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Measuring the Effects of the Clean Air Act Amendments on Ambient PM_{10} Concentrations: The Critical Importance of a Spatially Disaggregated Analysis

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Measuring the Effects of the Clean Air Act Amendments on Ambient PM_{10} Concentrations: The critical importance of a spatially disaggregated analysis*

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Abstract

We examine the effects of the 1990 Clean Air Act Amendments (CAAAs) on ambient concentrations of PM_{10} in the United States between 1990 and 2005. We find that non-attainment designation has no effect on the 'average monitor' in non-attainment counties, after controlling for weather and socioeconomic characteristics at the county level. In sharp contrast, if we allow for heterogeneous treatment by type of monitor and county, we do find that the 1990 CAAAs produced substantial effects. Our best estimate suggests that PM_{10} concentrations at monitors with concentrations above the national annual standard dropped by between $7\mu g/m^3$ and $9\mu g/m^3$, which is roughly equivalent to a 11-14% drop. We also show that monitors which were in violation of the daily standard experience two fewer days in violation of the daily standard the following year. Empirical results suggest that this treatment effect is independent of whether the EPA has finalized the non-attainment designation.

Keywords: Air Pollution, Clean Air Act, Spatial Modeling
JEL Codes: Q53, Q58

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1. Introduction

Two empirical regularities characterize the changes in the spatial distribution of particulate matter less than 10 microns in diameter (PM_{10}) in the United States between 1990 and 2005: First, average county level ambient concentrations of PM_{10} dropped by about 18%. Second, there was substantial spatial heterogeneity in reductions of PM_{10}. Monitors which recorded ambient concentrations above the federal standard experienced drops that were greater than the average of the remaining monitors in the same county.

This naturally raises the following two questions: First, what is the effect of the 1990 Clean Air Act Amendments (CAAAs) on ambient concentrations of PM_{10}? Second, what is the level of spatial aggregation - county versus monitor level - needed for the effects of the regulation to be properly captured? This paper attempts to shed light on these questions by combining monitor level data on annual average PM_{10} concentrations from the EPA's Air Quality System (AQS) between 1990 and 2005 with data from the Code of Federal Regulations (CFR) on county PM_{10} attainment status. We ask whether county non-attainment status is responsible for the drops in PM_{10} experienced in non-attainment counties.

Further, we examine the spatial distribution of these changes. The need for a spatially disaggregate analysis arises from the way the regulation is written, which in turn was likely motivated by the understanding of the health effects. The NAAQS specifies that a county is designated as non-attainment if *any* of the monitors within the county are in violation of the federal standard. This may lead to a heterogeneous treatment effect within counties, where local regulators focus their attention on monitors recording concentrations in violation of the federal standard and "ignore" the remaining monitors in the county.[1]

The epidemiological literature on the mortality impacts of particulate matter provides a clear motivation why federal regulators focused their attention on dirtier areas when designing the regulation. Early studies examining the dose response function for particulate matter and mortality assumed that the *logarithm* of mortality is linear in concentrations, suggesting a non-linear relationship between mortality and concentrations [6]. This convex damage function implies that reducing ambient concentrations at a dirty location by *e.g.* 10 $\mu g/m^3$ of PM_{10} may lead to a better overall health outcome than reducing concentrations by the same amount at a cleaner location. Only a spatially disaggregated analysis will have the ability to disentangle these heterogenous impacts of regulation.

Over the years, researchers have made considerable strides in measuring the effects of federal environmental regulations on ambient concentrations of several criteria pollutants. Studies vary by the time period, type of pollutant and level of data aggregation (county averages versus monitor level observations). [11] investigated the effects of ground level Ozone regulations in the United States for the period 1977-1987 on air quality and the migration of polluting facilities using concentrations of Ozone measured at the monitor level. He finds that county non-attainment status - the centerpiece of the CAAAs - led to a statistically significant 8.1% decrease in the median daily maximum concentrations for the month of July. He finds a weak or not statistically significant effect for three additional measures of Ozone concentrations examined.[2] Along the same lines, [2] and [3] examined the effects of total suspended particulates (TSPs) on infant health and capitalization of air quality into property values induced by the 1970 Clean Air Act Amendments. In their first stage regressions they find a statistically significant effect of predicted non-attainment status on mean annual concentrations of TSPs averaged to the county level. The estimated impact is between 9-12% for 1971-72 TSP concentrations and 11-12% for the 1975-76 non-attainment status on the difference between 1977-80 and 1969-72 concentrations. Both of these papers use ambient concentrations averaged across all monitors for each county. More recently, [9] examined the effects of the 1970 and 1990 CAAAs on county averaged Sulfur Dioxide (SO_2) concentrations. Using difference-in-difference and propensity score matching techniques, he shows evidence that the non-attainment designation at the county level did not have a detectable impact on average within county monitor concentrations for non-attainment counties.

Our interest here lies in examining whether due to the lack of a spatially-disaggregated analysis that can capture the heterogeneity in regulatory impact on ambient concentrations, these studies may have potentially “averaged out” the true effects of environmental regulation. This issue arises if air quality managers focus their regulatory efforts on “dirtier” parts of counties and reduce ambient concentrations by substantially larger amounts there as compared to “cleaner” areas of the same county. By averaging concentrations across low concentration and high concentration monitors for a given county one potentially averages away a source of policy induced variation. In the extreme case, this averaging could lead one to conclude that policy is responsible for only minor or no reductions in ambient concentrations of criteria pollutants. They may have, however, reduced concentrations significantly in the worst air quality regions, yet have left air quality somewhat constant in the cleaner parts of a county.

Studies using monitor level data suffer from a similar version of this problem, since they estimate an average treatment effect for all monitors in non-attainment counties. By modeling regulatory impacts via a non-attainment dummy, the estimated coefficient captures the average effect of non-attainment status across all monitors in a county. If there is underlying heterogeneity, one may falsely conclude that policy had no impact on ambient concentrations.

Finally, these studies implicitly assume that there is no regulatory effect in attainment counties. This assumption is only valid if the threat of non-attainment status designation does not lead to changes in monitor level concentrations in attainment areas.

This paper differs from the prior literature in three distinct ways. First, we look at the impact of federal air quality regulation on particulate matter less than 10 microns in diameter, which is often considered to be the "pollutant of the 90s". Second, while we conduct our analysis at the monitor level (as does [11]) we allow the regulation to have a differential effect on concentrations measured at the monitoring site depending whether a county is in attainment or not and whether a specific monitor was in violation of the federal standard in the previous period. Finally using previously unavailable weather data, we are able to control for weather impacts at the monitor (instead of the county average) level, allowing for within county heterogeneity of rainfall and temperature.

We address these issues by combining annual average concentrations of PM_{10} at the monitor level between 1990 and 2005 with county attainment designations for PM_{10}. Additional data were collected to account for other determinants of changes in PM_{10}, including climate and economic activity. We further control for monitor and year fixed effects as well as monitor specific time trends to remove any unobservable confounding factors constant and/or varying by monitor and year.

We use these data to estimate two sets of models. The first is a model that, for PM_{10}, replicates existing studies of the effects of environmental regulations at the county level on other criteria pollutants [9]. The second is a more spatially disaggregated model where we allow for the possibility of heterogeneous impacts of the regulation based on the concentration at monitors which recorded concentrations in violation of the federal standard. We estimate these two sets of models separately for violations of the annual and daily federal standard.

The rest of the paper is organized as follows. Section 2 provides a brief overview of PM_{10} regulation; section 3 describes the data sources and provides summary statistics on the trends in monitoring and PM_{10} concentrations between 1990 and 2005. Section 4 presents the econometric models and section 5 the results. Section 6 concludes.

2. Basic Aspects of PM_{10} Regulation

2.1 Brief Historical Facts About PM_{10} Regulation

Particulate Matter is a term used for a class of solid and liquid air pollutants. Total suspended particulates (TSPs) include particles less than 100 microns in diameter. The 1971 Clean Air Act authorized the Environmental Protection Agency to enforce a National Ambient Air Quality Standard (NAAQS) for TSPs. The standards for TSPs were phrased as primary and secondary standards. "Primary standards set limits to protect public health, including the health of sensitive populations such as asthmatics, children, and the elderly. Secondary standards set limits to protect public welfare, including protection against decreased visibility, damage to animals, crops, vegetation, and buildings" (see [16] for further discussion). Each standard is defined in terms of an annual benchmark average as well as 24 hour benchmarks. From April 30th 1971 until July 1st 1987 the primary annual standard for TSPs was 260 $\mu g/m^3$ for the 24-hour average and 75 $\mu g/m^3$ for the annual average. The secondary standard for TSPs was 150 $\mu g/m^3$ for the 24-hour average and 60 $\mu g/m^3$ for the annual average [13].

If *a single monitor within a county* exceeded the primary annual standard for one year or the primary 24-hour standard for more than a single day per year the entire county was considered to be in violation of the standard. By provisions in the Clean Air Act, the EPA can move to designate a county "non-attainment". After a lengthy review process, a non-attainment county was required to submit, in a state implementation plan (SIP), the strategy that it intends to use to become in attainment with the NAAQS. If the deficiency remains uncorrected, or if the EPA "finds that any requirement of an approved plan (or approved part of a plan) is not being implemented", the county is given 18 months to correct the deficiency. If the deficiency is not corrected the EPA administrator may impose sanctions on the county in violation, including the withholding of federal highway funds, and the imposition of technological "emission offset requirements" on new or modified sources of emissions within the county [14]. In the first stage of the sanctioning process only one of the sanctions is applied at the discretion of the EPA Administrator; if the county continues to be in violation 6 months after the first sanction, then both are applied. These sanctions are enforced not at the state level, but at the political subdivisions that "are principally responsible for such deficiency" [13].

In 1987, the U.S. Environmental Protection Agency refined their particulate policy to regulate particulates less than 10 micrometers in diameter (PM_{10}). The new standard required the annual arithmetic mean of PM_{10} concentration for each monitor in a county to be less than 50 $\mu g/m^3$. It further required that the 24 hour average concentrations at a monitor do not exceed 150 $\mu g/m^3$. In contrast to TSPs, for PM_{10} the primary and secondary standards were identical. This change was implemented because a growing body of scientific evidence indicated that the greatest health concern from particulate matter stemmed from PM_{10}, which can penetrate into sensitive regions of the respiratory tract.[3]

2.2 Local Regulatory Behavior

To understand the behavior of the local regulator, we emphasize the fact that federal regulators set federal standards with the understanding that the ultimate goal of the regulation is to protect public health. As such, and because of the non-linearities between pollution levels and health impacts, the federal regulator requires that, for a county to be in attainment, none of the monitors in that county can exceed the primary annual standards. The local regulators objective in turn is to minimize costs for the county. These costs consist of regulation costs (*e.g.* fines and SIP) as well as costs to lower PM_{10} levels. The federal regulation creates an incentive for the local regulator to closely track the monitors that put the county at risk of becoming out of attainment. The regulator then allocates effort in terms of monitoring and enforcement activities to the different monitors by comparing the future costs of getting out of attainment to the present costs associated with the reduction in the emissions around risky monitors. The resulting equilibrium is a schedule of heterogeneous monitoring efforts such that more effort is allocated to dirtier monitors, resulting in the maximized net benefit of emissions reductions.

2.3 Sources of PM_{10} Pollution

Particulate matter enters the atmosphere in one of two ways: primary particulate matter is emitted directly into the atmosphere as a solid or liquid; secondary particulate matter is formed in the atmosphere by reactions between precursor gases such as organic gases, nitrogen oxides (NO_x), and sulfur oxides (SO_x). In general, the contribution of the secondary PM_{10} precursor gases to total ambient PM_{10} is substantially larger than the contribution of primary particulate matter.

In California, for example, the California Air Resources Board estimates that in the year 2000, there were approximately 2,400 tons of primary PM_{10} emitted on a daily basis. Of these 2,400 tons, 6% was emitted by stationary industrial sources, 5% was emitted directly from mobile sources, 15% was generated from paved roads, and the remaining 74% was produced by area-wide sources. The area-wide sources include residential fuel combustion (7%), farming operations (9%), construction and demolition (9%), unpaved road dust (27%), fugitive windblown dust (12%), and burning and waste disposal (10%).

In addition to the primary PM_{10} emissions, 10,847 tons of secondary PM_{10} precursor gases were emitted into the atmosphere on a daily basis in California in the year 2000. These precursor gases include 3,591 tons of NO_x, 333 tons of SO_x, and 6,923 tons of organic gases [1]. The actual contribution of the secondary PM_{10} precursor gases to ambient PM_{10} concentration levels depends on the ambient concentrations of the precursor gases themselves, as well as the atmospheric chemistry of the region, including the relative humidity, temperature, wind speed and direction [8]. In this case one may find two areas with similar secondary PM_{10} precursor gas releases that have different secondary PM_{10} ambient concentrations, depending on their location-specific characteristics. In the case of the South Coast Air Basin, the PM_{10} reduction efficiency calculations, which allow one to estimate the primary and secondary emissions required to produce a single unit increase in the ambient concentration of PM_{10}, indicate that NO_x emissions in 1990 contributed to over half of the total ambient PM_{10} concentration [8].

3. Overview of the Trends in PM_{10} Concentrations and Regulations

To implement the analysis, we compiled the most detailed data available on concentrations, attainment status and other relevant determinants of concentrations, including climate and economic activity. This section describes the data sources and presents summary statistics on national trends in PM_{10}, the distribution of monitors and mean concentrations.

3.1 PM_{10} Concentrations and Attainment Status Data

The concentrations data were obtained from the *Air Quality Standards* (AQS) database, which is maintained by the EPA. For each PM_{10} monitor reporting to the EPA, these data include a number of monitor characteristics including the location of the monitor. Title 40 Part 58.12 and Title 40 Part 50 Appendix K of the Code of Federal Regulations prescribe the monitoring frequencies for PM_{10} monitors, as well as criteria for establishing whether a monitor is "representative" and therefore should be used in rule making.[4] For estimation purposes, we used the valid weighted annual mean at each monitor, which was provided by the EPA.[5]

The annual county attainment status designations were copied from the annual CFR. Since for PM_{10} the primary and secondary standards are identical we have a single indicator of non-attainment for each county and year.

3.2 Additional Data: Attainment Status for other criteria pollutants, Climate and Economic Activity

We supplement the data on PM_{10} concentrations and attainment status with additional relevant data, reflecting the need to capture other determinants of the change in PM_{10}. Since attainment status is not only assigned for PM_{10}, but for five other criteria pollutants, it is important to separate the impact of policy induced reductions in precursor emissions to the pollutant of interest. We therefore control for yearly county non-attainment status for TSP, Ozone, SO_x and NO_x collected from the CFR.[6]

In addition to regulation, there are other physical factors influencing ambient concentrations of PM_{10}. Temperature and rainfall affect the formation of secondary PM_{10} as well the presence of primary particulates. Since microclimates vary greatly within states and large counties, we do not use county averages, but use rainfall and temperature at the monitor location. We control for February and July rainfall and temperatures, which have been shown to be highly correlated with particulate concentrations, since they proxy for how cold/wet each winter was and how warm/dry each summer was at the monitor level. We use the [15] dataset, which provides monthly data based on all US weather stations extrapolated to a set of 4 km^2 grids covering the continental United States between 1990 and 2005, allowing us to construct weather observations at the pollution monitor location.

Finally, emissions of particulate matter are strongly correlated with economic activity. While GDP is not available at the county level, the Bureau of Economic Analysis (BEA) releases annual estimates of personal income at the county level. This indicator has been widely used in the Environmental Kuznets Curve literature at the state level [12]. We include the real personal income for each year and county in our sample. We also control for population and employment, using county level estimates reported by the BEA. In the econometric analysis we will further control for monitor specific time variant and invariant unobservables.

3.3 National Trends in Monitoring and Concentrations

Table I presents annual summary information for the monitors included in our analysis. The second column reports the number of active monitors for each year. As a result of the 1990 CAAAs, both the number of operating monitors and the geographical coverage of PM_{10} readings increased substantially between 1988 and 2005. The number of active monitors increased roughly fourfold between 1988 and 1996; as the third column indicates, the number of monitored counties increased from 173 in 1988 to 543 in 1997. The peak in PM_{10} monitoring in 1997 is not surprising, since federal regulators began a national program to monitor $PM_{2.5}$ levels in 1997. At the peak of monitoring 172 million people lived in counties with at least one valid monitor, which represents roughly 65% of the US population.

Column (5) shows the number of monitored non-attainment counties. In 1990, for example, 64 non-attainment counties had at least one monitor satisfying the EPA data requirements mentioned above. Column (6) displays the complete count of counties designated as non-attainment. In 1990, 76 counties were designated as being in non-attainment. The numbers in brackets report the counties being newly designated as non attainment and back in attainment for each year respectively. From 1993 to 1994, for example, six counties were newly designated as being out of attainment raising the number of non-attainment counties from 77 to 83. From 1994 to 1995 one county was newly designated as being out of attainment and two counties were designated as being back in attainment bringing the number of non-attainment counties down to 82 from 83. Identification in our model comes from the monitors which are located in counties that go into or out of attainment over the period covered by our sample. These monitors account for 22% of the monitors in the sample.[7] Figure (1) displays the spatial distribution of monitored counties by attainment status for our sample. The overall spatial distribution of monitors reflects the EPA's concerns of measuring concentrations in highly populated areas.

Columns (7) and (8) in Table I indicate that average annual concentrations across all monitors show a 18% decrease between 1990 to 2005. In addition the variability in emissions as measured by the standard deviation has decreased by roughly 14%. For the entire sample the overall standard deviation of ambient concentrations is 8.93 $\mu g/m^3$, while the within monitor standard deviation is much smaller at 3.62 $\mu g/m^3$. Column (9) of the table displays the number of monitors in each year, which are in violation of the daily standard, which also displays a downward trend. The question central to this paper is to determine how much of this drop at which type of monitor is due to the CAAAs. Figure (2) shows the trend of average annual concentrations in counties which were always in attainment in the left panel. The right panel shows the trend in average ambient concentrations for counties which were designated as non-attainment for at least one year of our sample. In absolute terms both types of counties experienced a drop in mean concentrations of about $10\mu g/m^3$ between 1988 and 2005. Casual inspection of this figure could lead one to conclude that county-level attainment status does not have a detectable impact on average concentrations. The goal of this paper is to determine whether indeed attainment status affects all monitors in non-attainment counties, or whether regulation affects only monitors with concentrations above the federal standard.

Before attempting to identify the effects of regulation using econometric methods, it is worth examining trends at three types of monitors at the time regulation was first introduced. Figure (3) examines the changes in mean concentrations at a) monitors in counties which were in attainment throughout the period of our sample (the control group) b) monitors in counties that were designated as non-attainment in 1990, yet had concentrations below the federal standard and c) monitors in counties that were designated as non-attainment in 1990, yet had concentrations above the federal standard. The figure centers the three series according to their 1990 average concentration. The figure shows quite clearly that the monitors in attainment counties (dotted line) and the attainment monitors in non-attainment counties (triangles) followed an almost identical trajectory. The trajectory for monitors in non-attainment counties which were in violation of the standard, is quite different. The average concentrations at these monitors were increasing leading up to the regulation year 1990, which is when a sharp trend reversal occurred and concentrations began to drop. Two years after the first non-attainment status designations were put in place, concentrations at these dirties monitors were roughly 6.5 $\mu g/m^3$ lower than right before the designation year. This graphical evidence motivates us to examine this effect conditional on confounding variables at the monitor level using econometric methods, which is what we turn to in the next section.

4. Econometric Model

In this section, we describe the econometric strategy adopted to measure the effects of the CAAAs on changes in concentrations. Let $D_{j,t}$ be an indicator variable that equals one when county j is designated as non-attainment in year t and 0 if it is in attainment. Let $Y_{i,t}^{j}$ denote the PM_{10} concentrations of monitor i in county j in year t. Consistent with the literature, our basic econometric model is equation 1 below:

$$Y_{i,t}^{j} = \alpha_1 D_{j,t} + \boldsymbol{X}_{j,t}\boldsymbol{\beta} + \boldsymbol{P}_{i,t}\boldsymbol{\varphi} + \theta_t + \delta_i + \eta_{i,t} \tag{1}$$

where α_1 is the parameter of interest and measures the difference in PM_{10} concentrations between non-attainment and attainment counties. Formally, α_1 represents the average treatment effect of attainment status in non-attainment counties, and is given by:

$$\alpha_1 = \mathrm{E}\left[Y^j_{i,t}|D_{j,t}=1;\boldsymbol{X}_{j,t},\boldsymbol{P}_{i,t}\right] - \mathrm{E}\left[Y^j_{i,t}|D_{j,t}=0;\boldsymbol{X}_{j,t},\boldsymbol{P}_{i,t}\right]$$

where $\boldsymbol{X}_{j,t}$ is a vector of controls, which vary over time at the county level. These include non-attainment status of monitors in county j for other criteria pollutants (i.e TSP, NOx, SOx and Ozone) in the same year that $D_{j,t}$ is measured, as well as county-level measures of income, population and employment. $\boldsymbol{P}_{i,t}$ is a vector of controls, which vary at the monitor level. In this paper we include rainfall and temperature at the monitor level, as described in the data section. θ_t is a year fixed effect that is common to monitors located in attainment and non-attainment counties, δ_i is a monitor fixed effect that controls for monitor specific unobservables that are invariant over time and $\eta_{i,t}$ is the idiosyncratic unobserved error component. As is standard in the literature, we estimate model (1) in first differences, which eliminates the monitor fixed effects:

$$\Delta Y^j_{i,t} = \alpha_1 \Delta D_{j,t} + \Delta \boldsymbol{X}_{j,t}\boldsymbol{\beta} + \Delta \boldsymbol{P}_{i,t}\boldsymbol{\varphi} + \theta_t + \Delta\eta_{i,t}. \tag{2}$$

From an estimation point of view, a specification in differences is conservative, since we remove monitors which only have single years satisfying the EPA criteria. Differencing effectively limits us to sites which report at least two adjacent years of data. The model described by equation (1) is appropriate to measure the average effect of attainment status on the average PM_{10} county concentrations. However, it does not allow us to disentangle the potential differential impact of the non-attainment status on the three types of monitors of interest. We define a variable $OOC_{i,t}$, which is equal to one if monitor i had a recorded year t mean annual concentration greater than the federal standard of $50\mu g/m^3$ and zero otherwise. We estimate two augmented specifications below, which allow us to test for heterogeneous treatment effects at the three types of monitors:

$$\begin{aligned}\Delta Y^j_{i,t} &= \alpha_1 \Delta D_{j,t} + \alpha_2 \Delta D_{j,t}\cdot OOC_{i,t-1} + \Delta \boldsymbol{X}_{j,t}\boldsymbol{\beta} + \Delta \boldsymbol{P}_{i,t}\boldsymbol{\varphi} + \theta_t + \Delta\eta_{i,t}, &(3)\\ \Delta Y^j_{i,t} &= \alpha_1 \Delta D_{j,t} + \alpha_2 \Delta D_{j,t}\cdot OOC_{i,t-1} + \alpha_3 \Delta(1-D_{j,t})\cdot OOC_{i,t-1} + &(4)\end{aligned}$$

$$\Delta \boldsymbol{X}_{j,t}\boldsymbol{\beta} + \Delta \boldsymbol{P}_{i,t}\boldsymbol{\varphi} + \theta_t + \Delta\eta_{i,t}.$$

The coefficient interpretation for α_1 in equation (3) remains the same as in the standard model given by equation (2). It captures the average change in concentrations at monitors in non-attainment counties. α_2 captures the average drop in concentrations at monitors which exceeded the federal standard and are located in non-attainment counties. One could regard this as a treatment of having exceeded the standard in a previous period. This specification only allows regulation to affect ambient concentrations in non-attainment counties - albeit differentially for monitors in and not in violation of the federal standard. We include $OOC_{i,t-1}$ as a lag in levels since non-attainment designation is based on concentrations in the past. Since the relevant unit of measurement is average concentrations over a calendar year, regulators will take action if they observe that the criterion for regulatory action is exceeded. Regulatory action will affect ambient concentrations with a lag, since air quality managers do not directly control emissions sources. As a robustness check consistent with [11], we also ran our models including $D_{j,t-1}$ instead of $D_{j,t}$ and the results are virtually identical.

In equation (4) we allow for a heterogenous impact of regulation on concentrations. The coefficient interpretation for α_1 captures the drop in concentrations at monitors not-in violation of the standard in counties which are designated as being out of attainment. α_2 captures the average drop in concentrations at monitors which have exceeded the federal standard in these non-attainment counties. α_3 captures the average drop in concentrations at monitors which have exceeded the federal standard yet are located in attainment counties. A county can be in attainment even if a single monitor was in violation of the federal standard in the previous year since non-attainment designation is based on a three-year average, not a single year.

If the CAAAs did indeed not have an effect on ambient concentrations, we would expect all $\boldsymbol{\alpha}$ parameters to be statistically insignificant. However, a finding of $\alpha_1 < 0$ would imply that local regulators targeted all monitors in non-attainment counties, regardless of whether a specific monitor location was in violation of the federal standard or not. A finding of $\alpha_2 < 0$ would suggest that non-attainment status designation led to decreases in ambient concentrations at monitors in violation of the standard in the previous period. A finding of $\alpha_3 < 0$ would suggest that there was a reduction in ambient concentrations at violating monitors in attainment counties following an exceedance of the federal standard. This outcome would suggest that the CAAAs do not only work through the actual designation yet also through the threat of future non-attainment designation. Finally, it is not just the absolute but also the relative magnitude of the coefficients. Specifically, a finding of $\alpha_2 < \alpha_1$ would suggest that regulators focus more on the dirtiest monitors to reach attainment (since these are expected to be negative). A finding of $\alpha_2 < \alpha_3$ would suggest that regulators engage in higher effort when the costs of regulation are highest since they are being forced to take actions to return to attainment status through the State Implementation Plan.

5. Results

Table II displays the central results from the estimation conducted in differences. The entries are the parameter estimates and their estimated standard errors in parentheses, which are calculated using a covariance matrix clustered at the county level.[8] In all models we control for income, February and July temperature and precipitation non-linearly as quadratics. In addition, as in [9], we control for annual county population and employment.[9]

Model (1) provides the estimates for equation (2). The key finding from the first specification is that, after controlling for weather and socioeconomic characteristics as well time invariant unobservables at the monitor level, the county non-attainment designation does not explain a statistically significant share of the variation in PM_{10} concentrations. In fact, the point estimate of the coefficient is an increase in ambient concentrations of 0.173 $\mu g/m^3$, yet this is not statistically different from zero.

Once we estimate the augmented specification given in equation (3), we show that the significance and magnitude of the parameter estimate for α_1 does not change, yet the coefficient estimate for α_2 is large and statistically different from zero at the 1% level. The interpretation of this point estimate is that ambient concentrations at monitors, which have recorded concentrations above the 50 $\mu g/m^3$ annual standard, have experienced a drop in concentrations of 5.43 $\mu g/m^3$ relative to compliant monitors in non-attainment counties, which is equivalent to an 8.9% decrease. This point estimate leads us to believe that the CAAAs did have a significant effect on concentrations at monitor locations with recorded ambient concentrations above 50 $\mu g/m^3$ in non-attainment counties.

Model (3) includes a dummy for monitors having recorded an annual average concentration in excess of the annual standard during the previous period and being located in an attainment county. The reason a monitor can have recorded concentrations in violation of the standard for a given year and the county still being in attainment in the next period, is that non-attainment designation is based on a three-year average, not a single year. The coefficient estimate for the parameter α_3 is large, negative and statistically different from zero. The point estimate indicates that ambient concentrations at monitors, that are located in counties not in violation of the national standard but are still above the 50 $\mu g/m^3$ national standard for non-attainment, have experienced a drop in concentrations of 7.19 $\mu g/m^3$. The coefficient estimate for α_2 remains almost unchanged. While we fail to reject the null of $\alpha_2 = \alpha_3$ in this model, we note that the point estimate for dirty monitors in attainment counties is a larger negative number than for the non-attainment counties.[10]

Models (1) - (3) control for year and monitor specific unobservables. Models (4) - (6) add monitor specific time trends to the model, which allows for differential trends in the unobservables at the monitor level. The results are even stronger for these models. The estimated treatment effects increase by roughly 1-2 $\mu g/m^3$, suggesting that concentrations at monitors with concentrations higher than the federal annual standard dropped by 7.57 and 8.11 $\mu g/m^3$ in non-attainment and attainment counties respectively.

We interpret these empirical results as being consistent with regulators taking strong action at locations, which are out of attainment with a national standard. As outlined in section 2.2, the motivation in non-attainment counties comes from being obligated to undertake measures to bring all monitors in a county back into attainment. The motivation for air quality managers in attainment counties is to prevent the future costs of being designated as non attainment.

The treatment effect so far has assumed a discrete threshold at the federal standard. One could build an argument that there is a stronger regulatory response at monitors far above the standard. We conduct the following two step experiment, which allows for a flexible functional form of the response. The first step of the experiment sets the threshold for defining $OOC_{i,t}$ at a value ϕ ranging from 10$\mu g/m^3$ to 75 $\mu g/m^3$. For each value of ϕ we estimate equation (4) and record our estimates for α_2 and α_3 as well as their estimated standard errors. Figure (4)plots the point estimates and 90%

confidence interval for the estimated α_2 and α_3 for each value ϕ. The plot shows a small negative effect at low cutoff levels, yet the magnitude of the effect grows drastically as we let the cutoff value increase. Testing for non-linearities, we cannot conclusively favor a linear versus an exponential fit, yet it is clear that air quality managers take stronger actions at higher levels of ambient concentrations. Further, the shape of the curve is not qualitatively different for attainment versus non-attainment counties. It is quite apparent from both plots that the dirtier the monitor, the larger the response.

The results so far have focused on explaining impacts of regulation on annual average concentrations. Counties can be designated as being out of attainment by violating the daily standard as well. We therefore estimate the same class of models, but using the number of days each monitor is in violation of the daily standard as the dependent variable. As in the previous specifications, we use county non-attainment status as our pooled measure of treatment. We then relax the pooled treatment assumption by estimating separate treatment effects for monitors which were in violation of the daily standard in the previous period for both attainment and non-attainment counties. Specifically, OOC_{t-1} is now defined according to whether the monitor violated the daily standard in the previous period. Table III lists the results, which are qualitatively identical to those shown in Table II. County non-attainment status does not have a statistically detectable effect on the number of daily violations. However, monitors which had violated the standard in previous periods did experience a drop of 3.05 days for non-attainment counties and a drop of 2.17 days for counties in attainment. This suggests again, that regulation affects both types of counties at the monitors in violation of the federal standard.

In order to check for robustness of our results, we conduct two additional estimations. First, we exclude the years after $PM_{2.5}$ was moved into regulatory focus. While all $PM_{2.5}$ is also PM_{10}, the reverse is not true. Table IV shows these results in columns (1) - (3). The results are almost identical to those presented in Table II. Next we acknowledge California's long history of stringent air quality regulation. While California is subject to the same federal standards, it has developed quite effective air quality regulatory institutions, such as the California Air Resources Board and the Air Quality Management Districts. These institutions have pioneered implementation of many regulatory tools, such as the RECLAIM program. Southern California also has historically suffered from the worst air quality in the nation. In order to ensure that California is not driving our results, we exclude

California monitors from our sample and rerun the models including monitor specific time trends. Models (4)-(6) in Table IV show these results. Again, these results are almost identical to those shown in Table II reaffirming our confidence in the robustness of our results.

Finally we wanted to examine what we gain from using the monitor specific weather observations. Existing models in the literature have historically used weather measured at the county level. In order to determine what we gain from using monitor level weather data, we conduct the following experiment. We estimate model (6) from Table II without the weather variables. We then construct "county-weather" observations by averaging each weather observation across monitors within a given county. We then compare these estimated treatment effect parameters to the ones obtained in model (6) from Table II. The estimated coefficients on the α parameters, which for space reasons are not shown here, are almost identical across all three specifications. Introducing weather results in slightly smaller point estimates on the treatment effects. The $\boldsymbol{\alpha}$ coefficients for the county and monitor weather specifications are identical to the second decimal. We also calculate the marginal effect for each observation for February and July temperature as well as rainfall. We compare these estimated marginal effects to the ones obtained from model (6). We find an almost perfect correlation between the marginal effects from each approach. The smallest of the three Pearson correlation coefficients is 0.9932. This is an encouraging result, reassuring us that the use of county averaged weather data does not seem to introduce bias in the estimated coefficients in previous studies.

6. Conclusions

This study contributes to the literature on the effects of environmental regulation (e.g. [9, 11]) by testing whether the decline in PM_{10} concentrations between 1990 and 2005 can be attributed to the 1990 CAAAs. A central point of this work was to stress the importance of spatially disaggregated analysis motivated by a non-linear dose-response function between mortality and PM_{10} or the monitor specificity of the federal regulation.

We have conducted our analysis at the monitor level and allowed the regulation to have a differential impact on concentrations measured at the monitoring site depending whether a monitor recorded concentrations in violation of the national standard and whether a monitor is located in a county designated as non-attainment. In addition to controlling for the standard determinants of criteria pollutants changes, we use a novel weather data set, which allows us to construct weather observations at the pollution monitor location.

Our key finding reveals the importance of spatially disaggregated analysis in order to properly assess the effects of environmental regulations. First, we estimate a pooled treatment effect, which captures the average drop in concentrations due to non-attainment designation across all monitors in a county. For this specification we fail to reject the null hypothesis of no effect. When we allow for an interaction between non-attainment designation and lagged exceedance of the national standard, we find a statistically significant and sizeable effect. This heterogenous treatment effect suggests a potential distributional impact of federal environmental regulations, by creating incentives for local environmental regulators to target the dirtiest areas. Extending the specification, we find an identical effect for monitors exceeding the national standard in the previous period in attainment counties. The magnitude of the estimated effect ranges between 11% and 14%, which is similar to the effect estimated for TSPs in the 1970s [2, 3]. Further, using a flexible functional form, we show that reductions in ambient concentrations at dirtier monitors do not only occur right at the regulatory threshold concentrations, but they are continuous starting at very low concentrations.

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Notes

[1]Conversations with local air quality managers confirm that special attention is paid to monitors with recorded concentrations above the federal standard, regardless of county attainment status.

[2]The concentrations examined are second highest daily maximum concentration, mean annual reading, median of daily maximum July and mean July reading. The mean July reading is significant at the 10% level.

[3]For a concise analysis of the health effects from exposure to PM_{10}, see [5, 7, 10]. For an analysis of the impact of air pollution on infant health, see [2, 4].

[4]In the AQS data, a criteria flag is set based on data completeness criteria so that if it is set to "Y", then the assumption can be made that the data represent the sampling period of the year. These summary criteria are based on 75% or greater data capture and data reported for all 4 calendar quarters in each year. EPA confirms that we are using the correct sample of monitor readings.

[5]We exclude monitors located in Puerto Rico as well as monitor year observations, which are flagged as observations tainted by "extreme natural events" beyond human influence.

[6]In 1997 the EPA began to regulate fine particulates. Non-attainment designations for fine particulates were first assigned in 2005. We further do not control for lead non-attainment status.

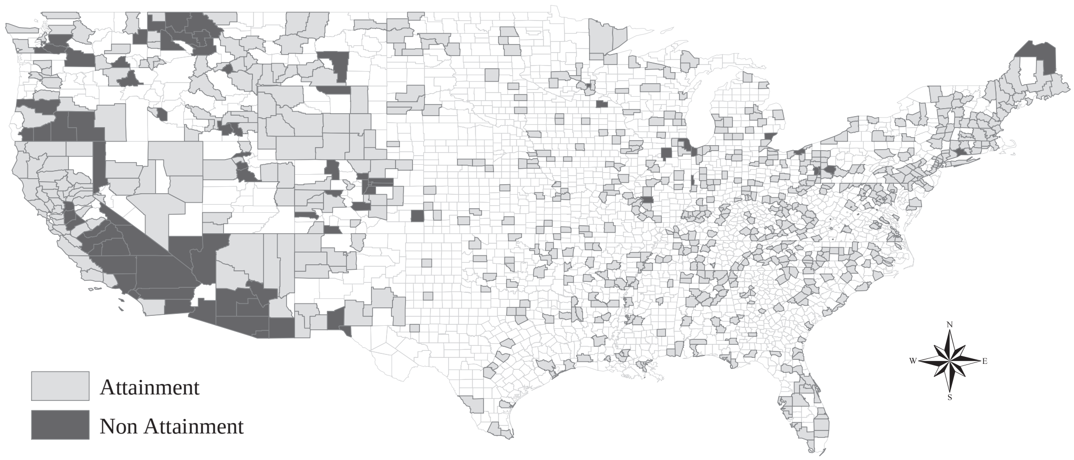
[7]As a replication of EPA's non-attainment designations, we ran a logit of the 1990 non-attainment designation on an indicator of whether the three year moving average was in violation of the annual standard and an indicator of 24-hour standard violations. As we would expect, a violation of the daily standard and a violation of the annual standard result in equal increases in the probability of being designated as non-attainment. We correctly classified 89.41% of the observations based on this regression, which we interpret as a sign of adequate data quality. [9] also notes having problems replicating the attainment status designation perfectly. The reason we may not be able to replicate the attainment assignment perfectly, may be due to the fact that attainment status is assigned based on measured and modeled air quality concentrations. We could not gain access to the modeled data from the EPA.

[8]We also estimated the covariance matrix by clustering at the monitor level and the results are almost identical.

[9][11] controls for the number of polluting facilities at the county level. We do not have access to the confidential PACE survey data, so cannot control for this. Since we show that the CAAAs work on dirty monitors in both attainment and non-attainment counties, concerns about bias here are not warranted.

[10]While this difference is not statistically significant, one referee raised the concern that these point estimates may be due to "other trends in PM regulation that only hit the dirtiest monitors, regardless of attainment status." Since we cannot explicitly test for this, we have run our models by allowing for attainment status specific trends and the results are very similar.

Figure 1: Monitored Counties and Attainment Status



Note: Counties are included in the map if they appear in the data for at least two consecutive years. Counties are shown as non-attainment if they were designated as such for at least one year of our sample.

Figure 2: Trends of Ambient PM_{10} Concentration Levels by Attainment Status

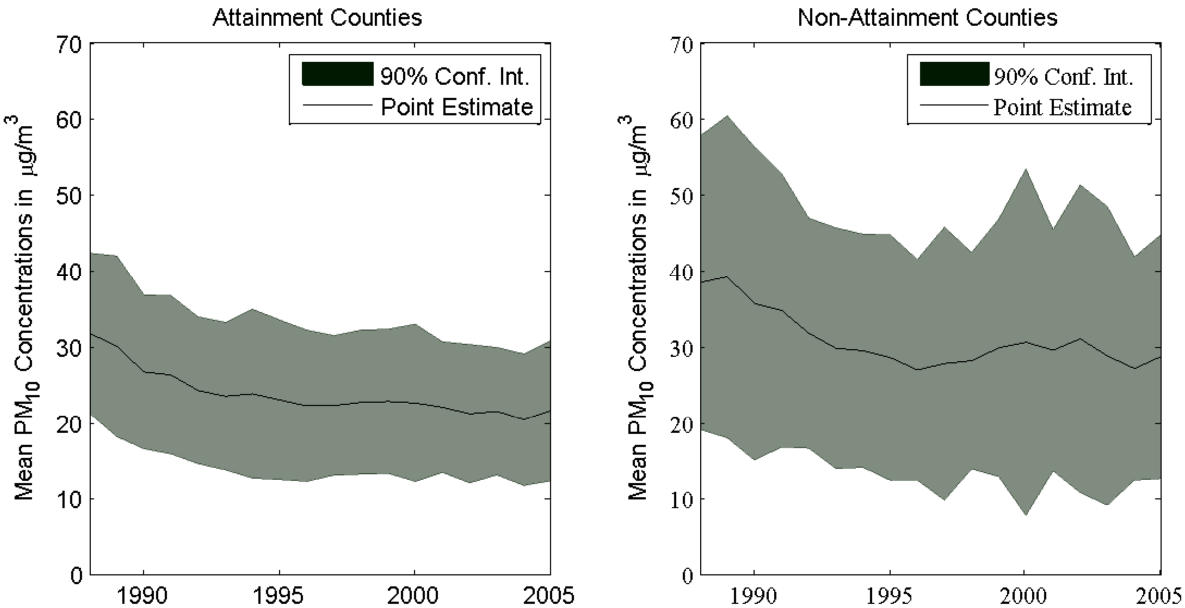


Figure 3: Changes in PM_{10} Concentrations Prior and Post First Non-Attainment Status Designations

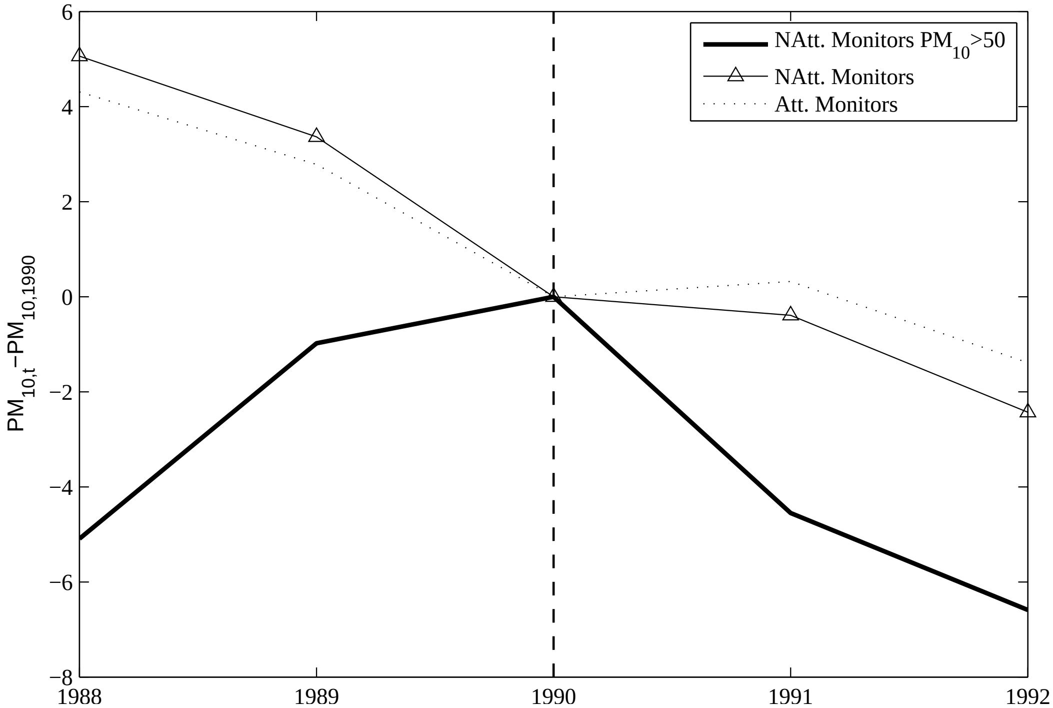
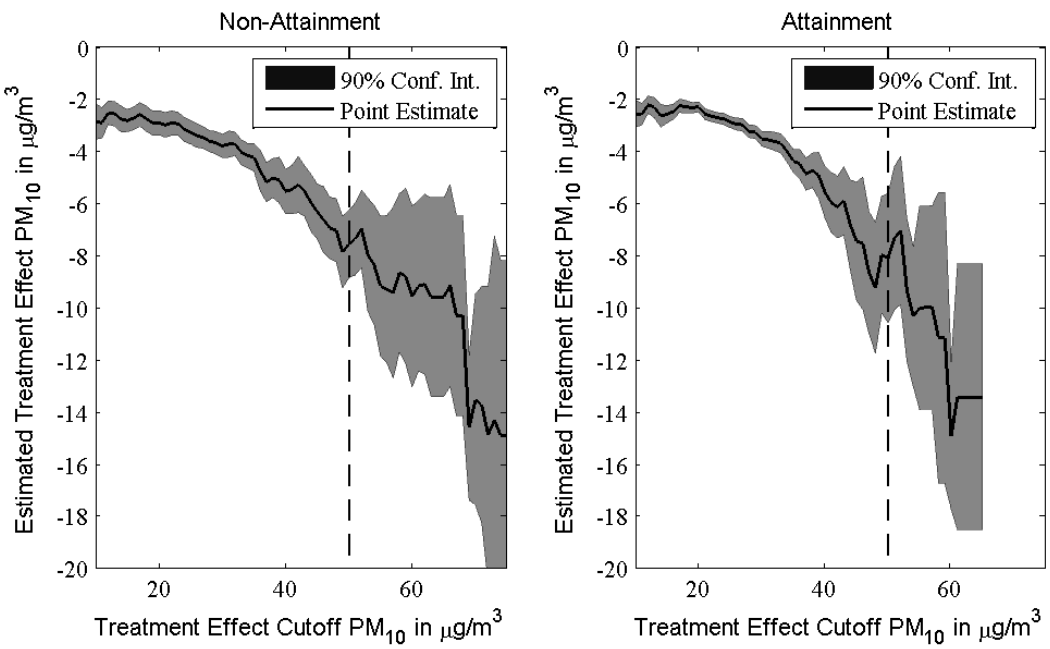


Figure 4: Heterogeneous Treatment Effect for Varying PM_{10} Cutoff Levels



Note: The vertical axis for the left panel shows the estimated coefficient α_2 on the variable $I(PM_{10,t-1} > \phi$ & Non-Attainment) from model (6) in Table II. The vertical axis for the right panel shows the estimated coefficient α_3 on the variable $I(PM_{10,t-1} > \phi$ & Attainment) from model (6) in Table II. The original model (6) fixes ϕ at 50 $\mu g/m^3$. In this figure we vary it from $10\mu g/m^3$ to $75\mu g/m^3$.

Table I: Summary Statistics: Trends in PM_{10} Monitoring and Regulation

(1) Year	(2) Number of Monitors	(3) Number of Counties	(4) Population in Monitored Counties (in millions)	(5) Number of Monitored Non-Attainment Counties	(6) Total Number of Non-Attainment Counties (Δ N.Att/Δ Att.)	(7) Mean Annual Concentrations ($\mu g/m^3$)	(8) Standard Deviation ($\mu g/m^3$)	(9) # of Monitors Exceeding Daily Standard
1988	267	173	81	N/A	N/A	33.94	10.30	N/A
1989	595	307	140	N/A	N/A	32.31	11.67	N/A
1990	781	410	154	64	76 (76/0)	28.43	10.08	59
1991	859	442	158	62	76 (0/0)	27.80	9.43	58
1992	951	458	155	57	76 (0/0)	25.57	8.17	34
1993	1068	515	169	69	77 (1/0)	24.41	8.25	31
1994	1097	517	168	70	83 (6/0)	24.55	8.73	21
1995	1129	539	168	68	82 (1/2)	23.81	8.59	33
1996	1112	531	166	67	80 (0/2)	22.76	7.98	25
1997	1101	543	172	69	78 (0/2)	22.97	8.45	30
1998	815	393	139	64	78 (0/0)	23.53	7.96	22
1999	743	371	135	61	77 (0/1)	23.54	8.78	29
2000	764	378	134	62	70 (0/7)	23.38	10.99	39
2001	765	403	140	52	69 (0/1)	22.47	8.15	24
2002	729	390	133	46	60 (0/9)	21.92	9.75	31
2003	685	362	129	43	56 (0/4)	22.07	8.93	38
2004	762	382	139	49	55 (0/1)	21.03	7.89	28
2005	713	346	132	44	50 (0/5)	22.50	8.67	33

Note: Ambient concentration data were obtained from the Environmental Protection Agency's Air Quality Monitoring System. The attainment status designation was obtained from the corresponding years of the Code of Federal Regulations (CFR). Observations for any given year and monitor were included if the criteria flag was set to yes, which indicates that a monitor is representative and its yearly weighted arithmetic mean is based on a sufficient number of samples taken in each quarter of the year. These observations are used for making attainment status designation decisions.

Table II: Effect of Attainment Status and Lagged Standard Violations on PM_{10} Concentrations.

Regressand: Δ PM_{10}	(1)	(2)	(3)	(4)	(5)	(6)
Non-Attainment (α_1)	0.173	0.177	0.190	0.166	0.213	0.204
	(0.60)	(0.60)	(0.60)	(0.68)	(0.69)	(0.69)
I($PM_{10,t-1}$ >50 & Non-Attainment) (α_2)		-5.435	-5.450		-7.550	-7.567
		(1.00)***	(1.00)***		(0.90)***	(0.90)***
I($PM_{10,t-1}$ >50 & Attainment) (α_3)			-7.191			-8.105
			(1.16)***			(1.70)***
Monitor FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Trends	No	No	No	Yes	Yes	Yes
Monitor Nonlinear Income	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Nonlinear Weather	Yes	Yes	Yes	Yes	Yes	Yes
County Employment	Yes	Yes	Yes	Yes	Yes	Yes
County Population	Yes	Yes	Yes	Yes	Yes	Yes
Other County Attainment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10010	10010	10010	10010	10010	10010
R^2	0.13	0.15	0.16	0.11	0.14	0.15
Monitor Count	1912	1912	1912	1912	1912	1912

Note: Standard errors are in parentheses and are clustered at the county level.
significant at 10%; ** significant at 5%; *** significant at 1%

Table III: Effect of Attainment Status and Lagged Standard Violations on Daily Violations (DVs) PM_{10} Concentrations.

Regressand: Δ Daily Violations (DVs)	(1)	(2)	(3)	(4)	(5)	(6)
Non-Attainment (α_1)	0.043	0.050	0.058	0.038	0.062	0.071
	(0.08)	(0.08)	(0.07)	(0.10)	(0.08)	(0.08)
I(DVs_{t-1} > 1 & Non-Attainment) (α_2)		-2.083	-2.090		-3.081	-3.105
		(0.30)***	(0.30)***		(0.34)***	(0.34)***
I(DVs_{t-1} > 1 & Attainment) (α_3)			-1.939			-2.171
			(0.40)***			(0.29)***
Monitor FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Trends	No	No	No	Yes	Yes	Yes
Monitor Nonlinear Income	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Nonlinear Weather	Yes	Yes	Yes	Yes	Yes	Yes
County Employment	Yes	Yes	Yes	Yes	Yes	Yes
County Population	Yes	Yes	Yes	Yes	Yes	Yes
Other County Attainment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10010	10010	10010	10010	10010	10010
R^2	0.01	0.16	0.2	0.01	0.21	0.24
Monitor Count	1912	1912	1912	1912	1912	1912

Note: Note: Standard errors are in parentheses and are clustered at the county level.
significant at 10%; ** significant at 5%; *** significant at 1%

Table IV: Robustness Checks for Effect of Attainment Status and Lagged Standard Violations on PM_{10} Concentrations: (1) - (3) Subsample Prior to $PM_{2.5}$ Regulation; (4)- (6) Subsample Without California

Regressand: Δ PM_{10}	(1)	(2)	(3)	(4)	(5)	(6)
Non-Attainment (α_1)	-0.247	-0.214	-0.221	0.235	0.295	0.283
	(1.54)	(1.46)	(1.46)	(0.67)	(0.67)	(0.68)
I($PM_{10,t-1}$ >50 & Non-Attainment) (α_2)		-8.149	-8.15		-8.855	-8.86
		(1.26)***	(1.26)***		(1.17)***	(1.18)***
I($PM_{10,t-1}$ >50 & Attainment) (α_3)			-6.98			-8.697
			(1.96)***			(1.96)***
Monitor FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Monitor Trends	Yes	Yes	Yes	Yes	Yes	Yes
Nonlinear Income	Yes	Yes	Yes	Yes	Yes	Yes
Nonlinear Weather	Yes	Yes	Yes	Yes	Yes	Yes
Other Attainment	Yes	Yes	Yes	Yes	Yes	Yes
California Included	Yes	Yes	Yes	No	No	No
Years > 1997 Included	No	No	No	Yes	Yes	Yes
Observations	6157	6157	6157	8867	8867	8867
R^2	0.09	0.11	0.12	0.11	0.13	0.14
Monitor Count	1527	1527	1527	1725	1725	1725

Note: Standard errors are in parentheses and are clustered at the county level.
significant at 10%; ** significant at 5%; *** significant at 1%