Does Rain Wash Out Particulate Matter? An Application to the Effect of Air Pollution on Infant Mortality

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Abstract

This paper analyzes the impact of climate change on particulate air pollution and applies this exogenous causal effect to study the effect of air pollution on infant health. Using daily weather data, daily data on PM10 from 1990-2013 and daily data on PM2:5 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. I utilize information on Clean Air Act Nonattainment designations, to estimate differential impacts of lesser and infrequent precipitation on air pollution in non-attainment counties vs counties compliant with the federal regulations. I find that lower as well as less frequent rainfall will lead to larger concentrations of particulates in ambient air. The effects are even larger in non-attainment counties, potentially driven by the higher level of precursors and pollution sources. 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 µg/m3 decrease in ambient PM10 concentrations would imply almost 27 fewer infant deaths per 100,000 live births.

Keywords: Particulate Matter, Precipitation, Regulation, Infant Mortality

Main Conference Topic: Economics

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 48th 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.

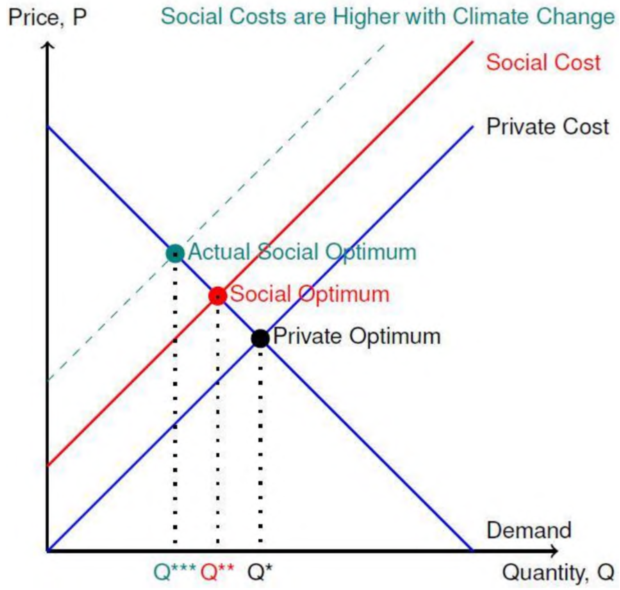
One of the major social costs of climate change is the resultant increase in air pollution that it causes. Particulate matter is one of the air pollutants that have the most severe health impacts, and interestingly, it is also directly affected by the climate system. The EPA has designated six commonly 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 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 PM10 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 PM10 precursor gases to total ambient PM10 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 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: Costs of Climate Change on Air Pollution



Hence, estimates of the e ect 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-bene t 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. Speci cally, I estimate the causal e ect of the level and frequency of precipitation on particulate air pollution (both $P M_{10}$ and $P M_{2:5}$). Apart from the reasons mentioned above, these estimates can also be used technically, to study the e ect of air pollution on health. The bene t 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 e ect. In this paper I propose that we can use the level of precipitation as an instrumental variable for particulate matter and estimate its e ect on infant mortality. The rest of the paper proceeds as follows; Section 2 provides a background on particulate matter, its formation, sources and health e ects; 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 ndings; Section 7 discusses the application of these results to study the e ect of particulate air pollution on infant mortality and Section 8 concludes.

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, composition or method of formation. Generally, these suspended particles are classi ed 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:

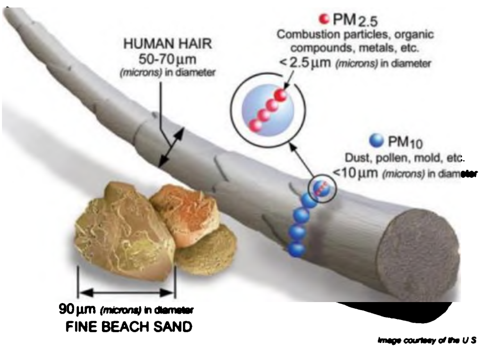
1) Ultra- ne particles (< 0:1 m)

2) Fine particles (0:1 2:5 m)

3) Coarse particles (2:5 10 m)

where 1 m is 1 millionth of a meter. This paper studies $P\ M_{2:5}$, which comprises of particles having an aerodynamic diameter less than 2.5 m, and $P\ M_{10}$, which includes particles having an aerodynamic diameter less than 10 m. Figure 2 provides a size comparison of $P\ M_{10}$ and $P\ M_{2:5}$ to human hair and beach sand.

Figure 2: Size comparison of PM to human hair



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

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.

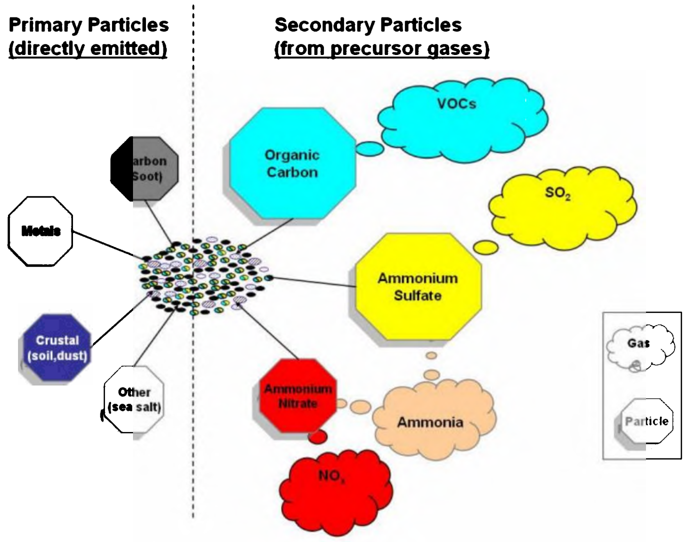
4) Coagulation- two or more particles might collide and stick together to form larger particles.

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 (V OCs) 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 rst 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 3 provides a schematic view of the composition of particulate matter.

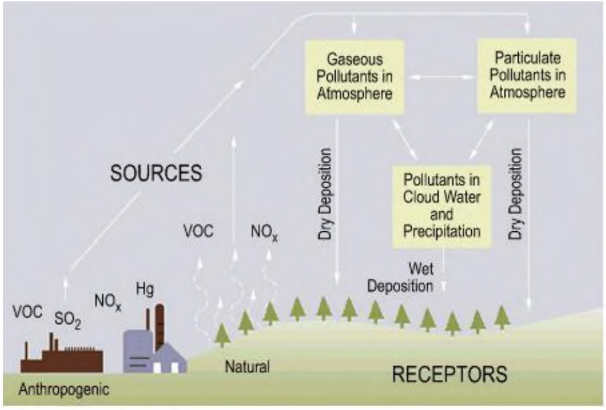
Gases as well as suspended particles can be transferred from the earth's atmosphere to the ground by dry and wet deposition processes. Wet Deposition refers to the removal of species from the atmosphere by precipitation, such as rain, fog and snow. Particulate matter concentrations in ambient air are expected to decrease with increasing precipita-tion, as wet deposition provides the main PM sink. Figure 4 provides an overview of the processes leading to wet and dry deposition of particles.

Figure 3: Composition of Particulate Matter



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

Figure 4: Wet Deposition of Particles



Source: U.S. EPA

Particulate matter can cause serious health hazards. The EPA is particularly con-cerned about particles less than 10 m 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 heart-beat, heart attacks, aggravated asthma, decreased lung function, coughing or di culty 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.

Data

In order to estimate the causal e ect 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 speci cation, I have used an unbalanced panel of PM monitors. I have eliminated monitor-days for which exceptional events that might potentially a ect air quality, such as wild res, 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 5 depicts the geographical location of the nal sample of PM_{10} monitors and also the spatial distribution by the nine di erent climatic regions. Table 1 illustrates the PM_{10} monitoring network for the full sample, as well for each year, by the nine di erent climatic regions. I have the daily maximum PM_{10} measurements for a total of 2,922,523 monitor-days , with su cient 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 6 illustrates the geographical location of these $PM_{2:5}$ monitors by the nine climate regions and Table 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 su cient representation from each climate region across the country.

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 e ect 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 7 and 8 in depict the matched weather stations for the PM_{10} monitors as well as for the $PM_{2.5}$ monitors in the nal sample.

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 de ned by the EPA, in any given year. In my preferred speci cation, 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 9 and 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.

Having consolidated the data from the above three sources, I have constructed my nal 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 3 and 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 di erent climatic regions in US and the attainment status of counties. Table 3 provides these statistics for the sample of PM_{10} monitors from 1990-2013 whereas, Table 4 provides the same information for the sample of $PM_{2:5}$ monitors from 1997-2013. From Table 3, we see that the average PM_{10} across all monitors, years and regions is about 25.5 $g=m^3$, 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 4, we see that the average $PM_{2:5}$ across all monitors, years and regions is 11.4 $g=m^3$ 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 nd that the Southeast and Ohio Valley are among the wettest regions whereas the Southwest is the driest. As expected, we nd 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 nd, 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 e ect of particulate matter concentrations, might indirectly have an e ect 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 11 and 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 illus-trates the negative correlation between the frequency of rainfall and particulate matter concentrations. Lastly, Figures 15, 16 ,17 and 18 depict these correlations, by the nine di erent 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.

Empirical Methodology

I exploit plausibly random, daily variation in precipitation, precipitation frequency and maximum temperature [4] in order to estimate the causal e ect of the level and frequency of precipitation on the daily maximum concentrations of PM_{10} and $PM_{2:5}$. To evaluate the average e ect of precipitation and precipitation frequency across all counties, and the causal e ect of of the Clean Air Act Non-Attainment on particulate pollution levels, I estimate the following speci cation:

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

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 PM10 or PM2:5 and I will separately estimate the e_ects 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 X, which represents Population and Per Capita Income, 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.

In order to evaluate the di erential e ects of the level and frequency of precipitation, in attainment and non-attainment counties, I augment the speci cation in Equation (1) to get my preferred econometric speci cation as described below.

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

Results

In this section I report my primary ndings regarding the impact of the level of precipitation and the precipitation frequency on daily maximum concentrations of PM_{10} and $PM_{2:5}$.

Main Results

Table 5 presents the e ects of the two di erent 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 rain-fall, 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 e ects 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 nd that a 1-mm decrease in total daily precipitation would lead to an increase of 0.23 $g{=}m^3$ 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 $g{=}m^3$, 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 CAAN AS does not alter our estimates of the e ect of the level and frequency of precipitation on PM_{10}. The coef-cient of the CAAN AS gives us a measure of the bene ts 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 $g{=}m^3$ [7]. In Columns (3) and (4), I have sequentially added county population and per capita income, in order to control for eco-nomic and demographic factors that might also have an e ect on the air pollution levels. Column (4) reports the e ects that I get from estimating equation (1) and we can see that the magnitude and signi cance of my estimates for the e ect of precipitation remain una ected by the addition of other controls. Comparing these estimates with the causal e ect of the Clean Air Act Non-Attainment Status, I nd that a 1-mm decrease in daily precipitation can potentially o set over 30% of the bene ts of the landmark regulation, through higher PM_{10} levels in ambient air.

Finally, in order to get the di erential e ects of the level and frequency of precipita-tion on PM_{10} between attainment and non-attainment counties, I estimate my preferred speci cation given by Equation (2) and the results are reported in Column (5). The interaction terms now give us the incremental e ects of lower or less frequent rainfall on PM_{10} concentrations in non-attainment counties. I nd that a 1 mm decrease in total daily precipitation leads to an increase of 0.2 $g{=}m^3$ of PM_{10} levels in attainment coun-ties whereas in non-attainment counties there is an additional increase of 0.18 $g{=}m^3$. Hence, in totality, a 1-mm decrease in daily precipitation level leads to 0.38 $g{=}m^3$ higher daily maximum PM_{10} levels in non-attainment counties. Similarly, I nd 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 $g{=}m^3$ whereas in non-attainment counties it will increase by an additional 0.41 $g{=}m^3$, making it a cu-mulative increase of 1.3 $g{=}m^3$. 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 pre-cursors. Hence, the estimates are aligned with economic intuition that we should have larger e ects 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 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 nd that a 1-mm decrease in total daily precipitation will lead to an increase of 0.08 $g{=}m^3$ 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 $g{=}m^3$. I also nd that a county going into non-attainment will have a decrease of 0.21 $g{=}m^3$ of $PM_{2:5}$ which captures the pure bene t from the Clean Air Act in terms of lower $PM_{2:5}$ concentrations. Hence, a 1-mm decrease in precipitation o sets over 38% of the bene ts achieved due to the Clean Air Act. Next, in Column (5), I again estimate the di erential impacts across attainment and non-attainment counties. Similar to PM_{10}, even for $PM_{2:5}$ concentrations, I nd larger e ects 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 $g{=}m^3$ of $PM_{2:5}$ in attainment counties whereas an increase of 0.14 $g{=}m^3$ in non-attainment counties. A one unit decrease in precipitation frequency on the other hand, would lead to an increase of 0.38 $g{=}m^3$ of $PM_{2:5}$ in attainment counties whereas an increase of 0.56 $g{=}m^3$ of $PM_{2:5}$ in counties that are out of attainment.

Application: Effect of Particulate Matter on Infant Mortality

There has been a consensus among economists, policy makers and governments of various nations, on the e ect 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-bene t analysis of the 1990 Clean Air Act amendments because of the lack of enough reliable scienti c 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 e ects of particles that are under 10 $g{=}m^3$ in diameter as these particles can enter through the throat and nose and potentially reach our lungs. Scienti cally, one of the leading theories behind the above mentioned impact of particulate pollution on health is an in ammatory 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 anal-yses of the correlation between air pollution in U.S. cities and adult mortality rates [Lave and Seskin (1977), 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 di erent regions, i.e. there are a host of other factors a ecting pollution concentrations and also having a direct e ect 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 e ects 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 ex-posure and hence deaths today might actually re ect 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 e ect 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, speci cally focusing on the developing country context and analyzing this link between air pollution and infant mor-tality using data from Mexico City [Arceo-gomez et al. (2012)]. However, almost all of the above mentioned studies have either looked at a speci c 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 di culty in nding large scale data on a variable which only a ects infant mortality, through its e ect on air pollution levels and can be used as an instrument for air pollution [12].

In this section, I utilize the exogenous causal e ect of the level of rainfall on P M_{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, uctuations in rainfall do not directly a ect infant mortality through factors other than particulate matter concentrations. Since I also explicitly control for county and year xed e ects, 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 e ect is immediate versus adult mortality where the e ect 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 rst describing the data sources, then the empirical methodology and lastly, the results.

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 le and a county level national population le, spanning the years 1968-2014. I have used informa-tion from the CMF for the years 1990-2013 [13], in order to match it with the pollution and weather data. The mortality le 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 rst 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 le, 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.

P M_{10} and Weather Data: I have used the same sample of P M_{10} monitors and asso-ciated 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 de ned as more than 30 consecutive days of no rainfall and Floods, de ned as more than 2 consecutive days recording more than 25mm (1 inch) of rainfall. Similarly, I have de ned 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 P M_{10}, rainfall as well as extreme events at the county-year level which has then been merged with the mortality data to get my nal sample of 11,299 county-years, comprising of an unbal-anced sample of 861 counties spread over 48 states in contiguous United States. Table 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 $g{=}m^3$ 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 19 illustrates the close positive association between the average infant mortality rate and the average concentrations of PM_{10}. Figure 20 on the other hand illustrates the close negative association between pollution levels and the instrument, which is rainfall level.

Empirical Methodology:

My objective is to estimate the e ect of PM_{10} pollution (PM_{cy}) on the number of deaths per 100,000 live births ($Mort_{cy}$), in a county and year. Speci cally, I would like to estimate

β_1 from the following speci cation:

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

However, as discussed above, there are reasons to believe that there will be confounding factors that can potentially bias $_1$ upwards or downwards. I use the instrumental vari-ables 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 signi cant e ect on particulate matter, as it provides the main atmospheric sink for suspended particles. Since, extreme weather events can potentially have a direct e ect on infant mortality [16], I explicitly control for these in my preferred speci cation 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 PM10 concentrations in county c and year y; 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 e_ect 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 a_ect infant mortality. Z represents time-invariant covariates (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 e_ects 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:

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

Results

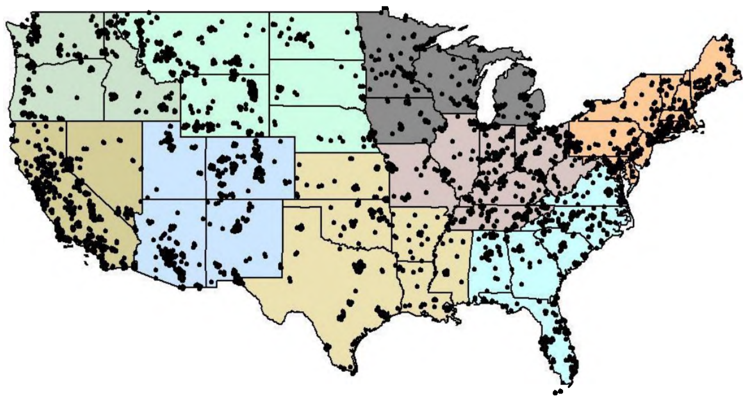
Table 14 illustrates the results from the 2SLS estimation of Equation (3). Extreme weather events, county and year xed e ects have been controlled in all the speci cations. All the other controls, as describes above, have been added sequentially moving from Column (1) to Column (3). In Column (4) I have tried an alternative measure of Droughts, Heat Waves, and Cold Waves [17]. I have de ned them using deviations from the climate normal [18] Taking an average of all four speci cation, I nd that a 1 g=m^3 decrease in PM_{10} will lead to 27 fewer infant deaths. The Cragg-Donald Wald F-statistic is su ciently large to reject the weak IV test, meaning that the instrument is not weak. Table 15 illustrates the rst stage results from estimating Equation (4) and we nd that precipitation always has a highly signi cant and negative e ect on average PM_{10} concentrations. A 1-mm decrease in total precipitation leads to an increase of 0.22 g=m^3 of PM_{10} concentrations.

Conclusion

In this paper, I estimate the causal e ect 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 e ects. Firstly, I nd that a 1 mm decrease in rainfall level will lead to an increase of 0.23 g=m^3 increase in PM_{10} and an increase of 0.08 g=m^3 of $PM_{2:5}$. Comparing these estimates with the causal e ect of the Clean Air Act Non-Attainment Status in Column (4) of Table 5, I nd that a 1-mm decrease in daily precipitation can potentially o set over 30% of the bene ts of the land-mark regulation, through higher PM_{10} levels in ambient air. The e ect is almost 38% of the bene ts of the Clean Air Act, when we look at the estimates for $PM_{2:5}$ from Table 6. On the other hand, if precipitation frequency decreases by a day, then PM_{10} will increase by 1.04 g=m^3 whereas $PM_{2:5}$ will increase by 0.39 g=m^3. Using information on the county non-attainment status of the National Ambient Air Quality Standards for par-ticulate matter, I also nd signi cantly di erent e ects 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 nd substantial spatial heterogeneity of my main estimates. Finally, using these causal estimates, I analyze the e ect of PM_{10} on infant mortality and nd that a 1 g=m^3 de-crease 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 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.

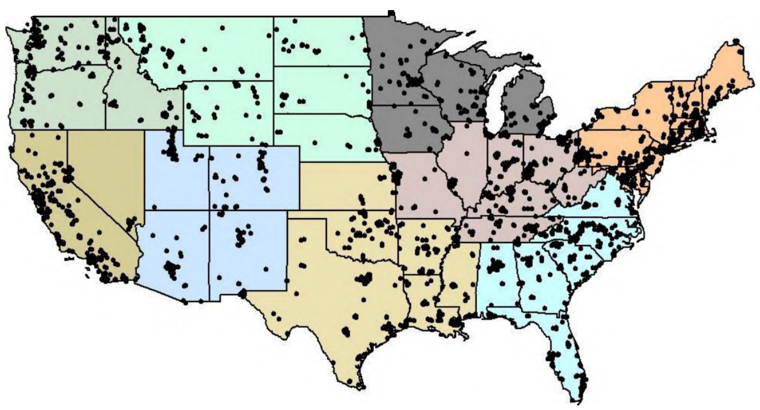
This paper contributes to the literature on the linkages between air pollution and climate change in the following ways. Firstly, by consolidating a large and detailed daily dataset at the pollution monitor level, I provide the rst causal estimates of the e ect of precipitation as well as precipitation frequency on PM_{10} and $PM_{2:5}$. Secondly, by estimating this causal e ect 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 e ect of precipitation on particulate matter. To do so, I have used precipitation in an instrumental variables approach to study the e ect 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 impor-tant 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 var-ious mechanisms and adjustments made by economic agents to adapt to climate change. Lastly, with this e ect of climate change on air pollution understood, we might want to analyze whether and how rms, industries and other pollution emitters internalize this linkage in deciding how much to produce.

Figure 5: $P M_{10}$ Monitors from 1990-2013



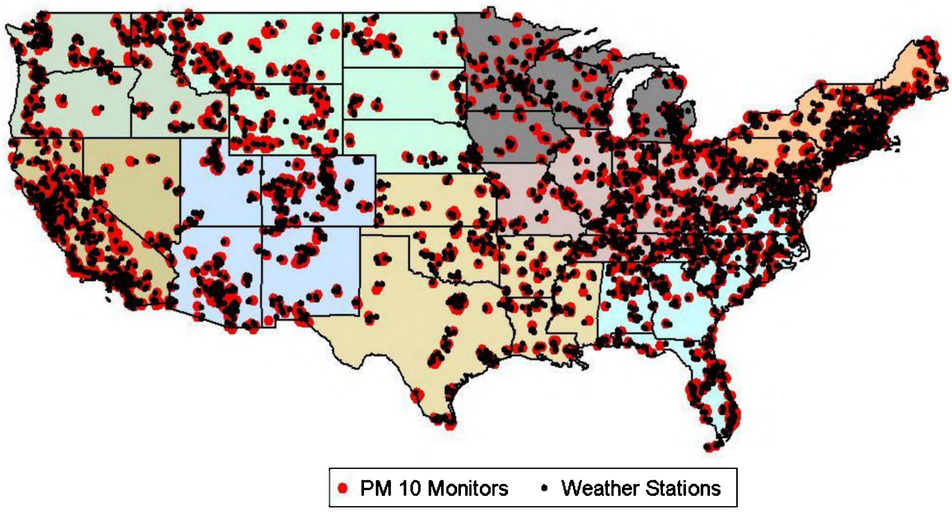
Notes: Each shaded region represents a single climatic region as de ned by the NOAA. Figure 5 illustrates the geographic location of 3264 $P M_{10}$ monitors in our sample, using the latitude and longitude information as obtained from the EPA.

Figure 6: $P M_{2:5}$ Monitors from 1997-2013



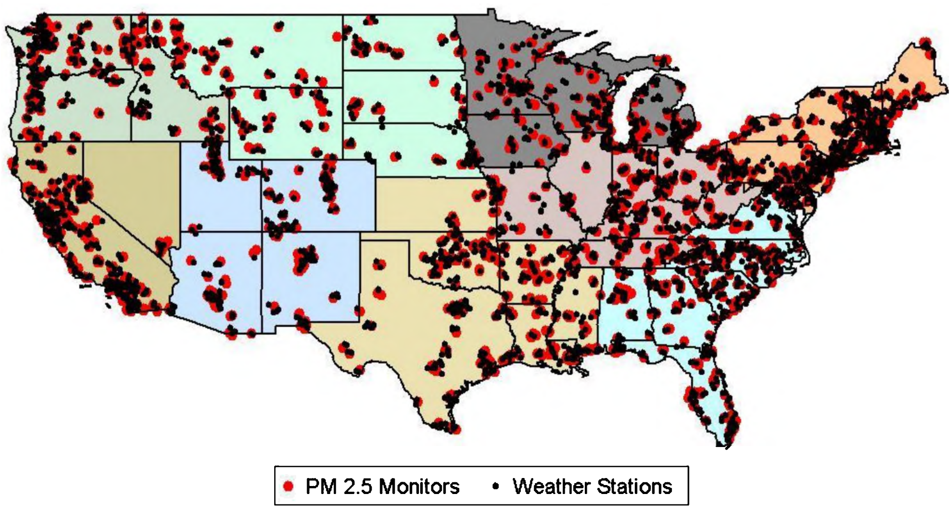
Notes: Each shaded region represents a single climatic region as de ned by the NOAA. Figure 6 illustrates the geographic location of 2162 $P M_{2:5}$ monitors in our sample, using the latitude and longitude information as obtained from the EPA.

Figure 7: P M_{10} Monitors and Matched Weather Stations from 1990-2013



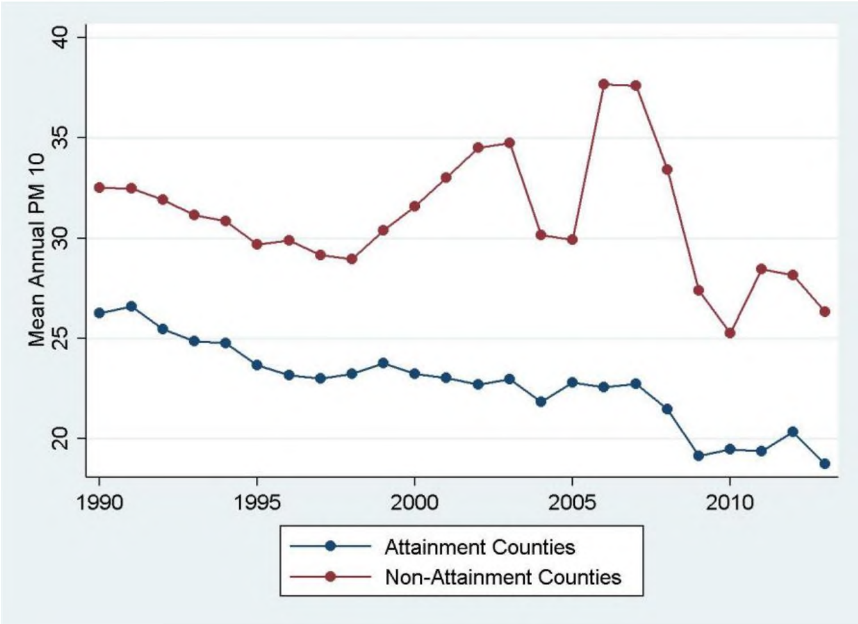
Notes: Each shaded region represents a single climatic region as de ned by the NOAA. Figure 7 illustrates the geographic location of 3264 P M_{10} monitors in our sample along with the weather stations matched to each pollution monitor, using the latitude and longitude information as obtained from the EPA.

Figure 8: P $M_{2:5}$ Monitors and Matched Weather Stations from 1997-2013



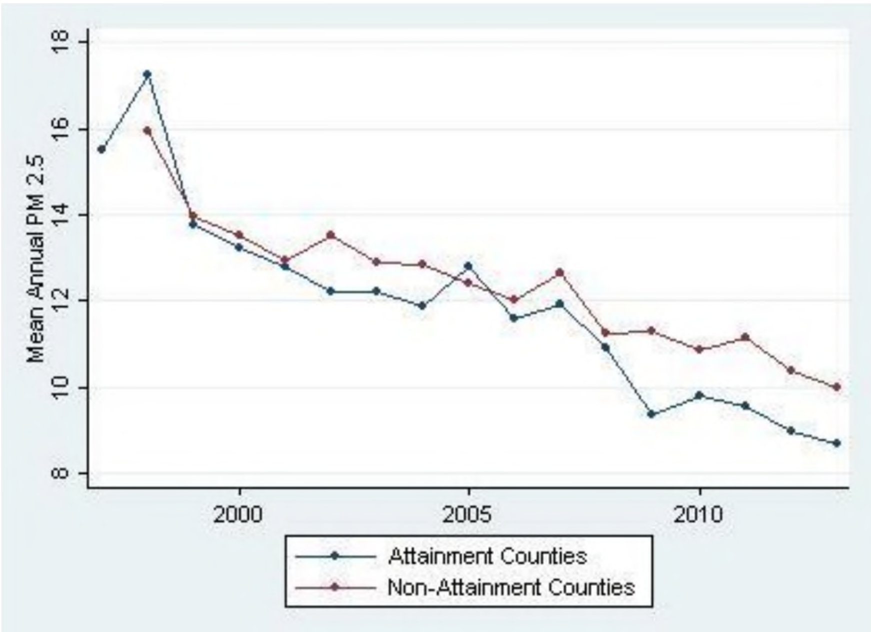
Notes: Each shaded region represents a single climatic region as de ned by the NOAA. Figure 8 illustrates the geographic location of 2162 P $M_{2:5}$ monitors in our sample along with the weather stations matched to each pollution monitor, using the latitude and longitude information as obtained from the EPA.

Figure 9: Mean Annual PM_{10} by CAA Attainment Status



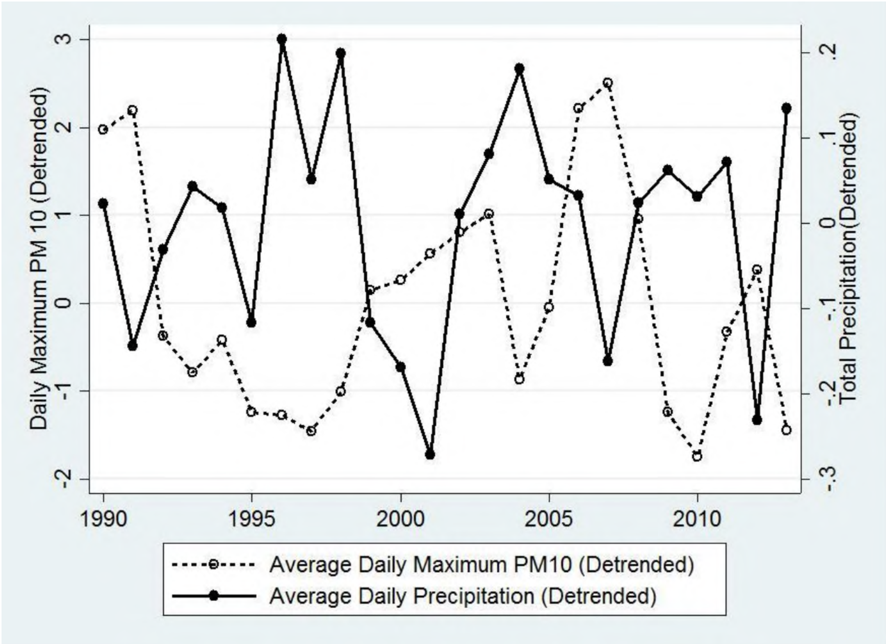
Notes: This gure represents the average annual PM_{10} concentrations across all monitors in attainment (blue line) and all monitors in non-attainment (red line) for each year between 1990-2013.

Figure 10: Mean Annual $PM_{2:5}$ by CAA Attainment Status



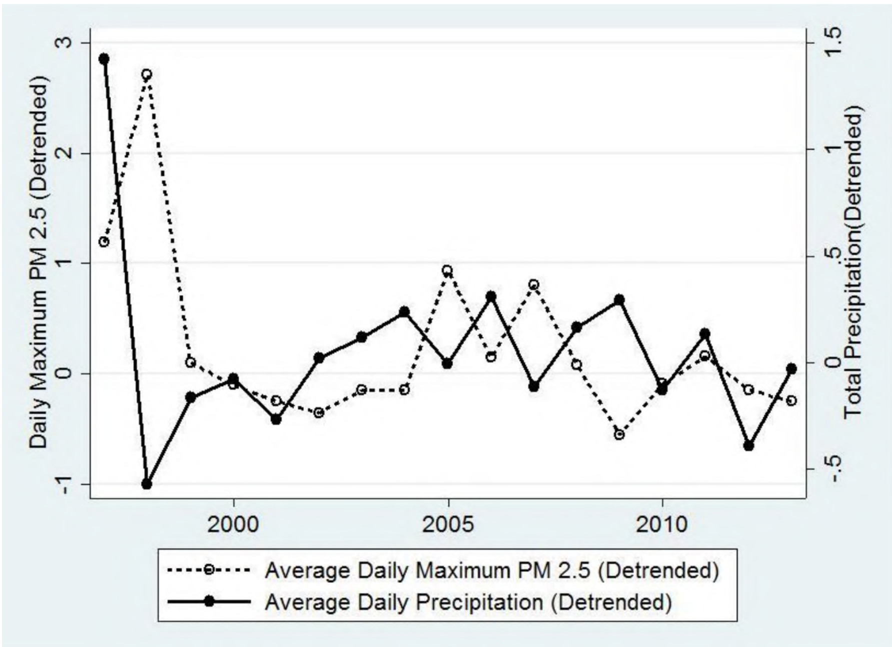
Notes: This gure represents the average annual $PM_{2:5}$ concentrations across all monitors in attainment (blue line) and all monitors in non-attainment (red line) for each year between 1997-2013.

Figure 11: Level of Precipitation and PM_{10}



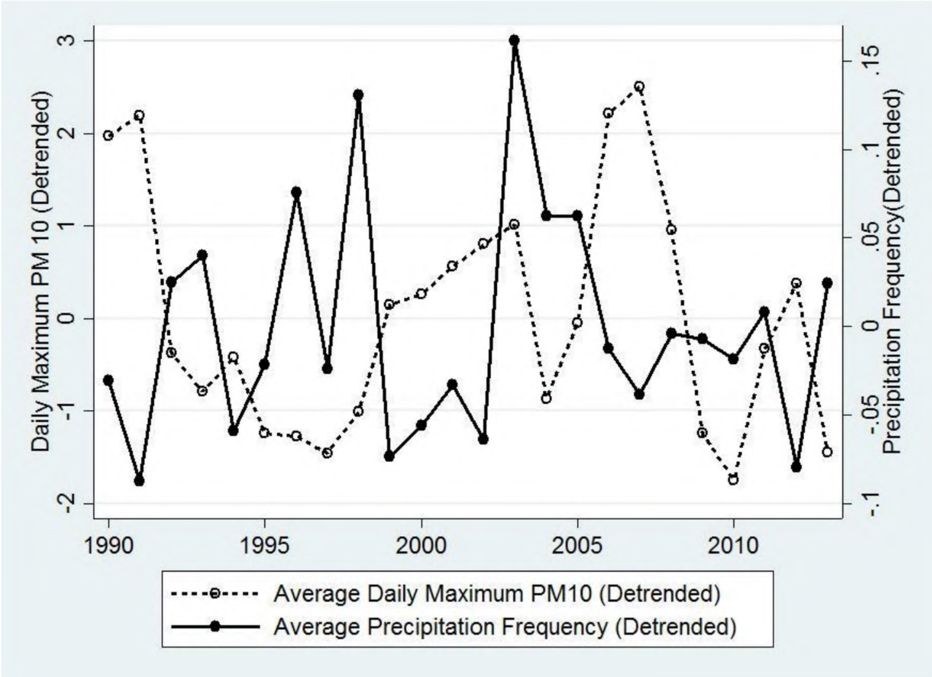
Notes: This gure represents the daily maximum PM_{10} concentrations and daily total precipitation, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 12: Level of Precipitation and $PM_{2:5}$



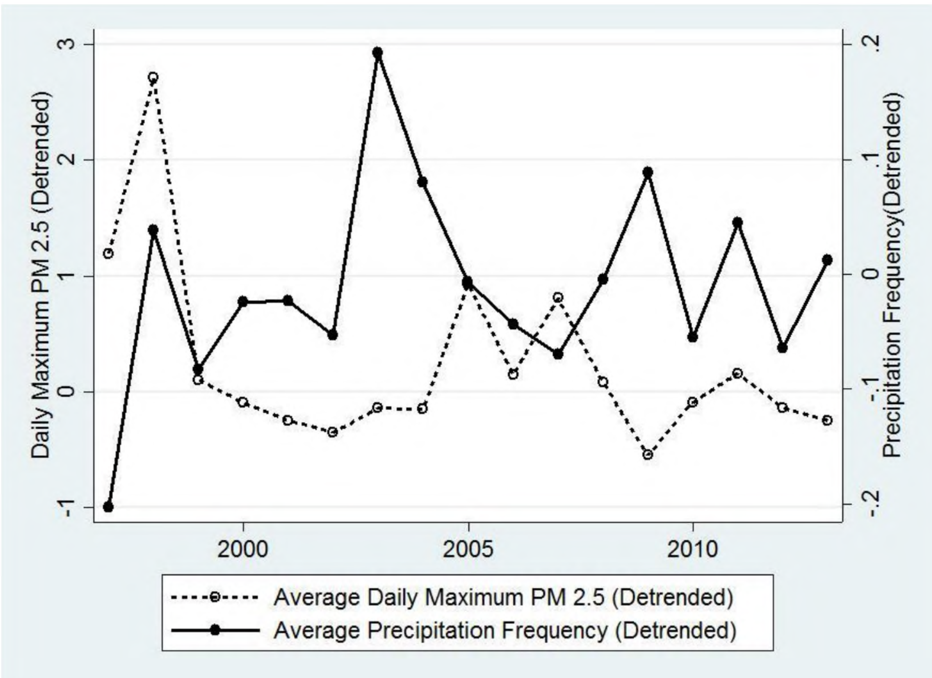
Notes: This gure represents the daily maximum $PM_{2:5}$ concentrations and daily total precipitation, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 13: Precipitation Frequency and PM_{10}



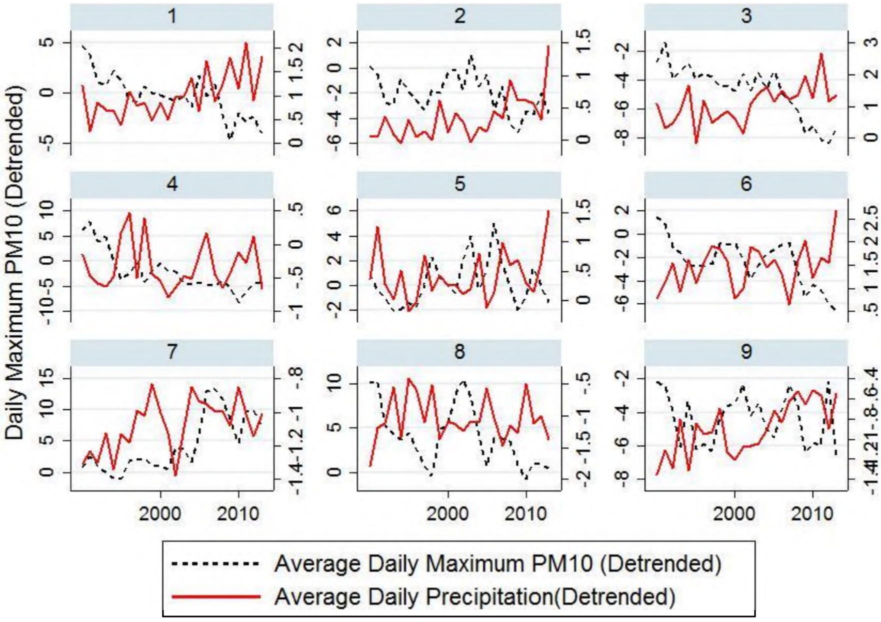
Notes: This gure represents the daily maximum PM_{10} concentrations and precipitation frequency, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 14: Precipitation Frequency and $PM_{2:5}$



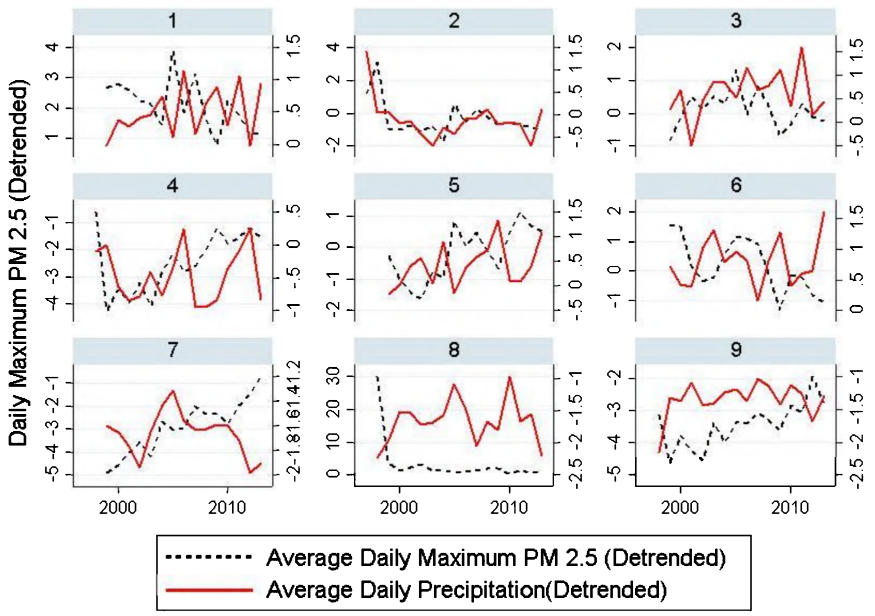
Notes: This gure represents the daily maximum $PM_{2:5}$ concentrations and precipitation frequency, averaged across all monitor-days for each year. The variables have been detrended in order to eliminate the time trend.

Figure 15: Level of Precipitation and PM_{10}- By Climate Regions



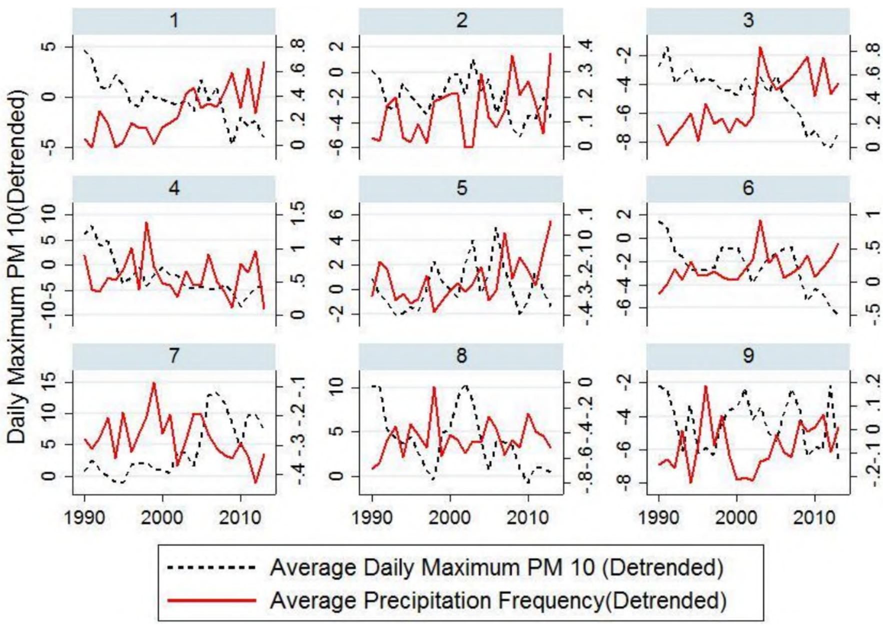
Notes: This gure represents the daily maximum PM_{10} concentrations and daily total precipitation, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 16: Level of Precipitation and $PM_{2:5}$- By Climate Regions



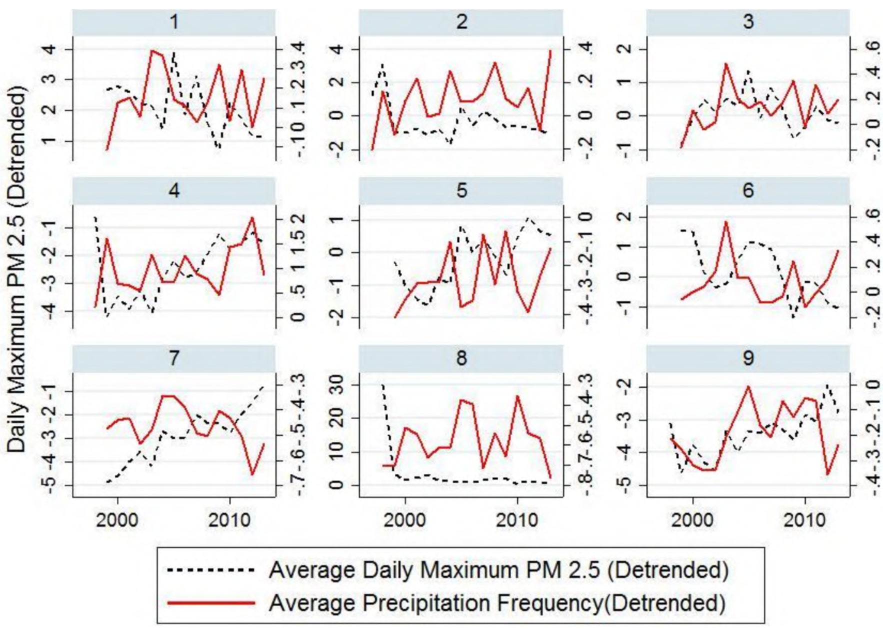
Notes: This gure represents the daily maximum $PM_{2:5}$ concentrations and daily total precipitation, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 17: Precipitation Frequency and P M_{10}- By Climate Regions



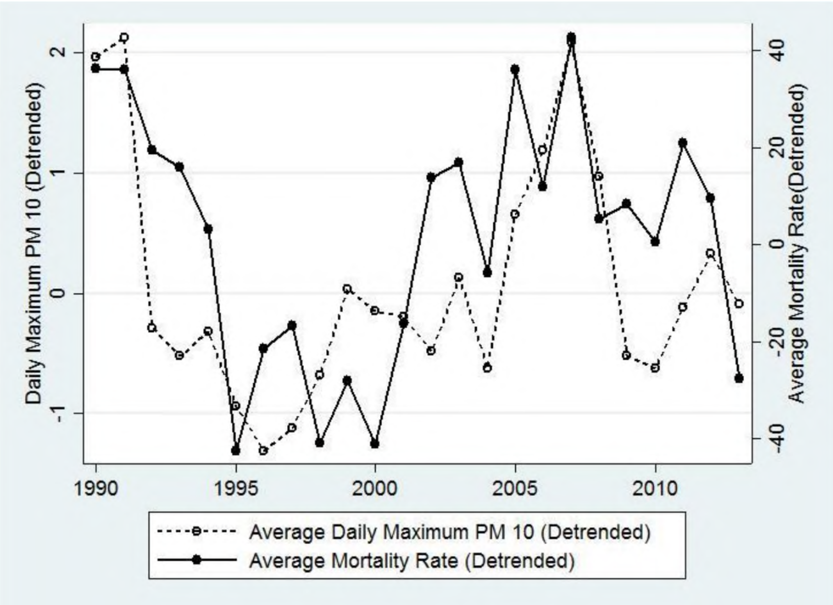
Notes: This gure represents the daily maximum P M_{10} concentrations and precipitation frequency, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 18: Precipitation Frequency and P $M_{2:5}$- By Climate Regions



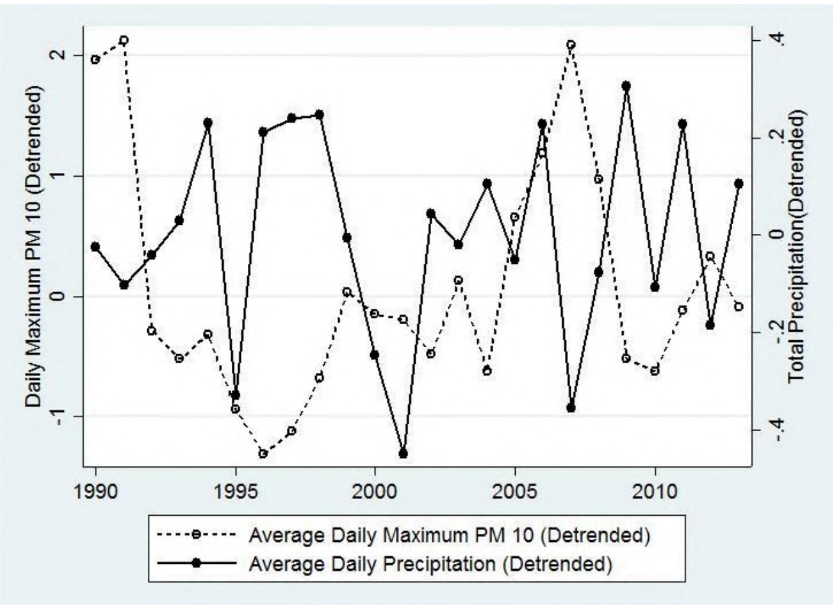
Notes: This gure represents the daily maximum $PM_{2:5}$ concentrations and precipitation frequency, averaged across all monitor-days for each year and climate region. The variables have been detrended in order to eliminate the time trend.

Figure 19: Level of Precipitation and Infant Mortality Rate



Notes: This gure 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 20: Level of Precipitation and PM_{10}



Notes: This gure 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.

Table 1: P M_{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

Table 2: P $M_{2:5}$ 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

Table 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 4: P $M_{2:5}$ 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

Table 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 xed e ects 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 signi cance at the 1%, 5% and 10% level respectively.

Table 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 xed e ects 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 signi cance at the 1%, 5% and 10% level respectively.

Table 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 xed ectse 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 cancesigni at the 1%, 5% and 10% level respectively.

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Table 8: Effect of Level and Frequncy of Precipitation on P $M_{2:5}$ 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 xed ectse 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 cancesigni at the 1%, 5% and 10% level respectively.

Table 9: Robustness- Balanced Panel of P M_{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 xed e ects 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 P M_{10} monitors. Standard errors are clustered at the monitor level. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

Table 10: Robustness- Balanced Panel of P $M_{2:5}$ 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 xed e ects 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 P $M_{2:5}$ monitors. Standard errors are clustered at the monitor level. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

Table 11: Robustness- Dependence on Wind Speed

VARIABLES	PM_{10} (1)	PM_{10} (2)	$PM_{2.5}$ (3)	$PM_{2.5}$ (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 xed e ects 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 5. Standard errors are clustered at the monitor level. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

Table 12: Robustness- Non-linear Effects of Level and Frequency of Precipitation on P M

VARIABLES	P M 10		P M 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 xed e ects for PM Monitors, Trimester*Year x Climate Region, Trimester*Year x Monitor Latitude and Trimester*Year x Monitor Longitude. Positive coe cients of the non-linear controls imply a convex relationship. Standard errors are clustered at the monitor level. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

Table 13: Summary Statistics of Infant Mortality, PM_{10} and Precipitation, County/Year Level

	Panel A: Particulate Matter $PM_{10}(g=m^3)$		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 nedde as [Total Deaths/Total Births]* 100,000.

Table 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 E ects	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 xed e ects. Standard errors are estimated using the Eicker-White formula to correct for heteroskedasticity. Extreme precipitation events (i.e. droughts and oods) and extreme temperature events (i.e. heat waves and cold waves) have been controlled for. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

Table 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 E ects	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 xed e ects. Standard errors are estimated using the Eicker-White formula to correct for heteroskedasticity. Extreme precipitation events (i.e. droughts and oods) and extreme temperature events (i.e. heat waves and cold waves) have been controlled for. ***, ** and * represent statistical signi cance at the 1%, 5% and 10% level respectively.

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Brief biographies of the authors

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Mehreen Mookerjee is an Assistant Professor in the School of Government and Public Policy at O.P. Jindal Global University. She completed her PhD in Economics from Cornell University in Ithaca, NY, USA. Her primary research interests lie in the fields of Environmental Economics and Development Economics. Within the field of Environmental Economics, she has a special interest in issues pertaining to changing climate patterns, and empirically evaluating the effects of such changing patterns of rainfall and temperature on ambient concentrations of harmful air pollutants forms the substantive core of her doctoral work. As a part of her research, Mehreen has also collaborated with professors at esteemed universities in USA such as Carnegie Mellon University and University of Southern California. Apart from research, Mehreen has gained invaluable teaching experience at Cornell for almost eight semesters. She enjoys teaching and is excited to have that as a part of her career. Prior to joining Cornell, Mehreen has also completed a B.A. (Hons) in Economics from Jadavpur University in Kolkata, her hometown; followed by a M.S. in Quantitative Economics from the Indian Statistical Institute, New Delhi.