THREE ESSAYS ON CLIMATE CHANGE AND AIR POLLUTION

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THREE ESSAYS ON CLIMATE CHANGE AND AIR POLLUTION

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In my dissertation, I have studied the link between the Earth's changing climate and air pollution. As we know, air pollution is an externality of any major industrial activity, day to day vehicle use, electricity generation etc. I establish the fact that rapidly changing temperature and rainfall patterns exacerbate the levels of multiple air pollutants, thus entailing larger social costs of the above mentioned activities. From a policy perspective, such estimates are crucial to reach the socially desirable level of emissions and technically, this exogenous causal link from climate change to pollutant formation can be used to get more precise estimates of the health consequences of air pollution.

In the first chapter, I analyze the impact of climate change on particulate air pollution, which has the most sever health consequences. Using daily weather data, daily data on PM_{10} from 1990-2013 and daily data on $PM_{2.5}$ from 1997-2013, I find the first causal estimates of the level of precipitation as well as the precipitation frequency on particulate matter concentrations in ambient air. Using my findings, I exploit exogenous rainfall variation in an instrumental variables approach to also estimate the effect of increases in ambient particulate matter on the number of infant deaths. My estimates suggest that a 1 $\mu g/m^3$ decrease in ambient PM_{10} concentrations would imply almost 27 fewer infant deaths per 100,000 live births.

In my second chapter, we propose a novel approach to estimate adaptation to climate change based on a decomposition of meteorological variables into

long-run trends and deviations from those trends (weather shocks). Our estimating equation simultaneously exploits weather variation to identify the impact of weather shocks, and climatic variation to identify the effect of longer-run observed changes. We then compare the short- and long-run effects to provide a measure of adaptation. We apply our methodology to study the impact of climate change on air quality and estimate the so-called climate penalty on ozone. We have three main findings. First, a temperature shock of 1°C increases ozone levels by 1.7 ppb on average. A change of similar magnitude in a 30-year moving average increases ozone concentration by 1.2 ppb. Second, we find evidence of adaptive behavior. For a change of 1°C in temperature, our measure of adaptation in terms of ozone concentration is 0.45 ppb. If adaptive responses are not taken into account, the climate penalty on ozone would be overestimated by approximately 17 percent. Third, adaptation in counties with levels of ozone above the EPA's standards appears to be over 66 percent larger than adaptation in counties in "attainment". This difference is what we call regulation-induced adaptation. The remainder is our measure of residual adaptation.

In the final chapter, we present a theoretical model that looks at a federal air pollution regulation and tries to analyze the variablity in attainment and non attainment designations of counties. Since many areas in the United States have been in non-attainment for prolonged periods, we argue that it must be an optimal choice for the counties, driven by parameters among which climate change is a major one. We find that counties having mild enough climate can actually choose to be in non-attainment, even after paying the penalties imposed by the regulation.

BIOGRAPHICAL SKETCH

Mehreen Mookerjee was born in Kolkata, India in February 1989. She completed her schooling from Our Lady Queen of the Missions School in her hometown. She was introduced to the subject of Economics during her high school years. Having liked the subject, she went on to pursue it further and completed her Bachelor of Arts (Honors) in Economics from Jadavpur University in Kolkata, in the year 2010. Following this, she successfully completed her Master of Science in Quantitative Economics from the Indian Statistical Institute, Delhi, before joining Cornell University in 2012 to pursue graduate studies in Economics.

To Maa and Baba

For teaching me that giving up is never a solution.

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I would like to thank my Ph.D. supervisors, Professors Ravi Kanbur and Antonio Bento, for their support and guidance throughout these past years. I am very grateful to Prof. Kanbur, for always being very helpful and supportive even in the most difficult situations. I always knew that no matter what, I could rely on him; and that assurance really meant a lot during these trying years of my life. I am grateful to Antonio for opening various opportunities for me that gave me much-needed experience in research and academia. I am especially thankful to him, for getting me involved in collaborative work with Edson and himself, as that has really provided me hands on training not only in conducting research, but also various other important factors such as teamwork, presenting at academic conferences, meeting deadlines as well as developing good writing and communication skills which I believe are integral to success in an academic career. I would also like to thank Prof. Stephen Coate, for his invaluable advice at various stages of my Ph.D. I will be forever grateful to Edson Severnini, whom I have been privileged to work with over the past 3 years. Edson has, in many instances, been my first point of contact whenever I ran into any problems with my paper and I really could not have managed to complete this dissertation without his support. Without even being a part of my dissertation committee, Edson's willingness to support and encourage me at every stage, hearing out my frustrations and motivating me to move forward, has made him more of a friend than a colleague and I am indebted to him for that.

I would like to thank the two most important people in my life, my mother, *Maa*, and my father, *Baba*, for making me who I am today. I am exceptionally fortunate to have my best friends, philosophers, and guides in the form of my parents, who literally walk me through every phase of life. I can never forget

how Maa, willingly, and with a smiling face, put her flourishing career on a back seat and focused her undivided attention on my upbringing, to ensure that I can grow up to be a successful and independent woman. She has literally been the wind beneath my wings, in the truest sense. Baba, on the other hand, has always been the rock in our family- on whom we can blindly rely. I cannot really imagine how I will manage myself and my life without him. As my friends would humorously put it- whenever any unexpected thing happens, my first phone call has to be to Baba. I am thankful to my parents because jointly, they have provided me a very secure, liberal and intellectually stimulating home, which, I think can be directly seen in my character and the person I am today. It's my very good fortune that I have parents, with whom I can share literally everything that is going on in my life, whether it's a professional disturbance or an emotional turmoil, knowing that they will be able to perceive the problem and also guide me towards a resolution of the same. I wish I could be as humble, dedicated and selfless as my mother and as knowledgeable, disciplined and organized as my father. I am truly blessed to be their daughter.

I am very fortunate to have found my best friend and companion in Sanket, whom I have known for the past 10 years. I think we struck a chord way back in our undergraduate days in Kolkata, and have always found him by my side ever since. I cannot emphasize enough how much I have been emotionally and academically dependent on him over all these years. Having been with me in Ithaca during my Ph.D., Sanket was the one who had to deal with my bouts of anxiety, frustration, and depression and always did so patiently. He is the one who has always given me positivity and the ability to see the brighter side of things and move forward. I certainly could not have reached the finish line, without him by my side. I feel that over the years we have both learnt how to

live life to the fullest even in the face of adversity and our commitment towards each other has been reinforced.

I would like to thank all my family members, friends and well-wishers for always having faith in me. I would especially like to thank my grandparents for their unconditional love and blessings. I am sure, wherever they are, they will be extremely proud and happy today. I thank my beloved *Nina* and *Abba Nana*, for always praying for my well-being and happiness. I am forever grateful to all my teachers for imparting the essential values that have made me a better human being. Finally, I would like to thank all my friends for making life enjoyable; the endless game nights in Villager, the unending *khawa dawa* and *adda* and the frequent dinners and parties were what pulled me through the roughest of patches during my graduate life at Cornell. I would also like to thank my friends from the Department of Economics at Cornell- Debi da and Tirupam for their guidance and advice and Isha for her support and motivation throughout the process. I would especially like to thank Anirudra, for teaching me that no problem is too big to be solved; Siddarth and Nidhi for always being there to help; Poornima, for her ever smiling and cheerful attitude towards life and Master, for inspiring me to be driven towards my goals.

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CHAPTER 1

DOES RAIN WASH OUT PARTICULATE MATTER? AN APPLICATION TO THE EFFECT OF AIR POLLUTION ON INFANT MORTALITY

1.1 Introduction

Over the last 50 years, we have seen a huge environmental movement across the globe, especially in the developed parts of the world such as the United States of America. In the 1970s, with the passage of the Clean Air Act, the Clean Water Act and the establishment of the Environmental Protection Agency (EPA), the United States took a huge step towards a cleaner environment and a more secure future. Today, as we approach the 48^{th} Earth Day [1], the United States has seen substantial improvements in air and water quality. However, we are now at a crucial juncture where we need to evaluate the past and understand the costs and benefits of pollution, in an era of rapidly changing climate, in order to implement effective policies for the future.

One of the major social costs of climate change is the resultant increase in air pollution that it causes. Particulate matter is one of the air pollutants that have the most severe health impacts, and interestingly, it is also directly affected by the climate system. The EPA has designated six commonly found air pollutants, namely, ground level ozone, particulate matter, sulphur dioxide, carbon monoxide, lead and nitrogen oxides as *criteria air pollutants*. Concentrations of each of these pollutants is regularly monitored by the EPA, under the Clean Air

[1] Each year, Aprill 22^{nd} is celebrated as the Earth Day globally, to mark the birth of the modern environmental movement in 1970. Almost 20 million Americans took to the streets, parks and auditoriums on April 22, 1970, to demonstrate for and demand a healthy sustainable environment.

Act and counties that fail to attain the federal thresholds are categorized as being in "non-attainment", hence implying stringent regulation. As mentioned by Dominici et al. (2014), The U.S. Office of Management and Budget (OMB) is required to provide annual estimates of the benefits and costs of any major federal regulation to the Congress, and interestingly, reduction in emissions of Particulate Matter (PM) alone has accounted for about one-third of the monetized benefits of all significant federal regulations. With these estimates playing such a crucial role in policy making, it is of paramount importance to know if we are indeed achieving *socially desirable* reductions in PM and also if we are under-estimating the costs of particulate pollution in the first place.

In the presence of rapidly changing climate, ever increasing temperatures and changing rainfall patterns, the costs of air pollution might be larger than in a counterfactual world having no climate change. Jacob and Winner (2009) provide a detailed review of the effects of climate change on various air pollutants and they propose that precipitation and precipitation frequency are one of the key meteorological factors that can affect PM levels in ambient air as increased rainfall leads to wet deposition and provides the major atmospheric sink for PM. The effect of climate change on PM is more complicated and hence fewer studies, as compared to ozone, have been performed on the same. Model perturbation studies have also found an effect of temperature on particulate matter, especially for sulphates, since higher temperatures lead to faster oxidation of sulphur dioxide. Barmpadimos et al. (2011) perform another small scale study using data from 13 monitoring stations in Switzerland, where they estimate the effects of various meteorological variables on PM concentrations. They find that the most important variables affecting PM concentrations in the winter, autumn and spring are wind gust and precipitation, whereas in the summer, afternoon temperature also plays a critical role. Auffhammer et al. (2009) examine the benefits of the 1990 Clean Air Act Amendments on PM_{10} concentrations in the United States from 1990-2005 and they find that in fact the Clean Air Act did produce substantial improvements in air quality. The authors mention that the actual contribution of the secondary PM_{10} precursor gases to total ambient PM_{10} concentrations depend critically on the atmospheric conditions including temperature, relative humidity, rainfall, wind speed and direction. Temperature and precipitation not only affect the formation of secondary PM but also affect the presence of primary particulate matter in the air.

The question of how much precipitation might affect particulate pollution has economic content because it is of central importance to guide more informed policy-making. The main intuition behind regulating heavy emitters is that the emissions caused by such activities (eg. industrial activity, vehicle use, construction etc.) implies a larger social cost of production as compared to the private cost that is accounted for by the emitter. Hence, as shown in Figure 1.1 below, the socially optimum level of production/consumption of the commodity is lower than the private optimum and hence the government needs to regulate such activities. However, the extent of this externality critically depends on the ever changing climate system around us and how much and to what extent it affects pollution. If drier weather implies higher concentrations of particulate matter, then in the presence of changing rainfall patterns, the social costs might be larger, implying an even lower socially optimal quantity of production.

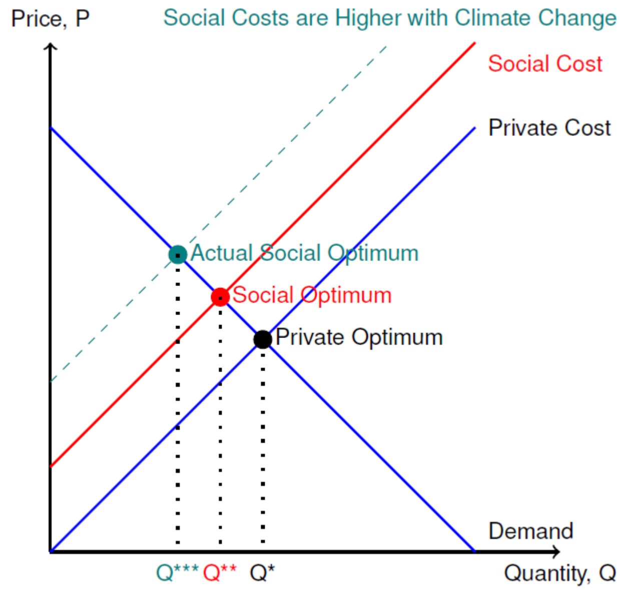


Figure 1.1: Costs of Climate Change on Air Pollution

Hence, estimates of the effect of climate change on air pollution are needed to know the *socially optimal level of emissions* which can then be implemented through regulations. Also, with wide variations in the level and frequency of rainfall across the nation, we might need different pollution thresholds for different climatic regions, internalizing their climate patterns. For example, if we compare the Southwest (driest region in the U.S.) to the Southeast or the Northeast (wetter regions of the U.S.), then the social costs of emitting the same levels of pollution precursors will be much larger in the Southwest, because in the absence of rainfall we will end up having more particulate matter in ambient air than in the other regions. Hence, in order to achieve similar reductions in PM in the Southwest we might need more stringent thresholds, so that lower levels of precursors are emitted into air. This might also entail much larger costs of implementing these regulations which would also enter the cost-benefit calculations in determining the feasibility and success of regulations on particulate matter.

In this paper, I estimate one such cost of climate change on air pollution. Specifically, I estimate the causal effect of the *level* and *frequency* of precipitation on particulate air pollution (both PM_{10} and $PM_{2.5}$). Apart from the reasons mentioned above, these estimates can also be used technically, to study the effect of air pollution on health. The benefit from public health, is the single most important reason for regulating air pollution and hence, having accurate estimates of the same is crucial. However, the presence of various confounding factors makes it econometrically challenging to estimate this effect. In this paper I propose that we can use the level of precipitation as an instrumental variable for particulate matter and estimate its effect on infant mortality. The rest of the paper proceeds as follows; Section 2 provides a background on particulate matter, its formation, sources and health effects; Section 3 provides a detailed description of the data sources and construction of the variables; Section 4 discusses the empirical methodology; Section 5 reports the main results; Section 6 discusses the robustness of my main findings; Section 7 discusses the application of these results to study the effect of particulate air pollution on infant mortality and Section 8 concludes.

1.2 Background on Particulate Matter

Particulate Matter (PM) is a complex mixture of solid and liquid particles, present in ambient air [2]. These particles often vary in their size, source, composi-

[2]Information on the background of particulate matter and PM chemistry, formation and sources has been obtained from the World Health Organization Report (2003) "Health Aspects of Air Pollution with Particulate Matter, Ozone and Nitrogen Dioxide" and Wheeler (2006),"Air Quality Modeling and Analysis of Additional Emission Controls on Tennessee Valley Authority

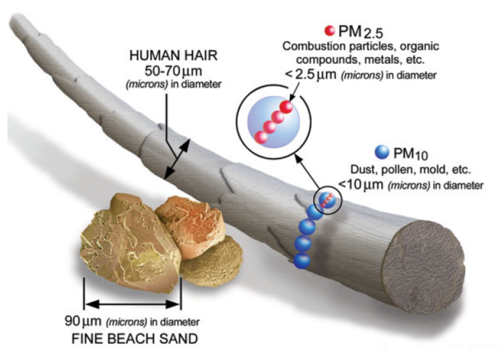
tion or method of formation. Generally, these suspended particles are classified by their aerodynamic properties because these characteristics govern the transport of particles from one place to another and also their removal from the air. Moreover, these aerodynamic properties also determine the deposition of particles within the human respiratory system. These properties are summarized by the *aerodynamic diameter* of particles, i.e. the size of a unit-density sphere having identical aerodynamic characteristics. Based on this aerodynamic diameter, particles are characterized into the following three major categories:

1) Ultra-fine particles ($< 0.1\mu m$)

2) Fine particles ($0.1 - 2.5\mu m$)

3) Coarse particles ($2.5 - 10\mu m$)

where $1\mu m$ is 1 millionth of a meter. This paper studies $PM_{2.5}$, which comprises of particles having an aerodynamic diameter less than 2.5 μm, and PM_{10}, which includes particles having an aerodynamic diameter less than 10 μm. Figure 1.2 provides a size comparison of PM_{10} and $PM_{2.5}$ to human hair and beach sand.



Size comparison of $PM_{2.5}$ and PM_{10} particles to human hair and beach sand.
Source: EPA, USA.

Figure 1.2: Size comparison of PM to human hair

Coal-Fired Power Plants”

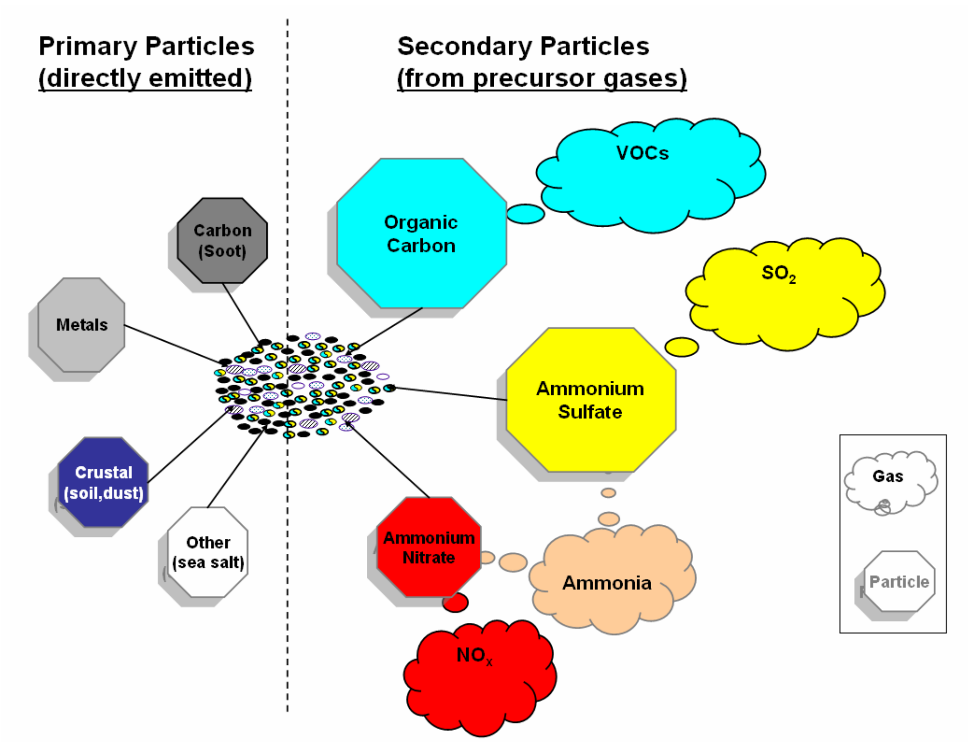
Particulate matter can be formed through four main processes:

1) Chemical Reaction- precursor gases can react to form particles.
2) Cloud or Fog processes- precursor gases might dissolve in water and then react chemically. When the water evaporates, particles are left behind.
3) Condensation- gases condense on solid particles to form a liquid droplet.
4) Coagulation- two or more particles might collide and stick together to form larger particles.

Particulate matter can be either *primary*, such as suspended dust, sea salt, organic carbon (OC), elemental carbon (EC) and metals from combustion, which are directly emitted into ambient air; or it can be *secondary*, such as particles which are formed when precursor gases undergo physical and chemical transformations in the atmosphere. For example, sulphur dioxide (SO_2) forms sulphate particles, nitrogen oxides (NO_x) form nitrate particles, ammonia (NH_3) forms ammonium compounds, and volatile organic compounds ($VOCs$) can form organic carbon particles, often referred to as, secondary organic aerosol (SOA). Most of the ambient sulphate particles are secondary in nature, formed from SO_2 emissions. Half of the SO_2 oxidation to sulphates happens in the gas phase through photochemical oxidation in the daytime. NO_x and hydrocarbons can enhance the photochemical oxidation rate. Some SO_2 oxidation also takes place in cloud droplets as air molecules react in clouds. Within clouds, soluble pollutant gases, such as SO_2, are scavenged by water droplets and rapidly oxidize to sulfate. Most cloud droplets evaporate and leave a sulfate residue or "convective debris". Typical rates for SO_2-to-sulfate conversion are 1% to 10% per hour.

The first step to formation of nitrates is the conversion of NO_2 to nitric acid

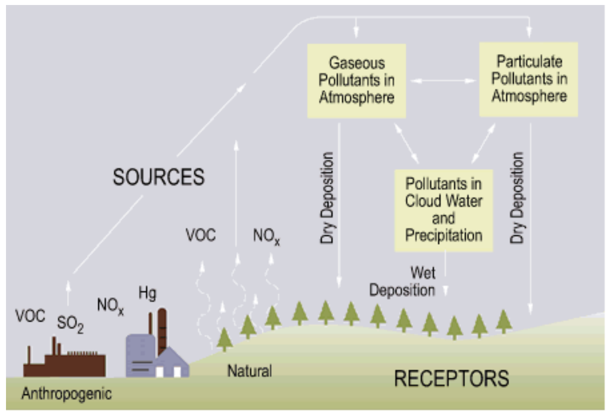
HNO_3, by reacting with hydroxyl (OH) radicals during the daytime. This conversion rate is generally about 10% to 50% per hour. At night however, NO_2 is converted to HNO_3 following a series of chemical reactions involving ozone and nitrate radicals. HNO_3 reacts with ammonia to form particulate ammonium nitrate, NH_4NO_3. Thus nitrate particles can be formed throughout the day as well as night. The major components of PM are *sulphate, nitrates, organic carbon* and *ammonium* and these components are mostly secondary in nature. Figure 1.3 provides a schematic view of the composition of particulate matter.



Source: "Air Quality Modelling and Analysis of Additional Emission Controls on Tennessee Valley Authority Coal Fired Power Plants", Expert Report, 2006.

Figure 1.3: Composition of Particulate Matter

Gases as well as suspended particles can be transferred from the earth's atmosphere to the ground by dry and wet deposition processes. *Wet Deposition* refers to the removal of species from the atmosphere by precipitation, such as rain, fog and snow. Particulate matter concentrations in ambient air are expected to decrease with increasing precipitation, as wet deposition provides the main PM sink. Figure 1.4 provides an overview of the processes leading to wet and dry deposition of particles.



Source: U.S. EPA

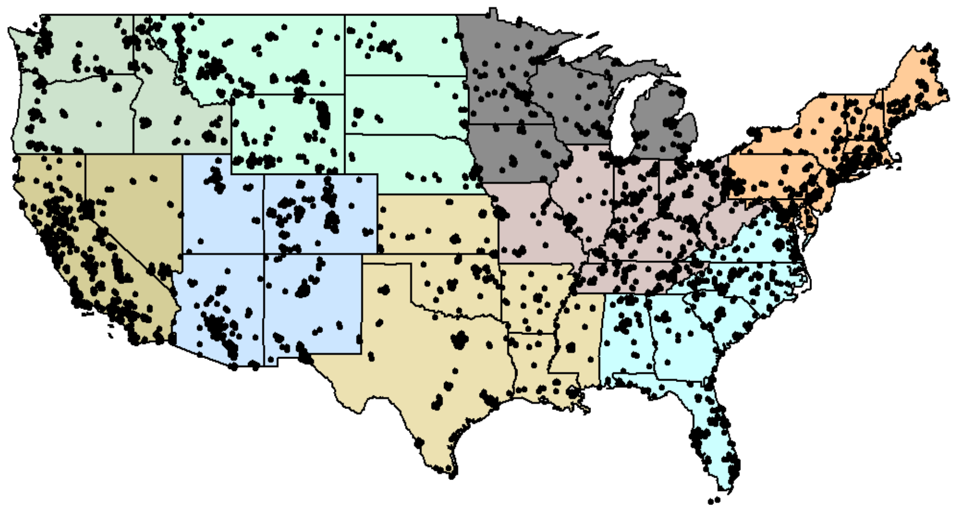
Figure 1.4: Wet Deposition of Particles

Particulate matter can cause serious health hazards. The EPA is particularly concerned about particles less than 10 μm in diameter (i.e. PM_{10} and $PM_{2.5}$) as they can enter through our throat and nose and reach deep into our lungs and may also enter our bloodstream. Particulate matter can cause a variety of problems such as irregular heartbeat, heart attacks, aggravated asthma, decreased lung function, coughing or difficulty in breathing etc. Long term exposures to particle pollution might lead to problems such as chronic bronchitis and even premature death. Whereas short term exposures (maybe hours or days) can aggravate lung diseases, asthma and also increase susceptibility to respiratory infections.

1.3 Data Sources

In order to estimate the causal effect of the *level* and *frequency* of precipitation on the daily maximum values of PM_{10} and $PM_{2.5}$ I utilize information from three major sources, as described below.

Data on Particulate Matter: For data on particulate matter (PM) concentrations I have used daily readings from the Environmental Protection Agency's (EPA) Air Quality Systems (AQS) database which provides daily readings of various criteria air pollutants from a nationwide network of air quality monitoring stations. These data were made available by a Freedom of Information Act (FOIA) request. In my preferred specification, I have used an unbalanced panel of PM monitors. I have eliminated monitor-days for which exceptional events that might potentially affect air quality, such as wildfires, have been recorded. For PM_{10}, I have constructed an unbalanced panel of 3264 monitors, spread over 876 counties for the years 1990-2013. Figure 1.5 depicts the geographical location of the final sample of PM_{10} monitors and also the spatial distribution by the nine different climatic regions. Table 1.1 illustrates the PM_{10} monitoring network for the full sample, as well for each year, by the nine different climatic regions. I have the daily maximum PM_{10} measurements for a total of 2,922,523 monitor-days , with sufficient data from each climate region in the country. The gradual drop in the number of PM_{10} monitors since 1998 is not surprising as the EPA started regulating $PM_{2.5}$ levels from 1997. Similarly, for $PM_{2.5}$ I have constructed an unbalanced sample of 2162 monitors spread over 713 counties over 1997-2013. Figure 1.6 illustrates the geographical location of these $PM_{2.5}$ monitors by the nine climate regions and Table 1.2 illustrates the $PM_{2.5}$ monitoring network by each year in the sample, segregated by the nine climate regions. I have daily maximum measurements of $PM_{2.5}$ for a total of 2,055,974 monitor-days, again with sufficient representation from each climate region across the country.

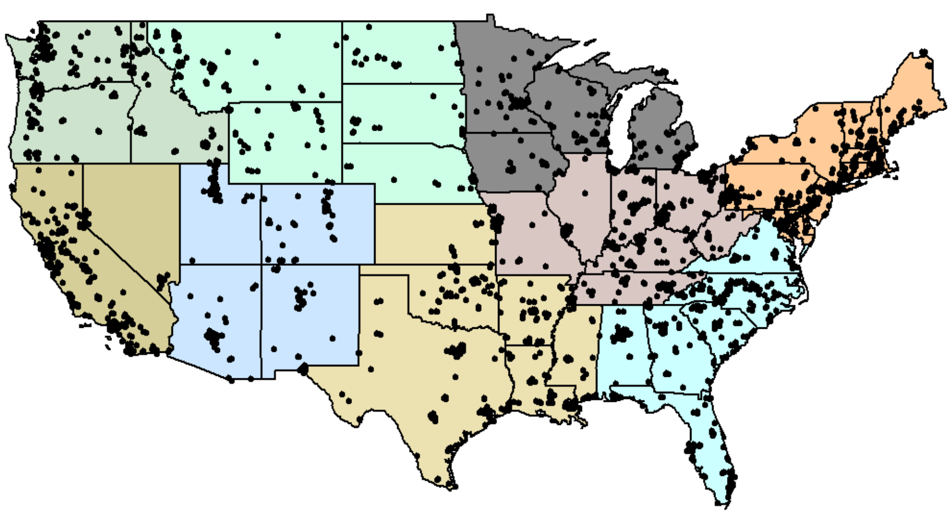


Notes: Each shaded region represents a single climatic region as defined by the NOAA. Figure 1.5 illustrates the geographic location of 3264 PM_{10} monitors in our sample, using the latitude and longitude information as obtained from the EPA.

Figure 1.5: PM_{10} Monitors from 1990-2013

Table 1.1: PM_{10} Monitoring Network by Year

				Number of Monitors in								
Year	Counties	Monitors	Observations	Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
1990-2013	876	3624	2,922,523	566	240	510	237	274	405	406	531	455
1990	569	1366	96,309	246	92	282	85	104	126	131	171	129
1991	595	1405	101,718	270	83	271	92	113	142	131	171	132
1992	626	1533	114,322	280	91	280	101	126	188	145	170	152
1993	634	1555	121,045	279	77	281	89	130	206	142	189	162
1994	657	1638	131,199	288	80	276	90	132	209	154	237	172
1995	674	1671	138,078	290	75	273	100	134	219	156	245	179
1996	676	1643	140,897	290	80	256	102	129	221	157	244	164
1997	670	1622	142,655	280	89	245	99	122	220	168	237	162
1998	589	1456	126,033	272	78	217	100	74	196	156	247	116
1999	509	1256	110,954	231	68	132	99	68	189	145	226	98
2000	532	1250	115,726	216	65	150	83	73	183	159	228	93
2001	519	1231	122,664	205	57	157	77	80	174	159	211	111
2002	500	1164	124,295	187	47	140	72	83	170	148	206	111
2003	463	1084	120,579	176	46	125	55	87	150	148	198	99
2004	453	1058	125,082	167	43	113	55	78	140	151	201	110
2005	441	1052	130,301	143	47	105	58	75	138	167	202	117
2006	413	1022	129,542	140	36	89	59	66	144	167	204	117
2007	388	971	122,629	135	36	85	44	72	139	163	184	113
2008	362	942	125,098	125	33	85	33	75	129	148	195	119
2009	355	904	123,401	129	36	72	34	71	118	152	188	104
2010	349	887	123,291	125	36	72	32	73	103	142	189	115
2011	339	877	126,813	119	36	70	27	76	99	145	175	130
2012	333	850	131,360	113	40	60	25	73	96	146	175	122
2013	314	785	78,532	106	40	57	20	67	79	133	166	117



Notes: Each shaded region represents a single climatic region as defined by the NOAA. Figure 1.6 illustrates the geographic location of 2162 $PM_{2.5}$ monitors in our sample, using the latitude and longitude information as obtained from the EPA.

Figure 1.6: $PM_{2.5}$ Monitors from 1997-2013

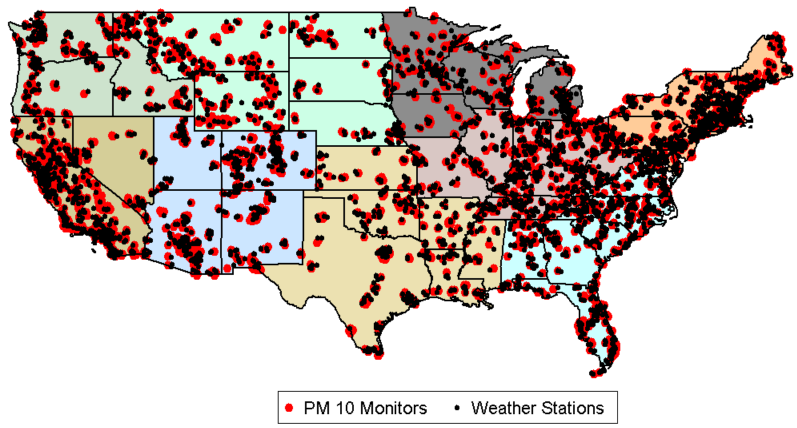
Table 1.2: $PM_{2.5}$ Monitoring Network by Year

				Number of Monitors in								
Year	Counties	Monitors	Observations	Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
1997-2013	713	2162	2,055,974	350	177	383	175	299	273	145	220	140
1997	3	3	128	0	3	0	0	0	0	0	0	0
1998	20	16	312	0	3	0	7	0	0	0	7	3
1999	974	520	93366	156	85	199	62	145	141	53	93	40
2000	1131	592	136417	177	98	224	75	179	155	72	98	53
2001	1178	604	148627	179	99	237	84	182	160	75	103	59
2002	1164	606	150265	183	96	235	86	184	156	67	102	55
2003	1137	589	132826	182	95	215	80	177	160	72	99	57
2004	1056	565	132067	179	88	190	62	140	174	68	98	57
2005	1082	557	127784	177	88	190	49	168	177	77	99	57
2006	1029	526	122141	186	86	178	40	131	184	78	97	49
2007	988	521	126428	184	82	179	42	105	179	73	97	47
2008	1011	519	127608	184	81	188	47	103	177	72	101	58
2009	1071	526	144160	201	85	192	48	104	178	73	121	69
2010	1081	524	158628	196	85	195	54	106	171	76	126	72
2011	1082	515	170128	200	90	190	49	102	167	83	128	73
2012	1064	506	173653	189	84	195	50	99	155	81	144	67
2013	1049	504	111436	192	88	208	46	95	148	73	138	61

Data on Precipitation: For meteorological data, I have utilized daily measurements of total precipitation, as well as maximum daily temperature from the National Climatic Data Center's Cooperative Station Data (NOAA 2008). This extensive dataset provides detailed daily information on various meteorological variables, at over 20,000 weather stations across the United States. I have acquired relevant data for the period from 1990-2013, to complement my data on particulate matter. As a data completeness requirement, for every weather station I have included data on years for which there are valid readings for total precipitation, maximum temperature and minimum temperature for atleast 75% of the total number of days.

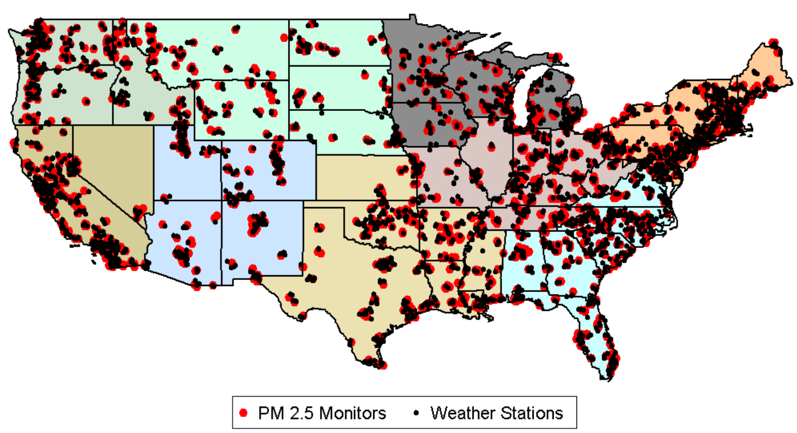
However, the geographical location of these weather stations typically do not coincide with the location of EPA's air pollution monitors and hence I use an algorithm (as described below) to match weather stations to pollution monitors and eventually get the *average weather* around each PM monitor in the sample. Firstly, using information on the geographical location of pollution monitors and weather stations, I calculate the distance between each pair of PM monitor and weather station using the Haversine formula. This formula gives us the *great circle* distance between any two points on a sphere using their latitude and longitude. Using this distance, for every pollution monitor, I then keep only the *closest two weather stations within a radius of 30 km from the monitor* [3]. In order to be able to estimate the effect of *precipitation frequency* on particulate matter, I have utilized the daily rainfall information to construct a new variable *Prcp Freq*, varying at the weather station-day level, which is the number of *consecutive* days that a weather station had recorded positive rainfall. For every weather station and day, *Prcp Freq* captures the repetitive incidence of rainfall. Finally, I construct the weighted average, using inverse distance squares as weights, to get the average level and frequency of precipitation at each pollution monitor. I use the above algorithm to construct weather realizations for both PM_{10} and $PM_{2.5}$ monitors respectively. To illustrate the accuracy of this matching process, Figures 1.7 and 1.8 in depict the matched weather stations for the PM_{10} monitors as well as for the $PM_{2.5}$ monitors in the final sample.

[3]As robustness checks, I have performed the analysis using weather stations within 100km, 150km and 200km as well and the results are robust



Notes: Each shaded region represents a single climatic region as defined by the NOAA. Figure 1.7 illustrates the geographic location of 3264 PM_{10} monitors in our sample along with the weather stations matched to each pollution monitor, using the latitude and longitude information as obtained from the EPA.

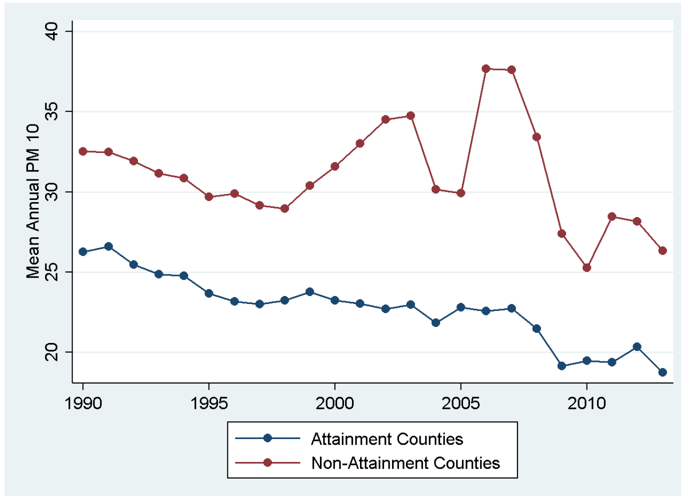
Figure 1.7: PM_{10} Monitors and Matched Weather Stations from 1990-2013



Notes: Each shaded region represents a single climatic region as defined by the NOAA. Figure 1.8 illustrates the geographic location of 2162 $PM_{2.5}$ monitors in our sample along with the weather stations matched to each pollution monitor, using the latitude and longitude information as obtained from the EPA.

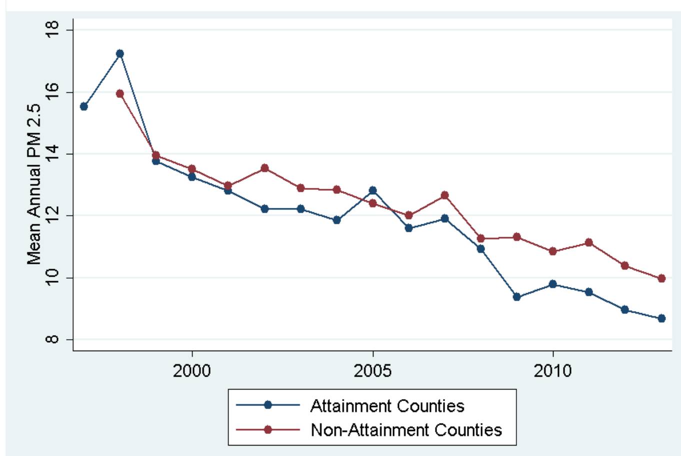
Figure 1.8: $PM_{2.5}$ Monitors and Matched Weather Stations from 1997-2013

Data on Non-Attainment Designations: Finally, I have used publicly available data on the Clean Air Act Non-Attainment Designations to generate our measure of non-attainment status for each county and year in the sample. This data is available from the EPA's Green Book of Non-Attainment Areas of Criteria Pollutants. *CAANAS*, or the Clean Air Act Non Attainment Status, is a binary variable that takes the value one for counties that fail to comply with the federal pollution threshold as defined by the EPA, in any given year. In my preferred specification, I have used a three year lagged version of this variable, because EPA gives heavy emitters at least this much time in order to comply with the regulation (i.e. all the thresholds are based on 3 year moving averages rather than just the contemporaneous level of particulate pollution). Figures 1.9 and 1.10 illustrate the daily maximum PM_{10} and $PM_{2.5}$ concentrations, averaged across all monitor-days for each year and we can see that even though there has been an overall decline in both PM_{10} and $PM_{2.5}$ over the last 20 years, the pollution levels in non-attainment counties, on average, are higher than that in attainment counties.



Notes: This figure represents the average annual PM_{10} concentrations across all monitors in attainment (blue line) and all monitors in non-attainment (red line) for each year between 1990-2013.

Figure 1.9: Mean Annual PM_{10} by CAA Attainment Status

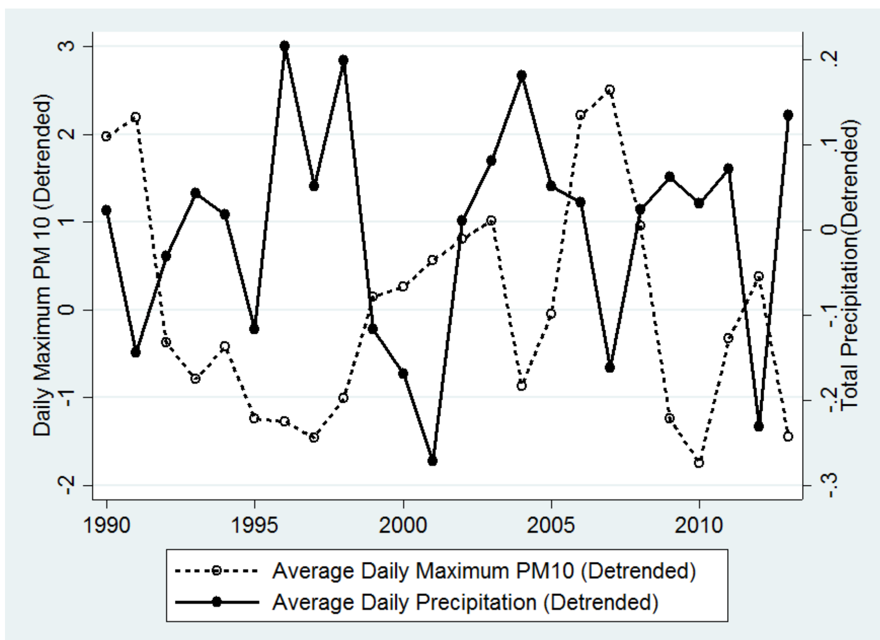


Notes: This figure represents the average annual $PM_{2.5}$ concentrations across all monitors in attainment (blue line) and all monitors in non-attainment (red line) for each year between 1997-2013.

Figure 1.10: Mean Annual $PM_{2.5}$ by CAA Attainment Status

Having consolidated the data from the above three sources, I have constructed my final sample of PM_{10} monitors from 1990-2013 and $PM_{2.5}$ monitors from 1997-2013, along with weather realizations for each monitor-day and CAA attainment designation for each county-year. Table 1.3 and 1.4 provides a detailed description and summary statistics for the main pollution and meteorological variables that are of interest in this paper, for the full sample, as well as, broken down by the nine different climatic regions in US and the attainment status of counties. Table 1.3 provides these statistics for the sample of PM_{10} monitors from 1990-2013 whereas, Table 1.4 provides the same information for the sample of $PM_{2.5}$ monitors from 1997-2013. From Table 1.3, we see that the average PM_{10} across all monitors, years and regions is about 25.5 $\mu g/m^3$, with the Southwest and West accounting for the highest average levels of pollution. In terms of precipitation, the average *level* of precipitation is about 2mm overall, whereas the average *frequency* of precipitation is 0.8 days. From Table 1.4, we see that the average $PM_{2.5}$ across all monitors, years and regions is 11.4 $\mu g/m^3$ with the West and Ohio Valley accounting for the highest levels of pollution. The average *level* of precipitation is 2.6mm whereas the average *frequency* is 1 day. From both our samples, we find that the Southeast and Ohio Valley are among the wettest regions whereas the Southwest is the driest. As expected, we find that the average PM_{10} as well as $PM_{2.5}$ levels are higher in non-attainment counties than in attainment counties, capturing the fact that counties in non-attainment have higher levels of pollution precursors. Interestingly, we also find, that in both the samples, both the level and the frequency of rainfall is higher in attainment counties than in non-attainment counties. This draws attention to the fact that rainfall, through its effect of particulate matter concentrations, might indirectly have an effect on the attainment designations of counties. For example, out of two counties that are undertaking similar adjustments in order to meet the federal pollution threshold, one might be pushed into non-attainment because of less rainfall or infrequent rainfall.

Figures 1.11 and 1.12 illustrate the strong negative correlation, observed in the data, between the level of rainfall and PM_{10} and $PM_{2.5}$ respectively. Figures 13 and 14 illustrates the negative correlation between the frequency of rainfall and particulate matter concentrations. Lastly, Figures 1.15, 1.16 ,1.17 and 1.18 depict these correlations, by the nine different climatic regions of USA and we can see that this negative association between the level/frequency of rainfall and particulate matter, is present across all regions.



Notes: This figure represents the daily maximum PM_{10} concentrations and daily total precipitation, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

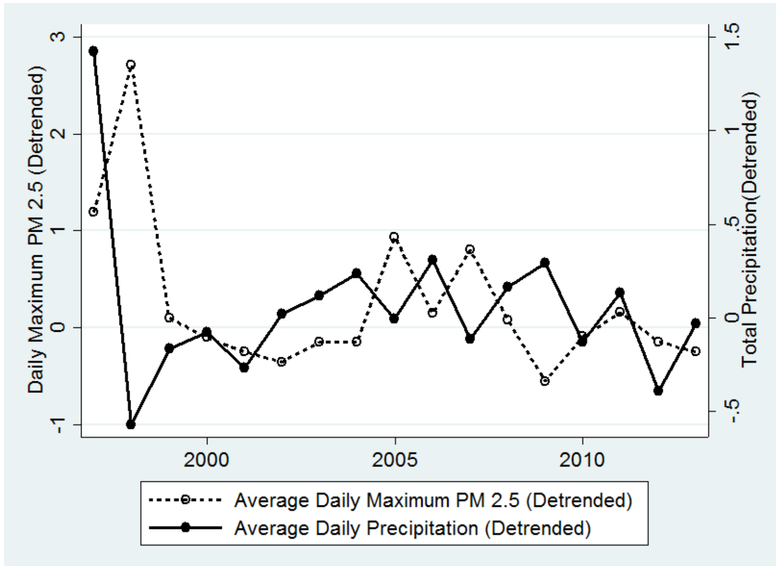
Figure 1.11: Level of Precipitation and PM_{10}

Table 1.3: PM_{10} Monitors-Summary Statistics by Climate Region and Attainment Status

	Panel A: Particulate Matter (PM_{10})			*Panel B: Total Precipitation (mm)*			*Panel C: Precipitation Frequency (days)*		
	Mean	SD	Observations	Mean	SD	Observations	Mean	SD	Observations
Full Sample	25.5	43.2	2,922,523	2	6.6	2,919,730	0.8	1.8	2,922,523
By Climate Regions:									
Ohio Valley	25.9	16.0	431,753	3.0	7.7	431,553	1.1	1.8	431,753
Upper Midwest	24.0	16.2	113,402	2.4	6.6	113,344	1.0	1.7	113,402
Northeast	21.7	14.5	342,964	3.1	7.7	342,852	1.2	2.0	342,964
Northwest	24.7	20.7	176,966	1.8	4.8	176,669	1.5	3.1	176,966
South	25.6	18.0	196,475	2.4	8.5	196,364	0.6	1.3	196,475
Southeast	23.0	13.4	346,581	3.5	9.7	346,399	1.0	2.2	346,581
Southwest	30.4	30.4	475,699	0.9	3.4	475,102	0.5	1.5	475,699
West	29.0	95.9	483,406	1.0	4.8	483,045	0.4	1.4	483,406
Rockies	20.8	17.6	355,277	1.1	3.8	354,402	0.8	1.7	355,277
By CAA Attainment Status:									
Attainment Counties	22.7	15.6	1,900,404	2.4	7.3	1,898,346	0.9	1.9	1,900,404
Non-Attainment Counties	30.8	69.5	1,022,119	1.3	4.7	1,021,384	0.7	1.8	1,022,119

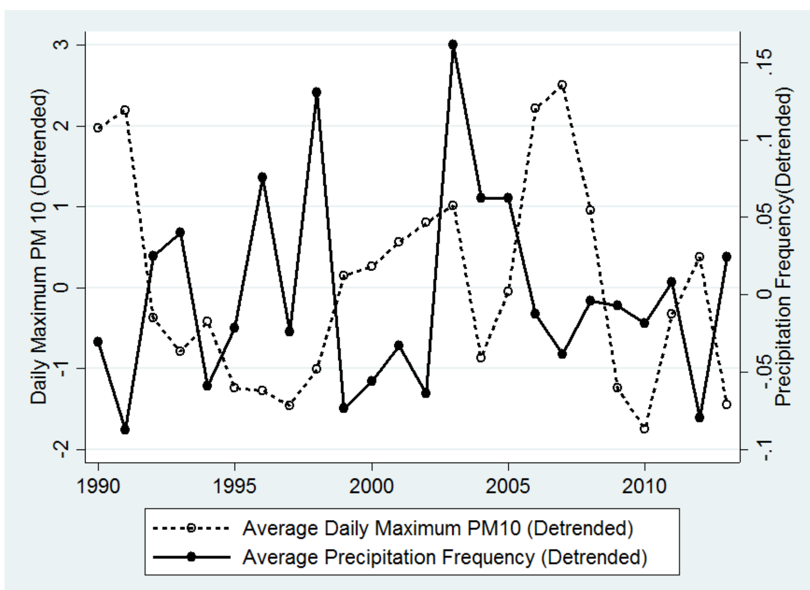
Table 1.4: $PM_{2.5}$ Monitors-Summary Statistics by Climate Region and Attainment Status

	Panel A: Particulate Matter (PM2.5)			*Panel B: total Precipitation (mm)*			*Panel C: Precipitation Frequency (days)*		
	Mean	SD	Observations	Mean	SD	Observations	Mean	SD	Observations
Full Sample	11.4	7.7	2,055,974	2.6	7.7	2,054,495	1.0	1.9	2,055,974
By Climate Regions:									
Ohio Valley	13.5	7.3	368,193	3.1	8.0	367,971	1.1	1.8	368,193
Upper Midwest	10.8	7.5	151,147	2.4	6.4	151,040	1.1	1.9	151,147
Northeast	11.5	7.5	405,797	3.2	8.4	405,628	1.1	1.8	405,797
Northwest	9.0	8.1	101,181	2.1	5.1	101,030	2.0	3.9	101,181
South	11.4	6.0	223,814	3.0	9.8	223,713	0.7	1.5	223,814
Southeast	11.7	6.7	346,889	3.4	9.3	346,756	1.0	2.0	346,889
Southwest	8.6	7.3	134,050	0.9	3.3	133,976	0.5	1.2	134,050
West	12.6	10.5	217,472	1.0	4.5	217,281	0.4	1.3	217,472
Rockies	7.8	6.5	107,431	1.3	4.3	107,100	0.8	1.7	107,431
By CAA Attainment Status:									
Attainment Counties	11.4	7.3	1,620,713	2.8	8.1	1,619,562	1.0	1.9	1,620,713
Non-Attainment Counties	11.7	9.2	435,261	1.8	6.0	434,933	0.8	1.9	435,261



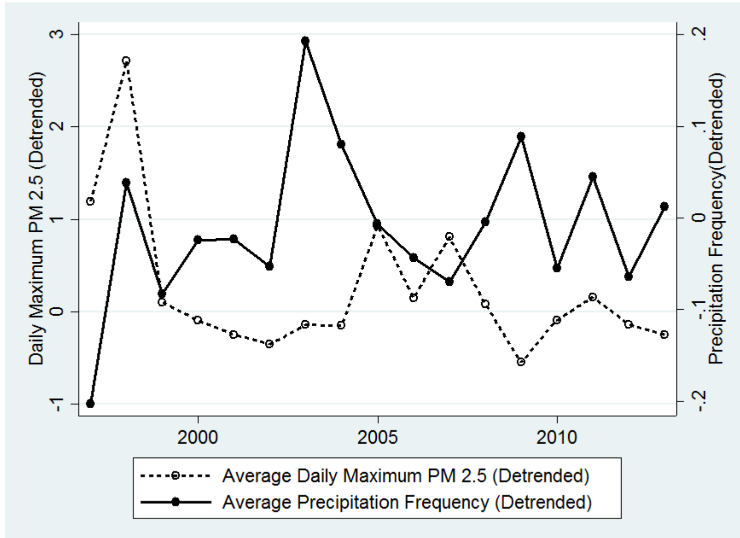
Notes: This figure represents the daily maximum $PM_{2.5}$ concentrations and daily total precipitation, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 1.12: Level of Precipitation and $PM_{2.5}$



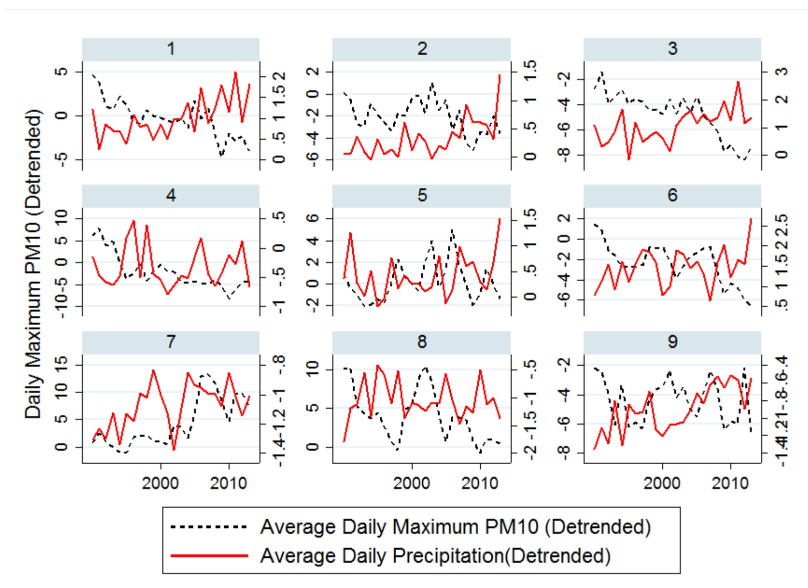
Notes: This figure represents the daily maximum PM_{10} concentrations and precipitation frequency, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 1.13: Precipitation Frequency and PM_{10}



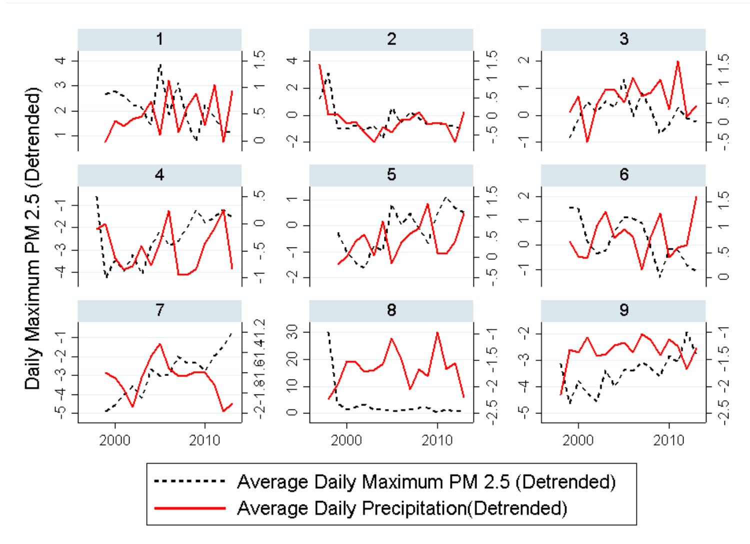
Notes: This figure represents the daily maximum $PM_{2.5}$ concentrations and precipitation frequency, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 1.14: Precipitation Frequency and $PM_{2.5}$



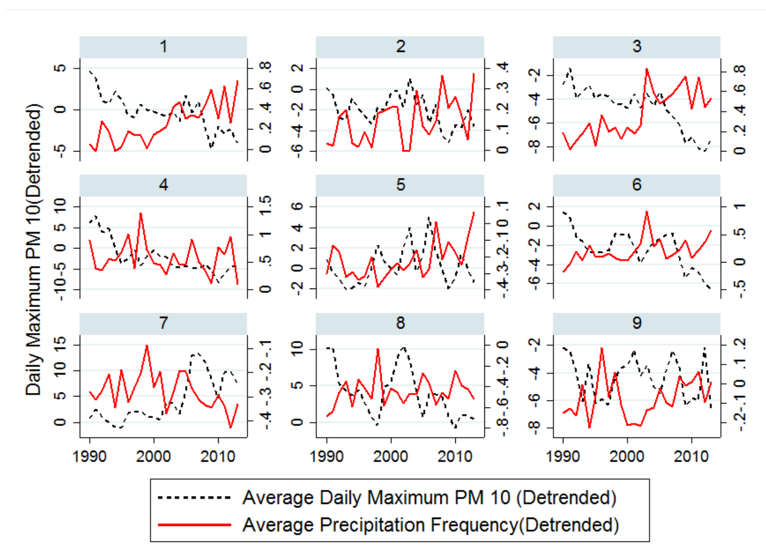
Notes: This figure represents the daily maximum PM_{10} concentrations and daily total precipitation, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 1.15: Level of Precipitation and PM_{10}- By Climate Regions



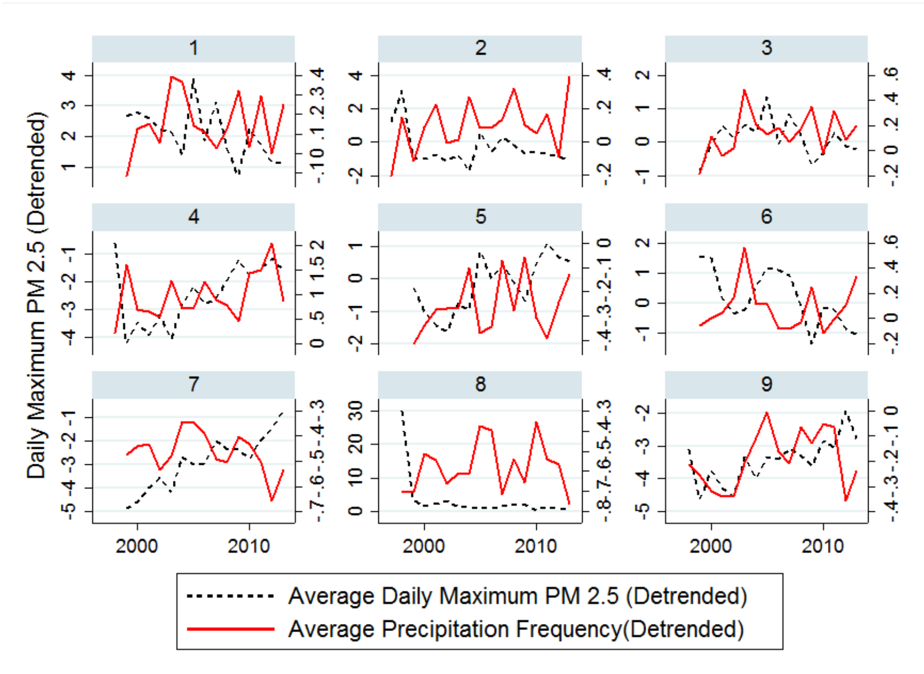
Notes: This figure represents the daily maximum $PM_{2.5}$ concentrations and daily total precipitation, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 1.16: Level of Precipitation and $PM_{2.5}$- By Climate Regions



Notes: This figure represents the daily maximum PM_{10} concentrations and precipitation frequency, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 1.17: Precipitation Frequency and PM_{10}- By Climate Regions



Notes: This figure represents the daily maximum $PM_{2.5}$ concentrations and precipitation frequency, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 1.18: Precipitation Frequency and $PM_{2.5}$- By Climate Regions

1.4 Empirical Methodology

I exploit plausibly random, daily variation in precipitation, precipitation frequency and maximum temperature [4] in order to estimate the causal effect of the *level* and *frequency* of precipitation on the daily maximum concentrations of PM_{10} and $PM_{2.5}$. To evaluate the *average* effect of precipitation and precipitation frequency across all counties, and the causal effect of of the Clean Air Act Non-Attainment on particulate pollution levels, I estimate the following speci-

[4] I also add maximum temperature in the econometric analysis. Although less important, Jacob and Winner (2009) point out that some components of PM, such as sulphates increase with temperature, due to faster SO_2 oxidation. In contrast, nitrates and organic semi-volatile components shift from the particle phase to the gas phase (Bowman (2001),Tsigaridis and Kanakidou (2007))

fication:

$$
\begin{aligned}
PM_{idmy} = & \alpha + \beta_1 Prcp_{idmy} + \beta_2 PrcpFreq_{idmy} + \beta_3 MaxTemp_{idmy} \\
& + \beta_4 CAANAS_{c,y-3} + \mathbb{X}_{cy} + \lambda_{ty} Z_i + \eta_i + \phi_{rty} + \epsilon_{idmy} \qquad (1)
\end{aligned}
$$

where i represents a PM monitor located in NOAA climate region r, and d stands for day, m for month, t for trimester (January-March, April-June, July-September and October-December) and y for year. The dependent variable PM captures the daily maximum concentrations of either PM_{10} or $PM_{2.5}$ and I will separately estimate the effects for each pollutant type. $Prcp$ measures the total daily precipitation, i.e. the *level* of rainfall recorded at pollution monitor i. $PrcpFreq$ measures the number of consecutive days that monitor i received positive rainfall and hence captures the *precipitation frequency.* $MaxTemp$ is the daily maximum temperature recorded at pollution monitor i. $CAANAS$ (Clean Air Act Non-Attainment Status) is a binary variable which equals one for counties that fail to comply with the National Ambient Air Quality Standards (NAAQS) for particulate matter. This variable is lagged by three years since the EPA gives heavy emitters at least three years to adjust and comply with the federal standards. Since emissions of particulate matter might be correlated with economic activity, I control for $\mathbb{X}$, which represents Population and Per Capita Income [5], varying at the county-year level. Z represents time invariant covariates (latitude and longitude of PM monitors), which have been interacted with trimester-by-year fixed effects in the econometric specification, η represents PM monitor fixed effects, ϕ represents region-by-trimester-by-year fixed effects and ϵ an idiosyncratic error term.

β_1 captures the average change in particulate matter concentrations, across

[5] Data on GDP is not available at the county level. However, the Bureau of Economic Analysis releases annual estimates of Population and Per Capita Income at the county level, which I have used in my econometric specification.

all counties, following a 1-mm change in the level of precipitation, whereas β_2 gives us the average change in particulate matter concentrations in response to a 1-day change in precipitation frequency. If rainfall indeed washes out particulate matter by providing its main atmospheric sink, then I would expect β_1 and β_2 to be negative, implying that if there is less rainfall, or if there is infrequent rainfall, we would have higher levels of particulate matter in ambient air. β_4 on the other hand gives us the causal effect of a county going into non-attainment on the levels of particulate matter in its air. Since counties that go into non-attainment face stringent regulations from the EPA and are forced to make adjustments in order to comply with the regulation, I would expect β_4 to be negative, hence implying that the particulate matter concentrations decrease in a county that goes into non-attainment. Thus, β_4 measures the *pure benefit* of the Clean Air Act regulations, in terms of decrease in particulate matter.

In order to evaluate the differential effects of the level and frequency of precipitation, in attainment and non-attainment counties, I augment the specification in Equation (1) to get my preferred econometric specification as described below.

$$\begin{aligned} PM_{idmy} =& \alpha + \beta_1 Prcp_{idmy} + \beta_2 PrcpFreq_{idmy} + \beta_3 MaxTemp_{idmy} + \beta_4 CAANAS_{c,y-3} \\ & + \gamma_1 Prcp_{idmy} * CAANAS_{c,y-3} + \gamma_2 PrcpFreq_{idmy} * CAANAS_{c,y-3} \\ & + \gamma_3 MaxTemp_{idmy} * CAANAS_{c,y-3} + \mathbb{X}_{cy} + \lambda_{ty} Z_i + \eta_i + \phi_{rty} + \epsilon_{idmy} \end{aligned} \tag{2}$$

The estimates from the above specification gives us the effect of the level and frequency of precipitation, separately for attainment and non-attainment counties. Unlike in Equation (1), β_1 and β_2 from Equation (2) measures the marginal effect of the level and frequency of precipitation in *attainment counties* only. Whereas, γ_1 and γ_2 measures the *incremental* effect in *non-attainment counties.* Hence the total effect of a 1-mm increase in the level of rainfall in non-attainment counties is given by $\beta_1 + \gamma_1$ whereas the total effect of a 1-day increase in precipitation frequency in non-attainment counties is given by $\beta_2 + \gamma_2$.

1.5 Results

In this section I report my primary findings regarding the impact of the level of precipitation and the precipitation frequency on daily maximum concentrations of PM_{10} and $PM_{2.5}$. Then, I also discuss these effects, disaggregated by the nine different NOAA climate regions in USA.

1.5.1 Main Results

Table 1.5 presents the effects of the two different aspects of precipitation, namely, the *level of precipitation*, as measured by the total daily precipitation, and the *precipitation frequency*, as measured by the number of consecutive days having recorded positive rainfall, on the daily maximum concentrations of PM_{10} in the ambient air. These estimates are based on data from 3264 PM_{10} monitors over the years 1990-2013. Columns (1) through (4) report *average* effects of the level and frequency of precipitation, across all counties in the sample. Column (1) reports the estimates, when I just control for the level and frequency of precipitation. I find that a 1-mm decrease in total daily precipitation would lead to an increase of 0.23 $\mu g/m^3$ of daily maximum PM_{10} concentration, which represents almost 1% of the average PM_{10} levels in the sample. Also, if precipitation becomes less frequent, i.e. if there is one less consecutive day having positive rainfall [6] then the daily maximum PM_{10} level will increase by 1.04 $\mu g/m^3$, which represents over 4% of the average PM_{10} levels in sample. Next, in Column (2), I also control for the Clean Air Act Non-Attainment status of counties, lagged by three years. This variable has been lagged by three years since the EPA gives emitters that much time to bring down their pollution levels. We see that the inclusion of the $CAANAS$ does not alter our estimates of the effect of the level and frequency of precipitation on PM_{10}. The coefficient of the $CAANAS$ gives us a measure of the benefits of the Clean Air Act in terms of lower PM_{10} levels. The estimates suggest that a county that goes into non-attainment has a decrease in PM_{10} concentrations by 0.85 $\mu g/m^3$ [7]. In Columns (3) and (4), I have sequentially added county population and per capita income, in order to control for economic and demographic factors that might also have an effect on the air pollution levels. Column (4) reports the effects that I get from estimating equation (1) and we can see that the magnitude and significance of my estimates for the effect of precipitation remain unaffected by the addition of other controls. Comparing these estimates with the causal effect of the Clean Air Act Non-Attainment Status, I find that a 1-mm decrease in daily precipitation can potentially offset over 30% of the benefits of the landmark regulation, through higher PM_{10} levels in ambient air.

Finally, in order to get the *differential* effects of the level and frequency of precipitation on PM_{10} between attainment and non-attainment counties, I estimate my preferred specification given by Equation (2) and the results are reported in Column (5). The interaction terms now give us the incremental effects of

[6] Basically, if we consider two different days, one for which the past 5 days has had rainfall; and another for which the past 4 days has had rainfall; then the PM_{10} concentration in the second day, will be 1.04 $\mu g/m^3$ higher than the first.

[7] It is important to note here that decrease in pollution levels after going into non-attainment does not signify that the pollution levels have become lower than that in attainment counties

Table 1.5: Main Estimates- Effect of Level & Frequency of Precipitation on PM_{10}

VARIABLES	(1)	(2)	(3)	(4)	(5)
Total Precipitation	-0.2331***	-0.2331***	-0.2337***	-0.2337***	-0.2001***
	(0.0055)	(0.0055)	(0.0056)	(0.0056)	(0.0052)
Precipitation Frequency	-1.0427***	-1.0425***	-1.0436***	-1.0435***	-0.8905***
	(0.0389)	(0.0389)	(0.0390)	(0.0391)	(0.0356)
Lag 3 of CAANAS		-0.8489***	-0.8572***	-0.7582***	-0.3100
		(0.2339)	(0.2336)	(0.2399)	(0.4305)
Lag 3 of CAANAS x Prec					-0.1794***
					(0.0150)
Lag 3 of CAANAS x Prec Freq					-0.4064***
					(0.0994)
Max Temperature	Y	Y	Y	Y	Y
Lag 3 of CAANAS x Max Temp	N	N	N	N	Y
Population	N	N	Y	Y	Y
Per Capita Income	N	N	N	Y	Y
Observations	2,909,576	2,909,576	2,894,899	2,894,899	2,894,899
R-squared	0.0809	0.0810	0.0808	0.0809	0.0811

Notes: Precipitation Frequency is measured as the number of consecutive days having positive rainfall. Regressions include fixed effects for PM_{10} Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

lower or less frequent rainfall on PM_{10} concentrations in non-attainment counties. I find that a 1 mm decrease in total daily precipitation leads to an increase of 0.2 $\mu g/m^3$ of PM_{10} levels in attainment counties whereas in non-attainment counties there is an additional increase of 0.18 $\mu g/m^3$. Hence, in totality, a 1-mm decrease in daily precipitation level leads to 0.38 $\mu g/m^3$ higher daily maximum PM_{10} levels in non-attainment counties. Similarly, I find that if there is one less consecutive day having recorded rainfall (i.e. a 1 unit decrease in precipitation frequency) then PM_{10} levels in attainment counties will increase by 0.89 $\mu g/m^3$ whereas in non-attainment counties it will increase by an additional 0.41 $\mu g/m^3$, making it a cumulative increase of 1.3 $\mu g/m^3$. As has been illustrated in the descriptive statistics, we know that pollution levels are higher in non-attainment counties and it is reasonable to believe that non-attainment counties have more sources of pollution and pollution precursors. Hence, the estimates are aligned with economic intuition that we should have larger effects on ambient air pollution levels, with the lack of rainfall or less frequent rainfall in non-attainment counties, as opposed to counties in attainment.

Table 1.6 reports similar estimates, but for the daily maximum concentrations of $PM_{2.5}$. These estimates are based on data from 2162 $PM_{2.5}$ monitors over the years 1997-2013. From Column (4), we find that a 1-mm decrease in total daily precipitation will lead to an increase of 0.08 $\mu g/m^3$ of $PM_{2.5}$, averaged across all counties in sample. Also, a decrease in precipitation frequency, i.e. if there is one less consecutive day receiving positive rainfall, the average $PM_{2.5}$ concentration across all counties will increase by 0.39 $\mu g/m^3$. I also find that a county going into non-attainment will have a decrease of 0.21 $\mu g/m^3$ of $PM_{2.5}$ which captures the pure benefit from the Clean Air Act in terms of lower $PM_{2.5}$ concentrations. Hence, a 1-mm decrease in precipitation offsets over 38% of the benefits achieved due to the Clean Air Act. Next, in Column (5), I again estimate the differential impacts across attainment and non-attainment counties. Similar to PM_{10}, even for $PM_{2.5}$ concentrations, I find larger effects in non-attainment counties, which follows economic intuition as has been explained above. The estimates suggest that a 1-mm decrease in total daily precipitation would lead to an increase of 0.08 $\mu g/m^3$ of $PM_{2.5}$ in attainment counties whereas an increase of 0.14 $\mu g/m^3$ in non-attainment counties. A one unit decrease in precipitation frequency on the other hand, would lead to an increase of 0.38 $\mu g/m^3$ of $PM_{2.5}$ in attainment counties whereas an increase of 0.56 $\mu g/m^3$ of $PM_{2.5}$ in counties that are out of attainment.

Table 1.6: Main Estimates- Effect of Level & Frequency of Precipitation on $PM_{2.5}$

VARIABLES	(1)	(2)	(3)	(4)	(5)
Total Precipitation	-0.0840***	-0.0840***	-0.0838***	-0.0838***	-0.0796***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0016)
Precipitation Frequency	-0.3944***	-0.3944***	-0.3945***	-0.3946***	-0.3759***
	(0.0108)	(0.0108)	(0.0108)	(0.0108)	(0.0105)
Lag 3 of CAANAS		-0.2046**	-0.2121**	-0.2114**	2.4659***
		(0.0932)	(0.0932)	(0.0935)	(0.3170)
Lag 3 of CAANAS x Prec					-0.0609***
					(0.0097)
Lag 3 of CAANAS x Prec Freq					-0.1172***
					(0.0393)
Max Temperature	Y	Y	Y	Y	Y
Lag 3 of CAANAS x Max Temp	N	N	N	N	Y
Population	N	N	Y	Y	Y
Per Capita Income	N	N	N	Y	Y
Observations	2,051,608	2,051,608	2,038,092	2,038,092	2,038,092
R-squared	0.2548	0.2549	0.2548	0.2548	0.2582

Notes: Precipitation Frequency is measured as the number of consecutive days having positive rainfall. Regressions include fixed effects for $PM_{2.5}$ Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

1.5.2 Results by Climate Regions

In this section, I aim to establish the spatial heterogeneity of my main estimates from Tables 1.7 and 1.8. To do so, I have estimated my preferred specification given by Equation (2) by the nine different climate regions in United States, as defined by the National Oceanic and Atmospheric Association (NOAA), through detailed climate analysis. All counties in a given climate region have comparable climatic conditions and very similar baselines of precipitation, temperature and other important meteorological variables. Hence, this provides a reliable criterion for sub-dividing the entire sample and also testing the heterogeneity of the impacts of both the level and the frequency of precipitation. Table 1.7 reports the findings based on the sample of PM_{10} monitors. For clarity of exposition, I have only reported the estimates for the level and frequency of precipitation, along with the interaction effects. I find that even though the overall direction and significance of the both these effects are consistent across regions, there is quite a bit of variability in their magnitudes. For example, I find that a 1 mm decrease in daily precipitation, will cause the largest increases in PM_{10} concentrations in the Northwest, Southwest and Rockies. In almost every region, I find that the effect is significantly larger for counties that are out of attainment, which follows our interpretation of the main estimates. On the other hand, if precipitation frequency decreases by 1 day, then we can see the largest effects in the South, Southwest, West and Upper Midwest, with non-attainment counties again mostly having larger effects. Along similar lines, Table 1.8 reports these estimates based on the sample of $PM_{2.5}$ monitors. Even in this table I find the direction and significance of effects to be consistent across space and also the fact that non-attainment counties mostly have larger impacts on air pollution as a result of changes in the level or frequency of precipitation. From the sample of $PM_{2.5}$, I find the largest effects of the level of rainfall in the Northwest, Southwest and West; whereas the largest effects of a change in precipitation frequency comes from the South and the West [8]

[8]Apart from a few exceptions, the regional results provide some hint towards a potential non-linear effect of precipitation and precipitation frequency on particulate matter. The regions having the largest effects generally have lower average levels of precipitation (both level and frequency). This can be seen by comparing Tables 1.7 and 1.8 with the summary statistics by climate regions. I will explicitly test for non-linear effects in the Robustness section.

Table 1.7: Effect of Level and Frequency of Precipitation on PM_{10} by Climate Regions

VARIABLES	Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
Total Precipitation	-0.2231***	-0.2246***	-0.1799***	-0.4599***	-0.1517***	-0.1649***	-0.4321***	-0.1839***	-0.3284***
	(0.0085)	(0.0147)	(0.0106)	(0.0357)	(0.0057)	(0.0124)	(0.0353)	(0.0153)	(0.0179)
Lag 3 of CAANAS x Precipitation	-0.0645***	-0.0272	-0.0430**	-0.1079**	-0.0627**	0.0144	-0.2720***	-0.1942***	-0.3158***
	(0.0154)	(0.0246)	(0.0176)	(0.0494)	(0.0316)	(0.0260)	(0.0799)	(0.0464)	(0.0477)
Precipitation Frequency	-1.0282***	-1.2296***	-0.7964***	-0.7508***	-1.2076***	-0.6256***	-1.2699***	-0.5410***	-1.1518***
	(0.0468)	(0.0707)	(0.0352)	(0.0805)	(0.0915)	(0.0833)	(0.1129)	(0.0745)	(0.0923)
Lag 3 of CAANAS x Prec Freq	-0.2480***	-0.2983***	-0.2074***	-0.0237	-2.2157***	-1.2395***	-0.1067	-2.4839***	-0.1311
	(0.0656)	(0.1034)	(0.0566)	(0.1148)	(0.4079)	(0.3632)	(0.4492)	(0.2261)	(0.1274)
Monitors	566	240	510	237	274	405	406	531	455
Full Sample:									
Additional Controls: Lag 3 of CAANAS, Maximum Temperature, Lag 3 of CAANAS x Max Temp, Population, Per Capita Income									
Observations	2,894,899								
R-squared	0.0819								

Notes: Regressions include fixed effects for PM_{10} Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

Table 1.8: Effect of Level and Frequncy of Precipitation on $PM_{2.5}$ by Climate Regions

VARIABLES	Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
Total Precipitation	-0.0983***	-0.0373***	-0.0717***	-0.2239***	-0.0603***	-0.0785***	-0.1449***	-0.1690***	-0.0283***
	(0.0033)	(0.0046)	(0.0029)	(0.0187)	(0.0019)	(0.0033)	(0.0201)	(0.0126)	(0.0052)
Lag 3 of CAANAS x Precipitation	0.0020	-0.0172**	0.0121	-0.0528**	-0.0642***	0.0238***	-0.0915***	-0.0428**	-0.1662***
	(0.0081)	(0.0085)	(0.0074)	(0.0214)	(0.0234)	(0.0042)	(0.0312)	(0.0208)	(0.0156)
Precipitation Frequency	-0.4471***	-0.3790***	-0.2746***	-0.2830***	-0.5025***	-0.3964***	-0.4240***	-0.7116***	-0.2338***
	(0.0121)	(0.0195)	(0.0111)	(0.0191)	(0.0154)	(0.0362)	(0.0891)	(0.0664)	(0.0323)
Lag 3 of CAANAS x Prec Freq	-0.0587	0.0071	0.0299	-0.0212	-0.5889***	-0.0914	-0.6709***	-0.9645***	-0.2040**
	(0.0388)	(0.0415)	(0.0252)	(0.0331)	(0.0933)	(0.0623)	(0.0979)	(0.1533)	(0.0855)
Monitors	350	177	383	175	299	273	145	220	140
Full Sample:									
Additional Controls: Lag 3 of CAANAS, Maximum Temperature, Lag 3 of CAANAS x Max Temp, Population, Per Capita Income									
Observations	2,038,092								
R-squared	0.2749								

Notes: Regressions include fixed effects for $PM_{2.5}$ Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

1.6 Robustness

1.6.1 Balanced Panel of Pollution Monitors

Muller and Ruud (2016) argue that the placement of pollution monitors might not necessarily be random. The authors claim that the U.S. Environmental Protection Agency maintains a dense network of pollution monitors across the country, mainly for two reasons. Firstly, it wishes to enforce the federal air quality standards for each criteria air pollutant and secondly, it also wants to be able to provide detailed informative data for the analysis of important questions linking air pollution with its various impacts. According to the authors, these two are conflicting interests since in order to enforce the NAAQS [9] the pollution monitors are generally placed in areas having already high levels of air pollution. However, in order to get informative as well as representative data, monitors should ideally be placed in areas having varied levels of air pollution. The authors assert that most of the monitors are in areas where air pollution levels have been high and compliance with the federal regulation is a concern. Going by the above argument, we may have reasons to believe that the location of PM monitors is essentially endogenous and hence by using an unbalanced panel of monitors over time I may be observing particulate matter concentrations at monitors which have relatively higher levels of pollution only.

In order to nullify such threats to identification, I now check the sensitivity of my main estimates reported in Table 1.5, by using a balanced panel of PM_{10} and $PM_{2.5}$ monitors. Starting from my original sample, I only use observations from PM_{10} monitors that have been in the sample for every year from 1990-2013 and

[9] National Ambient Air Quality Standards for criteria pollutants.

I am left with a balanced sample of 125 monitors. Similarly, I have constructed a balanced panel of 358 $PM_{2.5}$ monitors [10]. By doing so, I eliminate possible confounding factors that might be driving the positioning of pollution monitors and their subsequent selection into the sample. The results from estimating my preferred specification using a balanced sample of PM_{10} and $PM_{2.5}$ monitors have been reported in Tables 1.9 and 1.10. From Column (4) in Table 1.9, we see that a 1-mm decrease in precipitation leads to a 0.27 $\mu g/m^3$ increase in PM_{10} levels whereas if precipitation frequency decreases by a day, PM_{10} increases by 1.39 $\mu g/m^3$, on average across all counties in the sample. From Column (5), we see that in attainment counties, PM_{10} increases by 0.2 $\mu g/m^3$ following a 1-mm decrease in precipitation and by 0.96 $\mu g/m^3$ following a 1-day decrease in precipitation frequency. As in our main estimates, we find higher effects in non-attainment counties. Cumulatively, in non-attainment counties, PM_{10} increases by 0.41 $\mu g/m^3$ following a 1-mm decrease in precipitation and by 1.93 $\mu g/m^3$ following a 1-day decrease in precipitation frequency.

From Column (4) in Table 1.10, we see that a 1-mm decrease in precipitation leads to a 0.09 $\mu g/m^3$ increase in $PM_{2.5}$ levels whereas if precipitation frequency decreases by a day, $PM_{2.5}$ increases by 0.38 $\mu g/m^3$, on average across all counties in the sample. From Column (5), we see that in attainment counties, $PM_{2.5}$ increases by 0.09 $\mu g/m^3$ following a 1-mm decrease in precipitation and by 0.33 $\mu g/m^3$ following a 1-day decrease in precipitation frequency. As in our main estimates, we find higher effects in non-attainment counties. Cumulatively, in non-attainment counties, $PM_{2.5}$ increases by 0.17 $\mu g/m^3$ following a 1-mm decrease in precipitation and by 0.8 $\mu g/m^3$ following a 1-day decrease in precipitation

[10] I use $PM_{2.5}$ monitors that have been in the sample for every year from 1999-2013. I drop 1997-98 in the balancing process since there are only 16 monitors in those two years. Since $PM_{2.5}$ just started being regulated in 1997, the monitoring network was still very sparse, and by using those years we will not be left with enough observations.

frequency. Most of my estimates from using a balanced panel of monitors are actually larger than my main estimates reported in Table 1.5. This ensures that my central estimates are robust to potential errors caused by the non-random placement of monitors. This is because, had such concerns been valid and pollution monitors were indeed placed in areas of high pollution, then my main estimates from using an unbalanced sample, should have been overestimating the effects of precipitation on particulate matter, which do not seem to be the case.

Table 1.9: Robustness- Balanced Panel of PM_{10} Monitors

VARIABLES	(1)	(2)	(3)	(4)	(5)
Total Precipitation	-0.2632***	-0.2632***	-0.2657***	-0.2656***	-0.2028***
	(0.0214)	(0.0214)	(0.0220)	(0.0220)	(0.0164)
Precipitation Frequency	-1.3873***	-1.3869***	-1.3904***	-1.3903***	-0.9639***
	(0.1421)	(0.1419)	(0.1431)	(0.1430)	(0.1051)
Lag 3 of CAANAS		-0.7430	-0.8700	-0.6107	-0.1251
		(0.7286)	(0.7328)	(0.7390)	(1.0825)
Lag 3 of CAANAS x Prec					-0.2095***
					(0.0406)
Lag 3 of CAANAS x Prec Freq					-0.9699***
					(0.2826)
Max Temperature	Y	Y	Y	Y	Y
Lag 3 of CAANAS x Max Temp	N	N	N	N	Y
Population	N	N	Y	Y	Y
Per Capita Income	N	N	N	Y	Y
Observations	280,524	280,524	277,713	277,713	277,713
R-squared	0.3186	0.3187	0.3177	0.3178	0.3212

Notes: Regressions include fixed effects for PM_{10} Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Regressions are based on observations from a balanced panel of 125 PM_{10} monitors. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

Table 1.10: Robustness- Balanced Panel of $PM_{2.5}$ Monitors

VARIABLES	(1)	(2)	(3)	(4)	(5)
Total Precipitation	-0.0930***	-0.0930***	-0.0926***	-0.0926***	-0.0875***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0030)
Precipitation Frequency	-0.3792***	-0.3792***	-0.3814***	-0.3814***	-0.3322***
	(0.0248)	(0.0248)	(0.0249)	(0.0249)	(0.0218)
Lag 3 of CAANAS		0.0394	0.0243	0.0358	3.5873***
		(0.1546)	(0.1530)	(0.1556)	(0.6891)
Lag 3 of CAANAS x Prec					-0.0841***
					(0.0152)
Lag 3 of CAANAS x Prec Freq					-0.4682***
					(0.1112)
Max Temperature	Y	Y	Y	Y	Y
Lag 3 of CAANAS x Max Temp	N	N	N	N	Y
Population	N	N	Y	Y	Y
Per Capita Income	N	N	N	Y	Y
Observations	280,524	280,524	277,713	277,713	277,713
R-squared	0.3186	0.3187	0.3177	0.3178	0.3212

Notes: Regressions include fixed effects for $PM_{2.5}$ Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Regressions are based on observations from a balanced panel of 358 $PM_{2.5}$ monitors. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

1.6.2 Correlations with Wind Speed

Many studies in the atmospheric sciences literature have made qualitative observations on the relationship between suspended particulate matter and wind speed. Jacob and Winner (2009) mention in their review article that changes in wind speed has stronger effects on particulate matter than on ozone because of lower PM background concentrations. Jones et al. (2010) look at the dependence of PM_{10}, chloride, sulphate, nitrate, organic and elemental carbon as well as NO_x concentrations on the wind speed using data from three sites in London. They find that for particulate nitrates, there was a rapid reduction in concentrations associated with higher wind speeds. the authors suggest that this might be a result of limiting factors on the production of ammonium nitrate, generated from precursors, the concentrations of which are themselves governed by wind speed. Buch et al. (1976) perform a statistical analysis of the connection between airborne particles and wind speed and wind direction in Denmark. They also report that mean overall concentrations of particulate matter is decreasing with increasing wind speeds for most directions.

Hence, in order to check if my preferred estimates are predominantly being driven by the effect of wind speeds on PM, I have estimated my preferred specification, controlling for average daily wind speed, measured in meters/sec. Table 1.11 reports these estimates, both for PM_{10} and $PM_{2.5}$. I do find statistically significant effects of the wind speed on both PM_{10} as well as $PM_{2.5}$. Moreover, I find larger effects of wind speed on $PM_{2.5}$ which is potentially driven by the fact that lighter particles can be removed or blown away more easily than larger/heavier ones. However, most importantly, the effects of my variables of interest, namely, the level and frequency of precipitation, are robust to the inclusion of this additional control.

1.6.3 Non-linear Effects

In the analysis by climate region, we had seen some suggestive evidence for larger effects of precipitation and precipitation frequency in regions which had lower rainfall or less frequent rainfall. This points us toward checking for any potential non-linear effects of these variables on ambient particulate matter concentrations. To do so, I have controlled for the level and frequency of precipitation non-linearly and have also interacted these non-linear controls with the

Table 1.11: Robustness- Dependence on Wind Speed

VARIABLES	PM_{10}		$PM_{2.5}$	
	(1)	(2)	(3)	(4)
Total Precipitation	-0.2002***	-0.1749***	-0.0630***	-0.0604***
	(0.0071)	(0.0067)	(0.0017)	(0.0017)
Precipitation Frequency	-1.0909***	-0.9222***	-0.1997***	-0.1592***
	(0.0424)	(0.0371)	(0.0145)	(0.0139)
Lag 3 of CAANAS x Prec		-0.1546***		-0.0402***
		(0.0175)		(0.0110)
Lag 3 of CAANAS x Prec Freq		-0.4875***		-0.3755***
		(0.1056)		(0.0671)
Wind Speed	-0.5086***	-0.4979***	-1.2726***	-1.2670***
	(0.1126)	(0.1125)	(0.0330)	(0.0322)
Observations	1,376,429	1,376,429	1,266,539	1,266,539
R-squared	0.3064	0.3075	0.3027	0.3060

Notes: Regressions include fixed effects for PM Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Average daily wind speed, measured in meters/sec. Wind speed data is not available for many monitor-days and hence I have fewer observations compared to Table 1.5. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

nonattainment status, to estimate differential effects in attainment vs nonattainment counties as well. Table 1.12 reports the findings from the above estimation. Both for PM_{10} and $PM_{2.5}$ I find statistically significant evidence of non-linear effects of both the level and the frequency of precipitation. More specifically, I find evidence of a *convex* relationship between particulate matter and my main variables of interest [11].

These results validate our findings in the results by climate region. My estimates suggest that decreases in precipitation as well as precipitation frequency

[11] Although there is evidence of a convex relationship, the turning points are almost always above the 99th percentile of the precipitation and precipitation frequency distribution, implying a predominantly downward sloping and convex relationship.

leads to increases in particulate matter concentrations, at an increasing rate. Hence, there will be relatively larger effects of the same decrease in rainfall, in areas that are already dry and vice versa. As reported in Table 1.5, we see larger effects in nonattainment counties. However, from these results we also see more convex effects in nonattainment counties than in counties compliant with the regulations.

Table 1.12: Robustness- Non-linear Effects of Level and Frequency of Precipitation on PM

VARIABLES	PM_{10}		$PM_{2.5}$	
	(1)	(2)	(3)	(4)
Precipitation	-0.3599***	-0.2970***	-0.1280***	-0.1227***
	(0.0128)	(0.0091)	(0.0027)	(0.0025)
Precipitation Sq	0.0028***	0.0021***	0.0007***	0.0007***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Precipitation Frequency	-1.3831***	-1.2847***	-0.6996***	-0.5983***
	(0.1179)	(0.0595)	(0.0323)	(0.0280)
Prec Freq Sq	0.0324***	0.0386***	0.0797***	0.0661***
	(0.0106)	(0.0051)	(0.0056)	(0.0050)
Lag 3 of CAANAS x Precipitation		-0.3003***		-0.0742***
		(0.0305)		(0.0127)
Lag 3 of CAANAS x Precipitation Sq		0.0039***		0.0008***
		(0.0005)		(0.0002)
Lag 3 of CAANAS x Prec Freq		-0.3371**		-0.8728***
		(0.1655)		(0.1193)
Lag 3 of CAANAS x Prec Freq Sq		-0.0094		0.1207***
		(0.0134)		(0.0183)
Observations	2,894,899	2,894,899	2,038,092	2,038,092
R-squared	0.0816	0.0818	0.2517	0.2555

Notes: Regressions include fixed effects for PM Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Positive coefficients of the non-linear controls imply a convex relationship. Standard errors are clustered at the monitor level. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

1.7 Application: Effect of Particulate Matter on Infant Mortality

There has been a consensus among economists, policy makers and governments of various nations, on the effect of air pollution on public health. In the United States, one of the major goals in establishing the Environmental Protection Agency (EPA) as well as implementing the Clean Air Act Amendments in 1970, was to *protect public health.* However, the EPA did not include infant mortality in the primary cost-benefit analysis of the 1990 Clean Air Act amendments because of the lack of enough reliable scientific evidence linking air pollution to infant health [Currie and Neidell (2004)]. Particulate matter is widely accepted as being one of the most harmful air pollutant, and the EPA is particularly concerned about the health effects of particles that are under 10 $\mu g/m^3$ in diameter as these particles can enter through the throat and nose and potentially reach our lungs. Scientifically, one of the leading theories behind the above mentioned impact of particulate pollution on health is an inflammatory response which weakens the human immune system.

Even though quite a few studies have documented this statistical relationship between particulate matter and human health [Holland et al. (1979), Wilson (1996), Wang et al. (1997)], there are associated econometric concerns. There have been cross sectional analyses of the correlation between air pollution in U.S. cities and adult mortality rates [Lave ans Seskin (1997), Pope and Dockery (1996)], time series analyses at a given location [Dockery and Pope (1996)] and also cohort based longitudinal studies which indicates that particulate pollution might lead to excess mortality [Dockery et al. (1993), Pope et al. (1995)].

However, the reliability of such estimates have been questioned in the literature on air pollution and health for several reasons. Firstly, air pollution is not randomly assigned to different regions, i.e. there are a host of other factors affecting pollution concentrations and also having a direct effect on health. Although some such factors, such as economic conditions, population etc. might be controlled for, it can be argued that many of the above mentioned studies may not be controlling for adequate number of such confounding factors. For example, parents who are more aware about the environment and the harmful effects of pollution, might be relocating to less polluted areas which would bias the estimates upwards [Currie (2011)]. Secondly, if we are looking at adult mortality, current pollution exposure is not necessarily equivalent to lifetime exposure and hence deaths today might actually reflect pollution exposure that happened many years ago.

In recent years, there have been a few studies which have successfully analyzed this link between air pollution and infant health and tackled some of the econometric issues mentioned above. Examples of such work include the effect of air pollution on infant mortality and birth outcomes [Chay and Greenstone (2003), Currie and Neidell (2004), Currie et al. (2009), Currie and Walker (2011), Knittel et al. (2016)], contemporaneous health factors [Chay et al. (2003), Neidell (2001), Currie et al. (2008)] and life cycle outcomes [Sanders (2011)]. There has also been a study, specifically focusing on the developing country context and analyzing this link between air pollution and infant mortality using data from Mexico City [Arceo-gomez et al. (2012)]. However, almost all of the above mentioned studies have either looked at a specific state or region for the analysis, or looked at a very short time frame which basically leads to the lack of either spatial or temporal variation in the data. This is potentially driven by the difficulty in finding large scale data on a variable which only affects infant mortality, through its effect on air pollution levels and can be used as an instrument for air pollution [12].

In this section, I utilize the exogenous causal effect of the level of rainfall on PM_{10}, from the previous sections, to establish that *rainfall shocks* can be used as an instrument to analyze the statistical link between air pollution on infant mortality. As the importance of this question has already been discussed in detail, I propose that the availability of rich daily data on precipitation, ever since the 1950s, across more than 20,000 weather stations spread over the entire country provides enough temporal as well as spatial variation to analyze this question and get more general estimates for the entire nation. The key exclusion restriction here is the fact that apart from extreme weather events, fluctuations in rainfall do not directly affect infant mortality through factors other than particulate matter concentrations. Since I also explicitly control for county and year fixed effects, I believe that this is a plausible assumption. It should be mentioned, that by looking at infant deaths, we can more surely link pollution to health as the effect is immediate versus adult mortality where the effect might be driven by lifetime exposure to pollution. Also, infants form the most vulnerable section of our society and policy-makers as well as the general public are extremely motivated to protect them. I will present this section, by first describing the data sources, then the empirical methodology and lastly, the results.

[12] Chay and Greenstone (2003) have used the 1981-1982 economic recession to look at the effect of total suspended particles on infant mortality;Knittel et al. (2016) and Currie and Neidell (2004) have looked at data from California; Currie et al. (2009) have looked at New Jersey and Arceo-gomez et al. (2012) have used thermal inversions as an instrument, to study the question using Mexico City data.

1.7.1 Data Sources

Mortality and Births Data: The mortality and live births data is obtained from the Compressed Mortality Files (CMF) which is made available by the National Center for Health Statistics (NCHS). It is composed of a county level national mortality file and a county level national population file, spanning the years 1968-2014. I have used information from the CMF for the years 1990-2013 [13], in order to match it with the pollution and weather data. The mortality file provides the number of deaths for each county, by the year of death, race, sex, age group and the underlying cause of death. Firstly, since I am only interested in infant mortality I have used data for the first age group which is "*deaths within one year of birth*". Then, for each county, I have created the total number of infant deaths by summing the death counts in each category of race, sex and underlying cause. From the CMF population file, I have used information on *Total Births* for each county and year [14], in order to calculate the infant mortality rate, which is the number of infant deaths per 100,000 live births.

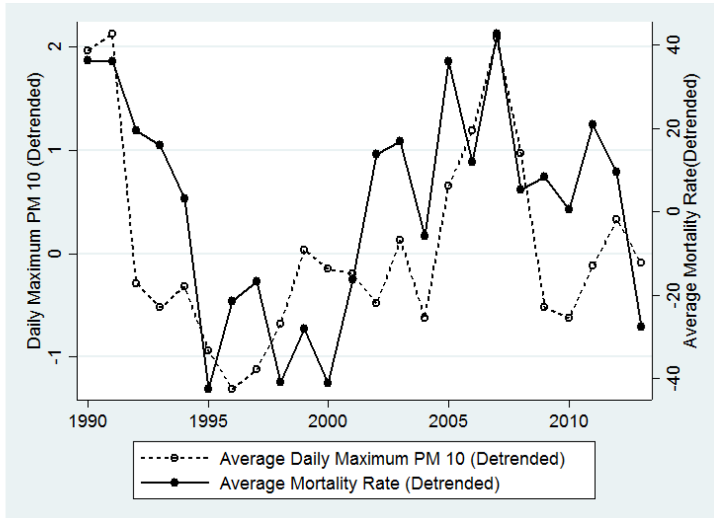
PM_{10} *and Weather Data:* I have used the same sample of PM_{10} monitors and associated weather data, as in the rest of the paper. However, I have used the daily weather data on rainfall, minimum and maximum temperature to construct measures of extreme weather events at each pollution monitor and year. Namely, I have used daily rainfall data to construct measures of *Droughts*, which I have defined as more than 30 consecutive days of no rainfall and *Floods*, defined as more than 2 consecutive days recording more than 25mm (~ 1 inch) of

[13]The Compressed Mortality Files for the years 1989-2014 are not available publicly, and was obtained under Part II Use Agreements, by signing a Data Use and Reporting Agreement with the NCHS

[14]I continue to use information on county-level Population and Per Capita income from the Bureau Of Economic Analysis (BEA) to maintain continuity with the rest of the paper.

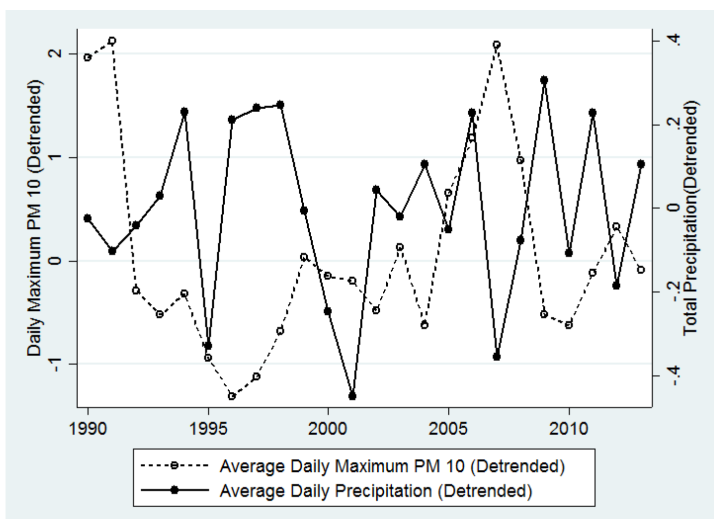
rainfall. Similarly, I have defined a *Heat Wave* to be more than 10 consecutive days recording daily maximum temperatures higher than 35°C and a *Cold Wave* to be more than 10 consecutive days recording daily minimum temperatures less than -10°C [15]. Finally, I have created the number of such instances of extreme weather at each pollution monitor for each year. Since the mortality data is at the county-year level, I have averaged the pollution and weather variables, to get the average PM_{10}, rainfall as well as extreme events at the county-year level which has then been merged with the mortality data to get my final sample of 11,299 county-years, comprising of an unbalanced sample of 861 counties spread over 48 states in contiguous United States. Table 1.13 illustrates the descriptive statistics for the three main variables used in this analysis, based on the data averaged at the county-year level. The average PM_{10} concentration across all years and counties is 23.2 $\mu g/m^3$ and the average annual infant mortality rate is around 785 deaths per 100,000 live births. In looking at the average levels by climate regions, we see that Ohio Valley, South, Southeast and Southwest have very high levels of particulate pollution and also high infant mortality rates. The average rainfall in the sample is 2.5 mm, with the Southwest and West being among the driest regions. Figure 1.19 illustrates the close positive association between the average infant mortality rate and the average concentrations of PM_{10}. Figure 1.20 on the other hand illustrates the close negative association between pollution levels and the instrument, which is rainfall level.

[15] 35°C and -10°C represent the 95th percentile and the 5th percentile of the daily maximum and minimum temperature distributions respectively.



Notes: This figure represents the average annual PM_{10} concentrations and annual infant mortality rate, averaged across all counties for each year. The variables have been detrended in order to eliminate the time trend.

Figure 1.19: Level of Precipitation and Infant Mortality Rate



Notes: This figure represents the average annual PM_{10} concentrations and the average level of precipitation, averaged across all counties for each year. This shows the close association between the endogenous regressor and the instrument used. The variables have been detrended in order to eliminate the time trend.

Figure 1.20: Level of Precipitation and PM_{10}

Table 1.13: Summary Statistics of Infant Mortality, PM_{10} and Precipitation, County/Year Level

	Panel A: Particulate Matter $PM_{10}(\mu g/m^3)$		*Panel B: Infant Mortality Rate (number of deaths per 100,000 live births)*		*Panel C: Precipitation (mm)*	
	Mean	SD	Mean	SD	Mean	SD
1990-2013	23.2	7.5	785.4	395.5	2.5	1.5
By Climate Regions:						
Ohio Valley	24.4	5.7	814.0	340.2	3.1	1.2
Upper Midwest	21.5	7.0	725.9	328.2	2.3	0.9
Northeast	20.6	6.3	705.1	259.5	3.1	1.1
Northwest	23.8	8.7	721.4	440.6	1.9	1.6
South	24.2	5.2	869.1	375.8	2.9	1.6
Southeast	22.2	5.2	924.0	395.7	3.4	1.3
Southwest	24.4	9.8	704.2	367.8	1.0	0.5
West	26.4	10.9	622.6	295.8	1.5	1.3
Rockies	21.1	7.6	884.4	678.6	1.2	0.7

Notes: These descriptive statistics have been created from a sample of 11,299 observations at the county-year level. The means reported above are across all years in the sample. The *Total Births* for each county and year has been used to compute the infant mortality rates. The average number of births across all counties and years is 5003. Infant Mortality Rate for each county-year is defined as [Total Deaths/Total Births]* 100,000.

1.7.2 Empirical Methodology:

My objective is to estimate the effect of PM_{10} pollution (PM_{cy}) on the number of deaths per 100,000 live births ($Mort_{cy}$), in a county and year. Specifically, I would like to estimate β_1 from the following specification:

$$Equation1 : Mort_{cy} = \beta_0 + \beta_1 PM_{cy} + \epsilon_{cy}$$

However, as discussed above, there are reasons to believe that there will be confounding factors that can potentially bias β_1 upwards or downwards. I use the instrumental variables strategy to tackle this concern, and use rainfall levels as an instrument for PM_{10}. As has been established in this paper, rainfall has a negative and significant effect on particulate matter, as it provides the main atmospheric sink for suspended particles. Since, extreme weather events can potentially have a direct effect on infant mortality [16], I explicitly control for these in my preferred specification described below:

$$\begin{aligned} Mort_{cy} = & \beta_0 + \beta_1 PM_{cy} + \beta_2 \mathbb{W}_{cy} + \beta_3 Population_{cy} && \text{[2nd Stage]} \\ & + \beta_4 Per\ Capita\ Income_{cy} + \lambda_y Z_c + \phi_{yr} + \eta_c + \epsilon_{cy} && (3) \end{aligned}$$

where c represents a county in climate region r and year y. $Mort$ is the total number of infant deaths in county c and year y per 100,000 live births; PM represents the average PM_{10} concentrations in county c and year y; $\mathbb{W}$ includes the four extreme weather events, namely, the average number of $Droughts$, $Floods$, $Heat\ Waves$ and $Cold\ Waves$ in county c and year y, which can have a direct effect on infant mortality rate $Mort$. I also include $Population$ and $Per\ Capita\ Income$ for each county and year in order to control for economic and demographic characteristics that may affect infant mortality. Z represents time-invariant covariates

[16]Deschenes and Greenstone (2011) show that extreme temperatures can have an effect on mortality rates.

(latitude and longitude varying at the county level) which has been interacted with year fixed effects; ϕ represents climate region-by-year fixed effects, η represents county fixed effects and ϵ is an idiosyncratic error term. PM being an endogenous regressor has been instrumented by $Prcp$ which is the average level of rainfall in county c and year y, using two stage least squares. The first stage relationship has been estimated as follows:

$$\begin{aligned} PM_{cy} =& \alpha_0 + \alpha_1 Prcp_{cy} + \alpha_2 \mathbb{W}_{cy} + \alpha_3 Population_{cy} && \text{[1st Stage]} \\ &+ \alpha_4 Per\ Capita\ Income_{cy} + \lambda_y Z_c + \phi_{yr} + \eta_c + \mu_{cy} && (4) \end{aligned}$$

Next, I summarize the results.

1.7.3 Results

Table 1.14 illustrates the results from the 2SLS estimation of Equation (3). Extreme weather events, county and year fixed effects have been controlled in all the specifications. All the other controls, as describes above, have been added sequentially moving from Column (1) to Column (3). In Column (4) I have tried an alternative measure of *Droughts*, *Heat Waves*, and *Cold Waves* [17]. I have defined them using deviations from the climate normal [18] Taking an average of all four specification, I find that a 1 $\mu g/m^3$ decrease in PM_{10} will lead to 27 fewer infant deaths. The Cragg-Donald Wald F-statistic is sufficiently large to reject the weak IV test, meaning that the instrument is not weak. Table 1.15 illustrates the first stage results from estimating Equation (4) and we find that precipitation

[17] I have not tried an alternative definition of Floods since I feel that floods might happen if we have heavy rainfall, even if its expected. Whereas, for Droughts, Heat Waves or Cold Waves, these events are often described as "abnormally" high/low temperatures, or "abnormally" low rainfall.

[18] 30-year moving average of maximum, minimum temperature and rainfall.

always has a highly significant and negative effect on average PM_{10} concentrations. A 1-mm decrease in total precipitation leads to an increase of 0.22 $\mu g/m^3$ of PM_{10} concentrations.

Table 1.14: Instrumental Variables Estimates- Effect of PM_{10} on Infant Mortality

VARIABLES	(1)	(2)	(3)	(4)
PM 10	25.7024*	25.8219*	28.2283*	27.1392*
	(14.7490)	(14.7027)	(16.5082)	(16.0963)
Extreme Prec and Temp Events	Y	Y	Y	Y
Per Capita Income	Y	Y	Y	Y
Population	N	Y	Y	Y
County Lat/Long-Year Fixed Effects	N	N	Y	Y
Alternative Measure of Extreme Events	N	N	N	Y
Cragg-Donald Wald F Statistic	28.85	29.06	23.87	24.84
Observations	11,104	11,104	11,104	11,104

Notes: Regressions include County and Year fixed effects. Standard errors are estimated using the Eicker-White formula to correct for heteroskedasticity. Extreme precipitation events (i.e. droughts and floods) and extreme temperature events (i.e. heat waves and cold waves) have been controlled for. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

1.8 Conclusion

In this paper, I estimate the causal effect of the *level of precipitation* as well as the *precipitation frequency* on daily maximum concentrations of PM_{10} and $PM_{2.5}$, which is the most harmful air pollutant in terms of health effects. Firstly, I find that a 1 mm decrease in rainfall level will lead to an increase of 0.23 $\mu g/m^3$ increase in PM_{10} and an increase of 0.08 $\mu g/m^3$ of $PM_{2.5}$. Comparing these estimates with the causal effect of the Clean Air Act Non-Attainment Status in

Table 1.15: First Stage Estimates- Effect of Precipitation on PM_{10}

VARIABLES	(1)	(2)	(3)	(4)
Total Precipitation	-0.2245***	-0.2253***	-0.2050***	-0.2094***
	(0.0403)	(0.0404)	(0.0407)	(0.0406)
Extreme Prec and Temp Events	Y	Y	Y	Y
Per Capita Income	Y	Y	Y	Y
Population	N	Y	Y	Y
County Lat/Long-Year Fixed Effects	N	N	Y	Y
Alternative Measure of Extreme Events	N	N	N	Y
Observations	11,104	11,104	11,104	11,104

Notes: Regressions include County and Year fixed effects. Standard errors are estimated using the Eicker-White formula to correct for heteroskedasticity. Extreme precipitation events (i.e. droughts and floods) and extreme temperature events (i.e. heat waves and cold waves) have been controlled for. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

Column (4) of Table 1.5, I find that a 1-mm decrease in daily precipitation can potentially offset over 30% of the benefits of the landmark regulation, through higher PM_{10} levels in ambient air. The effect is almost 38% of the benefits of the Clean Air Act, when we look at the estimates for $PM_{2.5}$ from Table 1.6. On the other hand, if precipitation frequency decreases by a day, then PM_{10} will increase by 1.04 $\mu g/m^3$ whereas $PM_{2.5}$ will increase by 0.39 $\mu g/m^3$. Using information on the county non-attainment status of the National Ambient Air Quality Standards for particulate matter, I also find significantly different effects in attainment vs non-attainment counties. Non-attainment counties, having higher stationary and non-stationary sources of pollution and higher levels of pollution precursors have larger impacts of both the level and the frequency of precipitation on ambient particulate matter concentrations. I also find substantial spatial heterogeneity of my main estimates. Finally, using these causal estimates, I analyze the effect of PM_{10} on infant mortality and find that a 1 $\mu g/m^3$ decrease in

PM_{10} would imply approximately 27 fewer infant deaths, per 100,000 live births in the United States. According to latest data from the Centers for Disease Control and Prevention, we have around 580 infant deaths per 100,000 live births in United States. Hence, my estimates suggest that a 1 $\mu g/m^3$ decrease in PM_{10} would signify more than a 4.6% reduction in the number of infant deaths per 100,000 live births.

This paper contributes to the literature on the linkages between air pollution and climate change in the following ways. Firstly, by consolidating a large and detailed daily dataset at the pollution monitor level, I provide the first causal estimates of the effect of precipitation as well as precipitation frequency on PM_{10} and $PM_{2.5}$. Secondly, by estimating this causal effect of precipitation on particulate matter, I have taken a step towards calculating the social costs of climate change, in terms of higher air pollution. I have illustrated that in the presence of changing rainfall patterns, pollution levels can be exacerbated, hence implying larger external costs of pollution emissions. Thus, such estimates are needed to guide more informed policy making and reaching the socially desirable level of emissions. Finally, I have also attempted to illustrate the econometric or technical gains from this exogenous causal effect of precipitation on particulate matter. To do so, I have used precipitation in an instrumental variables approach to study the effect of particulate matter on infant health. I propose that this exogenous link between precipitation and particulate air pollution can be exploited to study various other important economic questions because the availability of high frequency data having spatial and temporal heterogeneity provides an ideal platform to get reliable estimates. A potential direction for further research would be to design a methodology that could incorporate these estimates into designing the air pollution thresholds. Also, we might look into various mechanisms and adjustments made by economic agents to adapt to climate change. Lastly, with this effect of climate change on air pollution understood, we might want to analyze whether and how firms, industries and other pollution emitters internalize this linkage in deciding how much to produce.

CHAPTER 2

ADAPTATION AND THE CLIMATE PENALTY ON OZONE

2.1 Introduction

According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2013), the warming of the climate system is unequivocal, and global temperatures are likely to rise from 1.5 to 4 degrees Celsius over the 21st century, depending on the emissions scenario. While human influence on the climate system is clear, agents may also adapt to the new environment as the climate changes. Given enough time, or influenced by government institutions and policy, individuals and firms may adjust economic production processes by exploiting existing and new technological opportunities (e.g., Barreca et al., 2015, 2016). Adaptation is indeed a key issue, but the degree and nature of adaptive responses are still not well understood.

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

A key element of our approach is the decomposition of meteorological variables into two components: long-run trends and shocks, the latter defined as deviations from those trends. Taking advantage of high-frequency data, we decompose daily maximum temperature into a monthly moving average incorporating information from the past three decades, and a deviation from that lagged 30-year average often referred to as climate normal [1] . This decomposition is meant to have economic content. Agents can only respond to climatic variables they observe. The 30-year moving average is purposely lagged to capture all the information available to individuals and firms up to the year prior to the measurement of ozone levels, our outcome of interest. In contrast, agents cannot respond to weather shocks by definition. Our measure of adaptation is the difference between responses to weather shocks and responses to changes in lagged 30-year moving averages [2]. If policymaking can influence adaptive behavior, then variables representing governmental policies or regulations can be interacted with those two components of our decomposition to uncover measures of regulation-induced adaptation and residual adaptation.

For an example of regulation-induced adaptation, consider a county where emissions of ozone precursors are under control in the baseline. If a rise in temperature leads to higher ozone formation and the violation of EPAs ozone stan-

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

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

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

Besides providing the crucial pieces of our measure of adaptation, our decomposition allows us to understand the impact on air quality of not only one, but rather two dimensions associated with climate change. The public usually focuses on changes in average temperature, but extreme weather events are also expected to become more frequent (IPCC, 2013). The effects of realized weather shocks should be a good approximation for the effects of those extreme weather events to occur in future decades. The impact of changes in climate normals observed to date should represent well the impact of global warming by the mid-21st century. In fact, variation in these two components, likely present in high-frequency weather data, would allow one to estimate those two types of effects. Therefore, when addressing climate change, our approach implicitly takes into account both changes in temperature levels and changes in the frequency and intensity of daily temperature extremes.

We apply our methodology to study the impact of climate change on air quality. We tackle an issue that is of interest per se: the so-called climate penalty on ozone. Ground-level or "bad" ozone is not emitted directly into the air but rather created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC) in the presence of sunlight and warm temperatures. Hence, meteorological conditions do matter in determining surface ozone levels, and climate change may increase ozone concentration in the near future. While the projected impact is not uniform, modeling studies have shown that climate change has the potential to increase average summertime ozone concentrations in the contiguous U.S. by as much as 1-5 ppb by 2030, if greenhouse gas emissions are not mitigated (EPA 2009; Jacob and Winner, 2009) [3]. This climate penalty on ozone means that climate change might offset some of the improvements in air quality expected from reductions in emissions of ozone precursors, and therefore some of the improvements in public health [4]. Thus, stronger emission controls may be needed to meet a given air quality standard. In fact, when strengthening the standards for ground-level ozone from 75 to 70 ppb recently, the U.S. Environmental Protection Agency (EPA) has recognized the role climate change may play in driving air pollution in coming decades [5].

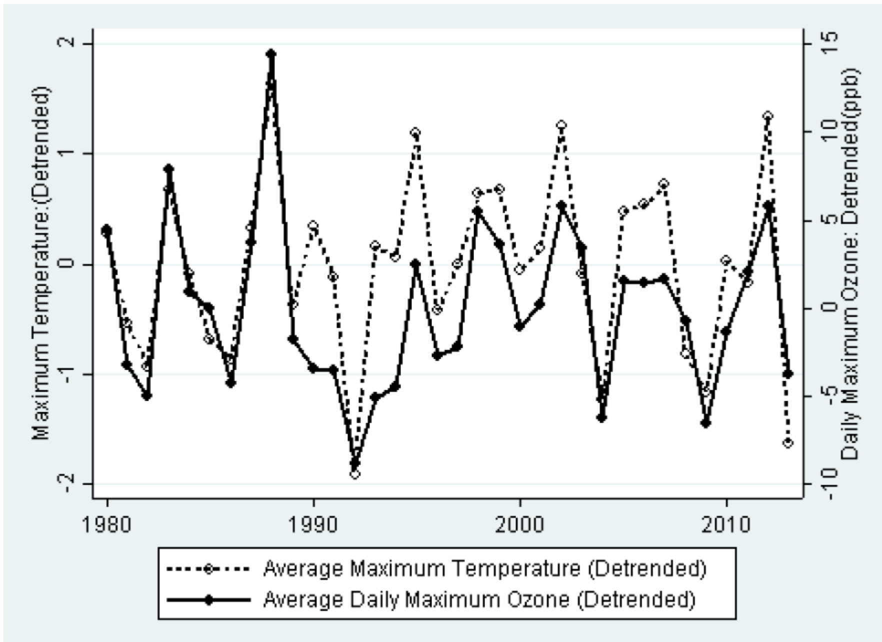
In our application, we focus on the effect of daily maximum temperature on daily maximum ozone concentration since 1980. We choose this outcome because EPAs ambient ozone standards have been built around it. Likewise, increases in temperature are expected to be the principal factor in driving any

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

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

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

ozone increases (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our sample, plotted in Figure 2.1, highlights the close relationship between these two variables.



Notes: Figure 2.1 illustrates the daily maximum temperature and ozone, averaged across all monitor-days, for each year. The variables have been detrended by eliminating the time trend.

Figure 2.1: Relationship between Ozone and Contemporaneous Temperature

We identify the impacts of climate change on ozone concentration by taking advantage of (i) daily measurements of ambient ozone levels from hundreds of air quality monitors across the U.S. during 1980-2013; and (ii) the rich spatial and temporal variation with which Clean Air Act regulations were rolled out. Through a Freedom of Information Act request, we obtained daily air pollution concentrations for each monitor based on the universe of the state and national pollution monitoring network. The Clean Air Act Amendments (CAAA) marked an unprecedented attempt by the federal government to mandate lower levels of air pollution. If pollution concentrations in a county exceed the federally determined ceiling, then EPA designates that county as nonattainment. Heavy emitters in nonattainment counties face far more stringent regulations than their counterparts in attainment counties. We, therefore, seek to identify changes in ozone concentrations due to observed changes in temperature at the times and locations in which the CAAA designations were in effect vis--vis places that were not facing the constraints associated with being out of attainment. We use a standard fixed-effects approach, but replace the direct measurements of temperature with the two components of our decomposition weather shocks and climatic changes. In our preferred specification, we interact such components with CAAA nonattainment designations.

We have three main findings. First, a changing climate appears to be affecting ground-level ozone concentrations in two ways. A shock in temperature of one degree Celsius increases ozone levels by 1.7 ppb on average. A change of similar magnitude in the 30-year moving average increases ozone concentration by 1.2 ppb. Therefore, by omitting climate normals, the standard fixed-effect approach would underestimate the impact of climate change on ambient ozone concentrations by over 40 percent. The total impact is rather 2.9 ppb, within the range of the climate penalty on ozone found by modeling studies. Furthermore, ozone levels seem to be more sensitive to temperature shocks than to changes in lagged climate normals, which are functions of the weather realized in the past 30 years. Agents may find it difficult to adjust to shocks, but could potentially respond to information available years in advance.

Second, we find evidence of adaptive behavior. For a change of one degree Celsius in temperature, our measure of adaptation in terms of ozone concentration is 0.45 ppb. When we compare our estimate of adaptation to the direct effect of the CAAA nonattainment designations, it is equivalent to over one-third of that effect. Also, if adaptive responses are not taken into account in the measurement of adaptation, then the climate penalty on ozone would be overestimated by approximately 17 percent.

Third, adaptation in counties with levels of ozone above the EPAs standards is estimated to be over 66 percent larger than adaptation in counties in attainment, and is equivalent to about 45 percent of the direct effect of the CAAA nonattainment designations. Counties out of attainment must reduce ozone concentration by making costly adjustments in their production processes (Greenstone, List, and Syverson, 2012). Thus, part of our measure of adaptation for these counties is regulation-induced adaptation. Nevertheless, counties complying with EPAs ozone standards might still adapt by exploiting technological advances such as photovoltaic panels, as explained before, or by unconscious behavioral responses. Therefore, part of our measure of adaptation is residual adaptation. For nonattainment counties, regulation-induced adaptation represents 40 percent of the total adaptation. For completeness, we have also found (i) a higher degree of adaptation in the 1980s relative to the following decades, (ii) a similar magnitude for the estimates of adaptation in the 1990s and 2000s, and (iii) a remarkable heterogeneity across the nine NOAA climate regions in the U.S.

This paper proceeds as follows: Section 2.2 explains the conceptual framework that we use to decompose meteorological variables into long-term trends and contemporaneous weather shocks and describes our measures of adaptation. Section 2.3 provides a detailed background on ozone formation, its relationship with the weather, and the history of ozone regulations. Section 2.4

describes our data, Section 2.5 presents our empirical methodology, and Section 2.6 reports our main findings. Section 2.7 illustrates the robustness of our estimates, and Section 2.8 exhibits the spatial and temporal heterogeneity of our results. Lastly, Section 2.9 concludes.

2.2 Conceptual Framework

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

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

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

In order to estimate the impact of climate change on ozone concentration, and ultimately uncover our measure of adaptation, we exploit both climatological and meteorological variation. The same estimating equation uses climatological variation to identify the causal effect of longer-run observed climatic changes (e.g. Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2005), and meteorological variation to identify the impact of weather shocks (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009). Afterward, the comparison between trend and shock effects should provide a measure of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016).

To take advantage of variation in both components, we decompose meteorological variables into long-run trends and weather shocks. A similar idea has been used in the literature of intergenerational mobility following Solons seminal work. Observed income is noisy: it includes a permanent and a transitory component. To establish a relationship between the permanent income of sons and fathers, Solon (1992) suggests averaging fathers income for a number of years to reduce the errors-in-variables bias. Importantly, the averaging is not needed for sons income, the dependent variable. We proceed in a similar way: we decompose only meteorological variables, not ozone levels, our outcome variable. Illustrating the decomposition with temperature ($Temp$), we can express it as

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

where $Temp^C$ represents climate patterns and $Temp^W (= Temp - Temp^C)$ deviations from those long-run patterns. The decomposition highlights the two sources of variation that have been used in the climate-economy literature [6].

A Measure of Adaptation to Climate Change

$Temp^C$ and $Temp^W$ in the decomposition above are associated with different sets of information. On one hand, $Temp^C$ includes climate patterns that economic agents can only gather by experiencing weather realizations over a long period of time. It can be thought of as climate normals. On the other hand, $Temp^W$ represents weather shocks, which by definition are revealed to economic agents only at the time of the weather realization. Now, one can only adjust to something they know. Therefore, adaptation can be measured as the difference between responses to changes in $Temp^C$ relative to effects of weather shocks $Temp^W$[7].

Important contributions to the literature have already pointed out that the comparison between the "short-" and "long-run" effects provides evidence of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016). Unlike previous work, however, we are able to estimate and test the equality of those effects within the same econometric model using insights from Solons (1992) seminal work on intergenerational mobility.

[6] In related work, Kala (2016) studies adaptation under different learning models. Hence, variance of climatological variables is an important element of her framework. In our approach, dispersion shows up only implicitly in the sense that long-run trends take into account the frequency and intensity of daily temperature extremes.

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

2.3 Ambient Ozone, Weather and Environmental Regulations

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

Most of the ozone in the air results from complex chemical reactions between pollutants directly emitted from vehicles, factories and other industrial sources, fossil fuel combustion, consumer products, evaporation of paints, and many other sources. These reactions involve volatile organic compounds (VOCs) and oxides of nitrogen (NOx) in the presence of sunlight. As a photochemical pollutant, ozone is formed only during daylight hours under appropriate conditions but is destroyed throughout the day and night. It is formed in greater quantities on hot, sunny, calm days. Therefore, ozone concentrations vary depending upon both the time of day and the location.

The ozone that the EPA regulates as an air pollutant is mainly produced close to the ground (tropospheric ozone). A layer of ozone high up in the atmosphere, called stratospheric ozone, reduces the amount of ultraviolet light entering the earths atmosphere. Without the protection of the stratospheric ozone layer, plant and animal life would be seriously harmed. Here, ozone refers to tropospheric ozone.

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

2.3.1 Formation and Depletion of Tropospheric Ozone

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

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

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

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

2.3.2 Role of Weather in Ozone Air Quality

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

Our basic understanding of meteorological processes associated with summertime ozone episodes has not changed over recent years. Major episodes of high ozone concentrations in the eastern U.S. and in Europe are associated with slow-moving, high-pressure systems. High-pressure systems are associated with the sinking of air, resulting in warm, generally cloudless skies, with light winds. The sinking of air results in the development of stable conditions near the surface that inhibit or reduce the vertical mixing of ozone precursors. The combination of inhibited vertical mixing and light winds minimizes the dispersal of pollutants emitted in urban areas, allowing their concentrations to build up. Photochemical activity involving these precursors is enhanced because of higher temperatures and the availability of sunlight.

Modeling studies indeed point to temperature as the most important weather variable affecting ozone concentrations. Dawson, Adams, and Pandisa (2007), for instance, examine how concentrations of ozone respond to changes in climate over the eastern U.S. The sensitivities of average ozone concentrations to temperature, wind speed, absolute humidity, mixing height, cloud liquid water content and optical depth, cloudy area, precipitation rate, and precipitating area extent were investigated individually. The meteorological factor that had the largest impact on ozone metrics was temperature. Absolute humidity had a smaller but appreciable effect. Responses to changes in wind speed, mixing height, cloud liquid water content, and optical depth were rather small.

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

(1) increased photolysis rates under meteorological conditions associated with higher temperatures;

(2) increased H2O concentrations with higher temperatures as this will lead to greater OH (hydroxyl; hydroxy) production;

(3) increase of anthropogenic hydrocarbon (e.g., evaporative losses) emissions or NOx emissions with temperature or both;
(4) the increase of natural hydrocarbon emissions (e.g., isoprene) with temperature;
(5) relationships between high temperatures and stagnant circulation patterns;
(6) advection of warm air enriched with O3.

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

2.3.3 Spatial and Temporal Variations of Ozone Concentrations

Ambient ozone concentrations can vary from non-detectable near combustion sources, where nitric oxide (NO) is emitted into the air, to several hundreds of ppb of air in areas downwind of VOC and NOx emissions. In continental areas far removed from direct anthropogenic effects, ozone concentrations are generally 20-40 ppb. In rural areas downwind of urban centers, ozone concentrations are higher, typically 50-80 ppb, but occasionally 100-200 ppb. In urban and suburban areas, ozone concentrations can be high (well over 100 ppb), but peak for at most a few hours before deposition and reaction with NO emissions cause ozone concentrations to decline (Chameides et al. 1992, Smith et al. 1997, Seinfeld and Pandis 1998, Finlayson-Pitts and Pitts 2000). Due to the lack of ozone-destroying NO, ozone in rural areas tends to persist at night, rather than declining to the low concentrations (<30 ppb) typical in urban areas and areas downwind of major urban areas that have plenty of fresh NO emissions.

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

Ozone concentrations also vary seasonally. Ozone concentrations tend to be highest during the summer and early fall months. In areas where the coastal marine layer (cool, moist air) is prevalent during summer, the peak ozone season tends to be in the early fall. The EPA has established ozone seasons for the required monitoring of ambient ozone concentrations for different locations within the United States and U.S. territories (CFR, 2000). Table 2.1 shows the ozone seasons during which continuous, hourly averaged ozone concentrations must be monitored. Note that ozone monitoring is optional outside of the ozone season and is monitored in many locations throughout the year.

Table 2.1: Ozone Monitoring Seasons by State

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

Source: U.S. EPA (2006, p. AX3-3). [1]The ozone season is defined differently in different parts of Texas.

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

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

As shown in Table 2.2, the first standard was put in place in 1971, following the Clean Air Act Amendments of 1970. It was not focusing on ozone, however, but rather all photochemical oxidants. The first NAAQS for ozone was established in 1979 when 120ppb was defined as the maximum 1-hour concentration that could not be violated more than once a year for a county to be designed as in attainment.

Table 2.2: History of Ozone NAAQS

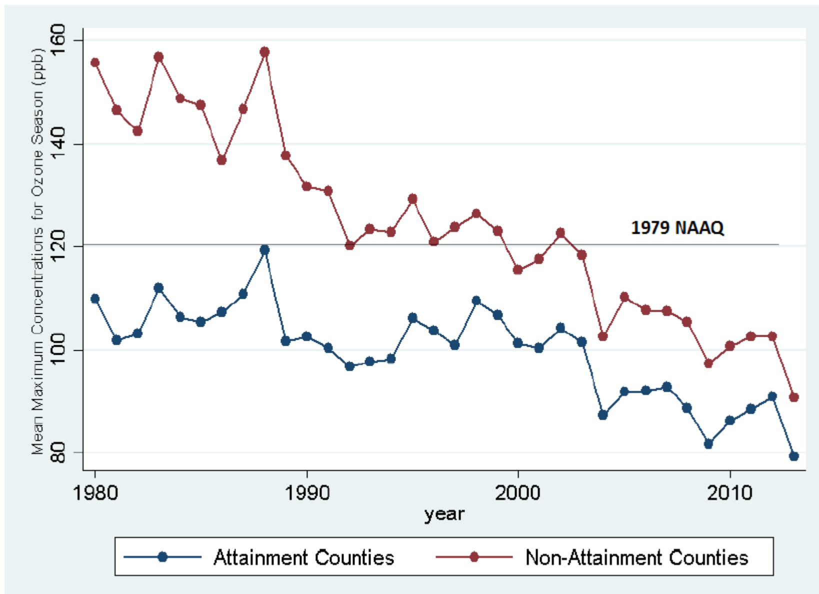
Final Rule/ Decision	Primary/ Secondary	Indicator	Averaging Time	Level	Form
1971	Primary and Secondary	Total photochemical oxidants	1-hour	80 ppb	Not to be exceeded more than one hour per year
1979	Primary and Secondary	Ozone	1-hour	120 ppb	Attainment is defined when the expected number of days per calendar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

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

In 1997, the standards were revised to be 80ppb, but with a different form for the threshold: annual fourth-highest daily maximum concentration averaged over 3 years. EPA justified the new form as equivalent to the empirical 1-hour maximum to not be exceeded more than once a year. *"The 1-expected-exceedance form essentially requires the fourth-highest air quality value in 3 years, based on adjustments for missing data, to be less than or equal to the level of the standard for the standard to be met at an air quality monitoring site. (U.S. EPA, 1997, p.38868) Another* *reason was the inherent lack of year-to-year stability in the measure of air quality on which the 1-expected-exceedance form is based. ... [A] more robust, concentration-based form would minimize such instability and provide some insulation from the impacts of extreme meteorological events that are conducive to O3 formation. Such instability can have the effect of reducing public health protection by disrupting ongoing implementation plans and associated control programs."* (U.S. EPA, 1997, p.38868) The new NAAQS was challenged in courts, and not implemented until 2004.

The NAAQS for ozone were revised again in 2008 and 2015, and the current 8-hour threshold is 70ppb. In the last revision, EPA raised concerns about how climate change might affect air quality. *"In addition to being affected by changing emissions, future O3 concentrations may also be affected by climate change. Modeling studies in the EPAs Interim Assessment (U.S. EPA, 2009a) as well as a recent assessment of potential climate change impacts (Fann et al., 2015) project that climate change may lead to future increases in summer O3 concentrations across the contiguous U.S. While the projected impact is not uniform, climate change has the potential to increase average summertime O3 concentrations by as much as 1-5 ppb by 2030, if greenhouse gas emissions are not mitigated. Increases in temperature are expected to be the principal factor in driving any O3 increases, although increases in stagnation frequency may also contribute (Jacob and Winner, 2009). If unchecked, climate change has the potential to offset some of the improvements in O3 air quality, and therefore some of the improvements in public health, that are expected from reductions in emissions of O3 precursors."* (U.S. EPA, 2015, p. 65300) This suggests that the present study may contribute to such an important policy debate.

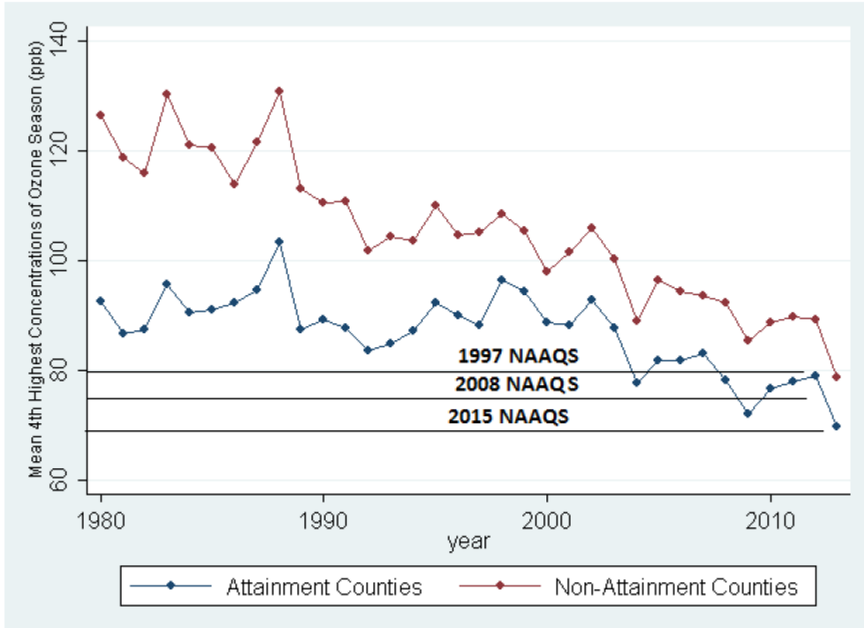
Regarding the patterns of ozone concentration over time, Figures 2.2 and 2.3 depict how much maximum and fourth-highest ozone levels have declined with the establishment of the NAAQS. As we can see in Figure 2.2, maximum concentrations decreased sharply in the late 1980s for the counties designated to be out of attainment. The same is not true for NAAQS 1997 and 2008. As Figure 2.3 shows, counties in non-attainment seem to be adjusting slowly to the new standards.



Source: Authors' compilation based on EPA data.

Figure 2.2: Evolution of Maximum Ozone Concentration

It is important to mention that the observed delay in complying with the NAAQS is expected. As reported in Table 2.3, for example, EPA allows heavy emitters up to 20 years to adjust their production processes. *"Each area designated nonattainment for ozone shall be classified at the time of such designation as a Marginal Area, a Moderate Area, a Serious Area, a Severe Area, or an Extreme Area based on the design value for the area. For each area , the primary standard attainment date for ozone shall be as expeditiously as practicable but not later than the date provided."* (U.S. Code, 2011, p.6325).



Source: Authors' compilation based on EPA data.

Figure 2.3: Evolution of Fourth Highest Ozone Concentration

Table 2.3: Period to Comply with NAAQS 1979

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

Source: U.S. Code (2011).

2.4 Data Sources

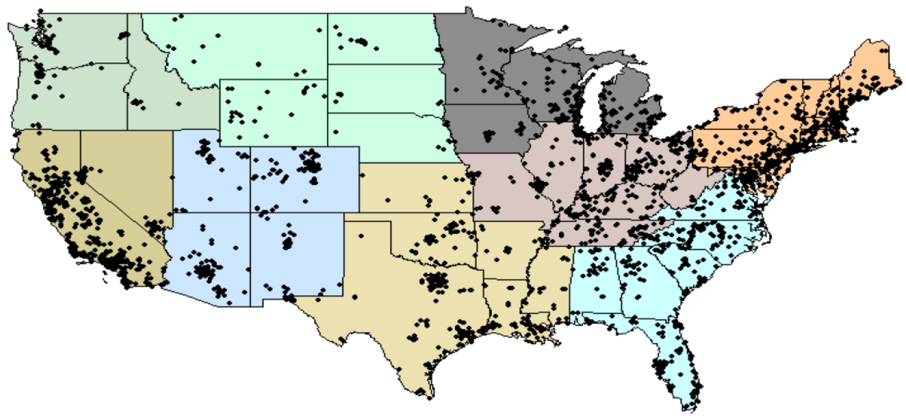
To examine the impact of climate change on surface ozone concentrations, and ultimately estimate our measure of adaptation, we utilize information from three major sources, as described below.

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

Figure 2.4 shows the geographical location of our final sample of ozone monitors and highlights the spatial heterogeneity of our sample. Figure 2.5 depicts the evolution of our sample of monitors over the three decades in our data, and illustrates the expansion of the network over time.

Table 2.4 provides some summary statistics regarding the increase in the number of monitors, and the decrease in ozone concentration decade by decade. We have valid ozone measurements for a total of 5,037,851 monitor-days. The number of monitors increased from 672 in the 1980s to 1026 in the 2000s, indicating a growth of 17.6 percent of the ozone monitoring network per decade. The number of monitored counties in our sample also grew from 390 in the 1980s to 601 in the 2000s. Table 2.18, in the Appendix, describes the sample of ozone monitors used in our analysis, for every year between 1980 and 2013.

Data on Non-Attainment Designations: We use publicly available data on the



Notes: Each shaded region represents a single climatic region as designated by the NOAA. According to the EPA, daily measurements are valid for regulation purposes only if (i) 8-hour averages are available for at least 75% of possible hours of the day, or (ii) the daily maximum 8-hour concentration is higher than the standard. Firstly, we only include monitors having valid daily information. Secondly, for every year between 1980-2013, we include monitors having valid monitor-days for at least 75% of the ozone season. Figure 2.4 illustrates our final sample of ozone monitors.

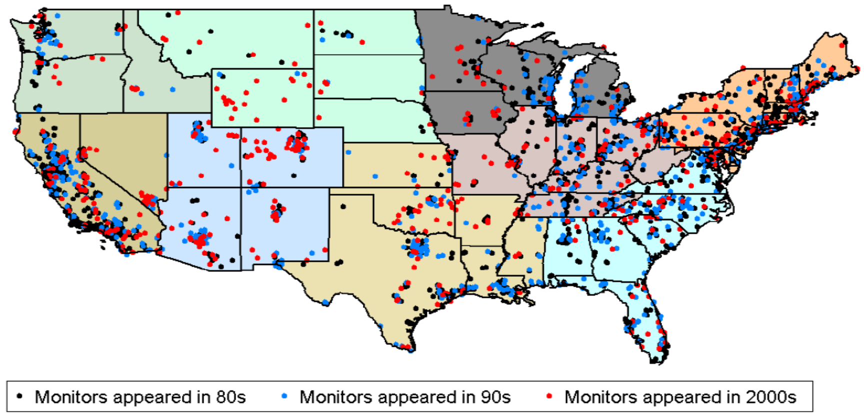
Figure 2.4: Ozone Monitors in Sample

Table 2.4: Summary Statistics for Monitoring Network by Decades

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

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

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



Notes: Each shaded region represents a single climatic region as designated by the NOAA. Figure 2.5 illustrates the ozone monitors in our final sample, by decade of first appearance.

Figure 2.5: Ozone Monitors by Decade of First Appearance

ozone.

Weather Data: For meteorological data, we use daily measurements of maximum and minimum temperature as well as total precipitation from the National Climatic Data Centers Cooperative Station Data (NOAA, 2008). This dataset provides detailed weather measurements at over 20,000 weather stations across the country. We have acquired information for the period 1950-2013. These weather stations are typically not located adjacent to the ozone monitors. Hence, we develop an algorithm to obtain a weather observation at each ozone monitor in our sample. Using the information on the geographical location of pollution monitors and weather stations, we calculate the distance between each pair of pollution monitor and weather station using the Haversine formula. Then, for every pollution monitor, we exclude weather stations that lie beyond a 30 km radius of that monitor. Moreover, for every pollution monitor, we use weather information from only the closest two weather stations within the 30 km radius. Once we apply this algorithm, we exclude ozone monitors that do not have any weather stations within 30km [8]. Figure 2.11, in Appendix A, illustrates the geographical location of the weather stations that we have used from 1950-2013, and Figure 2.12 illustrates the proximity of our final sample of ozone monitors to these matched weather stations.

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

Table 2.5 reports the summary statistics for our main meteorological variables, for each decade. Table 2.19, in the Appendix, presents this information at a more disaggregated level, for each year in our sample from 1980-2013.

Table 2.5: Summary Statistics for Meteorological Variables

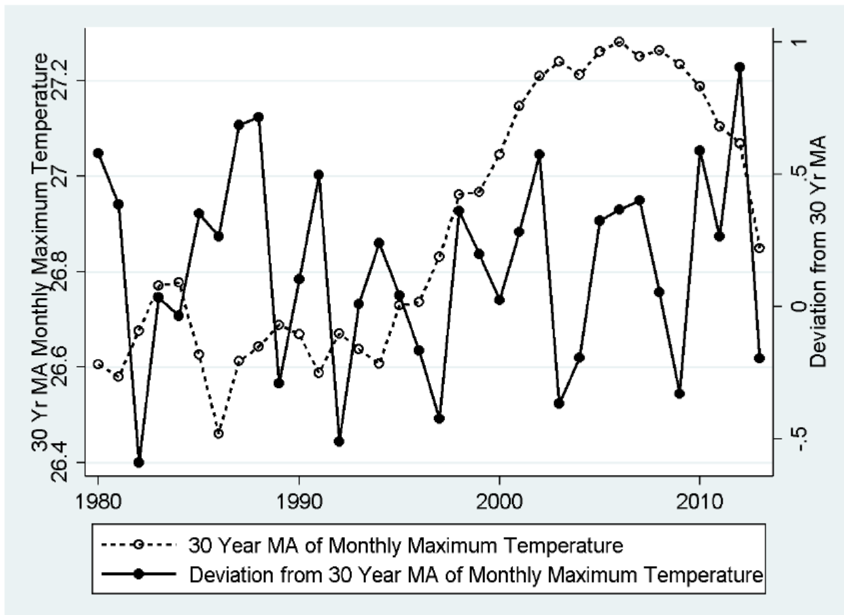
Decade	Max Temperature		30 Yr MA of Max Temperature		Temp Deviations	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
1980s	26.8	6.7	26.6	5.3	0.2	4.3
1990s	26.9	6.8	26.8	5.5	0.1	4.1
2000s	27.4	7.0	27.2	5.7	0.2	4.1

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

Figure 2.6 illustrates the variation we have in both components of the me-

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

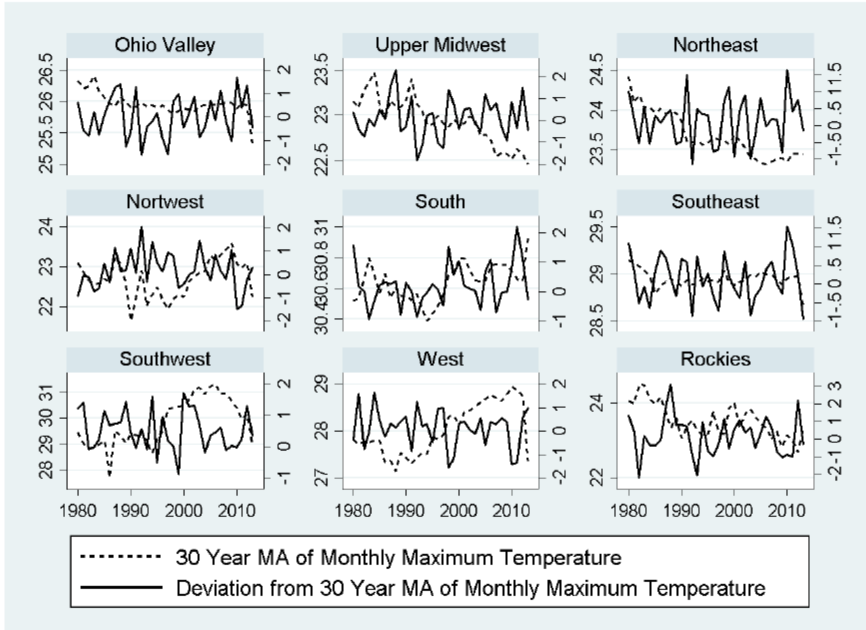
teorological variables, namely, the weather shocks and the long-term climate trends. Figure 2.7 depicts this variation for each of the nine different NOAA climate regions.



Notes: Figure 2.6 illustrates the variation in both the components of the meteorological variables. The weather shock is a deviation of contemporaneous daily maximum temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year.

Figure 2.6: Meteorological Variables- Trends and Shocks

Consolidating information from the above three sources, we reach our final unbalanced sample of ozone monitors over the period 1980-2013. In our application, we focus on the effect of daily maximum temperature on daily maximum ozone concentration since 1980. We choose this outcome because EPA's ambient ozone standards have been built around it. Likewise, increases in temperature are expected to be the principal factor in driving any ozone increases (Jacob and Winner, 2009). Indeed, data on ozone and temperature from our sample, plotted in Figures 2.1 and 2.8, highlights the close relationship between these two variables. Interestingly, we see that not only does contemporaneous temperature



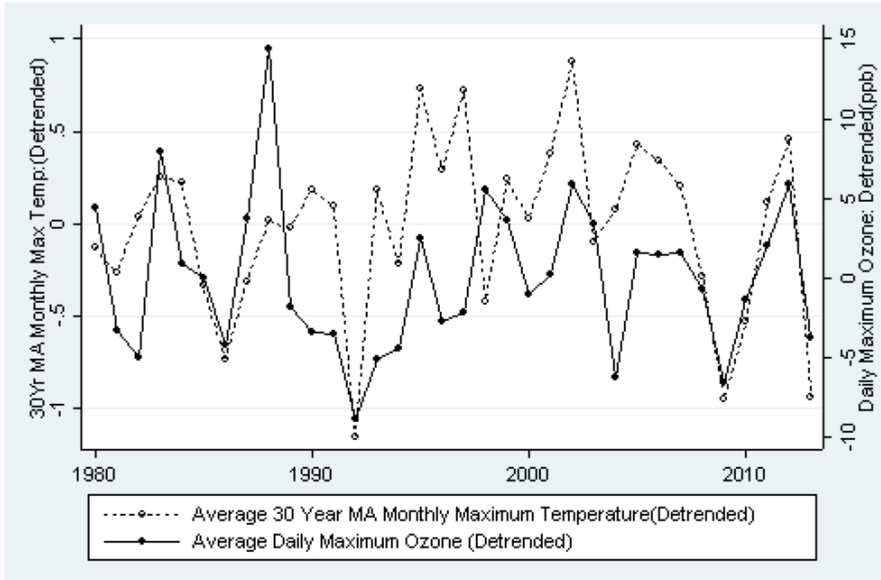
Notes: Figure 2.7 illustrates the variation in both the components of the meteorological variables, by the climate regions. The weather shock is a deviation of contemporaneous daily maximum temperature from the 30-year moving average. The variables have been averaged across all monitor-days in a given year.

Figure 2.7: Meteorological Variables- Trends and Shocks by Region

have an effect on ground level ozone, but the long-term temperature trend also seems to be affecting it very closely. Figures 2.9 and 2.10 illustrate the spatial heterogeneity of this close relationship between ground level ozone and these two different components of the meteorological variables for the nine NOAA climate regions.

2.5 Empirical Methodology

In this section, we present our methodology to examine the impact of climate change on ambient ozone concentration. First, we provide an empirical counterpart for the decomposition of meteorological variables described previously.



Notes: Figure 2.8 illustrates the 30-year monthly moving average of daily maximum temperature and ozone, averaged across all monitor-days, for each year. The variables have been detrended by eliminating the time trend.

Figure 2.8: Relationship between Ozone and Moving Average of Temperature

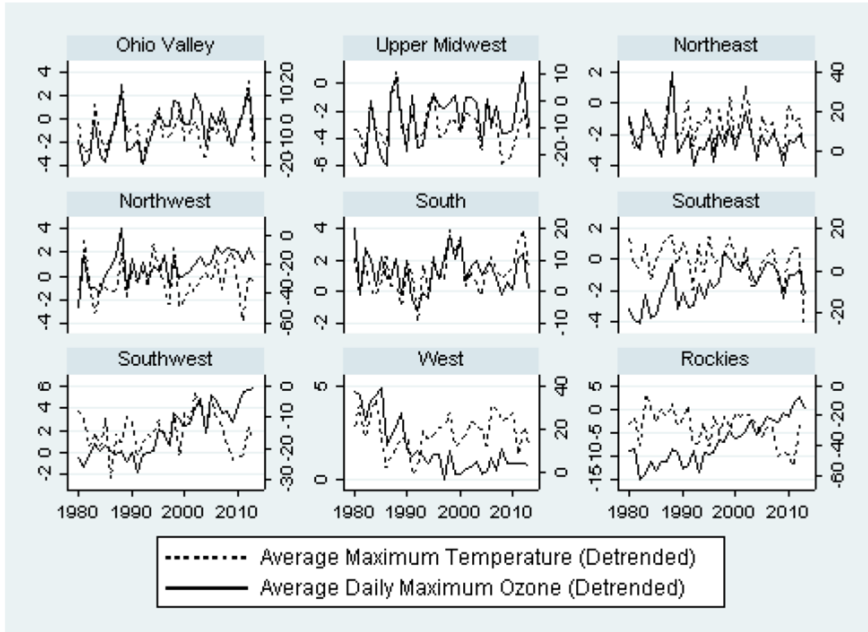
Second, we introduce and discuss features of our econometric model to estimate the effects of the two components of weather on ozone levels. Lastly, we use our novel way to measure adaptation to climate change to estimate behavioral responses in our application to air pollution.

Decomposition of Meteorological Variables: An Empirical Counterpart

Focusing on temperature ($Temp$), our primary variable of interest [9], we express it around ozone monitor i in day d of month m and year y as

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

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

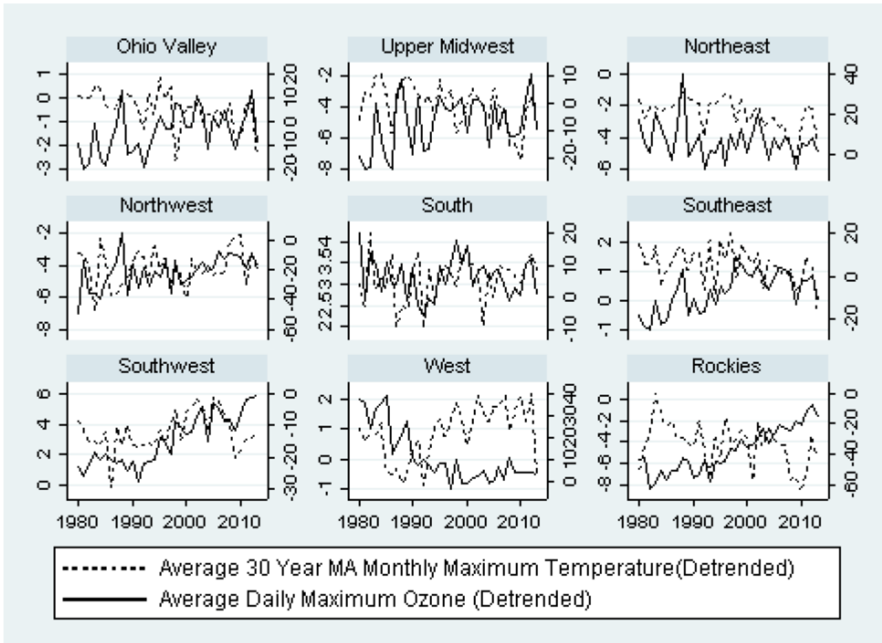


Notes: Figure 2.9 illustrates the daily maximum temperature and ozone, averaged across all monitor-days, for each year and climate region. The variables have been detrended by eliminating the time trend.

Figure 2.9: Relationship between Ozone and Contemporaneous Temperature by Regions

$Temp^C$ represents climate normals and is defined as a 30-year monthly moving average (MA) of past temperatures. To make this variable part of the information set held by economic agents at the time that ground-level ozone is measured, we lag it by one year. For example, the 30-year MA associated with May 1982 is the average of May temperatures for all years in the period 1952-1981. Therefore, economic agents have had one year to respond to unexpected changes in climate normals at the time ozone is measured. We average temperature over 30 years because it is how climatologists usually define climate normals, and because we wanted individuals and firms to be able to observe climate patterns for a long period of time, enough to potentially make adjustments [10]. We use monthly MAs because it is likely that individuals recall climate

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



Notes: Figure 2.10 illustrates the 30-year monthly moving average of daily maximum temperature and ozone, averaged across all monitor-days, for each year and climate region. The variables have been detrended by eliminating the time trend.

Figure 2.10: Relationship between Ozone and Moving Average of Temperature by Regions

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

$Temp^W$ represents weather shocks and is defined as the deviation of the daily temperature from the lagged 30-year monthly MA. By definition, these shocks are revealed to economic agents only at the time that ozone is being measured. Thus, in this case, agents may have had only a few hours to adjust, limiting their ability to respond to such unexpected temperatures [12].

averages.

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

[12] Because precise weather forecasts are made available only a few hours before its realization, economic agents may have limited time to adjust prior to the ozone measurement. This might be

Econometric Model

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

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

where i represents an ozone monitor located in county c in NOAA climate region r, and d stands for the day, m for a month, s for season (Spring or Summer), and y for the year. As mentioned in the data section, our analysis focuses on the most common ozone season in the U.S. -April to September - in the period 1980-2013. The dependent variable *Ozone* captures daily maximum ambient ozone concentration. $Temp's$ and $Prcp's$ [13] account for the two components of the decomposition proposed above for both meteorological variables [14]. *CAANAS* (Clean Air Act Non-Attainment Status) is a binary variable which equals one for counties not complying with the NAAQS for ground-level ozone counties designated as "nonattainment" following regulations derived from the Clean Air Act (CAA) Amendments. This variable is lagged by three years because EPA

true even during Ozone Action Days. An *Ozone Action Day* is declared when weather conditions are likely to combine with pollution emissions to form high levels of ozone near the ground that may cause harmful health effects. Individuals and firms are urged to take action to reduce emissions of ozone-causing pollutants, but only hours in advance

[13]We also add precipitation in our econometric analysis. Although less important than temperature, Jacob and Winner (2009) point out that higher water vapor in the future climate may decrease ground-level ozone concentration.

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

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

As should be clear by now, we exploit plausibly random, monthly variation in climate normals and daily variation in weather within a season to estimate the impact of climate change on ambient ozone concentration. Identification of the effect of weather shocks relies on monitor-level daily variation in the deviation of meteorological variables from lagged climate normals after controlling non-parametrically for regional shocks to ozone concentration at the season-by-year level. For instance, let us consider the variation of May 1st, 1982 relative to the Spring (April-June) of 1982 in the Northeast region. The question we ask is the following: what happens to ozone concentration in a May 1982 day when the deviation of temperature from the May 1981 climate normal is one degree Celsius above the average daily temperature shock in the Northeast in the Spring (April-June) of 1982? Conditional on business-as-usual ozone precursor emissions, a higher temperature should lead to more ozone formation and, consequently, higher ozone concentration.

Identification of the effect of climatic changes on ground-level ozone levels relies on plausibly random, monitor-level monthly variation in lagged 30-year MAs of meteorological variables after controlling non-parametrically for regional shocks to ozone concentration at the season-by-year level. As an example, let us consider variation of *lagged* 30-year MA temperature in May 1982 relative to the Spring (April-June) of 1982 in the Northeast region. Again, the question we ask is the following: what happens to ozone concentration in a May 1982 day when the normal temperature around the monitor in May 1981 is one degree Celsius warmer than the average of all 30-year monthly MAs of temperature in the Northeast in the Spring (April-June) of 1981? If economic agents pursued full adaptive behavior, the unexpected increase in normal temperature would lead to reductions in ozone precursor emissions to avoid an increase in ozone concentration of identical magnitude of the weather shock effect in the same month of the following year. In other words, agents would respond to "permanent" changes in temperature by adjusting their behavior or production processes to offset that increase in normal temperature. Unlike weather shocks, which influence ozone formation by triggering chemical reactions conditional on a level of ozone precursor emissions, changes in the 30-year MA affect the level of emissions.

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

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

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

Measuring Adaptation

Once we credibly estimate the impact of the two components of temperature - shocks, and changes in long-run trends on ambient ozone concentration, we uncover our measure of adaptation. The average adaptation across all counties in our sample is the difference between the coefficients β_T^W and β_T^C in equation (3). If economic agents engaged in full adaptive behavior, β_T^C would be zero, and the magnitude of the average adaptation would be equal to the size of the weather shock effect on surface ozone concentration. As explained before, agents would react to "permanent" increases in temperature by reducing ozone precursor emissions to offset potential increases in ozone concentration.

We can split our measure of average adaptation into two parts: regulation-induced versus residual adaptation, as shown in Table 2.6.

Table 2.6: Measures of Adaptation

Dependent Variable: Ambient Ozone	Average Adaptation [equation (3)]	Regulation-Induced Adaptation [equation (4)]	Residual Adaptation [equation (4)]
Marginal Effect of Weather Shocks	β_T^W	δ_T^W	γ_T^W
Marginal Effect of Climatic Changes	β_T^C	δ_T^C	γ_T^C
Measures of Adaptation	$\beta_T^W - \beta_T^C$	$(\delta_T^W - \delta_T^C)$	$(\gamma_T^W - \gamma_T^C)$

Notes: Estimates of Equation (3) gives us measures of average adaptation across all counties in our sample. The difference between the response to unexpected weather shocks, β_T^W, and observed climate trends, β_T^C, gives us a measure of adaptation by economic agents. In the absence of any adaptation, we would have $\beta_T^W = \beta_T^C$. Relative to this scenario, we find average adaptation to be $(\beta_T^W - \beta_T^C)$. Estimates from Equation (4) gives us levels of adaptation in attainment and non-attainment counties, using the interaction effects. Counties out of attainment have regulation-induced adaptation given by $(\delta_T^W - \delta_T^C)$. All counties exhibit residual adaptation, given by $(\gamma_T^W - \gamma_T^C)$. For more details, please refer to Table 2.8.

Regulation-induced adaptation reflects adjustments made by heavy emitters in "nonattainment" counties to comply with ozone NAAQS. EPA mandates those facilities to cut emissions by using the best pollution abatement technologies available. Because ozone formation depends on both emissions and meteorological conditions, by reducing emissions to abide by the CAA regulations, agents may be actually adapting to climatic changes [15]. Residual adaptation reflects adaptive responses by economic agents in counties under no pressure from stringent CAA regulations. They react unintentionally to climatic changes by changing electricity production and consumption patterns or driving behavior, for example.

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

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

Second, Leard and Roth (2016) find that mean temperatures above 80°F (relative to 50°-60°F) imply 5 percent fewer trips per household by light-duty vehicles, which seems to be partially compensated by higher travel demand by ultralight duty vehicles. The overall decrease in travel demand and the change in vehicle composition induced by temperatures higher than expected can be seen as adaptive responses and should imply fewer emissions of ozone precursors by vehicles. Therefore, places with a monthly 30-year MA temperature higher than average in the previous year may observe an effect on ozone that is less than the impact of weather shocks because households might have already adjusted their travel behavior. They may have already acquired bikes and motorcycles, and planned outdoor activities not involving too much driving in that particular month [16] .

[16] Graff Zivin, Hsiang, and Neidell (2015) provide another example of unconscious adaptive response to climate change. They find that short-run changes in temperature beyond 26°C lead to statistically significant decreases math performance. In contrast, their long-run analysis reveals no effect of climate on human capital, consistent with the notion that adaptation, par-

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

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

In our preferred econometric specification, behavioral responses are allowed to occur only in the year after the change in temperature trend is observed. Those adjustments, however, might be related to innovations in temperature

ticularly unconscious compensatory behavior, plays a significant role in limiting the long-run impacts from short-run weather shocks.

happening both in the previous year and 30 years before. Indeed, the "moving" feature of the 30-year MA is, by definition, associated with the removal of the earliest observation included in the average - 30 years before -, and the inclusion of the most recent observation - one year before. Nevertheless, in the robustness checks, we consider cases where economic agents can take a decade or two to adjust. Because EPA may give heavy emitters up to two decades to comply with ozone NAAQS [17] , adaptive responses many years after agents observe changes in temperature trends may be plausible. As Kousky (2012) points out in her review of the costs of natural disasters, *"(...) end-of-the-pipe adjustments, like shutters or increasing the market penetration of air conditioning, will underestimate how fully communities are adapted to their present disaster risk: infrastructure, building architecture, street geometries, and even institutions such as emergency response are all adapted to a current climate, and changing these to fit with a new risk profile, if sufficiently different, could be a very long-term process (...)."* (p.39).

Heterogeneity of Temperature Effects and Measures of Adaptation

Equations (3) and (4) are the econometric specifications used to estimate our main results. We can adjust them, however, to shed light on the impact of climate change on ambient ozone concentration for different decades, and for different NOAA climate regions.

In an additional specification, we basically interact the two components of meteorological variables and the $CAANAS$ with each decade included in our sample - the 1980s, 1990s, and 2000s. In another specification, we interact those same variables with each climate region as defined by NOAA - Ohio Valley,

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

Upper Midwest, Northeast, Northwest, South, Southeast, Southwest, West, and Rockies, as shown in the data section. Once we have the estimates associated with weather shocks and lagged 30-year MAs in these two cases, we are able to provide measures of adaptation for each decade and each climate region in our sample.

2.6 Results

In this section, we report our findings regarding (i) the impact of temperature on ambient ozone concentration, and (ii) the extent to which economic agents adapt to climate change in the context of ozone pollution [18]. Then, we provide evidence of the robustness of our main results to alternative specifications and sampling strategies. Lastly, we explore heterogeneity of our estimates by decade (the 1980s, 1990s, and 2000s) and by NOAA climate region.

Impact of Temperature on Ambient Ozone Concentration

Table 2.7 presents the effects on ambient ozone of two components of observed temperature: climate, represented by the *lagged* 30-year monthly MA [19] , and weather shock, represented by the deviation from that long-run trend. Although they are uncovered by estimating equation (3), Columns 1 and 2 benchmark them against effects that would have been found if one had exploited either only the cross-sectional (e.g. Mendelsohn, Nordhaus, and Shaw, 1994;

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

[19]As mentioned before, even though we use monthly moving averages in our main estimates, as a robustness check we also estimate our preferred specifications using daily moving averages. The results are almost the same and are reported in Table 2.20 in the Appendix A.

Schlenker, Hanemann, and Fisher, 2005) or only the longitudinal (e.g. Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) structure of the data.

Table 2.7: Main Estimates

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

Notes: Column (1) reports cross-sectional estimates using *average* temperature and ozone concentrations at 2535 ozone monitors in the sample. Having averaged the variables over all the years from 1980-2013, these estimates capture the effect of a change in the long-term *climate trend*. Column (2) reports the effect of daily temperature on ozone, exploiting day-to-day variation in maximum temperature and hence capturing the effect of a change in short term *weather*. In Column (3), we decompose daily temperature into *climate trends* and *weather shocks* in the same estimating equation, exploiting high-frequency data. In Column (4), we control for the lagged Clean Air Act Non-Attainment Status and in Column (5) we include interactions of weather shocks and climate trends with the CAANAS to estimate heterogeneous effects across attainment and non-attainment counties. Column (1) has fixed effects for climate region, monitor latitude and monitor longitude. Columns (2)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Column 1 reports results from a cross-sectional estimation of daily maximum ozone concentration on daily maximum temperature and total precipitation around each monitor, averaged over the entire period of analysis 1980-2013.

These variables capture information for all the years in our sample and are good proxies for the average pollution and climate at each monitor. The estimate suggests that a 1°C increase in average maximum temperature is associated with a 1.10ppb increase in ozone concentration, approximately. Column 2 reports the effect of temperature on ozone identified by exploiting day-to-day variation in maximum temperature. The coefficient indicates that a 1°C increase in maximum temperature leads to a 1.53ppb increase in maximum ground-level ozone concentration. When we decompose daily maximum temperature into those two components in Column 3, the overall effect on ozone concentration goes to 2.9ppb. A 1°C shock increases ozone concentration by 1.7ppb, and a 1°C change in trends in the same month of the previous year increases ozone concentration by 1.2ppb. Therefore, by including the two components of temperature - the lagged 30-year MA and deviations from it - the impact of changes in observed maximum temperature doubles or triples when compared to the panel or cross-sectional approaches, respectively.

To emphasize, both unexpected spikes in temperature and rises in long-term temperature trend have a positive and significant effect on ozone concentrations. The total effect of a higher temperature is almost 2.9 ppb, which is in line with previous studies in the literature. Jacob and Winner (2009), in their review of the effects of climate change on air quality, find that climate change alone can lead to a rise in summertime surface ozone concentrations by 1-10 ppb. The EPA, in their Interim Assessment (2009) also claim that *"the amount of increase in summertime average ... O_3 concentrations across all the modeling studies tends to fall in the range 2-8 ppb"*.

Column 4 shows that the estimates do not change when we include the Clean

Air Act Non-Attainment Status (CAANAS) in the regression, but Column 5 indicates important heterogeneity in the effect of each component of temperature across counties in or out of attainment regarding the ozone NAAQS. We find that in non-attainment counties, daily maximum ozone concentrations are around 1.22 ppb lesser as compared to counties in attainment. A 1-degree Celsius rise in the climate trend (as measured by the lagged 30-year MA of temperature) also has differential impacts in attainment and non-attainment counties. In attainment counties, it leads to around 0.98 ppb rise in ozone concentrations, whereas in non-attainment counties we find an additional increase of around 0.47 ppb, which implies a cumulative increase of 1.45 ppb of summertime surface ozone levels. Similarly, we find heterogeneity in the effect of the weather shock; a 1-degree Celsius increase in the weather realization increases ozone levels by 1.3 ppb in attainment counties, whereas it leads to an additional 0.69 ppb increase in non-attainment counties.

Measuring Adaptation to Climate Change

The comparison between the short- and long-run effects of temperature may provide a measure of adaptive responses by economic agents (Dell, Jones, and Olken, 2009, 2012, 2014; Burke and Emerick, 2016). When we compare the impact of long-run temperature on ozone concentration in Column 1 of Table 2.7 with the effect of a temperature shock in Column 2, the measure of adaptation is approximately 0.44ppb. Interestingly, our measure of adaptation - also a comparison between the impact of the long-run temperature (lagged 30-year MA) and the effect of the temperature shock (deviation from the MA) - is very similar: 0.45ppb.

Our results indicate that temperature shocks have a larger impact on ozone levels compared to long-term temperature trends. This points to the fact that economic agents may potentially *adapt* to climate trends. We summarize our measures of adaptation in Table 2.8. By comparing the coefficients of the temperature shock and the temperature trend in Column (4) of Table 2.7, we find that on average across all counties, the *level of adaptation* is 0.45 ppb. If we ignore such adaptive responses by economic agents, then we would be overestimating the climate penalty on ozone by over 17 percent [20] . We find that the level of adaptation is roughly 37 percent of the direct effect of the Clean Air Act regulation, which means that our measure of adaptation is economically sizeable.

Using our estimates from Column 5 of Table 2.7, we can now disentangle the overall adaptation into *regulation-induced* adaptation and *residual* adaptation. The coefficients of the interaction terms now give us the *incremental impacts* of weather shocks and climate change in non-attainment counties. From this specification, we find that the regulation-induced adaptation (in non-attainment counties) is 0.22 ppb, whereas the residual level of adaptation [21] (both, in attainment and non-attainment counties) is 0.33 ppb, as shown in Table 2.8. Thus, in non-attainment counties, we find a total adaptation of 0.55 ppb. More than 40 percent of this cumulative level of adaptation in non-attainment counties should be driven by the Clean Air Act regulations.

Non-attainment counties adapt over 66 percent more than attainment counties in absolute terms. To give a sense of the magnitude of our adaptation estimates by attainment status, we can compare them to the impact of the CAA

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

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

Table 2.8: Adaptation- Main Estimates

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

Notes: For Non-Attainment counties: Level of adaptation (ppb) = Residual ($\gamma^W_T - \gamma^C_T$) + Regulation-induced ($\delta^W_T - \delta^C_T$) from column (5). Attainment Counties: Level of adaptation (ppb) = ($\gamma^W_T - \gamma^C_T$) from column (5) based on equation (4). Overestimation of Climate Penalty for Non-attainment counties= $(2*(\gamma^W_T + \delta^W_T)*100)/(\gamma^W_T + \delta^W_T + \gamma^C_T + \delta^C_T)$; for Attainment Counties: $(2*\gamma^W_T*100)/(\gamma^W_T + \gamma^C_T)$. Estimates for attainment and non-attainment counties are derived from column (5) of Table 2.7 and estimates for all counties are derived from Column (4) in Table 2.7; Average Level of adaptation (ppb) for All Counties = $\beta^W_T - \beta^C_T$ from column (4), based in equation (3). Note that in all above calculations, the effect of the CAA regulation is given by δ as estimated by equation (3). The proportion of counties in non-attainment in the entire sample is 0.54. Adaptation estimates for all counties are averages for estimates for attainment and non-attainment counties, weighted by the proportion of counties in non-attainment.

regulations. As we found in Column 3 of Table 2.7, the CAA regulations reduce ozone levels by around 1.22 ppb. Hence, in *attainment counties*, it represents 26.7 percent of the effect of being out of attainment and in *non-attainment counties* almost 45 percent. Therefore, our estimates of adaptation seem sizeable. By ignoring such adaptive measures, we would be overestimating the climate penalty in attainment counties by 14.5 percent, and by over 16 percent in non-attainment counties.

2.7 Robustness Checks

2.7.1 Nonlinearities

Because ozone formation may be intensified with higher temperatures, we also look at the non-linear effects of daily maximum temperature on surface ozone concentrations. Instead of using daily maximum temperature continuously, we have categorized the contemporaneous daily maximum temperature and also its monthly average into temperature bins of 5°C. We have put temperatures below 20°C (just over the 10th percentile of our temperature distribution) into our lowest bin and those above 35°C (90th percentile of our temperature distribution) into our highest bin. We have then taken the lagged 30-year moving averages of these temperature bin dummies, to get a measure of the long-term climate trend; the measure of our weather shock has been constructed by taking the difference between the contemporaneous temperature bins and the 30 years monthly moving average of temperature bins. In Table 2.9, we have reported our estimates from this non-linear specification.

By interacting our temperature bins, with the regulatory variable, as before, we can analyze the nature and degree of regulation induced and residual adaptation at different points of the temperature distribution. From Column 2, as expected, we find that higher temperatures increasingly lead to hike in ozone concentrations. As each bin is of 5°C, we can see that for temperatures between 20°C and 25°C, a 1 degree C increase would raise ozone levels by 1.22 ppb on average; whereas for temperatures between 25-30°C, 30-35°C and above 35°C, the effects are 3.1 ppb, 4.76 ppb, and 6.54 ppb respectively. From our estimates in Columns 3 and 4, we have the following results about the degree of adaptation

Table 2.9: Non Linear Effects of Temperature

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

Notes: In Columns (1)-(5) we report non-linear effects of daily maximum temperature on surface ozone levels. We categorize daily maximum temperature into 5 bins from <25ºC to >35ºC with 5ºC intervals in between. Column (1) reports cross-sectional estimates using *average* temperature and ozone concentrations at 2535 ozone monitors in the sample. Having averaged the variables over all the years from 1980-2013, these estimates capture the effect of a change in the long-term *climate trend*. Column (2) reports the effect of daily temperature on ozone, exploiting day-to-day variation in maximum temperature and hence capturing the effect of a change in short term *weather*. In Column (3), we decompose daily temperature into *climate trends* and *weather shocks* in the same estimating equation, exploiting high-frequency data. In Column (4), we control for the lagged Clean Air Act Non-Attainment Status and in Column (5) we include interactions of weather shocks and climate trends with the CAANAS to estimate heterogeneous effects across attainment and non-attainment counties. Column (1) has fixed effects for climate region, monitor latitude and monitor longitude. Columns (2)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

at different levels of temperature, which are summarized in Table 2.10.

Average Adaptation (across all counties:) From Column 4 of Table 2.9, like we had for our main results, we find that the average level of adaptation across all counties ranges from 0.51 ppb for temperatures between 20-25°C, to 0.16 ppb

Table 2.10: Adaptation Estimates for Nonlinearities

	Average Adaptation (ppb)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	% Regulation Induced
A. 20-25 Celsius				
Non-Attainment Counties	0.57	0.14	0.43	24.6
Attainment Counties	0.43	--	0.43	--
All Counties	0.51	0.08	0.43	15.7
B. 25-30 Celsius				
Non-Attainment Counties	0.21	0.08	0.13	38.10
Attainment Counties	0.13	--	0.13	--
All Counties	0.16	0.03	0.13	18.75
C. 30-35 Celsius				
Non-Attainment Counties	0.56	0.35	0.21	62.5
Attainment Counties	0.21	--	0.21	--
All Counties	0.45	0.24	0.21	53.3
D. Above 35 Celsius				
Non-Attainment Counties	1.02	0.35	0.67	34.3
Attainment Counties	0.67	--	0.67	--
All Counties	0.82	0.15	0.67	18.3

Notes: Adaptation estimates have been calculated using estimates from Table 2.9, and dividing that by 5 to get adaptation in response to a 1ºC change in temperature. Adaptation measures are calculated, as explained in Table 2.8.

for temperatures between 25-30°C; 0.45 ppb for temperatures between 30-35°C, and lastly almost 0.82 ppb for temperatures in our highest bin. So we see that a lot of the adaptation is driven by the 20-25°C bin. As the USA as a whole is predominantly NOx-limited, we would expect that changes in electricity usage might drastically reduce ozone concentrations (since electricity use is a major source of NOx, also, since ozone formation has a Leontief like production function in terms of NOx and VOCs, reduction in electricity use in a NOx-limited region would imply large changes in ozone formation.) In the below 20°C bin or at a temperature above 25°C people are generally more dependent on either the heater or the air conditioner and hence might not be able to adjust their electricity use.

However, temperatures between 20-25°C represent very pleasant weather which might potentially induce people to cut down on electricity demand and hence cut down on NOx which might be driving the high degrees of adaptation in this bin. This again points to the fact that most of this adaptation is driven by the lower temperature bins, where adapting to a warming climate is relatively easier. In a recent paper (Deschenes and Greenstone, 2011), the authors analyze the non-linear effects of daily average temperature on residential energy consumption and quite interestingly, they document a U-shaped function such that the hottest and coldest days are the highest energy consumption ones. Energy consumption at intermediate levels of temperature of around 60-80 degrees Fahrenheit (comparable to our intermediate temperature bin of 20-25°C), is the lowest. This also justifies our estimates of adaptation at different levels of temperature. At intermediate levels of daily temperature, economic agents can adjust and bring down their energy consumption, hence leading to large decreases in ozone concentrations. Interestingly, we also see a relatively high level of adaptation above 35°C. This can be plausibly explained by the following reasons. As discussed in Leard and Roth (2016), higher temperatures signify more pleasant weather and can lead to changes in transportation patterns in a way that people might prefer walking or biking rather than driving. Such behavioral changes might be driving the higher levels of residual adaptation that we see across all counties. Also, in regions having temperatures above 35°C, we would expect a higher incidence of sunlight which might be leading to the more extensive use of solar panels to generate electricity or heating. Thus, higher temperatures might be creating an environment that is more suited to shift away from conventional and dirtier sources power generation, thus leading to higher levels of adaptation. Lastly, regions having higher temperatures have a larger climate penalty on ozone and hence are more strongly regulated. This might be driving the larger levels of regulation induced adaptation that we see in the higher temperature bins.

Regulation-induced adaptation + Residual Adaptation(in non-attainment counties): Similar to our main results, we find a higher degree of adaptation in non-attainment counties at every level of temperature. However, out of the total adaptation in non-attainment counties, the proportion of regulation-induced adaptation varies from around 25 percent for temperatures between 20-25°C to around 62.5 percent for temperatures between 30-35°C.

Residual Adaptation (in attainment and non-attainment counties). From Column 5 of Table 2.9, we find that the residual adaptation, ranges from 0.13 ppb for temperatures between 25-30°C, to around 0.67 ppb, for temperatures above 35°C.

2.7.2 Lagged Responses

Another potential concern with our preferred specification might be the fact that we have used the lagged 30 years moving average to capture the long-term climate trend; hence to avoid such concerns, we test the sensitivity of our estimates using the lagged 20 years and lagged 10 years monthly moving averages of temperature and precipitation. The results which have in reported in Table 2.21 in Appendix A, prove to be quite robust and the magnitudes are very similar to our main results in Table 2.7. This is potentially being caused because of the 30 years monthly moving average that we use in our preferred specification, already has all the information that is present in the 20 years, or the 10-year moving average. In all the three kinds of moving average used, agents are getting just one year to adapt. Hence, a more interesting robustness check could be to look at the effects, when agents get 10 years and 20 years to adapt, instead of just one. In Table 2.11, we provide estimates from our preferred specification; however, by using 20-year moving averages of temperature and precipitation (*lagged by 10 years*); and 10-year moving averages (*lagged by 20 years*). By doing so, we are providing agents more time to adapt to climate change. Even though we expect that the effects of the weather shocks would be similar, we anticipate the effects of the climate trend to be slightly smaller than before, as agents should now be able to adapt more than before. This is what we find from our estimates reported in Table 2.11.

2.7.3 Non-Random Citing of Ozone Monitors

In a recent working paper (Muller and Ruud, 2016), the authors argue that the location of pollution monitors are not necessarily random. They claim that the U.S. Environmental Protection Agency (EPA) maintains a dense network of pollution monitors in the country for two major reasons. Firstly, it wishes to check and enforce the National Ambient Air Quality Standards (NAAQs) for the criteria pollutants; and secondly, it wants to provide useful data for the analysis of important questions linking pollution with its varied impacts. The authors claim that these are conflicting interests because to check attainment status, the monitors are generally placed in areas where pollution levels are the highest, whereas, in terms of providing good quality representative data, monitors must be placed in regions having different levels of pollution.

Table 2.11: Lagged Responses

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

Notes: Columns (1)-(4) and Columns (5)-(8) are analogous to Columns (2)-(5) in Table 2.7. Here, we report similar estimates, however, by using 10 and 20 year lagged moving averages of temperature and precipitation. Columns (1)-(8) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at the monitor level. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

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

To nullify such threats to identification, we can check the sensitivity of our main estimates reported in Table 2.7, by using a balanced panel of ozone monitors. Starting from our original sample, we only use observations from monitors that have been in the data for every year from 1980-2013 and we are left with 92 pollution monitors. By doing so we eliminate the various possible confounding factors that might drive the positioning of monitors and their subsequent selection into the sample. The results from this estimation have been reported in Table 2.12. We find that a 1-degree Celsius increase in the daily maximum temperature leads to a rise in ozone concentrations by 1.88 ppb. Average adaptation is 0.44 ppb across all counties. We can further disentangle this to find that regulation induced adaptation in non-attainment counties is 0.24 ppb whereas residual adaptation in attainment, as well as non-attainment counties, is 0.25 ppb. The effects using a balanced panel are actually even larger than those in our main results reported in Table 2.7. This ensures that our central estimates are robust to any sort of errors potentially caused by the endogenous placement of ozone monitors because had such claims been true, the effects should have been smaller when we use a balanced sample. As explained before, if monitors are expected to be placed endogenously in areas having high pollution levels, then when we use an unbalanced panel in our preferred sample, we should be overestimating the effect of temperature on ozone concentrations, which does not seem to be true.

Table 2.12: Non Random Citing of Ozone Monitors

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

Notes: Columns (1)-(4) are analogous to Columns (2)-(5) in Table 2.7. Here, we report similar estimates, however, by using a balanced panel of 92 ozone monitors. Columns (1)-(4) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

2.7.4 Dependence on Wind Speed and Sunlight

Although temperature is the primary meteorological factor affecting tropospheric ozone concentrations, other factors such as wind speed and sunlight have also been noted as potential contributors. Firstly, high wind speeds can dilute ozone concentrations locally and also potentially lead to the transportation of ozone to neighboring regions. Strong ventilation with high wind speeds prevents the build-up of high local pollutant concentrations. Ozone precursors, namely, NOx and VOCs can also be transported significant distances from their point of origin and hence can lead to elevated ozone levels in other areas. Secondly, ultraviolet solar radiation initiates the photolysis of NO2 to nitric oxide and a free oxygen atom which can then react with molecular oxygen to form ozone. In order to test if our main estimates are actually capturing the effects of wind speed and sunlight, we control for these variables in our preferred specification.

Table 2.13 reports these estimates. Columns 1 and 2 present our main results from estimating Equations (3) and (4) respectively. Next we present results from estimating Equation (4), however, having additionally controlled for average daily wind speed (meters/sec) in Column 3, total daily sunlight (mins) in Column 4 and both in Column 5. As expected, we find that higher wind speeds lead to lower ozone concentrations and more sunlight leads to higher concentrations. From Column 5, we find that a 1 meter/sec increase in average daily wind speed would decrease ozone concentrations by 2.2 ppb, whereas a 1 min increase in daily sunlight leads to 0.02 ppb increase in ozone concentrations. More importantly, by comparing Column 2 with Column 5, we find that our main results do not change dramatically, either in direction or magnitude, after the inclusion of these other meteorological variables. We still find that a shock in daily maximum temperature of 1°C leads to a 1.24 ppb increase in daily maximum ozone whereas a 1°C increase in the climate trend leads to a 0.72 ppb increase in ozone. Our estimates of the interaction terms suggest a regulation-induced adaptation of 0.17 ppb in non-attainment counties. Also, we still find a residual adaptation of 0.52 ppb, across all counties. This ensures that our primary estimates of the impact of temperature on ozone concentrations, and hence, our measures of adaptation, are not being driven by the dependence on other potentially important meteorological factors.

Table 2.13: Dependence on Wind Speed and Sunlight

VARIABLES	(1)	(2)	(3)	(4)	(5)
Dev from 30 Yr MA of Max Temp (Weather Shock)	1.6942***	1.3025***	1.4105***	1.3461***	1.2365***
	(0.0254)	(0.0191)	(0.0263)	(0.0593)	(0.0621)
30 Yr MA of Max Temp (Climate Trend)	1.2423***	0.9767***	0.7663***	0.9240***	0.7247***
	(0.0239)	(0.0219)	(0.0313)	(0.0577)	(0.0621)
Lag 3 CAANAS	-1.2197***	-14.0926***	-13.7245***	-16.1596***	-16.7932***
	(0.1771)	(0.8447)	(1.1532)	(2.0324)	(2.1615)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp		0.6967***	0.6454***	0.7119***	0.8247***
		(0.0345)	(0.0393)	(0.0708)	(0.0770)
Lag 3 CAANAS x 30 Yr MA of Max Temp		0.4743***	0.4676***	0.5491***	0.6477***
		(0.0273)	(0.0353)	(0.0592)	(0.0622)
Dev from 30 Yr MA of Prcp (Weather Shock)	-0.2263***	-0.2201***	-0.1679***	-0.0849***	-0.0615***
	(0.0040)	(0.0049)	(0.0063)	(0.0140)	(0.0125)
30 Yr MA of Prcp (Climate Trend)	-1.8042***	-1.6627***	-1.8777***	-0.9536**	-1.0373***
	(0.1219)	(0.1194)	(0.1239)	(0.4057)	(0.3841)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp		-0.0144**	-0.0261***	-0.0484***	-0.0399**
		(0.0066)	(0.0089)	(0.0187)	(0.0188)
Lag 3 CAANAS x 30 Yr MA of Prcp		0.0630	0.1175	-0.0372	-0.4943
		(0.1269)	(0.1561)	(0.3447)	(0.3448)
Average Daily Wind Speed			-2.1792***		-2.2289***
			(0.0931)		(0.2098)
Total Daily Sunlight				0.0150***	0.0144***
				(0.0006)	(0.0006)
Observations	4,974,155	4,974,155	2,019,634	581,465	455,533
R-squared	0.4225	0.4286	0.4183	0.4049	0.4366

Notes: Columns (1) and (2) are analogous to Columns (4) and (5) in Table 2.7. In Column (3) we control for average daily wind speed (meters/sec); in Column (4) we control for total daily sunlight (mins) and in Column (5) we control for both. Columns (1)-(5) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

2.8 Heterogeneity of Results

2.8.1 Results by Decades

In the following table, we present our results from estimating equation (4) by decades. We split our sample into three decades, 1980-90, 1991-2001 and 2002-2013 respectively, so that we have roughly the same number of years in each decade. In Table 2.14, we present the main results, where we see the heterogeneity of our results across time. All the effects discussed in the Main Results are present in each decade; however, we find that the effect of contemporaneous daily maximum temperature is decreasing over time. Also, looking at Columns 3 and 4, we find evidence of adaptation by economic agents, in every decade. The average adaptation across all counties in our sample ranges from 0.58 ppb in the 1980s to 0.39 ppb in the 1990s and 0.41 ppb in the 2000s. Also, from Column 4 we find that the regulation-induced adaptation in non-attainment counties decreases consistently from around 0.22ppb in the 1980s to about 0.09 ppb in the 2000s. Residual adaptation in attainment and non-attainment counties varied from 0.42 ppb in the 1980s to 0.27 ppb in the 1990s and 0.38 ppb in the 2000s. Hence, the 1980s, which marked the initial phases of the regulation and when the average pollution levels were also higher, exhibit, on one hand, the largest impacts of the climate on ground level ozone and on the other hand, also show the largest degree of adaptation over time. The temporal heterogeneity of our adaptation estimates has been illustrated in Table 2.15.

2.8.2 Results by Climate Regions

Next, we aim to establish the spatial heterogeneity of our results. We have estimated our main specification by the nine different climate regions as defined by the National Oceanic and Atmospheric Association (NOAA), through detailed climate analysis. Each of these regions have very similar climatic conditions and hence, very comparable baselines of temperature, precipitation, and other important meteorological variables, thus providing a reliable criterion for breaking up our main estimates to analyze heterogeneity across space. In Tables 2.16 and 2.17 we provide our main estimates from the regional regressions and also the heterogeneity of our adaptation estimates. In Table 2.16, the main estimates for

Table 2.14: Results by Decades

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

Notes: Columns (1)-(4) are analogous to Columns (2)-(5) in Table 2.7. We report our main estimates by the three decades in our sample: 1980-1990; 1991-2001 and 2002-2013. Columns (1)-(4) have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

each region have been reported. To avoid confusion, we have just presented the results from estimating equations (3) and (4), for each region. We find that even though the overall direction of effects of weather shocks as well as long term climate trends are consistent, their magnitudes are extremely varied across space. To make things clearer, Table 2.17 reports the adaptation estimates for each climate region; here, as before, using Column 3 we have first calculated estimates

Table 2.15: Adaptation Estimates by Decades

	Average Adaptation (ppb)	Regulation Induced Adaptation (ppb)	Residual Adaptation (ppb)	% Regulation Induced	Proportion in Non-Attainment
A. 1980s					0.71
Non-Attainment Counties	0.64	0.22	0.42	34.38	
Attainment Counties	0.42	--	0.42	--	
All Counties	0.58	0.16	0.42	27.59	
B. 1990s					0.54
Non-Attainment Counties	0.46	0.19	0.27	41.30	
Attainment Counties	0.27	--	0.27	--	
All Counties	0.39	0.12	0.27	30.77	
C. 2000s					0.45
Non-Attainment Counties	0.47	0.09	0.38	19.15	
Attainment Counties	0.38	--	0.38	--	
All Counties	0.41	0.03	0.38	7.32	

Notes: Adaptation estimates have been calculated using estimates from Table 2.14. Adaptation measures are calculated, as explained in Table 2.8.

on an average level and percentage of adaptation across all counties in each region. Then, using Column 4, we disentangle this into regulation-induced and residual adaptation. In this table we also provide the mean daily maximum temperature (climatic baseline) and the average proportion of counties in non-attainment in each region, using which we can try to interpret the results in an improved manner.

As we can observe from Table 2.17, almost all the regions exhibit adaptation to climate change, as we have discussed before. However, their magnitudes are quite different, and since we also have the baseline climate for each region, we can link these estimates to our estimates for non-linear temperature effects, reported in Table 2.9. As we can see here, most of the adaptation is driven by the Upper Midwest, Northeast, and Northwest, where average daily maximum temperatures fall in the range 20-25°C. This is consistent with our finding in

Table 2.10, where we claimed that a major portion of adaptation happens at such lower temperatures. Regions having average temperatures in the range 25-30°C, namely the Ohio Valley, Southeast, Southwest and West, exhibit lower degrees of adaptation, which is also consistent with our results on non-linear effects of temperature. If we analyze the estimates of residual and regulation-induced adaptation, we find that the West and the Northwest have 0.526 ppb and 0.724 ppb regulation induced adaptation, which is huge compared to most other regions. On the other hand, in the Northeast, we actually find evidence of intensification, rather than adaptation.

To understand this further, we can compare the Northeast and the Northwest, both having a climatic baseline between 20-25°C, hence implying feasible conditions for adaptation. However, we find that even though there is a high level of residual adaptation in both regions, the regulation-induced adaptation is a huge 0.724 ppb in the Northwest, whereas it is -0.151 ppb in the Northeast. This can potentially be explained by the fact that regulation in this states, has already reached the limit of effectiveness. This can be observed from the fact that in the Northeast, more than three-fourths of the counties are already being regulated as compared to the Northwest, where this proportion is only about 0.2. Northeast officials have stressed that they have done everything in their capacity to bring down emissions. However, a huge proportion of the ozone air pollution in these states are driven by cross-border pollutants from upwind Southern and Midwestern states. Officials have mentioned on multiple occasions that installing pollution abatement technology would be far less costly for Midwestern states than it would be for the Northeast. It has been estimated that the marginal cost of regulation in the Northeast is a whopping $10000 whereas, in the Midwest, it is only about $200. Hence, we find that regulation has no further effect in these states. Looking at the other climatic extreme, we can compare the Southwest and the West, both having average temperatures close to 30°C. Even though the West has a reasonably high proportion of counties in non-attainment, we find evidence that there is still some scope of regulation induced adaptation. However, in both regions, we find evidence of residual intensification, which is probably driven by the fact that temperatures are too high and hence unfeasible for economic agents to adjust their behavior patterns.

2.9 Conclusion

In this paper, we propose a novel methodology to study the effect of temperature on ambient ozone concentrations and measure adaptation to climate change. By decomposing high-frequency daily data on meteorological variables over the past 64 years, made available by the National Oceanic and Atmospheric Administration (NOAA), we are able to examine the impact on air quality of both long-term climatic trends and short-term deviations from such trends (i.e. weather shocks) in a single estimating equation. Using daily data on ambient ozone concentrations from EPA's Air Quality Systems (AQS) database, we find that unexpected spikes in temperature, as well as increases in the long-term temperature trend, have positive and significant impacts on surface ozone levels. A shock in daily maximum temperature of one degree Celsius increases ozone levels by 1.7 ppb, whereas a similar increase in the 30-year monthly moving average of temperature leads to a further 1.2 ppb increase in ozone, implying a total impact of 2.9 ppb. Hence, by ignoring the climate normal, we would *underestimate* the total effect - or the so-called climate penalty on ozone - by over 40 percent.

Table 2.16: Results by Climate Regions

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

Notes: Columns (1) and (2) for each climate region are analogous to Columns (4) and (5) in Table 2.7. We report our main estimates by the nine different NOAA climate regions in the United States. The climate regions are defined as follows: Ohio Valley: IL, IN, KY, MO, OH, TN and WV; Upper Midwest: IA, MI, MN and WI; Northeast: CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI and VT; Northwest: ID, OR and WA; South: AR, KS, LA, MS, OK and TX; Southeast: AL, FL, GA, NC, SC and VA; Southwest: AZ, CO, NM and UT; West: CA and NV; Rockies: MT, NE, ND, SD and WY. Columns (1) and (2) for each region have trimester-by-year-by-region FE; trimester-by-year-by-monitor latitude FE & trimester-by-year-by-monitor longitude FE. Standard errors are clustered at monitor level. ***, **, and * represent significance at 1%, 5% and 10% respectively.

Table 2.17: Adaptation Estimates by Climate Regions

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

Notes: Adaptation estimates have been calculated using estimates from Table 2.16. Adaptation measures are calculated, as explained in Table 8. The climate regions are defined as follows: Ohio Valley: IL, IN, KY, MO, OH, TN and WV; Upper Midwest: IA, MI, MN and WI; Northeast: CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI and VT; Northwest: ID, OR and WA; South: AR, KS, LA, MS, OK and TX; Southeast: AL, FL, GA, NC, SC and VA; Southwest: AZ, CO, NM and UT; West: CA and NV; Rockies: MT, NE, ND, SD and WY.

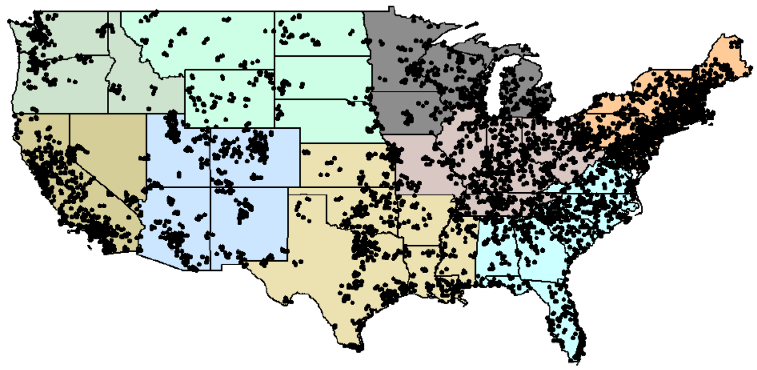
By comparing the long-term "climate effect" with the short-term "weather effect", we arrive at our measure of adaptation to climate change. We find an average adaptation of 0.45 ppb across all counties in our sample. This measure captures the fact that the long-term effect of temperature, although positive, is smaller than the effect of a sudden shock, thus signifying potential changes in the behavior of economic agents in response to a changing climate. In the absence of any adaptation, we would expect the impact of higher temperature to be twice as much as the effect of the temperature shock, i.e. a 3.4 ppb increase in ozone levels. Thus, by ignoring adaptation, we would *overestimate* the climate penalty on ozone by over 17 percent.

Using data on Clean Air Act Attainment designations from the EPA's Green Book of Nonattainment Areas for Criteria Pollutants, we are also able to disentangle our measure of adaptation into *regulation-induced adaptation*, occurring in counties facing stringent regulations for being out of attainment of ozone NAAQS, and *residual adaptation* occurring in all counties. We find that, in both attainment and non-attainment counties, the residual level of adaptation is 0.33 ppb. However, there is an additional 0.22 ppb regulation-induced adaptation in non-attainment counties. Hence, in comparison to attainment counties, non-attainment counties are adapting over 66 percent more in terms of ozone concentrations. Comparing our estimates to the benefits coming out of CAA regulations, we find that in attainment counties, adaptation represents 26.7 percent of the effect of being out of attainment, whereas in non-attainment counties, its almost 45 percent.

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

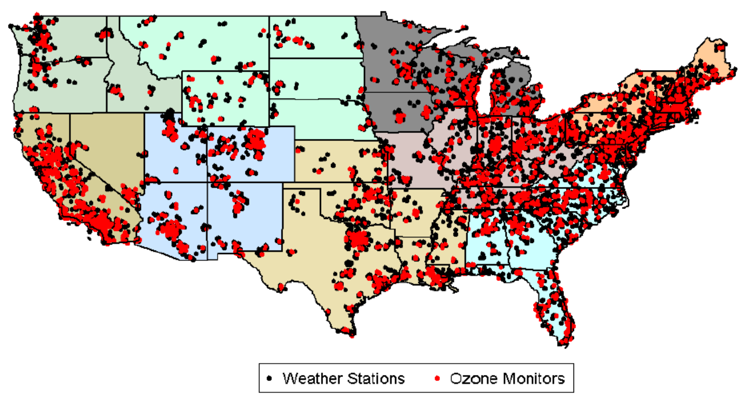
By estimating the causal effect of temperature on ambient ozone, we have taken the first step towards calculating the costs of climate change in terms of higher air pollution. We have illustrated that in the presence of climate change, pollution levels are exacerbated, hence implying larger external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

2.10 Appendix A- Additional Figures and Tables



Notes: Each shaded region represents a single climatic region as designated by the NOAA. Figure 2.11 illustrates the weather stations used from 1950-2013. For every ozone monitor in our final sample, we keep the closest two weather stations within a radius of 30 km.

Figure 2.11: Weather Stations from 1950-2013



Notes: Each shaded region represents a single climatic region as designated by the NOAA. Figure 2.12 illustrates the ozone monitors in sample from 1980-2013 and the matched weather stations. For each ozone monitor the closest 2 stations within a 30 km radius have been used.

Figure 2.12: Matched Ozone Monitors and Weather Stations

Table 2.18: Summary Statistics for Monitoring Network by Year

Year	Observations	Counties	Monitors	Number of Monitors by Climate Regions								
				Ohio Valley	Upper Midwest	Northeast	Northwest	South	Southeast	Southwest	West	Rockies
1980	91543	368	663	132	67	149	12	51	72	36	134	10
1981	102211	394	684	137	65	137	15	66	77	45	133	9
1982	102168	383	651	129	54	131	16	62	75	44	132	8
1983	102513	393	651	127	52	135	12	74	80	42	123	6
1984	104705	382	649	118	51	129	15	76	78	41	134	7
1985	106550	382	653	127	53	134	17	67	75	39	133	8
1986	104889	367	635	114	52	127	17	70	73	33	142	7
1987	110838	378	663	116	56	129	14	70	81	41	147	9
1988	114510	405	693	123	56	130	12	71	94	46	150	11
1989	119972	406	712	126	58	129	12	71	91	46	168	11
1990	126149	427	742	129	60	134	13	73	97	52	175	9
1991	131638	446	778	135	74	141	13	80	100	54	171	10
1992	136747	458	804	144	66	144	11	85	108	53	183	10
1993	144870	485	844	151	69	145	15	83	124	66	180	11
1994	147629	490	853	153	65	146	16	84	125	62	193	9
1995	151553	495	872	154	67	153	17	86	127	60	199	9
1996	150585	500	867	152	66	158	21	86	129	66	179	10
1997	157337	518	901	158	66	163	23	91	135	75	180	10
1998	160401	535	927	160	66	165	26	98	140	77	187	8
1999	165718	546	948	161	68	169	25	98	149	75	192	11
2000	168893	551	965	166	68	159	24	111	154	79	192	12
2001	177068	572	1014	168	68	175	25	121	164	82	198	13
2002	180316	579	1023	160	67	174	27	127	167	87	199	15
2003	182313	588	1036	160	73	173	29	133	168	89	195	16
2004	182229	596	1023	159	71	173	29	131	166	92	187	15
2005	180238	594	1019	154	72	174	27	131	159	99	184	19
2006	181903	598	1025	154	71	177	26	129	159	101	187	21
2007	183971	605	1036	155	69	180	26	129	155	113	188	21
2008	184197	607	1041	154	70	176	25	132	154	114	194	22
2009	186610	616	1048	154	71	179	25	132	153	117	192	25
2010	187713	623	1058	154	71	178	29	132	152	120	193	29
2011	190351	642	1076	161	73	186	29	129	161	120	185	32
2012	191206	637	1076	155	72	190	27	128	165	115	189	35
2013	128317	523	852	129	38	176	8	120	149	89	119	24

Notes: Decades are 1980-1990, 1991-2001 and 2002-2013 respectively. Data used in construction of this table uses monitor-days for which 8-hour averages were recorded for at least 18 hours of the day and monitor-years for which valid monitor-days were recorded for at least 75% of days between April 1st and September 30th. This table uses data for the months of April-September as that constitutes the ozone season. The nine different climatic regions are as defined by the National Oceanic and Atmospheric Association (NOAA).

Table 2.19: Summary Statistics for Meteorological Variables by Year

Year	Max Temperature	30 Yr MA of Max Temp	Temp Deviations
1980	27.2	26.6	0.6
1981	27.0	26.6	0.4
1982	26.1	26.7	-0.6
1983	26.8	26.8	0.0
1984	26.7	26.8	0.0
1985	27.0	26.6	0.3
1986	26.7	26.5	0.3
1987	27.3	26.6	0.7
1988	27.4	26.6	0.7
1989	26.4	26.7	-0.3
1990	26.8	26.7	0.1
1991	27.1	26.6	0.5
1992	26.2	26.7	-0.5
1993	26.7	26.6	0.0
1994	26.8	26.6	0.2
1995	26.8	26.7	0.0
1996	26.6	26.7	-0.2
1997	26.4	26.8	-0.4
1998	27.3	27.0	0.4
1999	27.2	27.0	0.2
2000	27.1	27.0	0.0
2001	27.4	27.1	0.3
2002	27.8	27.2	0.6
2003	26.9	27.2	-0.4
2004	27.0	27.2	-0.2
2005	27.6	27.3	0.3
2006	27.6	27.3	0.4
2007	27.6	27.3	0.4
2008	27.3	27.3	0.1
2009	26.9	27.2	-0.3
2010	27.8	27.2	0.6
2011	27.4	27.1	0.3
2012	28.0	27.1	0.9
2013	26.7	26.8	-0.2

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

Table 2.20: Daily Moving Averages

VARIABLES	(1)	(2)	(3)	(4)
Max Temp	1.5274***			
	(0.0231)			
Total Precipitation	-0.2434***			
	(0.0036)			
Dev from 30 Yr MA of Max Temp (Weather Shock)		1.6991***	1.6993***	1.3029***
		(0.0260)	(0.0259)	(0.0195)
30 Yr MA of Max Temp (Climate Trend)		1.2794***	1.2793***	0.9959***
		(0.0233)	(0.0233)	(0.0207)
Lag 3 CAANAS			-1.2095***	-15.1604***
			(0.1769)	(0.7952)
Lag 3 CAANAS x Dev from 30 Yr MA of Max Temp				0.7053***
				(0.0351)
Lag 3 CAANAS x 30 Yr MA of Max Temp				0.5099***
				(0.0278)
Dev from 30 Yr MA of Prcp (Weather Shock)		-0.2306***	-0.2306***	-0.2251***
		(0.0039)	(0.0039)	(0.0048)
30 Yr MA of Prcp (Climate Trend)		-0.4590***	-0.4593***	-0.4922***
		(0.0201)	(0.0201)	(0.0264)
Lag 3 CAANAS x Dev from 30 Yr MA of Prcp				-0.0120*
				(0.0065)
Lag 3 CAANAS x 30 Yr MA of Prcp				0.1112***
				(0.0386)
Observations	4,974,322	4,974,117	4,974,117	4,974,117
R-squared	0.4183	0.4209	0.4211	0.4275

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

Table 2.21: 20 Year and 10 Year Moving Averages

VARIABLES	(1) 20 Year Moving Averages	(2)	(3)	(4)	(1) 10 Year Moving Averages	(2)	(3)	(4)
Max Temp	1.5274***				1.5274***			
	(0.0231)				(0.0231)			
Total Precipitation	-0.2434***				-0.2434***			
	(0.0036)				(0.0036)			
Dev from MA of Max Temp (Weather Shock)		1.6902***	1.6904***	1.2994***		1.6889***	1.6890***	1.3001***
		(0.0253)	(0.0253)	(0.0191)		(0.0252)	(0.0252)	(0.0189)
MA of Max Temp (Climate Trend)		1.2511***	1.2509***	0.9834***		1.2509***	1.2509***	0.9776***
		(0.0241)	(0.0241)	(0.0220)		(0.0241)	(0.0240)	(0.0218)
Lag 3 CAANAS			-1.2124***	-14.2360***			-1.2328***	-14.5932***
			(0.1764)	(0.8445)			(0.1766)	(0.8274)
Lag 3 CAANAS x Dev from MA of Max Temp				0.6960***				0.6934***
				(0.0344)				(0.0343)
Lag 3 CAANAS x MA of Max Temp				0.4769***				0.4868***
				(0.0274)				(0.0274)
Dev from MA of Prcp (Weather Shock)		-0.2268***	-0.2268***	-0.2203***		-0.2280***	-0.2279***	-0.2212***
		(0.0040)	(0.0040)	(0.0049)		(0.0040)	(0.0040)	(0.0049)
MA of Prcp (Climate Trend)		-1.7213***	-1.7219***	-1.6083***		-1.4298***	-1.4345***	-1.3708***
		(0.1054)	(0.1055)	(0.1053)		(0.0784)	(0.0786)	(0.0817)
Lag 3 CAANAS x Dev from MA of Prcp				-0.0149**				-0.0149**
				(0.0066)				(0.0066)
Lag 3 CAANAS x MA of Prcp				0.0932				0.1244
				(0.1187)				(0.1002)
Observations	4,974,322	4,974,155	4,974,155	4,974,155	4,974,322	4,974,155	4,974,155	4,974,155
R-squared	0.4183	0.4222	0.4224	0.4286	0.4183	0.4220	0.4222	0.4284

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

2.11 Appendix B: Scientific Background on Ozone Formation

2.11.1 Formation and Depletion of Tropospheric Ozone

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

Nitrogen Cycle and the Photostationary-State Relationship for Ozone

The formation of ozone in the troposphere results from only one known reaction: addition of atomic oxygen (O) to molecular oxygen (O_2) in the presence of a third “body” (M). M is any “body” with mass, primarily nitrogen or oxygen molecules, but also particles, trace gas molecules, and surfaces of large objects.

$$O + O_2 + M \rightarrow O_3 + M \tag{B1}$$

The oxygen atoms are produced primarily from photolysis of NO_2 by the ultraviolet portion of solar radiation (hn).

$$NO_2 + hn \rightarrow NO + O \tag{B2}$$

Reaction 3 converts ozone back to oxygen and NO back to NO_2, completing the “nitrogen cycle.”

$$O_3 + NO \rightarrow NO_2 + O_2 \tag{B3}$$

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

The nitrogen cycle operates fast enough to maintain a photostationary state. The net effect of this cycle is neither to generate nor destroy ozone molecules. Therefore, for ozone to accumulate, an additional pathway is needed to convert NO to NO_2; one that will not destroy ozone. The photochemical oxidation of VOCs, such as hydrocarbons and aldehydes, provides that pathway.

The VOC Oxidation Cycle

Hydrocarbons and other VOCs are oxidized in the atmosphere by a series of reactions to form carbon monoxide (CO), carbon dioxide (CO_2) and water (H_2O). Intermediate steps in this overall oxidation process typically involve cyclic stages driven by hydroxyl radical (OH) attack on the parent hydrocarbon, on partially oxidized intermediate compounds, and on other VOCs. The hydroxyl radical is ever-present in the ambient air; it is formed by photolysis from ozone in the presence of water vapor, and also from nitrous acid, hydrogen peroxide, and other sources. In the sequence shown below, R can be hydrogen or virtually any organic fragment. The oxidation process usually starts with reaction 4, from OH attack on a hydrocarbon or other VOC:

$$RH + OH \rightarrow H_2O + R \tag{B4}$$

This is followed by reaction with oxygen in the air to generate the peroxy radical (RO_2).

$$R + O_2 + M \rightarrow RO_2 + M \tag{B5}$$

The key reaction in the VOC oxidation cycle is the conversion of NO to NO_2. This takes place through the fast radical transfer reaction with NO.

$$RO_2 + NO \rightarrow NO_2 + RO \tag{B6}$$

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

$$OH + HCHO \rightarrow H_2O + HCO \tag{B7}$$

$$HCO + O_2 \rightarrow HO_2 + CO \tag{B8}$$

$$HO_2 + NO \rightarrow NO_2 + OH \tag{B9}$$

Hydroperoxyl radical (HO_2) is generated by reaction 8, and the hydroxyl radical (consumed in reaction 7) returns in reaction 9 to complete the cycle. In addition, reaction 9 produces the NO_2 required for ozone formation, as described above. Also, the carbon monoxide (CO) generated by reaction 8 can react like an organic molecule to yield another hydroperoxyl radical.

$$OH + CO \rightarrow H + CO_2 \tag{B10}$$

$$H + O_2 + M \rightarrow HO_2 + M \tag{B11}$$

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

$$HCHO + hn \rightarrow H + HCO \tag{B12}$$

The hydrogen atom (H) and formyl radical (HCO) produced by this photolysis reaction yield two hydroperoxyl radicals via reaction with oxygen, as shown in reactions 8 and 11.

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

Ratio of Volatile Organic Compounds to Nitrogen Oxides in Ambient Air

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

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

CHAPTER 3

CLIMATE CHANGE AND ATTAINMENT STATUS

3.1 Introduction

The Clean Air Act is a federal level regulation in United States that was designed to control and regulate air pollution. The Environmental Protection Agency has designed National Ambient Air Quality Standards (NAAQs) for six major criteria pollutants namely, ground level ozone, particulate matter, carbon monoxide, sulphur dioxide, lead and nitrogen oxides. Counties are designated as being in attainment or non attainment depending on whether they are able to achieve these standards. Counties that are not in attainment face very strict regulatory control and states have to submit a State Implementation Plan to the EPA suggesting ways and means by which they can get non attainment counties back into attainment. Interestingly, even though the terms and conditions of the regulation are common knowledge, there is a huge number of counties that have been in non-attainment for prolonged periods of time. The fact that counties can be in non-attainment inspite of the fact that they have to bear some "costs" or penalties, points to the interesting question of what exactly defines this variablity in attainment status of counties? More specifically, is it possible to have conditions on parameters such that a county optimally chooses to be in non-attainment?

Quite clearly, the tradeoff facing a county is that of higher production and hence higher emissions vs lower production and hence no cost of being in non-attainment. It is documented that climate change (eg. higher temperatures) can lead to increases in air pollutants like ground level ozone and hence exacerbate the effects of emissions. An interesting question from here is, whether climate change can affect this tradeoff faced by counties and in doing so, can it affect the county's choice of being in attainment/non-attainment? As an extension to the model, we have also tried to incorporate how the federal government might be optimally choosing the *emissions threshold*, foreseeing the behavior of the counties and the firms. The analysis of this part of the paper is provided in the Appendix. For further work on this paper, we want to think of how exactly counties and firms react to climate change, in a multi-county and multi-firm setting. For instance, firms might find it profitable to relocate to other counties having milder climate, where they might produce and emit more but still avoid the penalties of being in non-attainment. On the other hand, counties, in trying to maximize their surplus, will foresee the migration behavior of firms and aim to strike a critical balance between the penalties imposed by the regulation and the number of polluting firms they hold on to. Ultimately, we would like to investigate whether allowing for such relocation and migration across regions having different climate realizations, can potentially offset the "costs" of climate change (say, the loss in output had there been no migration) completely.

There is a large body of work on migration and relocation of firms in response to tougher environmental regulations. Hanna (2010) analyzes how the Clean Air Act amendments affected the foreign production decisions of US based multinationals. Specifically, she finds that the Clean Air Act induced regulated US firms to increase their foreign assets by 5.3% and their foreign output by almost 9%. Greenstone (2002) also looks at the impacts of the Clean Air Act on measures of industrial activity and he finds that in the first 15 years of its operation, the Clean Air Act led to the loss of approximately 590,000 jobs, $37 billion capital stock and $75 billion of output in non-attainment counties.

Becker and Henderson (2000), Eskeland and Harrison (1997), Levinson (1996), List, McHone and Millimet (2004), List, Millimet, Fredriksson and McHone (2003) are some of the other papers that look at this imporant link between environmental regulations and the firms location and migration decisions.

A recent paper by Linnenluecke et al. (2011) looks at the the firms' migration decisions as an adaptive strategy in response to climate change. The authors argue that climate change will bring about large scale environmental changes like rising sea level, floods, droughts etc. Such extreme events might potentially cause significant disruptions to firm operations and it might become necessary to shift industrial activity away from regions having harsh climate. In this paper, we are trying to bring these two strands of literature together, by looking at how climate change affects the regulatory actions and how that in turn affects the firms' decisions to relocate to other areas having milder climate. More specifically, worse climate realizations exacerbate the levels of emissions by firms and hence, might cause certain areas to go into non-attainment. Thus, climate change can indirectly affect the extent of regulatory control on polluting firms and the amount they can produce or emit. As a result, firms might choose to relocate in order to avoid these costs of climate change.

In the next section, we present a simple theoretical model of a county having a single firm, facing a regulation on emissions. We will analyze how the county's choice of being in attainment or non attainment can be determined by climate change, and other parameters like the penalty the county has to pay per unit of excess emissions, the marginal increase in emissions per unit increase in output etc. In the Appendix, we provide a preliminary analysis of government's optimal choice of emissions threshold $\bar{e}$.

3.2 A Model of Attainment Designations

Consider a county having a single firm. The firm produces output y and its productive activities lead to emissions e. For simplicity, let us assume that the relationship between output and emissions is as follows:

$$y = \frac{1}{\alpha} e$$

where $\alpha > 0$.

The firm also has a cost of production given by:

$$c(e) = e^2$$

As mentioned before, since climate change is an important factor affecting air pollution, let us assume that $\theta > 1$ is the temperature realization in the county and that higher temperatures worsen the effect of emissions. More specifically, let us assume that the *effective emissions* in the county are given by the following:

$$\hat{e} = f(e; \theta) = \theta e$$

Now suppose that there is a federal regulation on air pollution such that if the *effective emissions* $\hat{e}$ exceed a threshold $\bar{e}$ then the county has to pay a penalty. Suppose the *penalty function* is as follows:

$$p(e;\theta) = \begin{cases} \beta(\hat{e} - \bar{e}) & \text{if } \hat{e} > \bar{e} \\ 0 & \text{if } \hat{e} \leq \bar{e} \end{cases}$$

where $\beta > 0$.

Suppose the county has an instrument $\lambda \in [0, 1]$ through which it can make the environment more or less conducive for the firm. That is, the county bears a portion λ of the penalty and passes on the remaining (1-λ) to the firm, when in non-attainment. Hence, we can think of this problem like a sequential game between the county and the firm such that the county moves first and chooses a λ. Observing this, the firm chooses its production and emissions; and then eventually based on the effective emissions the county is designated as being in attainment or non attainment. We will solve this by backwards induction.

3.2.1 Firm's Problem

Suppose the county is in non-attainment. The firm will want to maximize its profit given by the following:

$$\max_e \quad \pi = \frac{1}{\alpha}e - e^2 - (1-\lambda)\beta(\hat{e} - \bar{e})$$

F.O.C:

$$\frac{\partial \pi}{\partial e} = \frac{1}{\alpha} - 2e - (1-\lambda)\beta\theta = 0$$

since $\hat{e} = \theta e$

$$\Rightarrow 2e^{*} = \frac{1}{\alpha} - (1-\lambda)\beta\theta$$

$$\Rightarrow e^{*} = \frac{1-\alpha\beta\theta(1-\lambda)}{2\alpha}$$

Proposition 1 *(i) As the county bears an increasing share of the penalty, i.e. as λ increases, the emissions by the firm also increase and hence output y increases.*
(ii) With worse climate realizations (higher temperature), i.e. as θ increases, the firm decreases its emissions level in order to reduce the penalty.

3.2.2 County's Problem

The county foresees the behavior of the firm and chooses λ to maximize its objective (surplus) defined as follows:

$$\max_{\lambda} \quad R = \gamma e^{*}(\lambda) - \lambda\beta(\hat{e} - \bar{e})$$

where, $\gamma > 0$ is the county's marginal gain in surplus from a unit increase in emissions and $\lambda\beta(\hat{e} - \bar{e})$ is its share of the penalty.

Plugging back e^{*} from the firm's problem, the county maximizes the following:

$$\max_{\lambda} \quad R = \gamma(\frac{1-\alpha\beta\theta(1-\lambda)}{2\alpha}) - \lambda\beta\theta(\frac{1-\alpha\beta\theta(1-\lambda)}{2\alpha}) + \lambda\beta\bar{e}$$

$$\Rightarrow R = \frac{\gamma}{2\alpha} - \frac{\gamma\beta\theta(1-\lambda)}{2} - \frac{\lambda\beta\theta}{2\alpha} + \frac{\lambda(1-\lambda)\beta^2\theta^2}{2} + \lambda\beta\bar{e}$$

F.O.C:

$$\frac{\partial R}{\partial \lambda} = \frac{\gamma\beta\theta}{2} - \frac{\beta\theta}{2\alpha} + \frac{\beta^2\theta^2}{2} - \lambda\beta^2\theta^2 + \beta\bar{e} = 0$$

$$\Rightarrow \lambda^*\beta^2\theta^2 = \frac{\gamma\beta\theta}{2} - \frac{\beta\theta}{2\alpha} + \frac{\beta^2\theta^2}{2} + \beta\bar{e}$$

$$\Rightarrow \lambda^* = \frac{\gamma}{2\beta\theta} + \frac{1}{2} + \frac{\bar{e}}{\beta\theta^2} - \frac{1}{2\alpha\beta\theta}$$

S.O.C:

$$\frac{\partial^2 R}{\partial \lambda^2} = -\beta^2\theta^2 < 0$$

This λ^* maximizes the county's objective function including the penalty. However, since the emissions by the firm is directly proportional to λ, the county can reduce λ to a point such that the firm optimally chooses an emission level that ensures the county being in attainment.

Let $\bar{\lambda}$ be such that if $\lambda \leq \bar{\lambda}$, then $\theta e^* \leq \bar{e}$ and the county will be in attainment. Hence, if the county keeps reducing its own share of the cost burden, then there will be a threshold below which the firm will be forced to choose an emission level such that the federal standard is met (reducing λ would imply an increasing cost burden for the firm). We can calculate this threshold value of λ by using the firm's optimal emission level e^*.

At $\bar{\lambda}$ the county will just be in attainment, hence $\hat{e} = \theta e^* = \bar{e}$.

$$\Rightarrow \frac{\theta - \alpha\beta\theta^2(1-\lambda)}{2\alpha} = \bar{e}$$

$$\Rightarrow \theta - \alpha\beta\theta^2 + \alpha\beta\theta^2\lambda = 2\alpha\bar{e}$$

$$\Rightarrow \bar{\lambda} = \frac{2\alpha\bar{e} - \theta + \alpha\beta\theta^2}{\alpha\beta\theta^2}$$

$$\Rightarrow \bar{\lambda} = \frac{2\alpha\bar{e} - \theta}{\alpha\beta\theta^2} + 1$$

Note that if $2\alpha\bar{e} = \theta$ i.e. if $\frac{1}{2\alpha}\theta = \bar{e}$ then $\bar{\lambda} = 1$. This observation is of special interest because $\frac{1}{2\alpha}$ is nothing but the firm's *unrestricted* level of emission (what it would choose had there been no regulation.

Proposition 2 *If the unrestricted emissions level chosen by the firm is such the effective emission* $\frac{1}{2\alpha}\theta = \bar{e}$ *(federal threshold), then* $\bar{\lambda} = 1$ *implying that* $\forall\lambda \leq \bar{\lambda}$ *and hence* $\forall\lambda \in [0,1]$, *the county will be in attainment.*

If however, $\bar{\lambda} \in (0,1)$ then the *unretricted* effective emissions level is above the threshold. Thus it is not obvious that the county will be in attainment. It can choose λ^* and be in non-attainment (paying the penalty for it) or it can choose $\bar{\lambda}$ and force the firm to emit less than the threshold, hence coming into attainment.

This critical decision of the county will depend on its surplus under the two regimes. The county's surplus, as a function of λ can be summarized as follows:

$$R(\lambda) = \begin{cases} \frac{\gamma\bar{e}}{\theta} & \text{if } \lambda \leq \bar{\lambda} \\ \gamma e^*(\lambda) - \lambda\beta\theta e^*(\lambda) + \lambda\beta\bar{e} & \text{if } \lambda > \bar{\lambda} \end{cases}$$

Note that for $\lambda < \bar{\lambda}$ the firm will always choose $\frac{\bar{e}}{\theta}$ as the deviation from e^*_{UR} is lower and hence profit is larger, than if it chooses $e^*(\lambda) < \frac{\bar{e}}{\theta}$ (as $\theta e^*_{UR} > \bar{e}$). Since $e^*(\lambda)$ is increasing in λ we know that $\gamma e^*(\lambda) - \lambda\beta\theta e^*(\lambda) + \lambda\beta\bar{e}$ is a quadratic function that is maximized at λ^* (as shown in the previous section). We also know that for all $\lambda \leq \bar{\lambda}$ the county will be in attainment and for $\lambda > \bar{\lambda}$ the county is in non-attainment. Lastly, we know that at $\bar{\lambda}$, $\gamma e^*(\lambda) - \lambda\beta\theta e^*(\lambda) + \lambda\beta\bar{e} = \frac{\gamma\bar{e}}{\theta}$. Depending on the nature of the quadratic function, we can have the following two cases:

As can be seen from Figures 3.1 and 3.2, we can conclude whether or not a county chooses to be in attainment by comparing λ^* and $\bar{\lambda}$.

A county will choose to be in *attainment* if (as seen in Figure 1) $\lambda^* \leq \bar{\lambda}$.

$$\Rightarrow \frac{\gamma}{2\beta\theta} + \frac{1}{2} + \frac{\bar{e}}{\beta\theta^2} - \frac{1}{2\alpha\beta\theta} \leq \frac{2\alpha\bar{e} - \theta}{\alpha\beta\theta^2} + 1$$

$$\Rightarrow \frac{\gamma}{2\beta\theta} + \frac{\bar{e}}{\beta\theta^2} - \frac{1}{2\alpha\beta\theta} \leq \frac{2\alpha\bar{e} - \theta}{\alpha\beta\theta^2} + \frac{1}{2}$$

$$\Rightarrow \frac{\gamma\alpha\theta + 2\alpha\bar{e} - \theta}{2\alpha\beta\theta^2} \leq \frac{4\alpha\bar{e} - 2\theta + \alpha\beta\theta^2}{2\alpha\beta\theta^2}$$

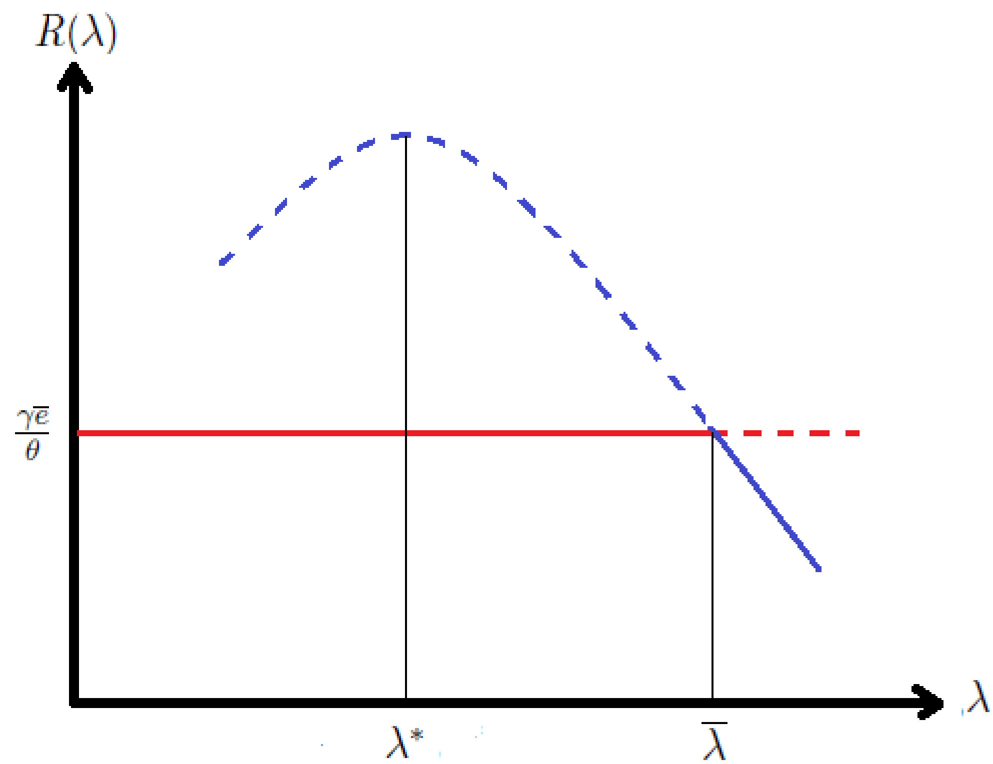


Figure 3.1: County chooses to be in Attainment ($\lambda^* \leq \bar{\lambda}$)

$$\Rightarrow \gamma\alpha\theta + 2\alpha\bar{e} - \theta \leq 4\alpha\bar{e} - 2\theta + \alpha\beta\theta^2$$

$$\Rightarrow \alpha\beta\theta^2 - \theta + 2\alpha\bar{e} - \gamma\alpha\theta \geq 0$$

$$\Rightarrow \theta[\alpha\beta\theta - 1 - \alpha\gamma] + 2\alpha\bar{e} \geq 0$$

Since $\theta > 0$ and $2\alpha\bar{e} > 0$ a *sufficient condition* for $\lambda^* \leq \bar{\lambda}$ is as follows:

$$\alpha\beta\theta - 1 - \alpha\gamma \geq 0$$

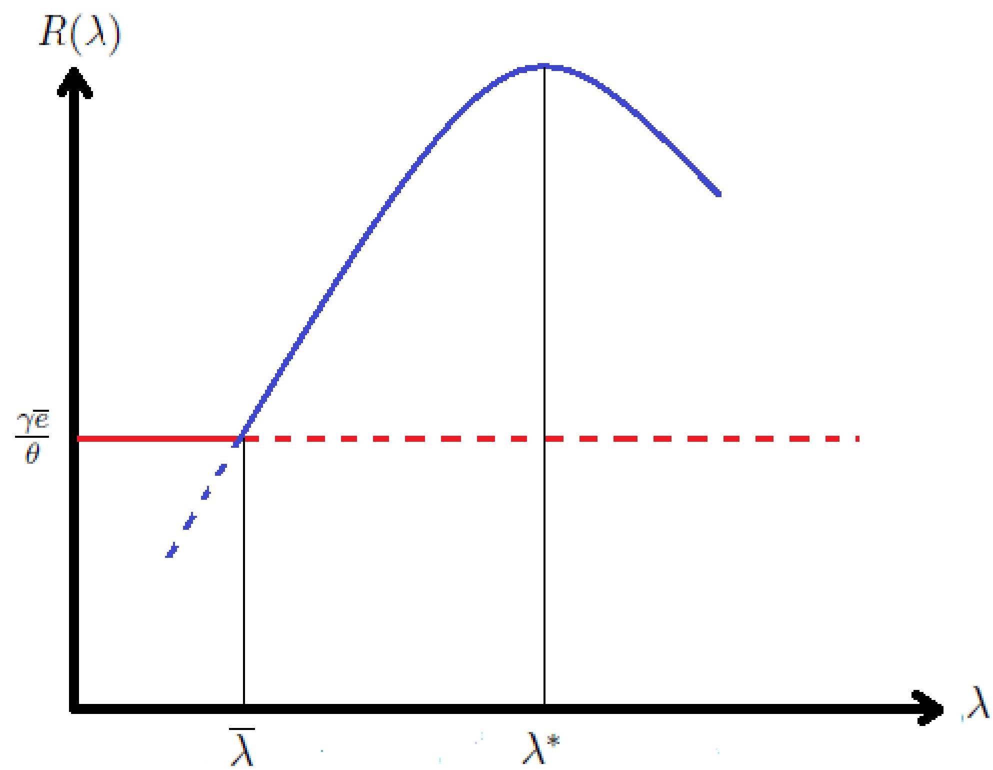


Figure 3.2: County chooses to be in Non-Attainment ($\lambda^* > \bar{\lambda}$)

$$\Rightarrow \alpha\beta\theta \geq 1 + \alpha\gamma$$

$$\Rightarrow \theta \geq \frac{1 + \alpha\gamma}{\alpha\beta} \equiv \theta^*$$

Hence we can conclude that a county chooses to be in attainment or non-attainment if $\alpha\beta\theta(\theta - \theta^*) + 2\alpha\bar{e} \gtrless 0$ respectively.

However, even though $\theta < \theta^*$ is a necessary condition for a county to choose non-attainment it is not sufficient. The county's choice of being in attainment vs non-attainment as a function of the various parameters has been summarized in the following proposition.

Proposition 3 *A county having a climate realization θ ceteris paribus (holding all other parameters constant), will choose to be in attainment or non-attainment as follows:*

(i) If $\theta \geq \theta^*$, i.e. if the county has a very bad climate realization (say, very high temperatures), it will surely choose $\lambda \leq \bar{\lambda}$ and be in attainment, since the climate will magnify its emissions tremendously leading to high costs of being in non-attainment.

(ii) If $\theta < \theta^*$ but $\alpha\beta\theta(\theta - \theta^*) + 2\alpha\bar{e} \geq 0$, the county still chooses to be in attainment.

(iii) If $\theta < \theta^*$ and $\alpha\beta\theta(\theta - \theta^*) + 2\alpha\bar{e} < 0$, the county will choose $\lambda = \lambda^*$ and be in non-attainment, since the loss due to the penalty of non-attainment will be outweighed by the gains from more production.

3.2.3 Comparative Statics

In this section, we will analyze how the other parameters in the model affect the climate threshold and how that in turn can affect the county's choice of being in attainment or non-attainment. As we know, $\theta^* = \frac{1+\alpha\gamma}{\alpha\beta}$. Hence,

$$\frac{\partial \theta^*}{\partial \gamma} = \frac{1}{\beta} > 0$$

$$\frac{\partial \theta^*}{\partial \beta} = \frac{-\alpha(1 + \alpha\gamma)}{\alpha^2\beta^2} < 0$$

$$\frac{\partial \theta^*}{\partial \alpha} = \frac{-\beta}{\alpha^2\beta^2} < 0$$

Using the above relationships and Proposition 1.3, we can infer how a county's choice (having a climate realization θ) might be affected by a change in γ (marginal gain in county surplus per unit increase in output/emissions), β (penalty per unit of excess emissions) and α (marginal increase in emissions per unit increase in output). These observations have been summarized in the following proposition.

Proposition 4 *(i) If $\theta \geq \theta^*$ and hence, the county chooses to be in attainment:*

(a) As γ increases(hence, θ^* increaes), the county's gain in surplus following an increase in output increases and the county might change its decision and be in non-attainment if $(\theta - \theta^*)$ becomes negative enough.

(b) As α or β increases (i.e. θ^* decreases), the per unit penalty or the marginal rate of emissions increase and the county sticks to its decision of being in attainment since $(\theta - \theta^*)$ becomes larger.

(ii) If $\theta < \theta^*$ however $\alpha\beta\theta(\theta - \theta^*) + 2\alpha\bar{e} \geq 0$ and hence, the county chooses to be in attainment:

(a) As γ increases, the county might now choose to be in non-attainment as $(\theta - \theta^*)$ becomes more negative. (b) As α or β increases, the county's decision will be ambiguous.

(iii) If $\theta < \theta^*$ and $\alpha\beta\theta(\theta - \theta^*) + 2\alpha\bar{e} < 0$ and hence, the county chooses to be in non-attainment:

(a) As γ increases, the county will continue to be in non-attainment as $(\theta - \theta^*)$ becomes more negative. (b) As α or β increases, the county's decision will be ambiguous.

3.3 Further Steps

Till now, in this paper we have just looked at a county having a single firm that undertakes production and hence leads to emissions. By using a very simple theoretical model, we look at how a county and a polluting firm located in that county responds to a federal level regulation on air quality, in the presence of climate change that aggravates the amount of emissions produced by the firm. We model the behavior of the county and the firm as a sequential move game where, after having seen the realization of climate, the county decides on how conducive it wants to be for the firm. Specifically, the county chooses the amount of penalty it will bear, in case it ends up being in non-attainment. Observing the county's choice, the firm then decides on the level of output and emissions it wants to produce. After these choices have been made, the county is designated as being in attainment or non-attainment based on the effective emissions. Interestingly we find that ceteris paribus, a county having mild enough climate can optimally choose to be in non-attainment. Even though very harsh climate is a *sufficient condition* for a county to choose to be in attainment, the behavior of counties having relatively mild climate, will also depend on other parameters like the marginal rate of emissions, the per unit penalty charged for exceeding the emissions threshold and also the marginal gain in county surplus per unit increase in output.

Using the insights from this model, we would like to extend the analysis in the following ways. Firstly, we would like to include multiple firms in a county, such that the effective emissions in the county will depend on the overall emissions as well as the climate realizations. In such a setup, firms can behave strategically and we can solve for the Nash equilibrium among the firms. Secondly, we would like to introduce the possibility for firms to relocate to other counties having different climate realizations. We can first analyze this setup, without allowing the county complete foresight; i.e. each county starts with a number of firms and chooses a λ, following which, each firm can decide to continue production in its own county and get the Nash equilibrium payoff or relocate to some other county. The equilibrium in this model can be defined by the equalization of profits across all counties. Lastly, we can allow for the counties to foresee the migration behavior of firms. We will then have a game between counties where each county chooses a λ, taking care of the fact that this will determine the number of firms it will end up having, and hence, affect the output, emissions and the attainment status. Comparing the models with and without migration possibilities, we should then be able to analyze if and to what extent the costs of climate change can potentially be undone by adaptive strategies.

3.4 Appendix

3.4.1 Optimal Choice of $\bar{e}$

So far, in the paper, we have assumed that the *emissions threshold* $\bar{e}$ is exogenously given by the government. However, a more complete model would be to incorporate the fact that the government also optimally chooses an $\bar{e}$ to maximize the social welfare, which is a function of the gains from output as well as the costs of emissions. In this appendix, we aim to extend the model to incorporate the governmenet's choice behavior, foreseeing the behavior of the county and the firm.

Suppose the government faces a social welfare function as follows:

$$W(\bar{e}) = e(\bar{e}) - \phi(\theta e(\bar{e}))^2$$

where $\phi \in (0, 1)$ is the weight that the government puts on effective emissions θe. Given any $\bar{e}$ that the government chooses, we will have an emissions level $e(\bar{e})$. The social cost of emissions e is $(\theta e)^2$ where $\theta > 1$ is the temperaure realization.

According to Proposition 2.3, a county having climate realization θ and facing an emissions threshold $\bar{e}$ will choose to be in *attainment* if:

$$\Rightarrow \alpha\beta\theta^2 - \theta + 2\alpha\bar{e} - \gamma\alpha\theta \geq 0$$

$$\Rightarrow \bar{e} \geq \frac{\theta + \alpha\gamma\theta - \alpha\beta\theta^2}{2\alpha}$$

Thus, given all other parameters in the model, $\exists\ E = \frac{\theta+\alpha\gamma\theta-\alpha\beta\theta^2}{2\alpha}$ such that:

1. If $\bar{e} \geq E$, then the county chooses to be in Attainment
2. If $\bar{e} < E$, then the county chooses to be in Non-Attainment

Proposition 5 *(Comparative Statics on E)*

(a) Since $\frac{\partial E}{\partial \alpha} < 0$ and $\frac{\partial E}{\partial \beta} < 0$, as the marginal rate of emissions or the per unit penalty

increases, the threshold of $\bar{e}$ decresaes. This means that even for stricter thresholds, the county chooses to be in attainment, since the costs of being in non-attainment will be larger.

(b) Since $\frac{\partial E}{\partial \gamma} > 0$, as the county's gain from output and emissions increases, the threshold of $\bar{e}$ increases. Thus, the county will only choose to be in attainment for very strict thresholds. This is because the benefits of being in non-attainment and producing more, are now larger.

(c) For $\theta > \frac{1+\alpha\gamma}{2\alpha\beta}$, $\frac{\partial E}{\partial \theta} < 0$. Thus, if the county already has very high temperatures, then a further worsening of climate would decrease the threshold of $\bar{e}$ and the county will choose to be in attainment even for stricter thresholds, since the costs of being in non-attainment will be larger.

Given the information that we have on how the county and the firm reacts to this regulation, we can now characterize the exact choices of $\lambda(\bar{e})$ and $e(\bar{e})$ that the county and the firm will make respectively.

Regime 1: $\bar{e} \geq$ E: In this case, the county chooses $\lambda = \bar{\lambda}$ to be in Attainment and the firm chooses emissions level $e^A = e(\bar{\lambda}) = \frac{\bar{e}}{\theta}$. Thus Social Welfare is

$$W^A = \frac{\bar{e}}{\theta} - \phi\bar{e}^2$$

Regime 2: $\bar{e} <$ E: In this case, the county chooses $\lambda = \lambda^*$ to be in Non-Attainment and the firm chooses emissions level $e^{NA} = e(\lambda^*) > \frac{\bar{e}}{\theta}$.

Plugging in the value of λ^*, we can get that the emissions level in the non-attainment regime will be

$$
\begin{aligned}
e^{NA} &= \frac{1-\alpha\beta\theta(1-\lambda^*)}{2\alpha} \\
&= \frac{1}{2\alpha} - \frac{\beta\theta}{2} + \frac{\beta\theta}{2}[\frac{\gamma}{2\beta\theta} + \frac{1}{2} + \frac{\bar{e}}{\beta\theta^2} - \frac{1}{2\alpha\beta\theta}] \\
&= \frac{1}{4\alpha} - \frac{\beta\theta}{2} + \frac{\gamma}{4} + \frac{\bar{e}}{2\beta\theta} \\
&= \frac{\beta}{2\alpha} - \frac{\beta^2\theta}{2} + \frac{\beta\gamma}{2} + \frac{\bar{e}}{\theta} \\
&= k + \frac{\bar{e}}{\theta}
\end{aligned}
$$

Thus, $e^{NA} = k + e^A$, where $k = \frac{\beta}{2\alpha} - \frac{\beta^2\theta}{2} + \frac{\beta\gamma}{2} > 0$ since we know that $e^{NA} > \frac{\bar{e}}{\theta} = e^A$. Thus Social welfare in this regime wil be

$$W^{NA} = \frac{\bar{e}}{\theta} + k - \phi(\bar{e} + \theta k)^2$$

As we can see from the expressions, both W^A and W^{NA} are quadratic functions in $\bar{e}$. However, in order to accurately represent these functions graphically, we will find the values of $\bar{e}$ that maximize each of these functions. [1]

Regime 1 (Attainment):

$$W^A = \frac{\bar{e}}{\theta} - \phi\bar{e}^2$$

F.O.C.:

$$\frac{1}{\theta} - 2\phi\bar{e} = 0$$

[1]From the first and second order conditions, we know that both W^A and W^{NA} are concave inverted-U shaped functions, attaining their maximum values at $\bar{e}^*_A$ and $\bar{e}^*_{NA}$ respectively. Secondly, since $\bar{e}^*_{NA} < \bar{e}^*_A$, we know that W^{NA} intersects W^A from above. Thirdly, we also know that both functions W^A and W^{NA} attain the same maximum value.

$$\Rightarrow \bar{e}_A^* = \frac{1}{2\phi\theta}$$

S.O.C.: $\frac{\partial^2 W^A}{\partial \bar{e}^2} = -2\phi < 0.$

$$\Rightarrow (W^*)_{max}^A = \frac{1}{4\phi\theta^2}$$

Regime 2 (Non-Attainment):

$$W^{NA} = \frac{\bar{e}}{\theta} + k - \phi(\bar{e} + \theta k)^2$$

F.O.C.:

$$\frac{1}{\theta} - 2\phi(\bar{e} + \theta k) = 0$$
$$\Rightarrow \bar{e}_{NA}^* = \frac{1}{2\phi\theta} - \theta k$$

S.O.C.: $\frac{\partial^2 W^{NA}}{\partial \bar{e}^2} = -2\phi < 0.$

$$\Rightarrow (W^*)_{max}^{NA} = \frac{1}{4\phi\theta^2} = (W^*)_{max}^A$$

The effective Social Welfare function facing the government can now be characterized as follows:

$$W(\bar{e}) = \begin{cases} W^{NA} = \frac{\bar{e}}{\theta} + k - \phi(\bar{e} + \theta k)^2 & \text{if } \bar{e} < E \\ W^A = \frac{\bar{e}}{\theta} - \phi\bar{e}^2 & \text{if } \bar{e} \geq E \end{cases} \qquad \text{(Condition A)}$$

where $k = \frac{\beta}{2\alpha} - \frac{\beta^2\theta}{2} + \frac{\beta\gamma}{2} > 0.$

Thus, given a realization of E, as a function of all exogenous parameters in the model, the government will *optimally* choose an $\bar{e}$ that maximizes $W(\bar{e})$. Using Condition A, we can trace out the social welfare function $W(\bar{e})$ facing the government. There can be three cases of interest, which have been summarized below:

Case 1: $E < \frac{1}{2\phi\theta} - \theta k$

As represented in Figure 3.3 below, in this case, the social welfare function facing the government is maximized at $\bar{e} = \frac{1}{2\phi\theta} > E$.

Following this choice of $\bar{e}$ the county will choose

$$\lambda = \bar{\lambda}(\bar{e}) = \frac{2\alpha\bar{e} - \theta}{\alpha\beta\theta^2} + 1$$

and the firm will choose an emissions level

$$e(\bar{e}) = \frac{\bar{e}}{\theta}$$

to be in attainment. [2]

Case 2: $E > \frac{1}{2\phi\theta}$

As represented in Figure 3.4 below, in this case, the social welfare function facing the government is maximized at $\bar{e} = \frac{1}{2\phi\theta} - \theta k < E$.

[2]Pluggin in the value of $\bar{e} = \frac{1}{2phi\theta}$ into $\bar{\lambda}(\bar{e})$ and $e(\bar{e})$ we can calculate the choices of the county and firm as a function of model parameters.

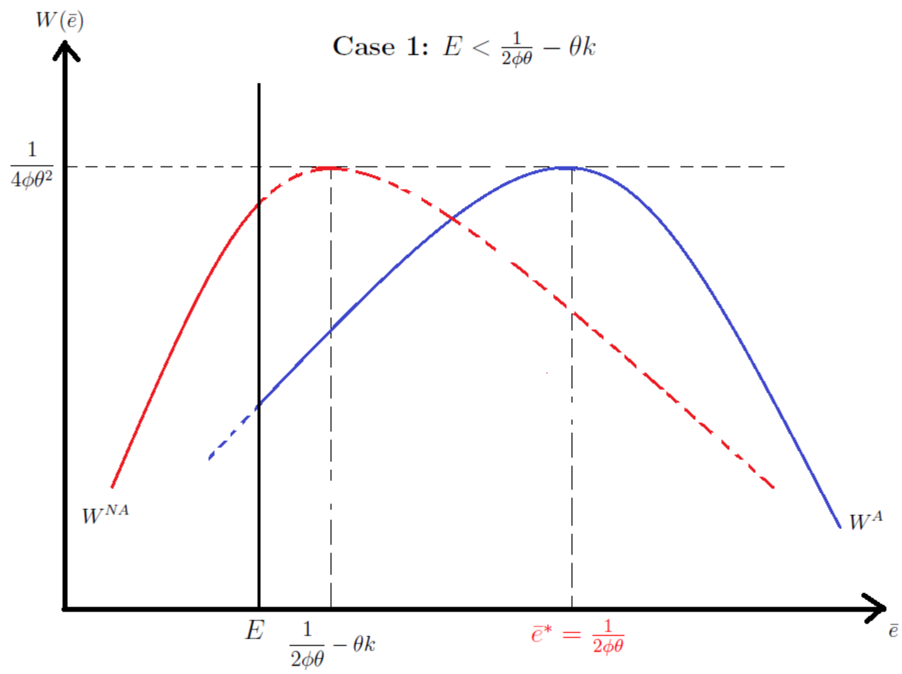


Figure 3.3: Government chooses $\bar{e} > E$ and County is in Attainment

Following this choice of $\bar{e}$, the county will choose

$$\lambda = \lambda^*(\bar{e}) = \frac{\gamma}{2\beta\theta} + \frac{1}{2} + \frac{\bar{e}}{\beta\theta^2} - \frac{1}{2\alpha\beta\theta}$$

and the firm will choose an emissions level

$$e(\bar{e}) = \frac{1 - \alpha\beta\theta(1 - \lambda^*(\bar{e}))}{2\alpha}$$

to be in non-attainment.

Case 3: $\frac{1}{2\phi\theta} \leq E \leq \frac{1}{2\phi\theta} - \theta k$

In this case the government will be indifferent between a choice of $\bar{e} = \frac{1}{2\phi\theta} - \theta k$

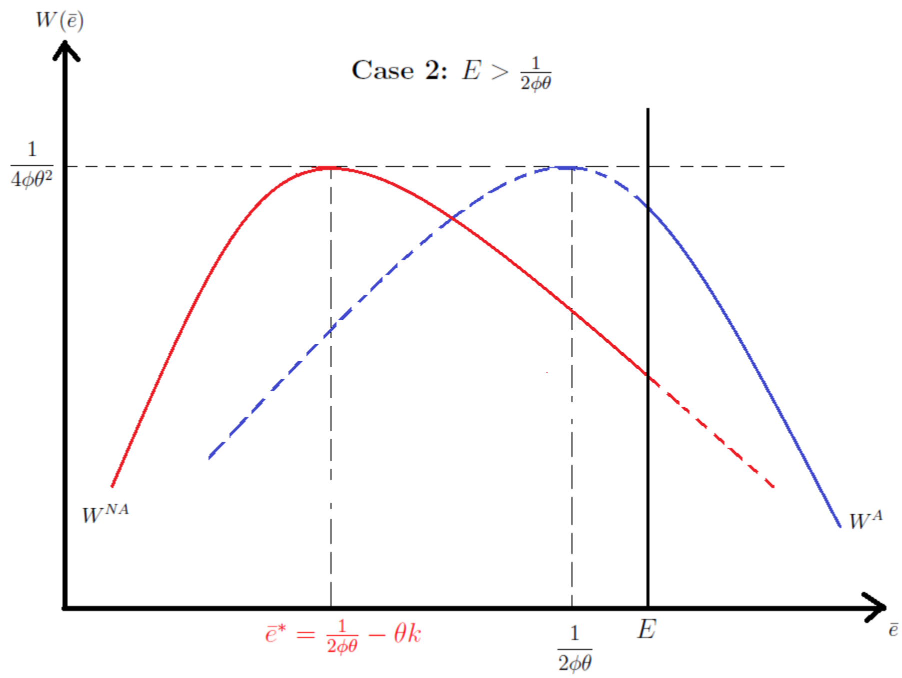


Figure 3.4: Government chooses $\bar{e} < E$ and County is in Non-Attainment

and $\bar{e} = \frac{1}{2\phi\theta}$ since the welfare function facing the government is maximized at both these values of $\bar{e}$. This has been represented in Figure 5 below.

Proposition 6 *Given all model parameters, and hence, a realization of* $E = \frac{\theta+\alpha\gamma\theta-\alpha\beta\theta^2}{2\alpha}$*, the government's choice of the emissions threshold* $\bar{e}$ *and the resultant choice of the county and firm to be in attainment or non-attainment of standards can be summarized as follows:*

(a) If $E < \frac{1}{2\phi\theta} - \theta k$*, where* $k = \frac{\beta}{2\alpha} - \frac{\beta^2\theta}{2} + \frac{\beta\gamma}{2} > 0$*, then the government optimally chooses* $\bar{e} = \frac{1}{2\phi\theta}$*. The county chooses to be in attainment.*

(b) If $E > \frac{1}{2\phi\theta}$*, then the government optimally chooses* $\bar{e} = \frac{1}{2\phi\theta} - \theta k$*. The county chooses to be in non-attainment.*

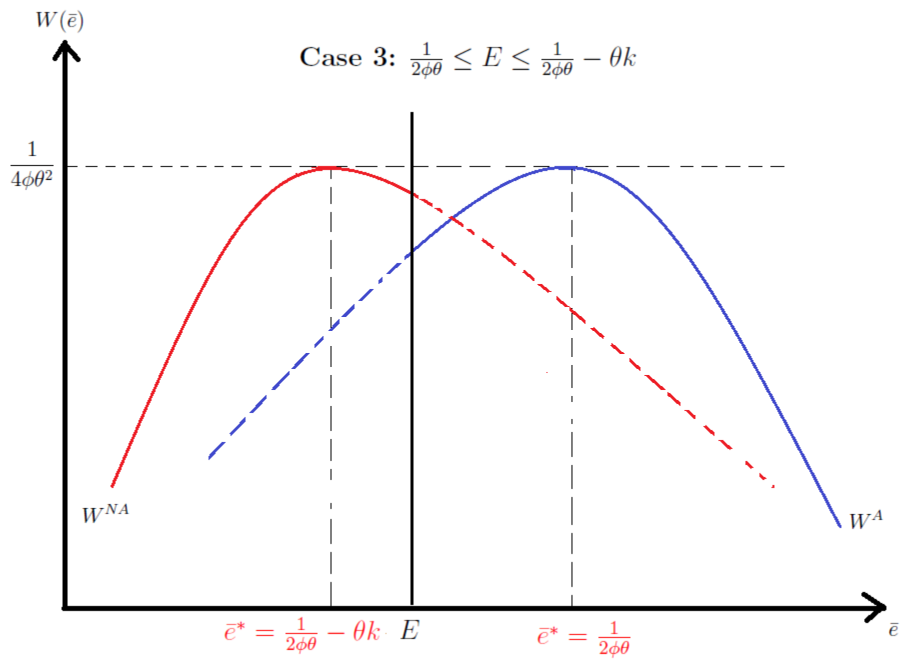


Figure 3.5: Government is indifferent between $\bar{e} = \frac{1}{2\phi\theta} - \theta k$ and $\bar{e} = \frac{1}{2\phi\theta}$. County can be either in Attainment or Non-Attainment

(c) If $\frac{1}{2\phi\theta} \leq E \leq \frac{1}{2\phi\theta} - \theta k$, then the government either chooses $\bar{e} = \frac{1}{2\phi\theta}$ or $\bar{e} = \frac{1}{2\phi\theta} - \theta k$. The county chooses to be in attainment or non-attainment respectively.

CHAPTER 4

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