estimating Climate Impacts. As a first step, we decompose the observed daily maximum temperature into a norm and a shock. The norm is operationalized by the 30-year monthly moving average (MA).[24] The shock is merely the deviation of the observed temperature from that norm. Because ozone formation is directly tied to temperature, as discussed in Section A, the impact of temperature on ambient ozone is the focus of our analysis. Given that decomposition, we estimate the following equation:

$$\begin{aligned} Ozone_{it} = {} & \beta_N^W (Temp_{it}^W \times Nonattain_{c,y-3}) + \beta_N^C (Temp_{it}^C \times Nonattain_{c,y-3}) \\ & + \beta_A^W (Temp_{it}^W \times Attain_{c,y-3}) + \beta_A^C (Temp_{it}^C \times Attain_{c,y-3}) \\ & + X_{it}\gamma + \eta_{is} + \phi_{rsy} + \epsilon_{it}, \end{aligned} \tag{2}$$

where i represents an ozone monitor located in county c of NOAA climate region r, observed on day t, season s (Spring or Summer), and calendar year y. Our analysis focuses on the most common ozone season in the U.S. – April to September, as mentioned in the background section – over the period 1980-2013. $Ozone$ represents daily maximum ambient ozone concentration, $Temp^W$ represents the weather shock, and $Temp^C$ the climate norm. Hence, the response of ambient ozone to the temperature shock β^W represents the short-run effect of weather, and the response to the climate norm β^C reflects the long-run impact of climate. $Nonattain_{cy}$ denotes nonattainment designation, which is a binary variable equals to one if a county c is not complying with the NAAQS for ambient ozone in year y. This variable is lagged by three calendar years because EPA allows counties with heavy polluters at least three years to comply with the ozone NAAQS, as discussed in the background section. X represents time-varying control variables such as precipitation, which is similarly

[24] To make this variable part of the information set held by economic agents at the time ambient ozone is measured, we lag it by one year. For example, the 30-year MA associated with May 1982 is the average of May temperatures for all years in the period 1952-1981. Therefore, economic agents should have had at least one year to respond to unexpected changes in climate normals at the time ozone is measured. Later, we discuss almost identical results for longer lags. Also, we use monthly MAs because it is likely that individuals recall climate patterns by month, not by day of the year. Indeed, 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 for that specific day. Later, we discuss qualitatively similar results when we use *daily* instead of *monthly* moving averages.

decomposed into a norm and shock. Although less important than temperature, Jacob and Winner (2009) point out that higher water vapor in the future climate may decrease ambient ozone concentration.[25] η represents monitor-by-season fixed effects, ϕ climate-region-by-season-by-year fixed effects, and ϵ an idiosyncratic term.[26]

We exploit plausibly random, daily variation in weather, and monthly variation in climate normals to identify the impact of climate change on ambient ozone concentration. Identification of the weather effect is similar to the standard fixed effect approach (e.g., Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009), with the exception that because we isolate the temperature shock as a first step, we do not need to include highly disaggregated time fixed effects (Frisch and Waugh, 1933; Lovell, 1963). Identification of the climate effect relies on plausibly random, within-season monitor-level monthly variation in lagged 30-year MAs of temperature after controlling non-parametrically for regional shocks at the season-by-year level.

To better understand the identification of climate impacts, consider the following thought experiment that we observe in our data many thousands of times: take two months in the same location and season (Spring or Summer). Now, suppose that one of the months experiences a hotter climate norm than the other, after accounting for any time-varying fluctuations in, e.g., atmospheric or economic conditions that affected the overarching climate region at the season-by-year level. Our estimation strategy quantifies the extent to which this difference in the climate norm affected the ozone concentrations observed on that month. Therefore, this approach controls for a number of potential time-invariant and time-varying confounding factors that one may be concerned with, such as the composition of the local and regional atmosphere and technological progress.

[25] Although temperature is the primary meteorological factor affecting tropospheric ozone concentrations, other factors such as wind and sunlight have also been noted as potential contributors. Later, we discuss qualitatively similar results for a subsample with information on wind speed and sunlight.

[26] In unreported analyses we examine specifications with alternative fixed effects structures, such as including latitude and longitude interacted with season-by-year, or replacing region-by-season-by-year with state-by-season-by-year. Estimates from our preferred, more parsimonious specification are similar in magnitude and significance to each of these alternatives.

Our ultimate goal, however, is not just to identify adaptation via estimates of climate impacts vis-à-vis weather shocks, but to identify whether there is a *different* level of adaptation in nonattainment versus attainment counties. As the EPA was given substantial enforcement powers to ensure that the goals of the Clean Air Act were met, policy variation itself is plausibly exogenous conditional on observables and the unobserved heterogeneity embedded in the fixed effects structure considered in our analysis (see, e.g., Greenstone, 2002; Chay and Greenstone, 2005). In order to reach compliance, some states initiated their own inspection programs and frequently fined non-compliers. However, for states that failed to adequately enforce the standards, EPA was required to impose its own procedures for attaining compliance. The inclusion of monitor-by-season fixed effects allows us to control for the strong positive association observed in cross-sections among location of polluting activity, high concentration readings, and nonattainment designations while preserving interannual variation in attainment status for each individual monitor. Thus, the variation used in our analysis comes from changes in status, as previously shown in Figure 2: from attainment to nonattainment, or vice versa.

Measuring institution-induced Adaptation. Once we credibly estimate the impact of the two components of temperature interacted with county attainment status, we recover a measure of institution-induced adaptation. The average adaptation in nonattainment counties is the difference between the coefficients β_N^W and β_N^C in Equation (2). If economic agents engaged in full adaptive behavior, β_N^C would be zero, and the magnitude of the average adaptation in those counties would be equal to the size of the weather effect on ambient ozone concentration (for a review of the concept of climate adaptation, see Dell, Jones and Olken, 2014). Indeed, under full adaptive behavior, the unexpected increase in climate norm would lead economic agents to pursue reductions in ozone precursor emissions to avoid an increase in ambient ozone concentration of identical magnitude of the weather effect in the same month of the following year.[27] In other words, agents would respond to "permanent"

[27] Again, later we consider cases where economic agents can take a decade or two to adjust. Because EPA

changes in temperature by adjusting their production processes to offset that increase in the climate norm. Unlike weather shocks, which influence ozone formation by triggering chemical reactions conditional on a level of ozone precursor emissions, changes in the 30-year MA should affect the level of emissions.

We can measure adaptation in attainment counties in the same way: $(\beta_A^W - \beta_A^C)$. This adaptation could arise from technological innovations, market forces, or regulations other than the NAAQS for ambient ozone. Sources of this type of adaptation would be, for example, the adoption of solar electricity generation, which reaches maximum potential by mid-day, when ozone formation is also at high speed, and other Clean Air Act regulations related to ozone – for example, restrictions on the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources (Auffhammer and Kellogg, 2011), and the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017).

Once we have measured adaptation in both attainment and nonattainment counties, we can express adaptation induced by the NAAQS for ambient ozone matching Equation (1) as

$$IIA \equiv \underbrace{(\beta^W - \beta^C)}_{\delta_C} \times \underbrace{(\mathbb{1}_N - \mathbb{1}_A)}_{dX} = (\beta_N^W - \beta_N^C) - (\beta_A^W - \beta_A^C). \tag{3}$$

An important advantage of this approach is to have all those coefficients estimated in the same equation. Hence, we can straightforwardly run a test of this linear combination to obtain a coefficient and standard error for the measure of institution-induced adaptation (IIA), and proceed with statistical inference.

V. Results

We begin by presenting our main findings on the impacts of temperature on ambient ozone concentration, average adaptation, and adaptation induced by the existing institution of the Clean Air Act – which we termed institution-induced adaptation. We then discuss the

may give counties with heavy emitters up to two decades to comply with ozone NAAQS, as discussed in the background section, adaptive responses many years after agents observe changes in climate norms may be plausible. Interestingly, we will find almost identical results.

robustness of our results to the consideration of the distance of ozone concentrations from the NAAQS threshold, and accounting for competing input regulations on ozone precursors in the analysis. Following this, we examine the role of local beliefs in altering the level of induced adaptation ultimately achieved. We report the heterogeneity of our results by local beliefs regarding the existence of climate change.[28] As we present our main findings, we also discuss a number of additional robustness checks regarding measurement of climate, alternative timing for economic agents to process changes in climate and engage in adaptive behavior, and further specification checks and sample restrictions, among others.

A. The Role of Institutions for Inducing Adaptation to Climate Change

Table 1 reports our main findings on the role of existing government institutions and policy in inducing climate adaptation. Before discussing the ozone NAAQS institution-induced adaptation, we present the average climate impacts and adaptation across all counties in our sample. For this purpose, we run a simplified version of Equation (2), where the temperature shock and norm are not interacted with attainment status. Column (1) shows that a 1°C temperature shock increases average daily maximum ozone concentration by about 1.65ppb. This can be seen as a benchmark for the ozone response to temperature because of the limited opportunities to adapt in the short run.[29] A 1°C-increase in the 30-year MA, lagged by one year and thus revealed in the year before ozone levels are observed, increases daily maximum ozone concentration by about 1.16ppb, an impact that is significantly lower than the response to a 1°C temperature shock, indicating adaptive behavior by economic agents. Indeed, column (3) presents the measure of adaptation – 0.49ppb – which is economically and statistically significant. If adaptation was not taken into consideration, the impact of

[28] In our robustness checks we contrast these results with those associated with unrelated beliefs, conducting a placebo exercise considering the local views on single parenthood

[29] We see it as a benchmark because we assume that economic agents are not be able to respond to weather shocks. In reality, there might be some opportunities to make short-run adjustments in the context of ambient ozone. Although developed countries have usually not taken drastic measures to attenuate unhealthy levels of ambient ozone because concentrations are generally low, developing countries have often constrained operation of industrial plants and driving in days of extremely high levels of ozone.

temperature on ambient ozone would be overestimated by roughly 42 percent.

The estimates above represent average treatment effects. Because we are interested in the role of institutions in potentially affecting adaptive behavior, we estimate heterogeneous treatment effects by attainment status, as specified in Equation (2). Table 1, column (2), reports the estimates disaggregated by whether the ozone monitors are located in attainment or nonattainment counties. Given that attainment counties have cleaner air by definition, on average their ozone responses to temperature changes are significantly lower. Column (4) shows that adaptation in nonattainment counties is over 107 percent larger than in attainment counties. As defined in Equation (3), the difference between those two adaptation estimates – 0.33ppb – is our measure of institution-induced adaptation, shown at the bottom of column (4). Therefore, a regulation put in place to correct an externality – the NAAQS for ambient ozone – generates a *co-benefit* in terms of adaptation to climate change, on top of the documented impact on ambient ozone concentrations (Henderson, 1996).[30]

Although it is not the focus of our study, it is imperative to discuss the degree of adaptation in attainment counties. The second estimate in column (4) – 0.31 ppb – indicates that adaptive behavior is also present in those jurisdictions. The underlying reasons might be technological innovation and market forces, as highlighted in previous studies (e.g., Olmstead and Rhode, 2011*a*,*b*; Hornbeck, 2012; Hornbeck and Naidu, 2014; Barreca et al., 2016), other regulations affecting both attainment and nonattainment counties (e.g., Auffhammer and Kellogg, 2011; Deschenes, Greenstone and Shapiro, 2017), or even preventive responses

[30] We examine the sensitivity of our results to a host of robustness checks in the Appendix. Table B1 varies our moving average measure of climate, Table B2 includes alternative timing for economic agents to engage in adaptive behavior, and Table B3 explores further specification checks and sample restrictions. Furthermore, we provide results using a variety of alternative matching rules between ozone monitors and weather stations in Table B4: varying the distance cut-off, the number of monitors in the matching, and the averaging procedure. Estimates in all of the above are relatively stable across these alternative approaches. Additionally, although it has been shown that, e.g., manufacturing plants have relocated in response to ozone nonattainment designations (Henderson, 1996; Becker and Henderson, 2000), results in Table B5 suggest that firms are not responding differentially based on climatic variables. Lastly, observe that our standard errors are clustered at the county level. Since the 30-year MAs and temperature shocks could be considered generated regressors, we also provide standard errors block bootstrapped at the county level for our main estimates in Appendix Table B6. Bootstrapped standard errors are all within 6% of those estimated via clustering at the county level. Because the changes were usually relatively minor, for simplicity we used clustered standard errors at the county level in the remainder of the analysis.

in counties with ozone readings near the threshold of the NAAQS for ambient ozone, as explained below. In that sense, our measure of institution-induced adaptation might represent a lower bound of how ozone NAAQS encourage adaptive behavior.

An example of adaptation triggered by innovation, market forces, and other regulations in the context of ambient ozone arises from the adoption of solar panels for electricity generation. Higher temperatures lead to more ozone formation, but they also constrain the operations of coal-fired power plants. Regulations under the Clean Water Act restrict the use of river waters to cool the boilers when water temperature rises (e.g., McCall, Macknick and Hillman, 2016). Because coal plants are important contributors of VOC and NOx emissions, those constraints lead to a reduction in the concentration of ozone precursors. At the same time, solar panels are more suitable for electricity generation in hotter areas, with higher incidence of sunlight; thus, more extensively used in those places. Now, higher temperatures combined with lower levels of ozone precursors – enabled by the adoption of solar panels – may lead to lower levels of ambient ozone. Hence, adaptation driven by innovation, market forces, and regulations other than the ozone NAAQS.

Estimates by Distance of Ozone Concentrations to NAAQS threshold. One may ponder that the ideal setting to identify institution-induced adaptation would be to randomly assign regulation, and compare the impact of climatic changes in regulated versus unregulated jurisdictions. Nevertheless, this would work only if the regulation was unanticipated and imposed only once. If regulations are anticipated, and can be assigned multiple times, in multiple rounds, such as the Clean Air Act nonattainment designations, economic agents may respond more similarly to the threat of regulation, even when it is randomly assigned. They might be indifferent between making adjustments before or after being affected by the regulation if more rounds of regulatory action are on the horizon. The intuition for these results is similar to the outcomes of finitely versus infinitely repeated games (or games that are being repeated an unknown number of times). Consider the prisoner's dilemma game. If played a finite number of times, defection in every game is the unique dominant-strategy

Nash equilibrium, following familiar backward-induction arguments. But if played an infinite (or an unknown) number of times, now the preferred strategy is not to play a Nash strategy of the stage game, but to cooperate and play a socially optimum strategy.

In the case of the Clean Air Act, EPA designates counties out of compliance with NAAQS if their pollution concentrations are above a known threshold. Such designations may change over time depending on the adjustments made by economic agents in those jurisdictions. For counties whose pollution concentration is around the threshold, economic agents may have incentives to make efforts to comply with NAAQS no matter whether those counties are just above or just below the threshold. If counties are even a little above the standards, EPA mandates them to adopt emissions control technologies and practices to reduce pollution, which is costly. If counties are a little under the standards, they may want to keep it that way to avoid regulatory oversight. As a result, they may end up making efforts to maintain the area under attainment. This somewhat similar adaptive behavior around the ozone standards may reduce the estimates for institution-induced adaptation near the NAAQS threshold.[31]

Table 2 reports estimates for subsamples of ozone monitor readings with concentrations falling within 20 percent, above or below, the NAAQS threshold in Panel A, within 20-40 percent of the threshold in Panel B, and over 40 percent away from the threshold in Panel C. The subsample for the within 20 percent readings consists of about 13 percent of the overall sample. As expected, the empirical evidence we provide for this subsample indicates limited differential adaptation across attainment and nonattainment counties, but still of nontrivial magnitude. The estimate for institution-induced adaptation, which is the difference between the adaptation estimates in columns (2) and (4), is still economically and statistically significant.

[31] It is important to mention that before the 1990 CAA amendments, EPA used a "too close to call" nonattainment category with minimal requirements for areas just violating the NAAQS. Areas in this category (with ozone levels up to 138ppb, hence above the threshold of 120ppb) were not subject to full SIP requirements, but rather watched closely to see if their air quality was getting worse (Krupnick and Farrell, 1996). This malleability in enforcement may also reduce the estimate for institution-induced adaptation near the NAAQS threshold.

For the subsamples with observations of ambient ozone concentration within 20-40 percent of the NAAQS threshold (25 percent of the overall sample), and over 40 percent away from the threshold (62 percent of the overall sample), we cannot rule out that the estimates of institution-induced adaptation reported in column (5) are similar to our main estimate. Given that these two subsamples make up 87 percent of the overall sample, it is fair to say that most of the institution-induced adaptation arises from monitors with ozone readings relatively far from the NAAQS threshold.

Estimates considering input regulation for ozone precursors. During our period of analysis (1980-2013), three other policies aiming at reducing ambient ozone concentrations were implemented in the United States: (i) regulations restricting the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources (Auffhammer and Kellogg, 2011), (ii) the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017), and (iii) the Regional Clean Air Incentives Market (RECLAIM) NOx and SOx emissions trading program (Fowlie, Holland and Mansur, 2012). Because our focus in this study is to estimate climate adaptation induced by the NAAQS for ambient ozone, it is imperative to examine the sensitivity of our estimates of institution-induced adaptation when taking into account these input regulations targeted at ozone precursors.

Auffhammer and Kellogg (2011) demonstrate that the 1980s and 1990s federal regulations restricting the chemical composition of gasoline, intended to curb VOC emissions, were ineffective in reducing ambient ozone concentration. Since there was flexibility regarding which VOC component to reduce, to meet federal standards refiners chose to remove compounds that were cheapest, yet not so reactive in ozone formation. Beginning in March 1996, California Air Resources Board (CARB) approved gasoline was required throughout the entire state of California. CARB gasoline targeted VOC emissions more stringently than the federal regulations. These precisely targeted, inflexible regulations requiring the removal of particularly harmful compounds from gasoline significantly improved air quality in California (Auffhammer and Kellogg, 2011). Therefore, we re-estimate our analysis removing the state of California from 1996 onwards. The results reported in Table 3 reveal that the estimate for institution-induced adaptation in column (2), derived from column (1) estimates of the impact of temperature shocks and norms on ambient ozone concentration, is remarkably close to our overall estimate of institution-induced adaptation. Hence, it appears that VOC regulations in California do not drive our estimate of climate adaptation induced by the NAAQS for ozone. This is not surprising because the regulation was extended to all counties in California – attainment and nonattainment counties.

Deschenes, Greenstone and Shapiro (2017) and Fowlie, Holland and Mansur (2012) both find a substantial decline in air pollution emissions and ambient ozone concentrations from the introduction of an emissions market for nitrogen oxides (NOx), another ozone precursor. The NOx Budget Trading Program (NBP) examined by Deschenes, Greenstone and Shapiro (2017) operated a cap-and-trade system for over 2,500 electricity generating units and industrial boilers in the eastern and midwestern United States between 2003 and 2008. Thus, we re-estimate our analysis excluding the states participating in the NBP, from 2003 onwards.[32] The RECLAIM NOx and SOx trading program examined by Fowlie, Holland and Mansur (2012) similarly operated a cap-and-trade system at 350 stationary sources of NOx for the four California counties within the South Coast Air Quality Management District (SCAQMD) starting in 1994. Thus, we again re-estimate our analysis, excluding the SCAQMD counties from 1994 onwards.[33] Table 3 reports the results excluding NBP states in columns (3) and (4), and excluding RECLAIM counties in columns (5) and (6). The estimate for institution-induced adaptation in columns (4) and (6) are quite similar to our overall estimate of institution-induced adaptation. Despite being effective in reducing NOx and ozone concentrations, the NBP and RECLAIM programs do not seem to affect climate adaptation induced by the NAAQS for ozone. Again, this is not surprising because it affected

[32]NBP participating states include: Alabama, Connecticut, Delaware, Illinois, Indiana, Kentucky, Maryland, Massachusetts, Michigan, Missouri, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, South Carolina, Tennessee, Virginia, and West Virginia, and Washington, DC. The NBP operated only in northeastern states on May 1 of 2003, and expanded to the other states on May 31 of 2004 (Deschenes, Greenstone and Shapiro, 2017).

[33]Participating counties include: Los Angeles, Riverside, San Bernardino, and Orange.

both attainment and nonattainment counties.

B. Climate Beliefs May Reinforce Co-Benefits from Institution-Induced Adaptation

So far we have demonstrated that existing government institutions and policy can be effective in inducing climate adaptation. Now, we examine whether climate change beliefs may alter the effectiveness of such policies. In the absence of direct climate policy at the national and international stage, action driven by local culture may help address the challenge of climate change (Stavins et al., 2014). 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 can be leveraged to push forward local actions supporting climate adaptation.[34] 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.[35] Appendix Table B7 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.

Table 4 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.

[34]Following North (1991), one may consider these preferences/beliefs *local institutions*. According to him, *"institutions (...) consist of both informal constraints (sanctions, taboos, customs, traditions, and codes of conduct), and formal rules (constitutions, laws, property rights)"* (p.97).

[35]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.

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 institution-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.

Placebo estimates considering local preferences unrelated to environmental amenities. 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 B8 reports the results in the same format as Table 4. 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 institution-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 play an important role in 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 institution-induced adaptation in precursor-limited areas. We explore this important feature of the production function of ozone in Appendix Table B9 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,[36] 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 institution-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.[37]

While the above analyses examine heterogeneity in adaptive response across inherently spatial dimensions, areas with different beliefs, or underlying atmospheric conditions, one may wonder how adaptation varies across other dimensions, such as time or the temperature distribution itself. When we examine the estimates by decade, as reported in Appendix Table B10, the magnitude of institution-induced adaptation in the 1980's is marginally larger, declining somewhat in the 1990's, and further still in the 2000's – for all three decades, however, estimates of institution-induced adaptation are not statistically different from our central result. Examining the estimates across the temperature distribution, in Tables B11a and B11b, we see an almost doubling of institution-induced adaptation above 30°C, and almost tripling above 35°C, relative to days where temperature was below 30°C – in line with the idea that nonattainment counties may be especially focusing adaptive efforts on those hottest days where they would be most likely to exceed the NAAQS threshold.

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

[37]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.

C. *Climate Adaptation Co-Benefits from Existing Institutions: Some Calculations*

Having presented our main findings, we now provide some back-of-the-envelope calculations on the *co-benefits* of the existing Clean Air Act institution associated with climate adaptation induced by the NAAQS for ambient ozone. Following the sufficient statistic approach (Harberger, 1964; Chetty, 2009; Kleven, forthcoming) as outlined in Section II, these calculations combine our main estimates from Table 1 with climate projections from the U.S. Fourth National Climate Assessment (Vose et al., 2017), and the social benefits of ozone reductions from Deschenes, Greenstone and Shapiro (2017). As detailed in Equation (3), all of these elements can be mapped directly into the components of Equation (1), allowing us to interpret the resulting values as welfare changes. Additionally, we also discuss how these co-benefits are affected by the projected changes in climate over the 21st century.

Formally, we map the components of Equation (1) to each of these three "sufficient statistics," summing across every county n in the set of counties ever designated as nonattainment (NA) within our sample period:

$$\Delta W \approx -\sum\nolimits_{n \in NA} \underbrace{r}_{DGS} \underbrace{\delta_C \Delta X_n}_{Table1} \underbrace{\Delta C_n}_{Vose}, \tag{4}$$

where r is treated as a fixed value, approximately equal to \$1.75 million (2015 US) per county per year, following Deschenes, Greenstone and Shapiro (2017). The value of ΔC varies depending on the chosen climate projection from Vose et al. (2017), while $\delta_C \Delta X$ varies depending on whether, and which type, of adaptation is being calculated, following directly from our central results in columns (2) and (4) of Table 1.[38]

Table 5 presents the costs of climate change, the savings from overall adaptation, and particularly the savings from institution-induced adaptation – the co-benefit of the CAA which is the focus of this study. We focus on the 509 counties most affected by the NAAQS for ambient ozone (nonattainment counties), representing about two thirds of the U.S. popu-

[38]As defined in Equation (1), emissions are taken as proportional to X; thus, although Equation (4) focuses on changes in ozone concentration, for simplicity and consistency we represent it here as ΔX.

lation. The row labeled costs "without adaptation" uses the estimated effects of temperature shocks on ambient ozone – β_N^W – and the one labeled "with adaptation" uses the estimated impacts of changes in climate norms (lagged 30-year MAs) – β_N^C. These are the main results reported in Table 1 – the estimated coefficients for nonattainment counties from column (2). In addition, the row labeled savings "from adaptation" report the difference between the costs with and without adaptation – $\beta_N^W - \beta_N^C$ – and the row labeled "institution-induced adaptation" displays the portion of the adaptation due to the NAAQS for ambient ozone – IIA as in Equation (3).

Column (1) reports the costs associated with increased ambient ozone, and potential savings from adaptation, from a 1°C increase in temperature – $\Delta C = 1$. The costs arising from additional ambient ozone amount to approximately $1.77 billion (2015 USD) per year when we use the benchmark effect of temperature shocks that do not take into account adaptation. They reduce to approximately $1.2 billion using the impact of changes in climate norms, which does incorporate adaptive behavior. The difference of $567 million per year is the total potential savings from adaptation, 52 percent of which is induced by the NAAQS for ambient ozone. The portion induced by the NAAQS represents the co-benefits of the Clean Air Act in terms of climate adaptation, and can be interpreted as additional societal welfare gains from that existing institution, as informed by Equation (1). In the next four columns, all estimates are scaled up with the temperature projections from Vose et al. (2017) – e.g., $\Delta C = 1.4$ in column (2). Institution-induced adaptation, in particular, reaches the range of $412-471 million per year by mid-century, and $824-1,412 million by the end of the century. These are nontrivial additional welfare gains brought about by the air quality standards regarding ambient ozone.

VI. Concluding Remarks

This study conceptualized and presented the first credible estimates of institution-induced adaptation. In the absence of new international agreements or new federal legislation to tackle climate change directly, we have demonstrated conceptually and empirically that *existing* government institutions and policy established for reasons unrelated to climate change may be already inducing adaptation to climate change. We examined the impact of temperature changes on ambient ozone concentration in the United States from 1980-2013, and measured the role of institution-induced adaptation. Our main finding was that adaptation in counties out of attainment with air quality standards was 107 percent larger than in counties under attainment, implying substantial institution-induced adaptation. But we also provided evidence that local beliefs about climate change appear to matter in those adaptive responses, suggesting an important role for local factors in second-best climate policy.

By establishing that government institutions and policy unrelated to climate change are enhancing climate adaptation, our study points to an alternative set of incentives encouraging adaptive behavior besides innovation and market forces, which have been highlighted in previous research.[39] At the same time, our findings reveal a different role for public policy relative to a few other studies which caution that government actions intended to protect the public may reduce the incentive to engage in private self-protection.[40] Our results differ from these studies because, in our case, the institution we examined corrects a market failure – an air pollution externality – whereas the government programs examined in prior work may have distorted private behavior. Again, the insight here goes to the heart of the second-best theory. When the outcome of interest is the result of market failures, climate change can exacerbate the magnitude of the local unpriced externality. Nevertheless, existing institutions created for reasons unrelated to climate change can then serve as a "surrogate tax" for the nonexistent or incomplete climate policy, and induce climate adaptation.[41] It

[39] Olmstead and Rhode (2008, 2011*a*,*b*) highlighted crop choice and biological innovation in agriculture; Hornbeck (2012), Hornbeck and Naidu (2014), and Deryugina and Molitor (2020) pointed to migration; and Barreca et al. (2016) called attention to changes in the use of existing technologies, such as air conditioning.

[40] Annan and Schlenker (2015) found that the federal crop insurance program deterred farmers from engaging in optimal protection against extreme heat. Similarly, Deryugina (2017) showed that social safety nets not specifically targeting areas affected by extreme weather events may have discouraged out-migration.

[41] Another example of institution-induced adaptation may arise in the context of the Clean Water Act (Keiser and Shapiro, 2019*a*,*b*). The cleaning of the rivers might allow drought-prone locations to have alternative sources of drinking water. Think of the western region of the United States, where droughts may become more frequent with climate change. Water shortages may be addressed by the rivers cleaned up by

is imperative to reiterate, however, that our findings do not imply that efforts to enact comprehensive climate policy should be undermined. Rather, they should be recognized as a stepping stone towards reducing the cost of inaction (Stavins, 2019; Goulder, 2020).

To the best of our knowledge, we provided the first direct estimates of *incidental* benefits of current public policy in terms of climate adaptation. Because we are studying climate change, the first-best policy fostering adaptation should be carbon pricing. When that option is politically infeasible, however, a second-best solution can be implementing or strengthening policies correcting market failures associated with outcomes that depend on climate. The NAAQS for ambient ozone – the focus of our study – not only address an externality but also stimulate adaptation because climate is an input in ozone formation.

Our findings may contribute to the design of pollution control policy as well. The EPA has recently reviewed the NAAQS for ambient ozone, and decided to maintain the current threshold of 70ppb (USEPA, 2020*b*). Almost concomitantly, EPA finalized a rule rebuking the use of *co-benefits* – or incidental benefits not directly related to a targeted pollutant – to justify regulation for that pollutant (USEPA, 2020*a*).[42] This might affect future reviews of the ozone standards because the last revision in 2015 relied heavily on the co-benefits arising from reductions in particulate matter (USEPA, 2015*a*,*b*).

To understand how our results may be useful in the design of ambient ozone regulation, let us discuss some back-of-the-envelope calculations incorporating climate projections. According to the 2015 EPA's Final Ozone NAAQS Regulatory Impact Analysis (USEPA, 2015*b*), the annual nationwide costs to reduce the ambient ozone standards by 1ppb were approximately \$296 million (2015 USD), and the ozone-only benefits from that reduction ranged from \$376-632 million.[43] On the other hand, the annual nationwide PM2.5 co-benefits of NOx reductions associated with the 1ppb reduction in the ambient ozone standards ranged

the establishment of the Clean Water Act.

[42]This change formalizes the view that cross-pollutant co-benefits should not carry the same weight as direct benefits, which has implications for future rulemakings, including the standards for ambient ozone.

[43]For reference, the 1997 NAAQS for ambient ozone (implemented in 2004 due to lawsuits) was 80ppb. That was revised downward to 75ppb in 2008, and 70ppb in 2015. Also, ozone-only benefits reflect short-term exposure impacts, and as such are assumed to occur in the same year as ambient ozone reductions.

from \$478-1,058 million, assuming a 7% discount rate, which was what EPA adopted in the main analysis. Now, under the RCP 4.5 climate change scenario for mid-century United States, institution-induced adaptation from the projected 1.4°C increase in average temperature would be 0.46ppb. As reported in Table 5, this represents \$412 million in indirect adaptation-related benefits for the 509 counties that had been ever out of attainment with the ozone NAAQS in the period of our analysis, representing about two thirds of the U.S. population. Scaling that up to make it comparable to the measures above associated with 1ppb, institution-induced adaptation of 1ppb – which is what would happen approximately by the end of the century under the RCP 8.5 scenario – would imply annual indirect adaptation-related benefits for those 509 counties in the order of \$1,412 million. Hence, only the indirect benefits in terms of institution-induced adaptation for about a third of the U.S. population would more than offset the annual nationwide costs of reducing the ambient ozone standards by 1ppb by mid-century.[44] Therefore, it is urgent that EPA takes climate change into account in regulatory impact analyses of ambient ozone standards.

[44]These back-of-the-envelope calculations should be interpreted with caution. These indirect benefits may be considered *co-benefits* as well; they are just not arising from pollutants other than ozone. Thus, from the legal point of view, it is unclear how EPA may consider them. Notwithstanding, it is important to recognize in the current and future revisions of the standards that the NAAQS for ambient ozone are already enabling adaptation to climate change.

References

Aldy, Joseph E., and Richard J. Zeckhauser. 2020. "Three Prongs for Prudent Climate Policy." *NBER Working Paper #26991.*

Aldy, Joseph E., Scott Barrett, and Robert N. Stavins. 2003. "Thirteen Plus One: A Comparison of Global Climate Policy Architectures." *Climate Policy*, 3(4): 373–397.

Annan, Francis, and Wolfram Schlenker. 2015. "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat." *American Economic Review: Papers & Proceedings*, 105(5): 262–66.

Auffhammer, Maximilian. 2018. "Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption Using Big Data." *NBER Working Paper #24397.*

Auffhammer, Maximilian, and Ryan Kellogg. 2011. "Clearing the Air? The Effects of Gasoline Content Regulation on Air Quality." *American Economic Review*, 101(6): 2687–2722.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy*, 124(1): 105–159.

Becker, Randy, and Vernon Henderson. 2000. "Effects of Air Quality Regulations on Polluting Industries." *Journal of Political Economy*, 108(2): 379–421.

Bento, Antonio, Daniel Kaffine, Kevin Roth, and Matthew Zaragoza-Watkins. 2014. "The Effects of Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector." *American Economic Journal: Economic Policy*, 6(3): 1–29.

Bento, Antonio, Noah Miller, Mehreen Mookerjee, and Edson Severnini. 2020. "A Unifying Approach to Measuring Climate Change Impacts and Adaptation." *NBER Working Paper #27247.*

Carleton, Tamma, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Amir Jina, Robert Kopp, Kelly McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Justin Simcock, Arvid Viaene, Jiacan Yuan, and Alice Zhang. 2019. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *University of Chicago Becker Friedman Institute Working Paper No. 2018-51.*

Chay, Kenneth Y., and Michael Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy*, 113(2): 376–424.

Chetty, Raj. 2009. "Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods." *Annual Review of Economics*, 1: 451–488.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2018. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." *NBER Working Paper #25147.*

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2009. "Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates." *American Economic*

Review: Papers & Proceedings, 99(2): 198–204.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 4(3): 66–95.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature*, 52(3): 740–798.

Deryugina, Tatyana. 2017. "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance." *American Economic Journal: Economic Policy*, 9(3): 168–98.

Deryugina, Tatyana, and David Molitor. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review*, 110(11): 3602–33.

Deschenes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97(1): 354–85.

Deschenes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics*, 3(4): 152–85.

Deschenes, Olivier, Michael Greenstone, and Joseph S. Shapiro. 2017. "Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program." *American Economic Review*, 107(10): 2958–89.

Fowlie, Meredith, Stephen P Holland, and Erin T Mansur. 2012. "What do emissions markets deliver and to whom? Evidence from Southern California's NOx trading program." *American Economic Review*, 102(2).

Frisch, Ragnar, and Frederick V. Waugh. 1933. "Partial Time Regressions as Compared with Individual Trends." *Econometrica*, 1(4): 387–401.

Goulder, Lawrence H. 2020. "Timing Is Everything: How Economists Can Better Address the Urgency of Stronger Climate Policy." *Review of Environmental Economics and Policy*, 14(1): 143–156.

Goulder, Lawrence H., and Ian W.H. Parry. 2008. "Instrument Choice in Environmental Policy." *Review of Environmental Economics and Policy*, 2(2): 152–174.

Goulder, Lawrence H., and Roberton C. III Williams. 2003. "The Substantial Bias from Ignoring General Equilibrium Effects in Estimating Excess Burden, and a Practical Solution." *Journal of Political Economy*, 111(4): 898–927.

Graff Zivin, Joshua, and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review*, 102(7): 3652–3673.

Grainger, Corbett, Andrew Schreiber, and Wonjun Chang. 2019. "Do Regulators Strategically Avoid Pollution Hotspots when Siting Monitors? Evidence from Remote Sensing of Air Pollution." *Mimeo.*

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy*, 110(6): 1175–1219.

Harberger, Arnold C. 1964. "The Measurement of Waste." *American Economic Review Papers & Proceedings*, 54(3): 58–76.

Harberger, Arnold C. 1971. "Three Basic Postulates for Applied Welfare Economics: An Interpretive Essay." *Journal of Economic Literature*, 9(3): 785–797.

Harberger, Arnold C. 1974. *Taxation and Welfare.* Chicago, IL: University of Chicago Press.

Henderson, J. Vernon. 1996. "Effects of Air Quality Regulation." *American Economic Review*, 86(4): 789–813.

Heutel, Garth, Nolan H. Miller, and David Molitor. forthcoming. "Adaptation and the Mortality Effects of Temperature Across U.S. Climate Regions." *Review of Economics and Statistics*.

Hines, James, R. 1999. "Three Sides of Harberger Triangles." *Journal of Economic Perspectives*, 13(2): 167–188.

Hornbeck, Richard. 2012. "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe." *American Economic Review*, 102(4): 1477–1507.

Hornbeck, Richard, and Suresh Naidu. 2014. "When the Levee Breaks: Black Migration and Economic Development in the American South." *American Economic Review*, 104(3): 963–990.

Howe, Peter D., Matto Mildenberger, Jennifer R. Marlon, and Anthony Leiserowitz. 2015. "Geographic variation in opinions on climate change at state and local scales in the USA." *Nature Climate Change*, 5(6): 596–603.

Jacob, Daniel J., and Darrel A. Winner. 2009. "Effect of Climate Change on Air Quality." *Atmospheric Environment*, 43(1): 51–63.

Jacobsen, Mark R., Christopher R. Knittel, James M. Sallee, and Arthur A. van Benthem. 2020. "The Use of Regression Statistics to Analyze Imperfect Pricing Policies." *Journal of Political Economy*, 128(5): 1826–1876.

Keiser, David A., and Joseph S. Shapiro. 2019*a*. "Consequences of the Clean Water Act and the Demand for Water Quality." *Quarterly Journal of Economics*, 134(1): 349–396.

Keiser, David A., and Joseph S. Shapiro. 2019*b*. "US Water Pollution Regulation over the Past Half Century: Burning Waters to Crystal Springs?" *Journal of Economic Perspectives*, 33(4): 51–75.

Kleven, Henrik J. forthcoming. "Sufficient Statistics Revisited." *Annual Review of Economics.*

Kousky, Carolyn. 2012. "Informing Climate Adaptation: A Review of the Economic Costs of Natural Disasters, Their Determinants, and Risk Reduction Options." *Resources for the Future Discussion Paper 12-28.*

Krupnick, Alan J., and Deirdre Farrell. 1996. "Six Steps to a Healthier Ambient Ozone Policy." *Resources for the Future Discussion Paper 96-13.*

Lipsey, R. G., and Kelvin Lancaster. 1956. "The General Theory of Second Best." *Review of Economic Studies*, 24(1): 11–32.

Lovell, Michael C. 1963. "Seasonal Adjustment of Economic Time Series and Multiple

Regression Analysis." *Journal of the American Statistical Association*, 58(304): 993–1010.

Lucas, Robert E., Jr. 1976. "Econometric Policy Evaluation: A Critique." *Carnegie-Rochester Conference Series on Public Policy*, 1: 19–46.

McCall, James, Jordan Macknick, and Daniel Hillman. 2016. "Water-Related Power Plant Curtailments: An Overview of Incidents and Contributing Factors." *National Renewable Energy Laboratory (NREL) Technical Report NREL/TP-6A20-67084*.

McGrath, Justin M., Amy M. Betzelberger, Shaowen Wang, Eric Shook, Xin-Guang Zhu, Stephen P. Long, and Elizabeth A. Ainsworth. 2015. "An Analysis of Ozone Damage to Historical Maize and Soybean Yields in the United States." *Proceedings of the National Academy of Sciences*, 112(46): 14390–14395.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*, 84(4): 753–71.

Moretti, Enrico, and Matthew Neidell. 2011. "Pollution, Health, and Avoidance Behavior: Evidence from the Ports of Los Angeles." *Journal of Human Resources*, 46(1): 154–75.

Muller, Nicholas Z., and Paul A. Ruud. 2018. "What Forces Dictate the Design of Pollution Monitoring Networks?" *Environmental Modeling & Assessment*, 23(1): 1–14.

Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." *Journal of Human Resources*, 44(2): 450–78.

NOAA, National Oceanic & Atmospheric Administration. 2014. "National Oceanic and Atmospheric Administration (NOAA), Global Historical Climatology Network." *ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/*, accessed on November 30, 2014.

Nordhaus, William. 2019. "Climate Change: The Ultimate Challenge for Economics." *American Economic Review*, 109(6): 1991–2014.

North, Douglass C. 1991. "Institutions." *Journal of Economic Perspectives*, 5(1): 97–112.

Olmstead, Alan L., and Paul W. Rhode. 2008. *Creating Abundance: Biological Innovation and American Agricultural Development.* New York, NY: Cambridge University Press.

Olmstead, Alan L., and Paul W. Rhode. 2011*a*. "Adapting North American wheat production to climatic challenges, 1839–2009." *Proceedings of the National Academy of Sciences*, 108(2): 480–485.

Olmstead, Alan L., and Paul W. Rhode. 2011*b*. "Responding to Climatic Challenges: Lessons from U.S. Agricultural Development." In *The Economics of Climate Change: Adaptations Past and Present.* , ed. Gary D. Libecap and Richard H. Steckel, Chapter 6, pp. 169–194. Chicago, IL:University of Chicago Press.

Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences*, 106(37): 15594–98.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. 2005. "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review*, 95(1): 395–406.

Stavins, R., J. Zou, T. Brewer, M. Conte Grand, M. den Elzen, M. Finus, J.

Gupta, N. Hohne, M.-K. Lee, A. Michaelowa, M. Paterson, K. Ramakrishna, G. Wen, J. Wiener, and H. Winkler. 2014. "International Cooperation: Agreements and Instruments." In *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* , ed. O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, Chapter 13, pp. 1001–1082.

Stavins, Robert N. 2011. "The Problem of the Commons: Still Unsettled after 100 Years." *American Economic Review*, 101(1): 81–108.

Stavins, Robert N. 2019. "The Future of U.S. Carbon-Pricing Policy." *NBER Working Paper #25912.*

Towers, Sherry, Gerardo Chowell, Rasheed Hameed, Matthew Jastrebski, Maryam Khan, Jonathan Meeks, Anuj Mubayi, and George Harris. 2013. "Climate Change and Influenza: The Likelihood of Early and Severe Influenza Seasons Following Warmer Than Average Winters." *PLoS Currents Influenza*, 5: ecurrents.flu.3679b56a3a5313dc7c043fb944c6f138.

USEPA, U.S. Environmental Protection Agency. 1979. "Revisions to the National Ambient Air Quality Standards for Photochemical Oxidants: Final Rulemaking." *Federal Register*, 44(28): 8202–8237. February 8, 1979.

USEPA, U.S. Environmental Protection Agency. 1997. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 62(138): 38856–38896. July 18, 1997.

USEPA, U.S. Environmental Protection Agency. 2004. "Final Rule To Implement the 8-Hour Ozone National Ambient Air Quality Standard – Phase 1." *Federal Register*, 69(84): 23951–24000. April 30, 2004.

USEPA, U.S. Environmental Protection Agency. 2008. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 73(60): 16435–16514. March 27, 2008.

USEPA, U.S. Environmental Protection Agency. 2015*a*. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 80(206): 65291–65468. October 26, 2015.

USEPA, U.S. Environmental Protection Agency. 2015*b*. "Regulatory Impact Analysis of the Final Revisions to the National Ambient Air Quality Standards for Ground-Level Ozone." Washington, DC: U.S. Environmental Protection Agency, Office of Air and Radiation and Office of Air Quality Planning and Standards, EPA-452/R-15-007.

USEPA, U.S. Environmental Protection Agency. 2020*a*. "Increasing Consistency and Transparency in Considering Benefits and Costs in the Clean Air Act Rulemaking Process." *Federal Register*, 85(247): 84130–84157.

USEPA, U.S. Environmental Protection Agency. 2020*b*. "Review of the Ozone National Ambient Air Quality Standards – Final Action." *Federal Register*, 85(251): 87256–87351.

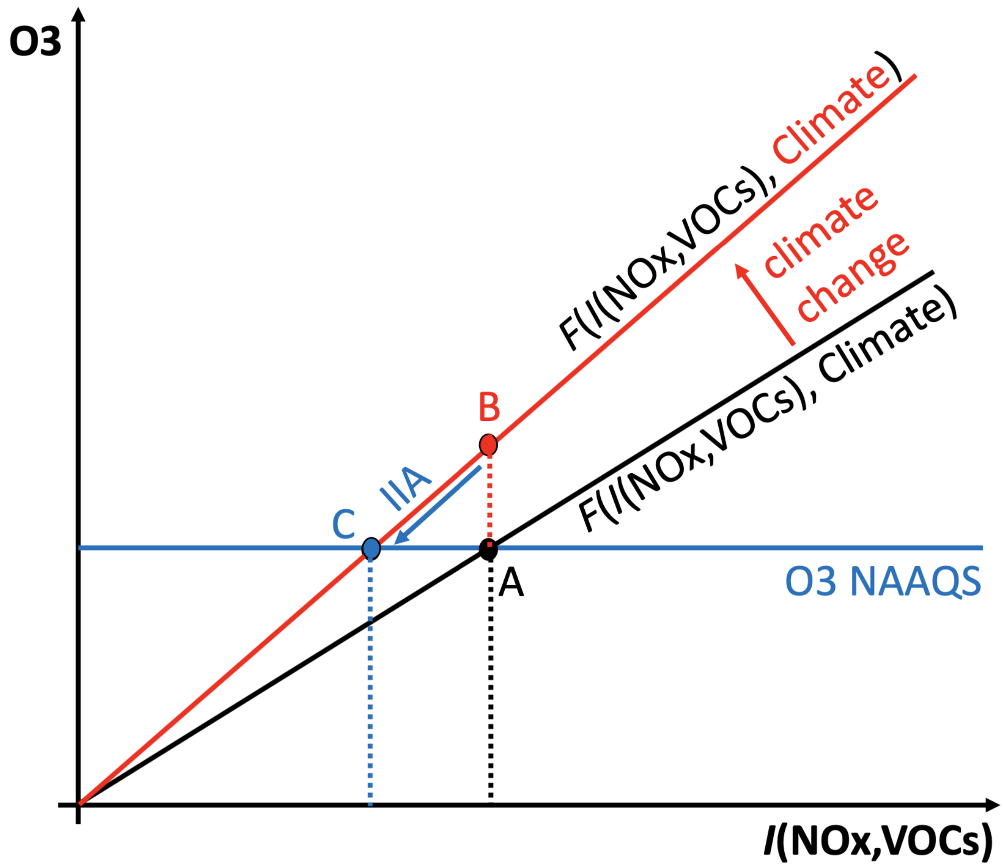
Vose, R.S., D.R. Easterling, K.E. Kunkel, A.N. LeGrande, and M.F. Wehner.

2017. “Temperature Changes in the United States.” In *Climate Science Special Report: Fourth National Climate Assessment, Volume I.* , ed. D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock, Chapter 6, pp. 185–206. Washington, DC:U.S. Global Change Research Program.

White, Corey. forthcoming. “Measuring Social and Externality Benefits of Influenza Vaccination.” *Journal of Human Resources.*

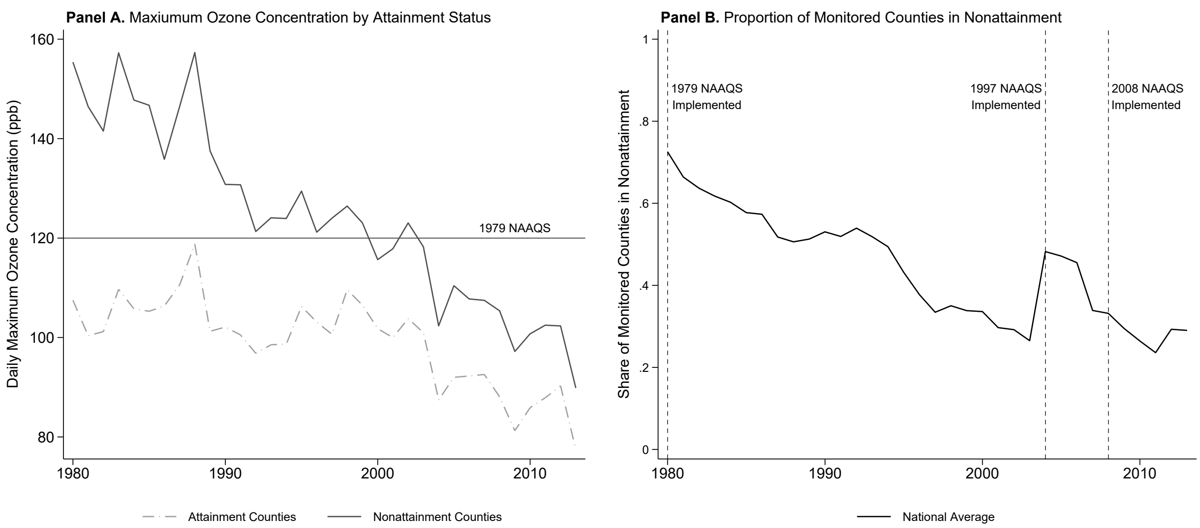
WMO. 2017. *WMO guidelines on the calculation of climate normals.* World Meteorological Organization Geneva, Switzerland.

Figure 1: Conceptual Framework on Institution-Induced Adaptation



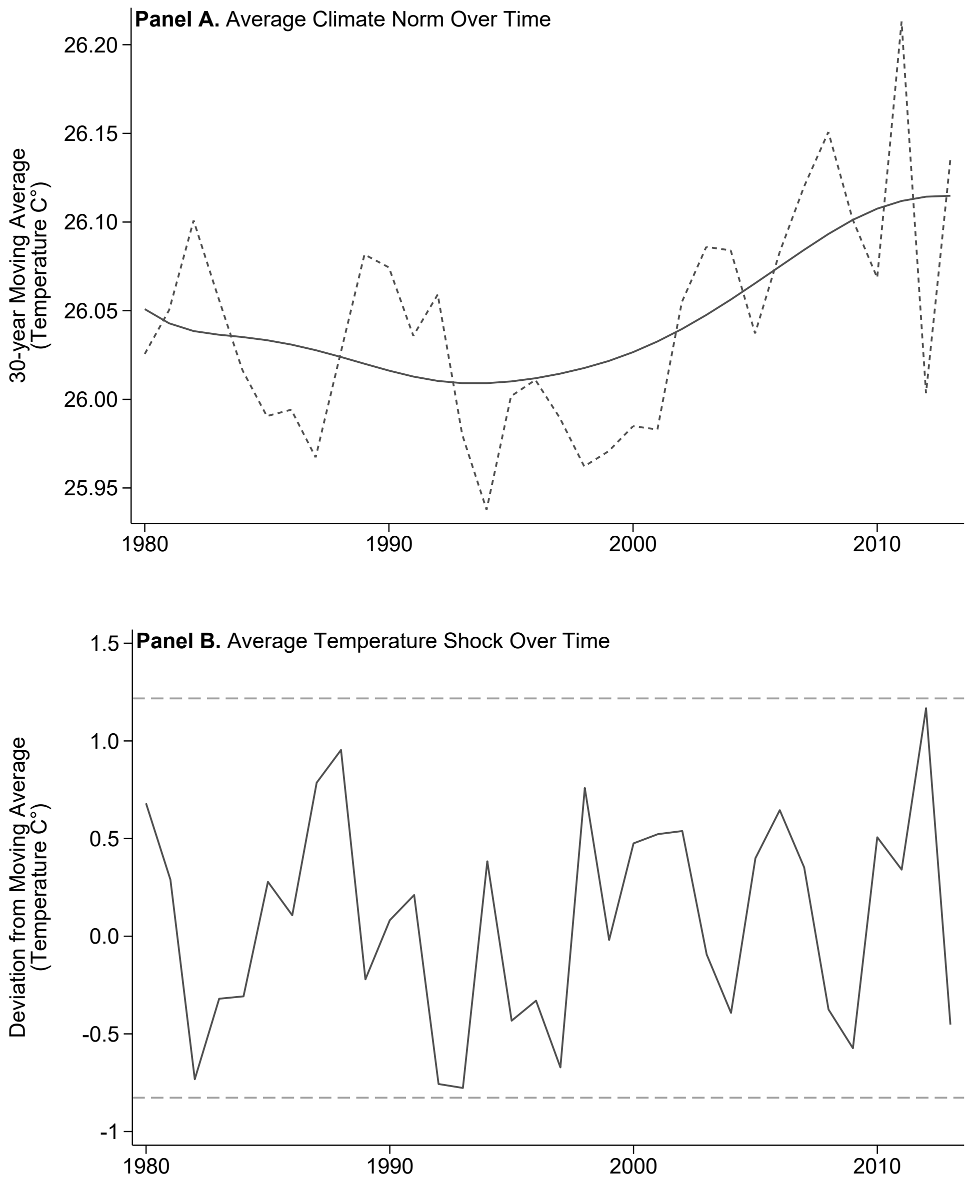
Notes: This figure provides a schematic representation of the conceptual framework used in our analysis. The the y-axis represents the output – ozone formation – and the x-axis represents a composite index $I(.)$ of two inputs – NOx and VOCs – whose levels move along the linear production function $F(I(\text{NOx,VOCs}),$ 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 ambient ozone. In point A, a county is complying with the standards. When average temperature rises, the production function shifts upward and to the left, and is now represented by the red upward-sloping curve. For the same level of the index I(NOx,VOCs), ozone concentration increases to point B. Because the county is now out of compliance with the the NAAQS, counties are required to make adjustments in their production processes to comply with the standards. As they take steps to reduce emissions of ozone precursors to reach attainment, moving along the new production function curve until point C, those economic agents are in fact adjusting to a changing climate. IIA stands for *institution-induced adaptation*, and represents the adaptation to climate change triggered by the existing institution of the Clean Air Act's NAAQS.

Figure 2: Evolution of Maximum Ozone Concentration and Counties in Nonattainment



Notes: This figure displays the evolution of maximum ambient ozone concentrations in the United States over the period 1980-2013 and the evolution of the proportion of counties violating the ambient ozone standards among the counties with ozone monitors. Panel (A) depicts daily maximum 1-hour ambient ozone concentrations over time (annual average), split by counties designated as in- or out- of attainment under the National Ambient Air Quality Standards (NAAQS). The 1979 NAAQS for designating a county's attainment status was based on an observed 1-hour maximum ambient ozone concentration of 120 parts per billion (ppb) or higher. Here we contrast this attainment status cutoff with the maximum yearly ozone concentrations of attainment and nonattainment counties. Appendix Figure A4 further compares these heterogeneous trends in ozone levels with the updated 1997 (implemented in 2004 due to lawsuits), 2008, and 2015 NAAQS levels. Panel (B) depicts the share of monitored counties that were out of attainment with the NAAQS for ozone during each year of our sample period. As can be clearly seen, this proportion has declined over time as the NAAQS regulations took effect. Also, observe that the policy change in 2004 resulted in many additional counties falling out of attainment, indicating that there was a nontrivial number of counties with average ozone levels at the margin of nonattainment.

Figure 3: Climate Norms and Shocks Over the Period of Analysis (1980-2013)



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 a complete, unbalanced panel of weather stations across the US from 1950 to 2013, restricting the months over which measurements were gathered to specifically match the ozone season of April–September, the typical ozone season in the US (see Appendix Table A2 for a complete list of ozone seasons by state). 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 daily observed maximum temperature and the climate norm. The solid line in Panel (A) smooths out the annual averages of the 30-year moving averages, and the horizontal dashed lines in Panel (B) highlights that temperature shocks are bounded in our period of analysis.

Table 1: Climate Impacts on Ambient Ozone and Adaptation

	Daily Max Ozone Levels (ppb)		Implied Adaptation	
	(1)	(2)	(3)	(4)
Temperature Shock	1.648***			
	(0.058)			
Climate Norm	1.161***		0.487***	
	(0.049)		(0.036)	
Nonattainment x Shock		1.990***		
		(0.079)		
Nonattainment x Norm		1.351***		0.639***
		(0.067)		(0.054)
Attainment x Shock		1.263***		
		(0.027)		
Attainment x Norm		0.956***		0.308***
		(0.035)		(0.029)
Institution Induced				0.332***
				(0.056)
Nonattainment Control	Yes	Yes		
Precipitation Controls	Yes	Yes		
Fixed Effects:				
Monitor-by-Season	Yes	Yes		
Region-by-Season-by-Year	Yes	Yes		
Observations	5,139,529	5,139,529		
R^2	0.428	0.434		

Notes: This table reports our main findings regarding the climate impacts on ambient ozone concentrations (in parts per billion – ppb) over the period 1980-2013, as well as the implied estimates of adaptation, in particular institution-induced adaptation. Column (1) reports climate impact estimates (national average), with daily temperature decomposed into climate norms and temperature shocks. Recall that the climate norm represents a 30-year monthly moving average of temperature, lagged by 1 year, while the temperature shock reflects the daily difference between observed temperature and this norm. In column (2) we interact the climate norm and temperature shock with indicators for whether counties have been designated as in- or out- of attainment under the National Ambient Air Quality Standards (NAAQS) for ambient ozone, to estimate heterogeneous effects across attainment and nonattainment counties, as specified in Equation (2). The attainment status is lagged by 3 years, because EPA allows at least this time period for counties to return to attainment levels. The last two columns report our adaptation estimates. By comparing the impacts of climate norm and temperature shock from column (1), we obtain our estimate of overall adaptation in column (3). Similarly, in column (4) we report the adaptation in attainment and nonattainment counties separately, which we obtain by comparing the impacts of climate norm and temperature shock reported in column (2). As defined in Equation (3), the difference between adaptation in nonattainment and attainment counties is our measure of institution-induced adaptation. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 2: Results by Distance of Ozone Concentrations to NAAQS Threshold

	Nonattainment		Attainment		Induced
	Ozone (ppb)	Adaptation	Ozone (ppb)	Adaptation	Adaptation
	(1)	(2)	(3)	(4)	(5)
Panel A. Ozone (ppb) Within 20% of NAAQS Threshold					
Temperature Shock	0.610***		0.382***		
	(0.024)		(0.014)		
Climate Norm	0.539***	0.071**	0.395***	−0.013	0.084***
	(0.033)	(0.034)	(0.017)	(0.014)	(0.029)
Observations	676,068		676,068		
R^2	0.825		0.825		
Panel B. Ozone (ppb) Within 20% - 40% of NAAQS Threshold					
Temperature Shock	0.758***		0.300***		
	(0.077)		(0.011)		
Climate Norm	0.484***	0.274***	0.264***	0.036**	0.238***
	(0.061)	(0.036)	(0.025)	(0.018)	(0.043)
Observations	1,300,386		1,300,386		
R^2	0.727		0.727		
Panel C. Ozone (ppb) Over 40% away from NAAQS Threshold					
Temperature Shock	1.225***		0.772***		
	(0.123)		(0.024)		
Climate Norm	0.673***	0.552***	0.479***	0.293***	0.259***
	(0.063)	(0.076)	(0.038)	(0.028)	(0.089)
All Controls	Yes		Yes		
Observations	3,162,755		3,162,755		
R^2	0.429		0.429		

Notes: This table reports results from our main specification in Equation (2) for subsamples of ozone monitor readings over the period 1980-2013 with concentrations falling within 20 percent of the NAAQS threshold in Panel (A), between 20-40 percent away from the threshold in Panel (B), and over 40 percent away from the threshold in Panel (C). Note that, within each panel, the estimates for nonattainment and attainment counties reported in columns (1) and (3) come from a single estimating equation. Columns (2) and (4) represent the implied measures of adaptation, while column (5) reports the resulting measure of institution-induced adaptation as the difference of column (4) from column (2). Recall that the climate norm represents a 30-year monthly moving average of temperature, lagged by 1 year, while the temperature shock reflects the daily difference between observed temperature and this norm. The full list of controls are the same as in the main model, depicted in column (2) of Table 1 for each panel in this table. For reference, the 1979 NAAQS was based on an observed 1-hour maximum ambient ozone concentration of 120ppb or higher, while the 1997 amendment (implemented in 2004 due to lawsuits) changed this to an observed maximum 8-hour average ambient ozone concentration of 80ppb or higher, and the 2008 update further reduced this to 75ppb. Standard errors are clustered at the county level. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table 3: Accounting for Competing Input Regulations Aiming at Ambient Ozone Reductions

	VOC Regulations (Excluding California)		NOx Regulations (Excluding NBP States)		NOx Regulations (Excluding RECLAIM Counties)	
	Ozone (ppb)	Adaptation	Ozone (ppb)	Adaptation	Ozone (ppb)	Adaptation
	(1)	(2)	(3)	(4)	(5)	(6)
Nonattainment x Shock	2.032***		2.050***		1.987***	
	(0.092)		(0.090)		(0.082)	
Nonattainment x Norm	1.370***	0.662***	1.430***	0.620***	1.320***	0.667***
	(0.061)	(0.064)	(0.080)	(0.062)	(0.055)	(0.061)
Attainment x Shock	1.275***		1.267***		1.263***	
	(0.028)		(0.031)		(0.027)	
Attainment x Norm	0.970***	0.305***	0.978***	0.290***	0.946***	0.317***
	(0.034)	(0.028)	(0.041)	(0.034)	(0.033)	(0.029)
Institution Induced		0.358***		0.331***		0.349***
		(0.065)		(0.063)		(0.062)
All Controls	Yes		Yes		Yes	
Observations	4,631,413		4,338,183		5,008,323	
R^2	0.432		0.443		0.439	

Notes: This table reports results from our main specification in Equation (2) but excluding locations with competing regulations – input regulations aimed at reducing ambient ozone concentrations via reductions in ozone precursors (VOCs and NOx). Three of these regulations were implemented in the United States over our sample period 1980-2013: (i) regulations restricting the chemical composition of gasoline, intended to reduce VOC emissions from mobile sources (Auffhammer and Kellogg, 2011), (ii) the NOx Budget Trading Program (Deschenes, Greenstone and Shapiro, 2017), and (iii) the Regional Clean Air Incentives Market (RECLAIM) NOx and SOx emissions trading program (Fowlie, Holland and Mansur, 2012). Because our goal is to estimate climate adaptation induced by the NAAQS for ambient ozone, here we examine the sensitivity of our estimates of institution-induced adaptation when accounting for these input regulations. Column (1) excludes California from 1996 onwards, when stringent VOC regulations were in place. Column (3) excludes the states participating in the NBP from 2003 onwards, when the program was in effect. Column (5) excludes the four California counties within the South Coast Air Quality Management District from 1994 onwards, when the RECLAIM was in operation. The implied adaptation estimates presented in columns (2), (4), and (6), are derived from the estimates reported in columns (1), (3), and (5), respectively. Recall that the climate norm represents a 30-year monthly moving average of temperature, lagged by 1 year, while the temperature shock reflects the daily difference between observed temperature and this norm. 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 4: 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 institution-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 5: Implied Impacts of Ambient Ozone Climate Penalty

	Nonattainment Counties				
	1°C Increase	RCP 4.5 Scenario		RCP 8.5 Scenario	
		2050	2100	2050	2100
	(1)	(2)	(3)	(4)	(5)
Costs (Millions 2015 USD/year)					
Without Adaptation	1,766	2,473	4,946	2,826	8,479
With Adaptation	1,199	1,679	3,357	1,918	5,755
Savings (Millions 2015 USD/year)					
From Adaptation	567	794	1,589	908	2,723
Institution-Induced Adaptation	294	412	824	471	1,412

Notes: This table reports some back-of-the-envelope calculations on a class of *co-benefits* of the existing Clean Air Act institution – climate adaptation induced by the NAAQS for ambient ozone. The calculations are derived from the main estimates in Table 1 and the costs associated with those climate penalties on ambient ozone in the United States, for all 509 counties ever in nonattainment in our sample, under a variety of climate scenarios. The social costs of ozone increases are inferred from the estimated willingness to pay (WTP) for a 1 ppb decrease in the mean 8-hour summer ozone concentration in the states participating in the U.S. NOx Budget Program – about \$1.7 million (2015 USD) per county per year (Deschenes, Greenstone and Shapiro, 2017, p.2985, Table 6, Panel D, Column 5). Column (1) reports the impacts of a 1° Celsius increase in temperature as a baseline effect, while columns (2) and (3) extend these effects to match the expected temperature increases under the Representative Concentration Pathway (RCP) 4.5 climate scenario at mid- and late- century. Similarly, columns (4) and (5) extend the effects out to mid- and late- century under the more damaging RCP 8.5 climate scenario. Temperature projections are based on global models and downscaled products from CMIP5 (Coupled Model Intercomparison Project Phase 5) using a suite of RCPs. The annual average temperature of the contiguous United States is projected to rise throughout the century. Increases for the period 2021-2050 relative to 1976-2005 are projected to be about 1.4°C (2.5°F) for a lower scenario (RCP4.5) and 1.6°C (2.9°F) for the higher scenario (RCP8.5). In other words, recent record-breaking years may be “common” in the next few decades. By late-century (2071-2100), the RCPs diverge significantly, leading to different rates of warming: approximately 2.8°C (5.0°F) for RCP4.5, and 4.8°C (8.7°F) for RCP8.5 (Vose et al., 2017, p.195). In this table, the first row reports the expected effect of the relevant temperature increase by using the estimate of temperature shock from column (2) of Table 1. The second row then reports what these impacts would be after including adaptation by instead using the estimate of climate norm from the same column of Table 1. Row three displays the implied savings, simply reflecting the difference between the first two rows. Further, by taking the difference between the measures of adaptation in nonattainment and attainment counties from Table 1, column (4), row four reports the component of these savings that can be attributed to adaptation induced by the NAAQS for ambient ozone, which we termed institution-induced adaptation.

Online Appendix for

Time is of the Essence:
Climate Adaptation Induced by Existing Institutions

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(for reference only; not for publication)

This appendix provides details on the construction of the data, descriptive figures, and the tabular results of robustness tests and explorations of heterogeneity using alternate specifications. In Appendix A, we provide 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 institution-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 early- to 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 **??**. 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 **??** 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 provided 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 B5 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.

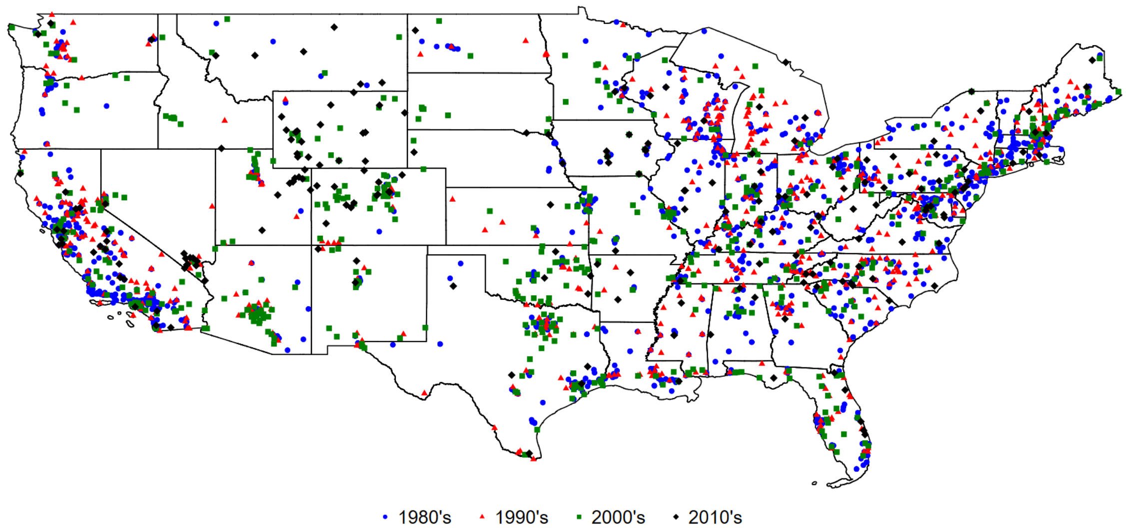
In Table 4 we examine heterogeneity in our results when separating counties into low- median- and high-levels of belief regarding the existence of climate change. These measures were constructed using county level survey data collected by Howe et al. (2015) in 2013 which estimate the percentage of each 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 B7 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 B8. 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.

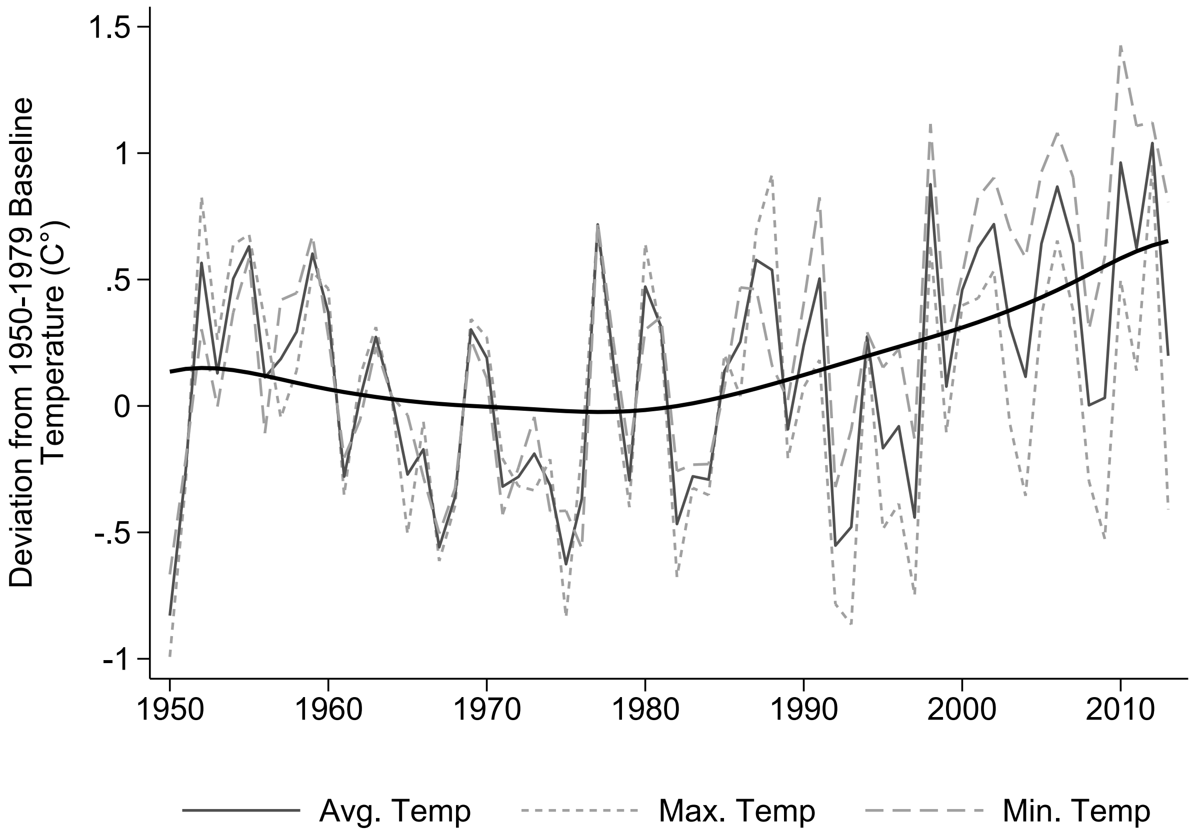
In Table B9 we use measures of whether a county is "VOC-limited" or "NOx-limited." These measures were constructed using data collected by the EPA's network of respective monitoring stations. Note, however, that these are often separate pollution monitors from our main sample of ozone monitors. Additionally, 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



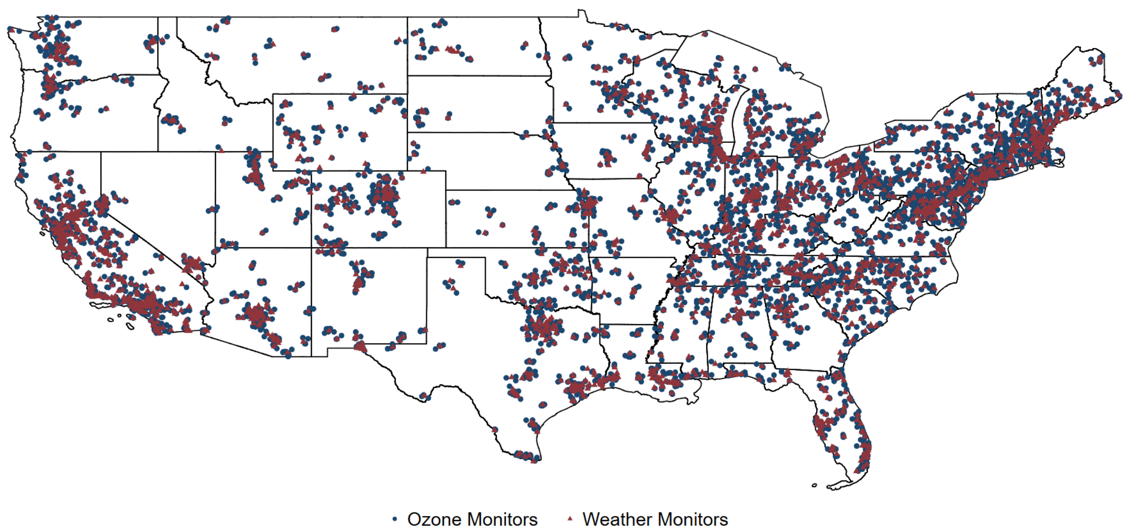
Notes: This figure depicts the evolution of ozone monitors in our sample over three decades and illustrates the expansion of the monitoring network. We use an unbalanced panel of ozone monitors, after making the following two restrictions. Firstly, we only include monitors if 8-hour averages are available 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)



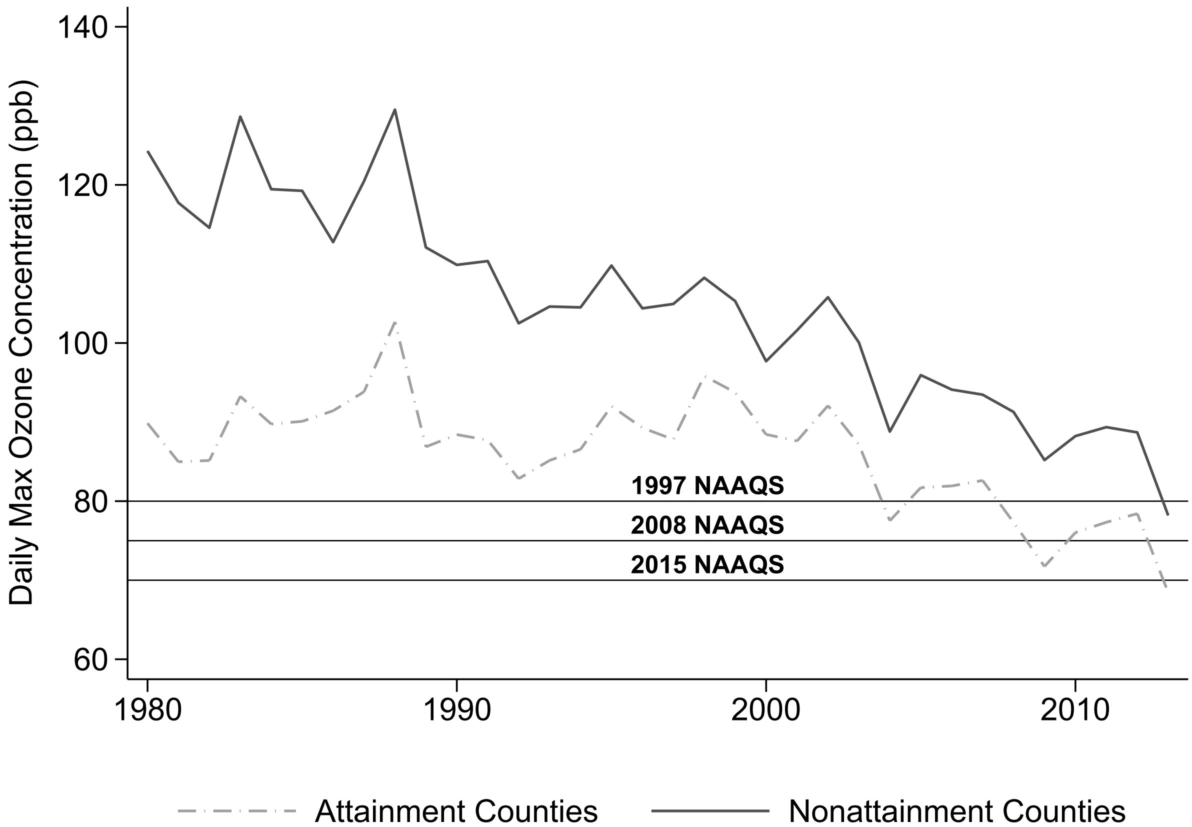
Notes: This figure depicts annual temperature fluctuations and the overall climatic trend for the ozone season in the US relative to a 1950-1979 baseline average. The baseline and the yearly deviations from it are constructed from the comprehensive sample of weather stations across the US from 1950 to 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



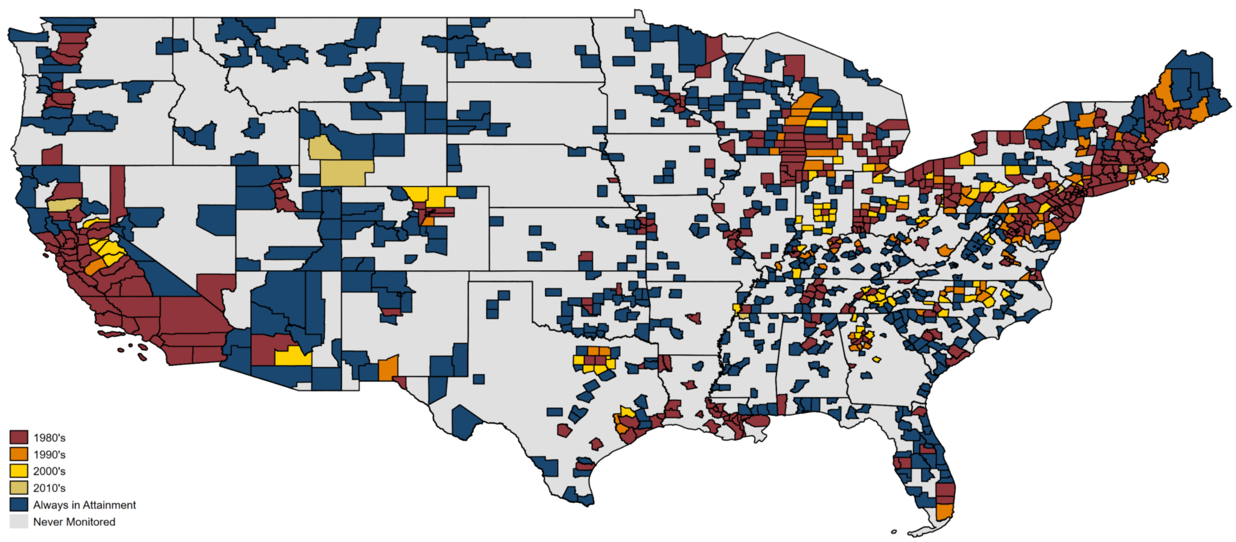
Notes: This figure illustrates the proximity of our final sample of ambient ozone monitors to the matched weather stations. Using information on the geographical location of pollution monitors and weather stations we calculate the Haversine distance between each pair of ozone monitor and weather station.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



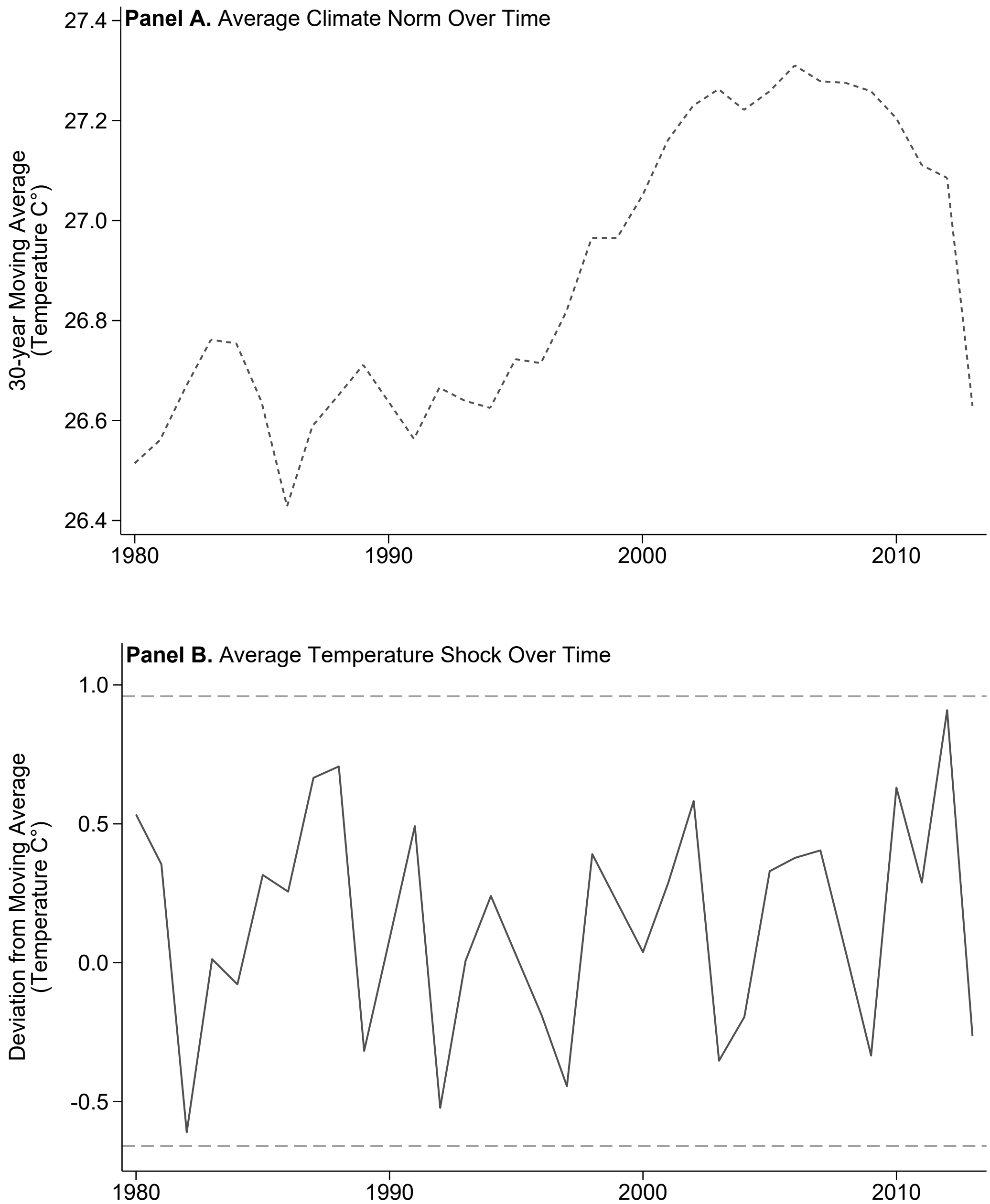
Notes: This figure depicts the national average of the annual 4th highest daily maximum 1-hour ambient ozone concentration over time in the US, split by counties designated as in- or out- of attainment under the National Ambient Air Quality Standards (NAAQS). The 1997, 2008, and 2015 NAAQS updates for 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



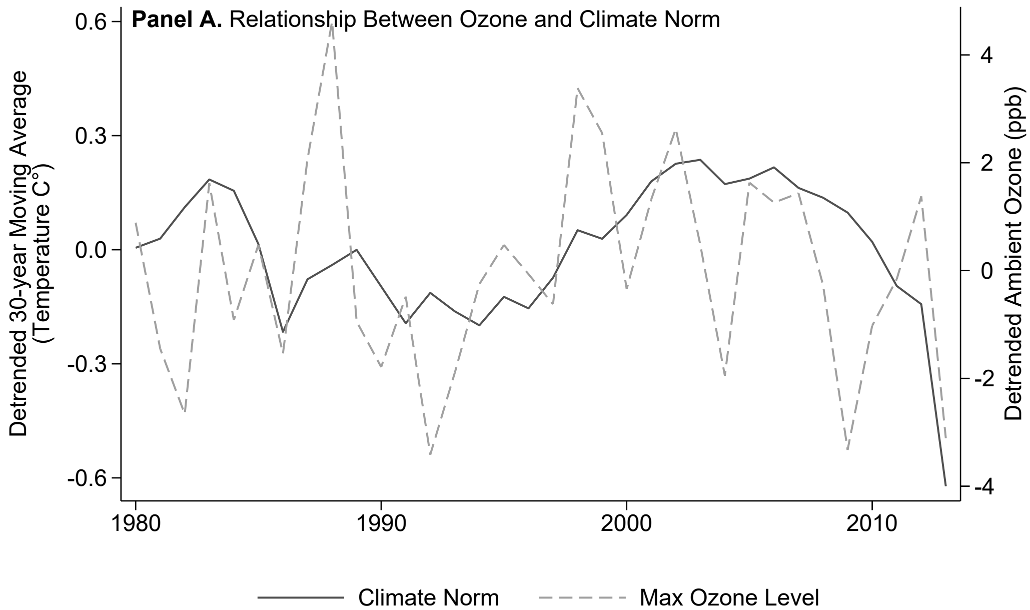
Notes: This figure illustrates all counties monitored under the NAAQS for ozone during the period 1980-2013, noting the decade in which they were first designated as in "nonattainment," if ever. While the structure of enforcement is dictated by the CAA and the EPA, much of the actual enforcement activity 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.

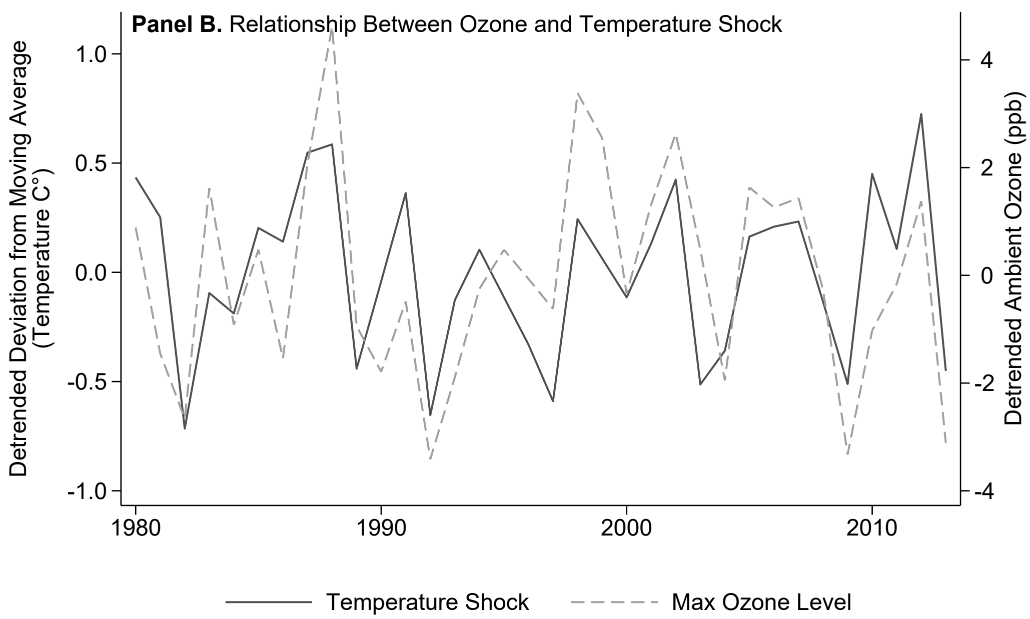
Figure A6: Climate Norms and Shocks (Final Sample)



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.

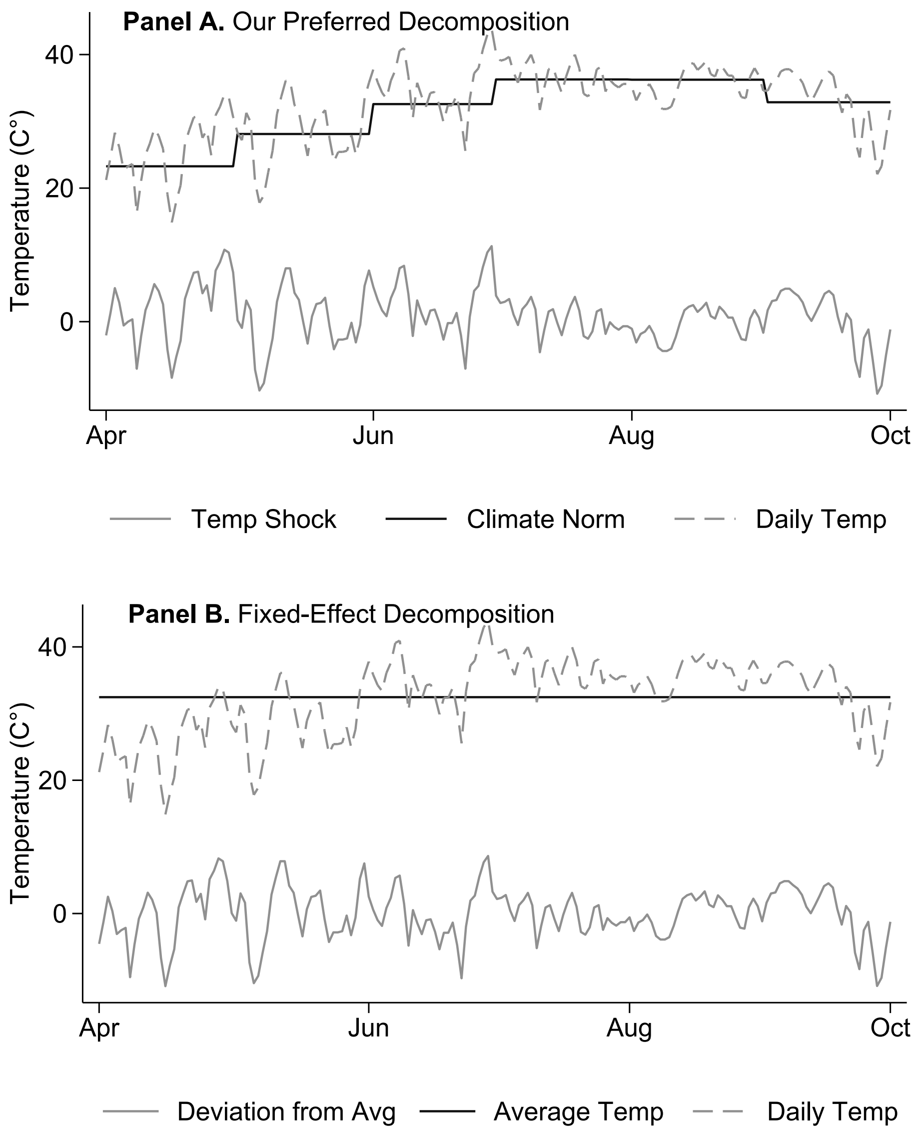
Figure A7: Relationship between Ambient Ozone and Temperature





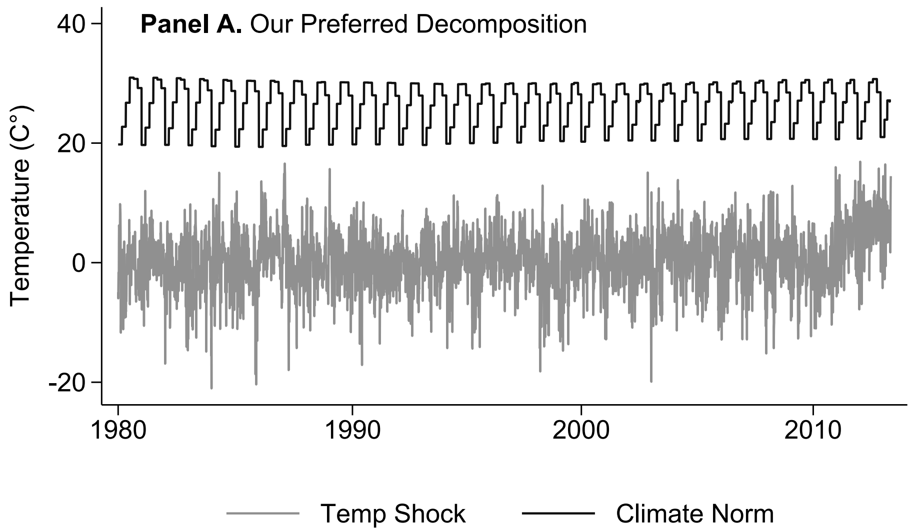
Notes: This figure depicts the general relationship between daily maximum ozone concentrations and temperature over the years in our sample (1980-2013) after decomposing temperature into our measure of climate norm and temperature shock and de-trending the data. Both the climate norm (Panel A) and the 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.

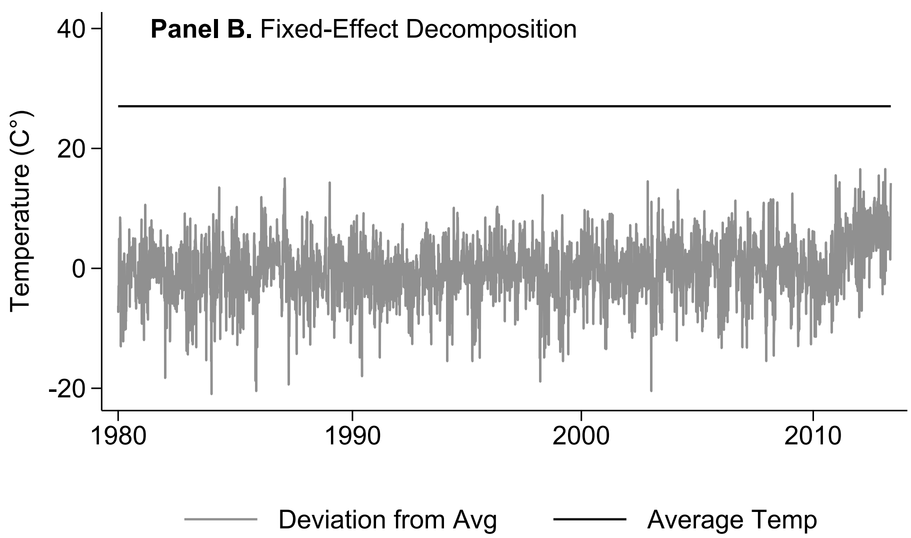
Figure A8: Decomposition of Temp. Norms & Shocks – Illustration (Los Angeles, 2013)



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.

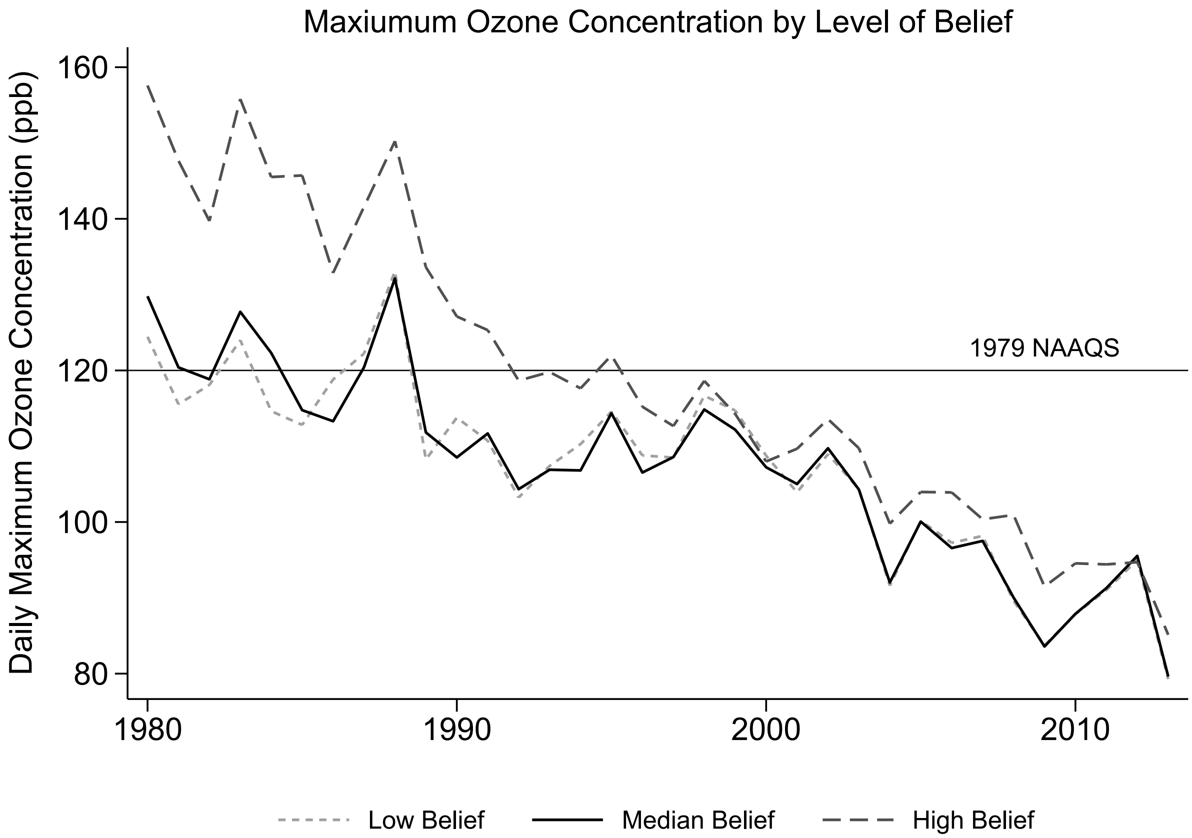
Figure A9: Decomposition of Temp. Norms & Shocks – Illustration (Los Angeles, All Years)





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. Alternative Criteria for Selection of Weather Stations

Table B5. Alternative Outcome Variables

Table B6. Bootstrapped Standard Errors

Table B7. Belief in Climate Change: Summary Stats

Table B8. Placebo: Preferences for Single Parenting

Table B9. Adaptation by VOC- or NOx-limited Atmosphere

Table B10. Results by Decade

Tables B11a & B11b. 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, institution-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 institution-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.

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 B4. 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 Decade — To examine temporal heterogeneity, Table B10 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 vs attainment counties, we can get our institution-induced adaptation measures in each decade. The estimates suggest that institution-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 B11a and B11b 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 institution-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 institution-induced adaptation increases substantially. Between 30-35°C, the magnitude of institution-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 institution-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)
Institution 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)
Institution 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)
Institution 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: 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)
Institution 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 B5: 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)
Institution 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 institution-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 B6: 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)
Institution 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 B7: 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 4. 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 B8: 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 institution-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 B9: 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)
Institution 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 the county was VOC-limited or NOx-limited. Using 5-year bins (1980-1984, 1985-1989, etc.) a county is designated as VOC-limited, NOx-limited, or neither for each bin based on whichever of these three categories the county observed the most days of. We restrict our sample to only those counties for which data on these precursor pollutants is available (approximately 20% of our full sample), and depict the results of our main specification under this restricted sample in columns (1) and (2) for comparison. In column (3), the main effect reflects the result for non-limited counties, while the interaction term depicts the relative difference in the effect of shocks and norms in precursor limited counties. Similarly, column (4) reports the implied measure of adaptation in non-limited counties, and the differential effect in limited ones. Recall that the 30-yr MA is lagged by 1 year, and the Clean Air Act attainment/nonattainment county designation is

Table B10: 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 institution-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 B11a: Nonlinear Effects of Temperature

	Panel A. Below 20°C		
	Max Ozone (ppb)	Implied Adaptation	Induced Adaptation
	(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 institution-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 institution-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 B11b: 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 B11a 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 institution-induced adaptation as discussed in Section II.

C.1. New vs. Existing Institutions 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 institutions and policy 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 institutions 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 hypothesize that local institutions, rather than national or global, might be also effective in shaping the responses to climate change.[15]

C.2. The Nature of Existing Institutions Inducing Adaptation

The potential for government institutions 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 (Bar-

[15]This hypothesis emerges from 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 local beliefs about climate change strongly associate with adaptation induced by existing government institutions and policy. Our prior is that local social norms/institutions may play a key role in determining the success of policies addressing environmental externalities.

reca et al., 2016). In this case, policymakers could weigh these costs and benefits in their 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 institution-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.[16] 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 institution-induced adaptation as clear as possible in the context we are studying, we use the schematic representation depicted in Figure 1. In this figure,

[16] 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, institution-induced adaptation.

the y-axis represents the output – ozone formation – and the x-axis represents one of the 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 institution-induced adaptation.[17]

[17] 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

Despite the contribution of current government institutions 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.[18]

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,

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

the world.

[18] 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 "institution-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.

References

Allcott, Hunt. 2011. "Social Norms and Energy Conservation." *Journal of Public Economics*, 95(9–10): 1082–1095.

Annan, Francis, and Wolfram Schlenker. 2015. "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat." *American Economic Review: Papers & Proceedings*, 105(5): 262–66.

Auffhammer, Maximilian, and Ryan Kellogg. 2011. "Clearing the Air? The Effects of Gasoline Content Regulation on Air Quality." *American Economic Review*, 101(6): 2687–2722.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy*, 124(1): 105–159.

Becker, Randy, and Vernon Henderson. 2000. "Effects of Air Quality Regulations on Polluting Industries." *Journal of Political Economy*, 108(2): 379–421.

Bento, Antonio, Daniel Kaffine, Kevin Roth, and Matthew Zaragoza-Watkins. 2014. "The Effects of Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector." *American Economic Journal: Economic Policy*, 6(3): 1–29.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2018. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." *NBER Working Paper #25147*.

Dawson, John P., Peter J. Adams, and Spyros N. Pandisa. 2007. "Sensitivity of Ozone to Summertime Climate in the Eastern USA: A Modeling Case Study." *Atmospheric Environment*, 41(7): 1494–1511.

Deschenes, Olivier, Michael Greenstone, and Joseph S. Shapiro. 2017. "Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program." *American Economic Review*, 107(10): 2958–89.

Ferraro, Paul J., and Michael K. Price. 2013. "Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-Scale Field Experiment." *Review of Economics and Statistics*, 95(1): 64–73.

Goulder, Lawrence H. 2020. "Timing Is Everything: How Economists Can Better Address the Urgency of Stronger Climate Policy." *Review of Environmental Economics and Policy*, 14(1): 143–156.

Goulder, Lawrence H., and Ian W.H. Parry. 2008. "Instrument Choice in Environmental Policy." *Review of Environmental Economics and Policy*, 2(2): 152–174.

Graff Zivin, Joshua, and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review*, 102(7): 3652–3673.

Henderson, J. Vernon. 1996. "Effects of Air Quality Regulation." *American Economic Review*, 86(4): 789–813.

Howe, Peter D., Matto Mildenberger, Jennifer R. Marlon, and Anthony Leiserowitz. 2015. "Geographic variation in opinions on climate change at state and local scales in the USA." *Nature Climate Change*, 5(6): 596–603.

Jacobsen, Mark R., Christopher R. Knittel, James M. Sallee, and Arthur A. van Benthem. 2020. "The Use of Regression Statistics to Analyze Imperfect Pricing Policies." *Journal of Political Economy*, 128(5): 1826–1876.

Kahn, Matthew E. 2007. "Do Greens Drive Hummers or Hybrids? Environmental Ideology as a Determinant of Consumer Choice." *Journal of Environmental Economics and Management*, 54(2): 129–145.

Kotchen, Matthew J., and Michael Moore. 2008. "Conservation: From Voluntary Restraint to a Voluntary Price Premium." *Environmental and Resource Economics*, 40(2): 195–215.

Lipsey, R. G., and Kelvin Lancaster. 1956. "The General Theory of Second Best." *Review of Economic Studies*, 24(1): 11–32.

McCall, James, Jordan Macknick, and Daniel Hillman. 2016. "Water-Related Power Plant Curtailments: An Overview of Incidents and Contributing Factors." *National Renewable Energy Laboratory (NREL) Technical Report NREL/TP-6A20-67084*.

Moretti, Enrico, and Matthew Neidell. 2011. "Pollution, Health, and Avoidance Behavior: Evidence from the Ports of Los Angeles." *Journal of Human Resources*, 46(1): 154–75.

Muller, Nicholas Z., and Paul A. Ruud. 2018. "What Forces Dictate the Design of Pollution Monitoring Networks?" *Environmental Modeling & Assessment*, 23(1): 1–14.

Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." *Journal of Human Resources*, 44(2): 450–78.

NOAA, National Oceanic & Atmospheric Administration. 2014. "National Oceanic and Atmospheric Administration (NOAA), Global Historical Climatology Network." *ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/*, accessed on November 30, 2014.

Nordhaus, William. 2015. "Climate Clubs: Overcoming Free-Riding in International Climate Policy." *American Economic Review*, 105(4): 1339–70.

Nordhaus, William. 2019. "Climate Change: The Ultimate Challenge for Economics." *American Economic Review*, 109(6): 1991–2014.

Phaneuf, Daniel J., and Till Requate. 2017. *A Course in Environmental Economics: Theory, Policy, and Practice.* New York, NY: Cambridge University Press.

Solon, Gary. 1992. "Intergenerational Income Mobility in the United States." *American Economic Review*, 82(3): 393–408.

Towers, Sherry, Gerardo Chowell, Rasheed Hameed, Matthew Jastrebski, Maryam Khan, Jonathan Meeks, Anuj Mubayi, and George Harris. 2013. "Climate Change and Influenza: The Likelihood of Early and Severe Influenza Seasons Following Warmer Than Average Winters." *PLoS Currents Influenza*, 5: ecurrents.flu.3679b56a3a5313dc7c043fb944c6f138.

USCFR, U.S. Code of Federal Regulations. 2005. "National Archives and Records Administration, Federal Register, Title 42 Public Health, Chapter 85, Subchapter 1, Part D, Subpart 1, Par. 7509."

USEPA, U.S. Environmental Protection Agency. 1979. "Revisions to the National Ambient Air Quality Standards for Photochemical Oxidants: Final Rulemaking." *Federal Register*, 44(28): 8202–8237. February 8, 1979.

USEPA, U.S. Environmental Protection Agency. 1997. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 62(138): 38856–38896. July 18, 1997.

USEPA, U.S. Environmental Protection Agency. 2004. "Final Rule To Implement the 8-Hour Ozone National Ambient Air Quality Standard – Phase 1." *Federal Register*, 69(84): 23951–24000. April 30, 2004.

USEPA, U.S. Environmental Protection Agency. 2006. "Air Quality Criteria for Ozone and Related Photochemical Oxidants — Volume II." Available at epa.gov/ttn/naaqs/aqmguide/collection/cp2/20060228_ord_epa600_r05-004bf_ozone_criteria_document_vol2.pdf, accessed on July 23, 2017.

USEPA, U.S. Environmental Protection Agency. 2008. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 73(60): 16435–16514. March 27, 2008.

USEPA, U.S. Environmental Protection Agency. 2015. "National Ambient Air Quality Standards for Ozone: Final Rule." *Federal Register*, 80(206): 65291–65468. October 26, 2015.

USEPA, U.S. Environmental Protection Agency. 2019. "Integrated Review Plan for the Review of the Ozone National Ambient Air Quality Standards." Washington, DC: U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, EPA-452/R-19-002.

Vose, R.S., D.R. Easterling, K.E. Kunkel, A.N. LeGrande, and M.F. Wehner. 2017. "Temperature Changes in the United States." In *Climate Science Special Report: Fourth National Climate Assessment, Volume I.* , ed. D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock, Chapter 6, pp. 185–206. Washington, DC:U.S. Global Change Research Program.

White, Corey. forthcoming. "Measuring Social and Externality Benefits of Influenza Vaccination." *Journal of Human Resources.*

Zhang, Yuzhong, and Yuhang Wang. 2016. "Climate-driven Ground-level Ozone Extreme in the Fall Over the Southeast United States." *Proceedings of the National Academy of Sciences*, 113(36): 10025–10030.