Essays on the Health, Wage and Employment Effects of the U.S. Clean Air Act

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Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Economics

May 31, 2020

Nashville, Tennessee

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Acknowledgments

I would like to thank Mark Cohen, who truly shaped this work from beginning to end. His kindness and generosity in always making his time freely available, in encouraging me to invest in building skillsets, to be the best possible researcher I can be have all shaped me. I would also like to thank Kathryn Anderson, who painstakingly went over every word of this dissertation and gave insightful feedback aiming at polishing this study. I would like to thank Kip Viscusi for always being very prompt with his guidance and feedback. I would also like to extend thanks to Matthew Zaragoza-Watkins for helping me brainstorm new ideas and move the work in interesting directions.

I would also like to thank my parents and sister, for their support, both emotional and monetary, throughout the past 7 years. I would not have been able to finish this dissertation without their help. Special thanks to Anisha Krishnan who has helped me in my hour of need throughout the last 7 years. Her confidence in me pushed me to finish and do my best.

Finally, a very big thank you to Samuel Eppink, who has been a wonderful friend, and whose generous support and time has made the past 7 years all the sweeter for having him in it.

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Chapter 1: The Impact of the Clean Air Act Amendment of 1990 on Adult Mortality

1.1 Introduction

The Clean Air Act is widely regarded as the most far-reaching federal initiative undertaken in the United States to combat air pollution. Originally passed in 1963 and amended in 1970, 1977 and 1990, the Act was the first piece of legislation that set mandatory requirements on state and local jurisdictions regarding air quality. The intent was to provide safeguards for public health and public welfare while establishing a minimum level of air quality. The Clean Air Act has been the subject of study in the economic literature for over two decades, with studies examining the economic impact of the Act's requirements as well as the health effects of regulatory actions undertaken to maintain air quality.

This paper makes a number of contributions to the field. While the impact of the Clean Air Act on employment and wages has been the subject of prior study, there are not many economic studies on the impact of the Amendments on mortality. To date there has been only one well-known paper examining the impact of the Clean Air Act on adult mortality (Chay et al. (2003)). The authors used the 1970 Amendment to the Clean Air Act as an instrumental variable to capture variation in pollution and the effects of this pollution on adult mortality. No paper to the best of my knowledge has studied the impact of the 1990 Amendment (the most recent Amendment) on (adult) mortality. This is an important gap in the literature as the 1990 Amendment represented a huge expansion of federal authority in the way air pollution was measured, monitored and regulated. Compared to the 1970

Amendment the 1990 Amendment made allowances for gradations of nonattainment when counties were in nonattainment of federal emissions standards. Accordingly the regulatory enforcement measures were delineated according to these gradations. There is thus a need in the literature to study the impact of the most recent federal Amendment governing air pollution. The final report published by the U.S. Environmental Protection Agency in 2011 on the benefits and costs of the 1990 Amendment estimated that in 2020 230,000 deaths would have been avoided thanks to the 1990 Amendment-related ozone and particulate matter reductions, valued at $1.8 trillion in 2006 dollars. Whether these estimates are confirmed in actuality is the subject of study of this paper. Accordingly, I look at how ozone and particulate matter nonattainment designations affect adult mortality rates.

Second, this paper is one of the first in the economic literature to consider age-adjusted mortality rates in the analysis of the impact of the Clean Air Act on mortality. While this practice is common in epidemiology, in the economic literature examining the impact of the Clean Air Act this has not been the case. Any study examining adult mortality that does not use age-adjusted rates runs into the risk of overstating the importance of certain subpopulations. For example, an analysis comparing the effect of a policy on crude death rates in Iowa and Florida may conclude that the policy had a much larger impact in Florida than Iowa. However this does not necessarily need to be the case, as it could be that the larger effect could be attributed to the population distribution in Florida being primarily skewed towards older individuals. Using an age-adjusted mortality rate thus ensures that the underlying age distribution of the population is appropriately weighted in the construction of the death rate. Chay et al. (2003) use crude death rates in their study and found that there were no significant effects of the 1970 Amendment on adult mortality. As I show in this paper the use of age-adjusted mortality rates instead of crude mortality rates makes an appreciable difference. I find that using crude death rates tends to underestimate the effects of air pollution intervention.

Third, it is the first paper to undertake a difference-in-difference approach to modelling the effects of the Clean Air Act Amendment of 1990 on adult mortality. The results of Chay et al. (2003) showed that the Clean Air Act did not have a significant impact on adult mortality. However as the authors pointed out, there were appreciable differences between nonattainment and attainment counties that rendered the validity of those results suspect. This paper considers a sample of counties where the counties that attain these pollution standards ("attainment counties") are very similar in observable characteristics to counties that do not attain these standards ("nonattainment counties"). I also find that nonattainment designations for ozone and particulate matter each had a highly statistically significant impact on adult mortality, with the effects ranging from 9.4% to 14.2%.

Lastly, the results shown by this paper suggest that the EPA's estimates of the health benefits attributable to the Clean Air Act are most likely overestimated. By directly examining the impact of the 1990 Amendment on mortality measures I show that while substantial gains have been made in the field of health through reductions in mortality rates, the value of these gains is, as of 2016, around a third of that hypothesized by the E.P.A. Summing up the value of lives saved due to ozone and particulate matter regulation I find that nearly $513 billion accrued in terms of health benefits directly from the ozone and particulate matter provisions of the Act. Assuming the costs of ozone and particulate matter compliance estimated in the 2011 E.P.A. report are reasonably accurate at $5.1 billion the 1990 Amendment-related National Ambient Air Quality Standards program (described in detail in section 2.2) still comes out ahead as a worthy investment. This is an important point in light of the loosening of air quality restrictions by the current E.P.A. administration, as in order to attain the benefits hypothesized by the 2011 study there is still a long road to go as far as pollution reductions are concerned.

The following sections discuss the history of the Act, the federal air quality standards set forth by the requirements of the Act, the mechanisms for mortality due to pollutant exposure, the empirical model, the data used in this paper, and the results before concluding.

1.2 The Clean Air Act

1.2.1 History

Federal efforts to curb air pollution did not play much of a role in pollution reductions prior to 1970 as this was mainly left as falling within states' purview. Without a federal framework federal sanctions were rarely enforced on polluters within states. In order to combat the prevalent high levels of carbon monoxide, sulfur dioxide, ozone and total suspended particulates the 1970 Clean Air Act was passed. The aim of the Act was to safeguard public health from polluting emissions by placing limits on the total ambient concentrations of key pollutants. The EPA was empowered by the Act to establish threshold national standards for maintaining air quality while requiring states to ensure compliance with these national standards. The 1977 Amendment to the Clean Air Act also required the EPA to annually assign attainment or nonattainment of standards status to each county for each criteria air pollutant on the basis of the ambient concentrations of the relevant pollutant in the county.

The law required states to develop local regulations for nonattainment counties so as to reduce point sources of pollution locally. These regulations governed both investments in pollution reduction technology by new or existing plants as well as the maximum allowable pollution limits detailed in permits. The Clean Air Act required that firms located in nonattainment counties had to achieve "lowest achievable emission rates" (LAER) technology without allowing for cost considerations. The 1990 Amendment also stipulated that increased emissions from new plants required offsets as well as limits at the individual firm level. In contrast attainment counties had to achieve "best available control technology" for large plants. Pollution reduction is therefore much less costly for large investments.

Increased emissions are not required to be offset. Nonattainment counties therefore enjoy wide restrictions compared to their counterparts who are in attainment (Greenstone (2002)).

The Amendment also stated that when a county is in nonattainment status for a criteria air pollutant the corresponding state is required by the EPA to enforce what is known as state implementation plans (SIPs) in order to ensure county compliance. SIPs are developed on the basis of inventories of emissions as well as computer models in order to determine whether violations of air quality standards will occur. The 1990 Clean Air Act Amendment requires the EPA to enforce sanctions in areas which do not submit an SIP, fail to submit an adequate SIP or fail to implement a SIP. If the state does not undertake adequate measures a 2-to-1 emissions offset for the construction of new polluting sources is imposed 18 months after notifying the state. This is accompanied by a ban on new federal highway grants, which is imposed 6 months later. It is up to the discretion of the EPA on whether to impose an air quality grant. If the state fails to submit and enforce an adequate SIP a federal implementation plan may be imposed.

1.2.2 National Ambient Air Quality Standards

Regarding air pollutants whose ambient concentrations result from a wide variety of sources the Clean Air Act required the EPA to establish National Ambient Air Quality Standards (NAAQS) to protect public health. With this directive the EPA created NAAQS for the following air pollutants: sulfur dioxide (SO_2), carbon monoxide (CO), ozone, nitrogen dioxide (NO_2), lead (Pb) and particulate matter ($PM_{2.5}$ and PM_{10}).

These standards are generally classified as primary and secondary standards. Primary NAAQS are set to protect public health, while secondary NAAQS are aimed at safeguarding public welfare, which includes tackling issues of visibility, damage to crops, vegetation, animals or buildings. Primary standards are designed to protect the health of at-risk populations with a reasonable margin of safety. The requirements of the Clean Air Act do not state that these air quality standards should be established at a zero-risk level, but instead at a level where the risk is sufficiently reduced so that public health is protected with a reasonable margin of safety. These margins are developed on the basis of criteria such as the strength of the scientific evidence and associated uncertainties, the type and degree of the effects of the air pollutant on health, the population size that is at risk and the threshold levels below which there are no health effects. The scientific literature so far has not provided any evidence of such thresholds for criteria air pollutants. EPA reviews, in particular, pay attention to the exposure and related health risks of vulnerable populations.

The Clean Air Act requires that the EPA conduct periodic reviews of the literature on the health and welfare effects of criteria air pollutants on a comprehensive basis. Such reviews provide the framework for the decision to retain or revise the federal air quality standards that specify the maximum allowable concentration of these criteria air pollutants. It was stated in the legislation that these standards must be reviewed and revised, if necessary, every five years. In practice the EPA has been sporadic in reviewing updates to scientific data and revising standards [1].

The initial deadline as postulated by the 1970 Clean Air Act required that the NAAQS

[1]Primary and secondary standards for carbon monoxide were established in 1971. In 1985 secondary standards for CO were revoked while primary standards were retained, as they were in 1994 and 2011 without revision.
For lead, primary and secondary standards were established in 1978, and both these standards were revised in 2008, and this revision was retained in 2016.
Both 24-hour and annual averaging primary and secondary standards for particulate matter were established in 1971. In 1987 standards for particulate matter were divided into separate sets of standards for PM_{10} and $PM_{2.5}$. Both sets of standards were revised in 1997, 2006 and 2012.
Sulfur dioxide had 24-hour and annual averaging primary standards and 3-hour and annual averaging secondary standards in 1971. These standards were partly revoked in 1973 and revised in 2010. Both secondary and primary standards were reviewed in 2012 and 2019 but without revision.
Ozone standards saw the highest number of revisions after 1971 (when primary and secondary standards were first established). Standards were revised in 1979, 1997, 2008 and 2015.

be attained by 1977. In practice, however, states found great difficulty in achieving this objective and so the deadline for attaining NAAQS was extended. This deadline has been further extended a few times, with the 1990 Amendment to the Clean Air Act stating that states which have not attained NAAQS must develop a compliance schedule which takes into account the difficulty of achieving the standards.

1.3 Mechanisms for Mortality

In this section I summarize the health effects of both particulate matter as well as ozone.

1.3.1 Particulate matter

A broad class of discrete particles (be they liquids or solids) are generically referred to as particulate matter. These particles comprise substances that vary widely in terms of chemical formulation and nature. The origin of these particles may be natural (as in the case of wildfires) or may stem from man-made sources (both stationary and mobile). In addition to direct emissions these particles may also be formed by atmospheric transformations of sulfur oxides, nitrogen oxides and volatile organic compounds. The EPA differentiates between particles on the basis of size by establishing standards for fine and coarse particles. PM_{10} is used to refer to coarse or thoracic particles, i.e. particles small enough to deeply penetrate the lungs when inhaled. In technical terms this refers to particles with an aerodynamic diameter of less than or equal to 10 micrometers (μm) [2]. $PM_{2.5}$ refers to fine particles, particles with an aerodynamic diameter of less than 2.5 μm. The EPA established standards for PM_{10} is 1987 and established standards for $PM_{2.5}$ in 1997.

There is scientific evidence supporting the harmful nature of both categories of particles, though the effects are much more pronounced for fine particles than for thoracic coarse particles. There are several serious effects associated with both short and long-term exposure

[2]For comparison, the size of a PM_{10} particle is about 1/7th the size of an average human hair.

to particulate matter. These include an exacerbation of respiratory and cardiovascular disease (as evidenced by a higher number of visits to hospitals and emergency departments), significant alterations in clinical and sub-clinical indicators of respiratory and premature mortality (U.S. EPA Report, 2009). $PM_{2.5}$ in particular is responsible for aggravation of allergies and respiratory symptoms and decreased lung functioning. Vulnerable populations include children, older adults, individuals with preexisting heart disease and lung problems (including asthma). Individuals with low socioeconomic status are particularly prone to ill effects from exposure to particulate matter (U.S. EPA Report, 2009).

There is considerable epidemiological evidence for the casual link between long-term $PM_{2.5}$ exposure and increased risk of mortality. The strongest evidence has been found for the relationship between exposure to $PM_{2.5}$ and cardiovascular mortality (Eftim et al 2009). There is also documented evidence of the relationship between $PM_{2.5}$ and lung cancer mortality (Dockery et al 1993). Overall, the consensus appears to be that there exists a causal relationship between long-term exposure to particulate matter and mortality.

1.3.2 Ozone

Unlike the stratospheric ozone layer that protects the earth from injurious ultraviolet radiation from the sun, ground-level ozone can have harmful effects on human health. Even short-term exposure can create problems such as cough, chest pain, burning in the chest, shortness of breath, wheezing, reduced lung function and inflammation of the lining of the lungs. Exposure can also aggravate vulnerability to respiratory infection. Ambient ozone has been related to exacerbation of asthma, emphysema and bronchitis, leading to secondary outcomes such as increased doctor and emergency department visits and hospital admissions. Permanent tissue damage from long-term exposure to ozone is possible, especially to the lungs.

Lipfert et al. (2000) found significant positive effects on mortality for people exposed to peak ozone concentrations (95th percentile). Smith et al. (2009) found weak evidence for a causal relationship between ozone concentrations and cardiopulmonary mortality while Jarrett et al. (2009) found an association between long-term ozone exposure and respiratory mortality. A recent study of several cohorts of Medicare recipients found evidence of an association between ozone exposure and total mortality in each cohort (Zanobetti and Schwartz, 2011).

1.4 Literature Review

While there have been several scientific studies that modeled the impact of the emissions reductions propelled by the Clean Air Act and its amendments on mortality, so far there have only been a few economic studies of the direct link between the passage of the Clean Air Act and mortality. The majority of these papers look at the relationship between air pollution (and relatedly the Clean Air Act) and infant mortality, as infants are considered particularly susceptible to the health effects of criteria air pollutants. Until now there has only been one economic study that considered the impact of the Clean Air Act on adult mortality (Chay et al. (2003)).

Chay and Greenstone (2003a) used an exogeneous event that was responsible for stark differences in air pollution across counties to study the impact of air pollution on infant mortality: the 1981-'82 recession which caused variation in pollution from 1980 to 1982. This recession induced sharp decreases in particulate matter concentrations in highly industrialized areas (due to shutdown of manufacturing plants, for example). The study found that a decrease in air pollution by 1 mg/m^3 resulted in roughly 4-8 fewer infant deaths per 100,000 live births. The study did not address the impact of the Clean Air Act on infant deaths.

Chay and Greenstone (2003b) study the impact of reductions in total suspended particulates induced by the Clean Air Act Amendment of 1970 on infant mortality. They use the nonattainment designation of counties as an instrument for air pollution in order to estimate its impact on infant mortality in the first year of the regulation. They find that not only does the regulation based on nonattainment status reduce air pollution, it also leads to sharp reductions in infant mortality from 1971 to 1972. They find that a 1% decline in suspended particulates leads to a 0.5% decrease in infant mortality rates. These results are robust to a variety of validity tests. According to their estimation, approximately 1,300 fewer infants died in 1972 than would have been the case if the Amendment had not passed.

Chay, Dobkin and Greenstone (2003) study the impact of the Clean Air Act of 1970 on adult and elderly mortality. Since air pollution can be correlated with economic conditions that may also affect health conditions, Chay, Dobkin and Greenstone (2003) use the exogeneous variation offered by the annual change in total suspended particulate matter due to the passage of the Clean Air Act Amendment of 1970 as an instrument for air pollution. The 1970 Amendment designated counties as being in nonattainment of federally mandated air quality standards for particulate matter if the average annual ambient concentration of suspended particles exceeded federal standards in these counties.

The authors compare changes in mortality rates across attainment and nonattainment counties in the first year the CAAA was in effect. As counties were divided into attainment and nonattainment categories based on their pollution levels Chay, Dobkin and Greenstone (2003) contend that the research has the potential to reduce omitted variable bias where unobservables affecting pollution . The results show that the Clean Air Act Amendment of 1970 significantly reduced concentrations of particulate matter in nonattainment counties. This effect however did not translate into reductions in adult and elderly mortality rates in nonattainment counties. Their results suggest that the Clean Air Act Amendment did not lead to any improvements in adult or elderly mortality.

As Chay Dobkin and Greenstone (2003) point out in their discussion, their data however did not balance the observable covariates in attainment and nonattainment counties. A glance at the observable characteristics show that attainment and nonattainment counties are systematically different. There is a significant difference in the age distribution of the counties which is problematic since the correlation between age and mortality is high. This means that the model is likely to be biased as it can mistakenly attribute effects to the policy that in fact result from changes in the underlying age composition of the population. The differences in pre-trends between attainment and nonattainment counties therefore suggests that the results are not very convincing. The null results on adult and elderly mortality must therefore be interpreted with caution. In defense of Chay and Greenstone, they consider the 1970 Clean Air Act Amendment, which would have been very early in the history of nonattainment designation. I consider the 1990 Amendment instead of the 1970 amendment, where the regulation-imposed requirements for nonattainment counties became much more stringent.

1.5 Research Design

My empirical design is based on the model used in Chay and Greenstone (2003a). Chay and Greenstone (2003a) adopt the following model to describe the relationship between mortality and air pollution:

$$Y_{ct} = X'_{ct}\beta + \gamma TSP_{ct} + \epsilon_{ct} \tag{1.1}$$

$$TSP_{ct} = X'_{ct}\Pi_X + \eta_{ct} \tag{1.2}$$

Y_{ct} represents adult mortality and TSP_{ct} is the mean concentration of air pollution in county c in year t. X_{ct} is a vector of demographic and socio-economic characteristics of county$c$ in year t. For the OLS estimator of γ to be unbiased the $E[\epsilon_{ct}\eta_{ct}] = 0$. That is, the unobserved shocks to air pollution levels must be uncorrelated with unobservables in the adult mortality rates. This requirement is unlikely to be met owing to the high correlation between air pollution and mortality rates.

Chay and Greenstone (2003a) next consider an instrumental variable Z_c that affects changes in air pollution without having a direct impact on adult mortality rates. An instrumental variable is necessary because pollution is frequently an endogeneous variable. For example higher pollution levels are associated with higher mortality rates. At the same time, disadvantaged communities that suffer higher mortality rates may have lower property values, causing polluting firms to locate in these communities. Utilizing an instrumental variable would remove the bias emerging from correlation between the error terms of equations (1) and (2). Chay and Greenstone (2003a) use the 1970 Clean Air Act regulation regarding total suspended particulates as an instrument. They use nonattainment designations decreed by the 1970 Amendment as the instrumental variable. I estimate a similar model and use the 1990 Clean Air Act Amendment-related attainment and nonattainment designations of counties as an instrument. The instrumental variable takes a value of 1 if the county is in nonattainment and 0 if it is in attainment. So then we have:

$$TSP_{ct} = X'_{ct}\Pi_X + Z_{c1990}\Pi_Z + \eta_{ct} \tag{1.3}$$

$$Z_{c1990} = 1(TSP_{ct} > \bar{T}) \tag{1.4}$$

Z_{c1990} is the nonattainment status of county c as specified by the 1990 regulation. 1[.] is an indicator function that takes the value of 1 if a county's mean concentration of an air pollutant is greater than the maximum allowable concentration of the air pollutant as specified by the 1990 policy.

In order to obtain a consistent estimate of γ we require two sufficient conditions to be satisfied: (1) $\Pi_Z \neq 0$ and (2) $E[\eta_{c1990}\epsilon_{ct}] = 0$. The first condition states that the 1990 regulation had an effect on the average county pollution levels. The second condition states that unobserved shocks to mortality rates are uncorrelated with unobservables affecting pollution levels.

It is possible however that the IV estimates may be biased if there are unobserved shocks that are correlated with both pollution and mortality rates. I therefore also use a difference-in-difference approach to directly estimate the effect of the policy on adult mortality rates.

My research design involves two margins of variation (three if you include variation in the type of criteria air pollutant considered): the nonattainment status of a county, where either a county is in attainment or nonattainment and variation in time and temporal variation where time periods are divided into pre and post regulation. The nonattainment designation for a county depends on the air pollutant; it is possible for a county to be in nonattainment for one criteria air pollutant, while being in attainment for another pollutant. In this case pollution regulations would only be imposed on the plants that emit the air pollutant for which the county is in nonattainment. Variation across time is reflective of the fact that the attainment/nonattainment status of a county changes according to the level of ambient air quality in that county. Such longitudinal variation allows me to include fixed effects at the county level. Thus the effects estimated are based on within-county differences across nonattainment status.

I denote nonattainment status for air pollutant P for county c by N_c^P. $1(t > 1991)$ is the "post" indicator, which takes on values 1 for the years after the regulation was put into place. I consider the following criteria air pollutants in the analysis: (1) particulate matter and (2) ozone.

The full-specification estimation equation thus becomes:

$$Y_c^t = \alpha_1 1(t > 1991) + \alpha_2 N_c^P + \alpha_3 1(t > 1991) \times N_c^P + \Gamma X_{ct} + \chi_{ct} + \mu_c + \epsilon_{ct}$$

The outcome variable Y_c^t is either the crude death rate or the age-adjusted mortality rate in county c and year t which is regressed on the attainment-nonattainment status and a set of control variables X_{ct}. α_1 and α_2 represents the coefficients on the post-regulation indicator and nonattainment designation respectively. $\alpha 3$ represents the difference-in-difference estimator that gives us the average effect of the 1990 regulation on mortality rates in a nonattainment county compared to that in an attainment county. X_{ct} represents a vector of time-varying county variables: average county income; average number of hours worked in a county; percentage of county population that is white; African American and Asian; the education level of residents in a county (percentage of population with a high school, bachelors, masters and doctorate education); average age of residents; percentage of population that is female; percentage of population that is married and the percentage of population that is unemployed. χ_{ct} is a vector of nonattainment $\times$ year effects to model shocks to nonattainment counties in a year. μ_c represents indicators for time-invariant characteristics of counties that may affect the mortality rate. The error term ϵ_{ct} represents unobservable county $\times$ year shocks that are uncorrelated with the nonattainment status of a county.

$$E[\epsilon_{ct} \times (N_c^P)|X_{ct}, \chi_{ct}, \mu_c] = 0$$

The identifying assumption in this model is that nonattainment designation is the only factor generating a difference in the mortality trends between attainment and nonattainment counties. This assumption is directly untestable, but I check for pre-trends by comparing the average levels of observable characteristics in nonattainment counties to attainment counties. Table 1 shows the means for a number of variables describing the counties in the sample. Comparing the averages for attainment and nonattainment counties we can see that the two sets of counties are highly similar. This provides support for the validity of a difference-in-difference estimation procedure. The two exceptions are the annual income of residents and income from unemployment insurance; individuals living in nonattainment counties are considerably wealthier than their counterparts living in attainment counties. This is an expected feature; studies have shown that there exists a correlation between pollution and economic growth (Greenstone (2003)). This may also reflect a compensating differential paid to workers living in more polluted areas (Walker(2013)). It is interesting to note however that people who live in nonattainment counties do not work much more than those in attainment counties, implying that wages must be higher in nonattainment counties. To account for this difference I explicitly control for income in my models. To further check for pre-trends I graph the event studies for each pollutant: ozone and particulate matter in Figures 4 and 5. The event study graphs show that the parallel trends assumption is satisfied for ozone and particulate matter. In both figures a data point represents the difference in the mean mortality rate in a nonattainment county relative to the difference in mean mortality rate in an attainment county. In other words a data point represents the difference-in-difference estimate for a given year. The convergence of all data points to zero prior to 1991 shows that the parallel trends assumption is likely to be satisfied, which suggests that the difference-in-difference model is likely to be valid.

1.6 Data Description

For mortality data I use the Compressed Mortality File produced by the National Center for Health Statistics (NCHS) at the Center for Disease Control and Prevention (CDC), which is a county-level national mortality and population database. This data are from 1987 to 2016, thereby spanning nearly 3 decades of data. These data describe mortality statistics by year of death and underlying cause of death. I can therefore extract mortality data for a particular cause of death; I look at all mortality cases that can be categorized as being having respiratory causes. I also obtain mortality data for respiratory mortality by age group, race and gender, in addition to place of death.

I primarily use the following measure of mortality: the age-adjusted death rate. The age-adjusted death rate is calculated by multiplying the age-specific death rate for each age group by the corresponding weight from the standard population, summing across all age groups, and then multiplying this result by 100,000. The crude death rate is obtained as follows:

$$\text{Crude Death Rate} = \frac{\text{Number of deaths}}{\text{Population}} \times 100,000$$

The age-adjusted mortality rate is calculated according to the the following formula:

$$\begin{aligned} \text{Age-Adjusted Death Rate} = \sum_{age} \text{Age-specific death rate} \\ \times \text{Standard Population Weight} \\ \times 100,000 \end{aligned}$$

The age-specific death rate is the number of deaths for a given age group divided by the population of that age group.

$$\text{Age Specific Death Rate} = \frac{\text{Number of deaths in age group}}{\text{Population of age group}}$$

The standard population weight for an age group is calculated by dividing the population for an age group by the sum of populations for all age groups. I use the 2000 population estimates as the standard population distribution for calculating age-adjusted rates. The population rates are multiplied by 100,000 in order to make the rate comparable across counties with below and above average-sized populations.

I obtain the historical nonattainment status for counties for the years 1992 to 2016 from the EPA's *Green Book*. For the years 1987 to 1991 I have data on the annual concentration of the air pollutant across site monitors in each county. I adopt the following standards for the years 1987 to 1991 as set forth in the Federal Register when determining nonattainment status:

Ozone : A county is deemed to be in nonattainment if the hourly average concentration is greater than 0.12 parts per million for more than one calendar day per year.

Particulate matter: A county is in nonattainment status if the daily 24-hour average concentration of PM_{10} exceeds 150 μgm per m^3.

I first compile the EPA data on nonattainment from 1987 to 2016. The set of counties under consideration includes counties that have been in nonattainment at least once. This means that counties that stayed in attainment throughout history are not included in the dataset. This is a source of measurement error in the data, but the EPA only reports a county in its dataset if it is in nonattainment in at least one year. This leads to 839 unique counties that have been in nonattainment for ozone at least once from 1987 to 2016, with 16,470 observations. A further decomposition shows that with respect to ozone nonattainment, 2,861 observations of nonattainment with 423 unique counties are recorded in the data, and 7,764 observations of attainment with 684 unique counties are recorded. Similarly, 3,462 observations with 299 unique counties are recorded for nonattainment for particulate matter, while 5,503 observations for attainment with 299 unique counties are recorded.

I merge the nonattainment dataset with the age-adjusted mortality data and Current Population Survey data. The final dataset has 219 attainment and 215 nonattainment counties for ozone, and 207 attainment and 206 nonattainment counties for particulate matter. I then construct two datasets: one with air pollution data, and one without air pollution data. The dataset with air pollution data contains 4,594 observations for ozone nonattainment, and 3,550 observations for particulate matter nonattainment. In the dataset without air pollution, there are 8,572 observations for ozone attainment-nonattainment and 7,466 observations for particulate matter attainment-nonattainment. I use these datasets to estimate the models described in Section 5.

1.6.1 Descriptive Statistics

Table 1.1 shows the means of attainment and nonattainment counties with respect to a number of county characteristics. The two sets of counties are similar in the level of most characteristics. The two types of counties differ in the level of annual household income; the average income in attainment counties being \$42,193 contrasted with \$47,044 in nonattainment counties. This difference is in keeping with earlier literature; Greenstone (2002) and Walker (2017) also show how nonattainment counties are likely to be wealthier owing to the positive correlations between polluting activity and economic growth. The average income from unemployment insurance is also higher in nonattainment counties. The average number of hours and quarters worked are very similar across attainment and nonattainment counties. The percentage of the population below the poverty line is also similar between the two sets of counties.

The population in nonattainment counties is slightly older; attainment counties have are more racially diverse, have a higher marriage rate and have a larger female population compared to nonattainment counties. In addition, people in attainment counties are better educated across all levels of education (in terms of percentage of population who have achieved a high school diploma, attained a Bachelor's degree, and achieved a Master's degree).

Table 1.1: Summary Statistics for Attainment and Nonattainment Counties

Variable	Attainment	Nonattainment
Demographic variables		
% African American	10.13	9.16
% Asian	1.27	1.09
% Married	67.90	67.84
% Female	26.01	24.63
% Completed High School	30.39	27.55
% Completed Bachelors	12.70	12.22
% Completed Masters	4.64	4.39
Age	40.98	41.74
Socioeconomic variables		
Annual Income	$42,193.28	$47,043.53
Hours Worked Per Week	42.34	42.36
Quarters Worked Per Year	3.85	3.83
Income from Unemployment Insurance	$197.59	$231.72
% Below Poverty Line	2.97	2.83
Number of Counties		
Ozone	219	215
$PM_{2.5}$	207	206
Sulfur Dioxide	51	43

1.7 Results

Table 1.2 shows the first stage of the IV 2SLS regressions. We can see that in all specifications nonattainment designation across pollutants had a negative impact on pollution levels. Tables 1.3 and 1.4 show the impact of air pollution on adult mortality rates for both criteria air pollutants: ozone and particulate matter. Table 1.3 shows the effect of ozone pollution on age-adjusted mortality rates; on average an increase in the ozone concentration of 1 part per million leads to a 0.628 increase in the mortality rate. Table 1.4 shows that when time trends are included, air pollution has a statistically significant positive effect on age-adjusted mortality rates though this result disappears when county fixed effects are included.

Tables 1.5 and 1.6 show the main results. I use various model specifications to check the robustness of the results. The regression of ozone nonattainment status on age-adjusted mortality rates is shown in Table 1.5. Column (1) shows the base regression, where nonattainment status has a highly significant and negative effect on the mortality. Column (2) includes county fixed effects, to account for unobservable shocks at the county level that are time-invariant. The column (3) specification includes socioeconomic control variables such as number of annual quarters worked, number of hours worked per week and average total earnings at the county. Column (4) includes a set of demographic controls, such as the percentage of county residents that are female, black, Asian, married, have a high school, Bachelors or Masters education. The model with the full specification shows that nonattainment designation for ozone reduced respiratory mortality rates by 11.66. Compared to an average mortality rate of 81.85 this represents a statistically significant decrease of 14.2%.

Table 1.6 shows the results of county particulate matter (specifically PM) nonattainment designation on age-adjusted mortality rates. The baseline effect is negative with mortality rates lower by 7.812 deaths per 100,000 people. When additional controls are included, the full specification indicates that PM nonattainment designation reduced age-adjusted mortality rates by 7.664 deaths per 100,000 people, which is a significant decrease of 9.4%. The event study graphs for ozone and particulate matter are shown in Figures 1.1 and 1.2 respectively, where one can see that the parallel trends assumption is fairly satisfied.

Table 1.2: First-Stage IV regression of Nonattainment on Air Pollution

	(1)	(2)	(3)
Nonattainment	-2.421***	-1.540***	-2.738***
	(0.279)	(0.282)	(0.271)
N	9344	9344	9344
Time FE	NO	YES	YES
County FE	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is air pollution in parts per million. Column (1) is the cross-sectional regression. Column (2) includes year fixed effects while column (3) includes county fixed effects.

Table 1.3: Second Stage IV regression of Ozone Pollution on Mortality

	(1)	(2)	(3)
Predicted Pollution	0.415***	0.0124	0.628**
	(0.0390)	(0.0403)	(0.307)
N	4594	4594	4594
Time FE	NO	YES	YES
County FE	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Column (1) is the cross-sectional regression. Column (2) includes year fixed effects while column (3) includes county fixed effects.

Table 1.4: Second Stage IV regression of PM Pollution on Mortality

	(1)	(2)	(3)
Predicted Pollution	1.026***	0.737***	-0.0934
	(0.0420)	(0.0551)	(0.214)
N	3550	3550	3550
Time FE	NO	YES	YES
County FE	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Column (1) is the cross-sectional regression. Column (2) includes year fixed effects while column (3) includes county fixed effects.

Table 1.5: Difference-in-difference regression of Ozone Nonattainment on Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	-5.929***	-13.73***	-12.33***	-11.66***
	(1.245)	(1.395)	(1.362)	(1.369)
N	8620	8620	8572	8572
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Table 1.6: Difference-in-difference regression of PM Nonattainment on Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	-7.812***	-9.266***	-8.888***	-7.664***
	(2.499)	(2.116)	(2.121)	(2.314)
N	7529	7529	7466	7466
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

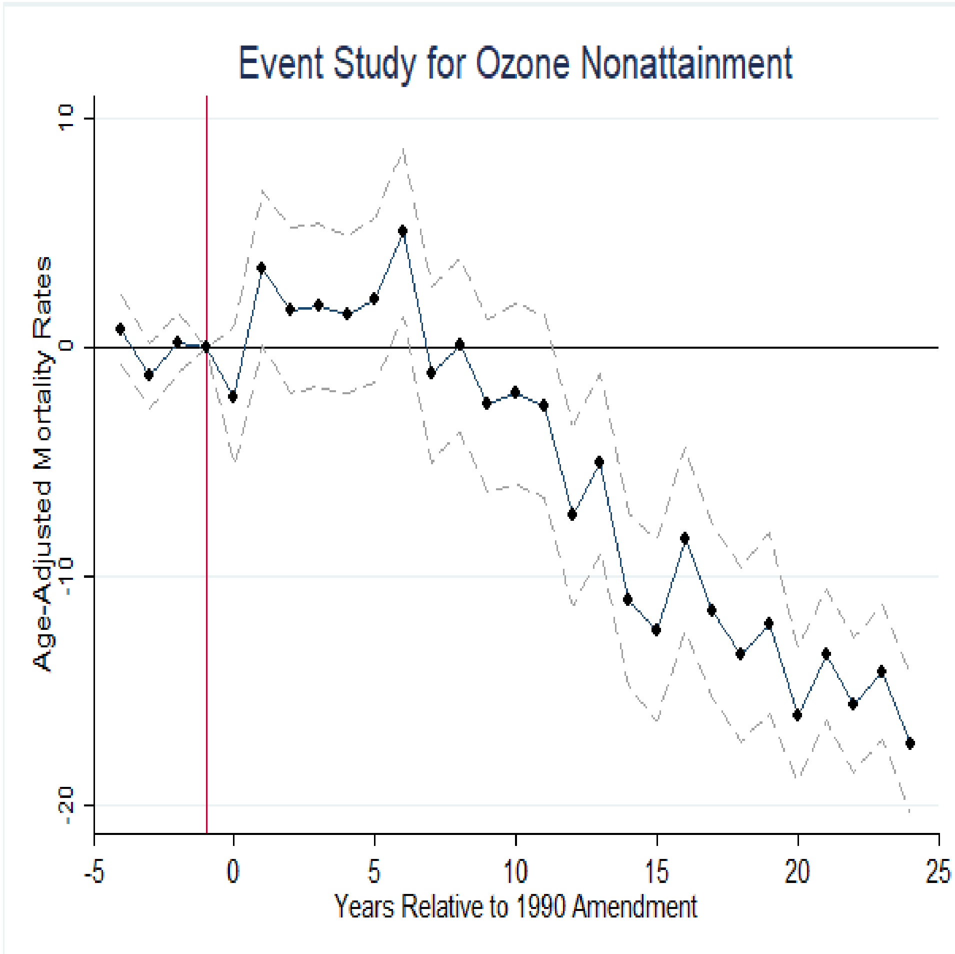


Figure 1.1: Event Study for Ozone Nonattainment

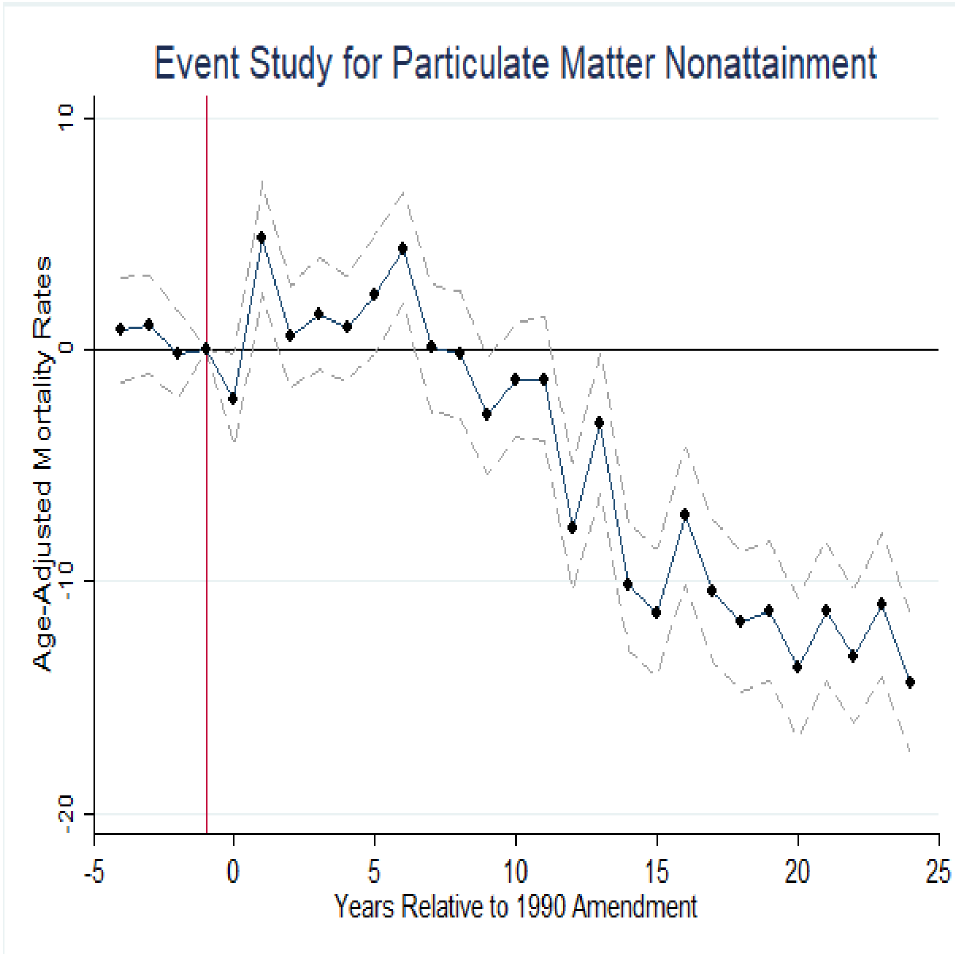


Figure 1.2: Event Study for Particulate Matter Nonattainment

1.7.1 Crude Rates Vs. Age-Adjusted Rates

Throughout this paper I utilize age-adjusted mortality rates which take into consideration the underlying age distribution of counties. This is important when attempting to estimate the impact of a measure aimed at reducing pollution, which in turn would reduce mortality rates. For the sake of comparison I estimate regressions of nonattainment designation on crude (respiratory) mortality rates. Tables 1.7 and 1.8 present the regression results on crude mortality rates. Table 1.7 shows the regression of ozone nonattainment designation on crude rates for respiratory mortality. As we can see by comparing tables 9 and 7, the effects are lower when we take into account crude rates compared to age-adjusted rates. With the full specification we can see that ozone nonattainment reduces crude mortality rates by 5.95 per 100,000 people (a reduction of 7.2%), compared to age-adjusted reductions of 11.66 per 100,000 people. The same trend is shown in Table 10, which gives the results from estimating the impact of PM nonattainment designation on crude respiratory mortality rates. As we can see the results are much lower, with specification (4) in Table 1.9 suggesting that when a full set of controls are employed PM nonattainment designation reduces crude mortality rates by 7.30 per 100,000 people (a change of 8.9%), in contrast to a reduction of 7.66 per 100,000 people (Table 8) when age-adjusted mortality rates are taken into consideration.

Table 1.7: Regression of Ozone Nonattainment on Crude Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	-4.234*	-6.044***	-5.890***	-5.949***
	(2.496)	(1.339)	(1.328)	(1.334)
N	8620	8620	8572	8572
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is crude mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

This comparison of crude and age-adjusted mortality rates suggests that using crude rates will tend to underestimate the true effect. This is somewhat surprising as intuitively using crude rates could be expected to overestimate the effect as heavily populated counties with a high number of deaths avoided could magnify the impact of the 1990 nonattainment designation. Instead, when weights are appropriately attached to the age distribution of counties the impact of nonattainment designation is much higher using age-adjusted mortality rates.

Table 1.8: Regression of PM Nonattainment on Crude Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	-8.289**	-7.853***	-7.663***	-7.307***
	(3.631)	(2.198)	(2.197)	(2.291)
N	7529	7529	7466	7466
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is crude mortality rate.Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.2 Treatment Heterogeneity by Gender, Race and Age Groups

Differences by Gender

Table 1.9 shows the regressions conducted separately for men and women for the case of ozone nonattainment designation. The impact on age-adjusted mortality rates is highly statistically significant for both men and women, though the effect is larger for men. Nonattainment designation reduces mortality rates by 14.25 (a decrease of approximately 17.4%) per 100,000 people for men while for women mortality rates are decreased by 12.50 per 100,000, a reduction of 7.6%. The impact of PM designation is shown in Table 1.10 where the effect on mortality rates is statistically insignificant for both men and women, with the effect being negative for men, who enjoy a 0.57% reduction in respiratory mortality as a result of particulate matter regulation. The effect for women is comparatively larger, with mortality rates being raised by 1.45 per 100,000 people.

The effect for ozone presents good news as evidenced by the facts in epidemiological literature. A 2002 study done by Moss and Manino on acute respiratory distress mortality cases from 1979 to 1996 found significant gender differences in annual age-adjusted mortality rates. These rates were continuously higher for men compared to women. The results in this paper therefore suggest that the largest benefits of the Clean Air Act Amendment of 1990 accrue to the individuals most vulnerable to air pollution.

Table 1.9: Difference-in-difference regression of Ozone Nonattainment on Mortality Rates for Men and Women

	(1) Male	(2) Female
$Nonattainment \times 1(\tau > 1990)$	-14.25***	-12.50***
	(4.937)	(3.354)
N	8546	8349
Time FE	YES	YES
County FE	YES	YES
Socioeconomic controls	YES	YES
Demographic controls	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Differences by Race

Differences in treatment effects by race are presented in Tables 1.11 and 1.12. Table 1.11 shows the regressions conducted for each race separately for the case of ozone nonattainment. The coefficients on nonattainment designation are negatively signed for each race, and the effects are statistically significant for white and black and Asian individuals. The 1990 Amendment reduced the mortality rate for whites by 9.084 per 100,000 people, a 11.1%

Table 1.10: Difference-in-difference regression of PM Nonattainment on Mortality Rates for Men and Women

	(1) Male	(2) Female
$Nonattainment \times 1(\tau > 1990)$	-0.472	1.450
	(5.251)	(4.580)
N	6265	6047
Time FE	YES	YES
County FE	YES	YES
Socioeconomic controls	YES	YES
Demographic controls	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

reduction in the mortality rate compared to the average mortality rate in a nonattainment county. The mortality effect is highest, however, for blacks who enjoyed a reduction in the mortality rate of 37.12%. In Table 1.12, which examines the treatment effects by race due to PM nonattainment designation, the effect is highest for whites, whose mortality rates fell by approximately 11.09%, while the effect was not statistically significant for blacks and Asians.

Differences by Age Group

Tables 1.13 and 1.14 show treatment effect heterogeneity by age group. Table 1.13 shows differences in treatment effects on crude mortality rates for each age group for the case of ozone nonattainment designation. The effects are largest for the oldest members of the sample. The crude mortality rate is reduced for individuals in the 45-54 year age group by 26.87 per 100,000 people. This effect is much larger for people in the 65-74 and 75-84 year age groups, with individuals in the 65-74 year age group showing a reduction in crude death rates

Table 1.11: Difference-in-difference regression of Ozone Nonattainment on Mortality Rates by Race

	(1) White	(2) Black	(3) Asian
$Nonattainment \times 1(\tau > 1990)$	-9.084***	-30.29***	-8.466***
	(1.651)	(7.562)	(1.618)
N	11520	3296	490
Time FE	YES	YES	YES
County FE	YES	YES	YES
Socioeconomic controls	YES	YES	YES
Demographic controls	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Table 1.12: Difference-in-difference regression of PM Nonattainment on Mortality Rates by Race

	(1) White	(2) Black	(3) Asian
$Nonattainment \times 1(\tau > 1990)$	-9.050**	2.114	0.925
	(4.174)	(9.764)	(2.628)
N	9253	2160	403
Time FE	YES	YES	YES
County FE	YES	YES	YES
Socioeconomic controls	YES	YES	YES
Demographic controls	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

by 16.3% compared to the average crude death rate for that age group in a nonattainment county. Individuals in the 75-84 year age groups enjoyed a reduction in the crude death rates of 14.5% compared to the average mortality rate.

Treatment heterogeneity for the case of $PM_{2.5}$ nonattainment with respect to age is shown in Table 1.14. Again, the effects are largest for the oldest individuals, with the magnitude of the effect rising as age groups shift to the right. Individuals in the 75-84 year age group show a reduction in crude death rates by 67.87 per 100,000 people, which is a reduction of 9.3% compared to the average crude mortality rate, while the effect of the air pollution regulation for people in the 85 plus age group is a reduction of 12.4% compared to the average. The largest reduction in the mortality rate is enjoyed by people in the 65-74 year age group, whose mortality rates were reduced by 13.05% compared to the average.

Table 1.13: Difference-in-difference regression of Ozone Nonattainment on Mortality Rates by Age Group

	(1)	(2)	(3)	(4)	(5)
	Below 45	45 - 54	55 - 64	65 - 74	75 - 84
$Nonattainment \times 1(\tau > 1990)$	-1.876	-26.87***	-35.81	-100.2	-44.16
	(8.274)	(9.043)	(23.78)	(75.71)	(212.4)
N	2099	5063	9132	11072	7379
Time FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Table 1.14: Difference-in-difference regression of PM Nonattainment on Mortality Rates by Age Group

	(1)	(2)	(3)	(4)	(5)
	¡ 45	45 - 54	55 - 64	65 - 74	75 - 84
$Nonattainment \times 1(\tau > 1990)$	17.40*	1.974	40.46	-8.374	178.5
	(10.45)	(8.094)	(31.19)	(44.62)	(275.7)
N	1045	3487	6815	8390	4958
Time FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.3 Falsification Test: Considering the Case of Sulfur Dioxide

Table 1.15 shows the IV estimates for sulfur dioxide and finds that when both time and county fixed effects are taken into account sulfur dioxide pollution has no effect on age-adjusted mortality rates. The difference-in-difference estimate of the effect of nonattainment designation for sulfur dioxide-producing counties is shown in Table 1.16. The estimates are more or less consistent across various model specifications. Column (4) with a full set of controls shows that nonattainment designation reduced mortality rates by 2.658 per 100,000 people. This represents a reduction of 3.25% in the age-adjusted mortality rate in nonattainment counties, though it is not statistically significant. The above results suggest that sulfur dioxide can behave as a falsification test of sorts for studying the impact of nonattainment designation on mortality.

Table 1.15: Second Stage IV regression of SO2 Pollution on Mortality

	(1)	(2)	(3)
Predicted Pollution	0.922***	0.906***	-0.594
	(0.0820)	(0.0977)	(0.415)
N	1200	1200	1200
Time FE	NO	YES	YES
County FE	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is predicted pollution from first-stage regression of nonattainment on pollution. Column (1) is the cross-sectional regression. Column (2) includes year fixed effects while column (3) includes county fixed effects.

Table 1.16: Difference-in-difference regression of SO2 Nonattainment on Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	1.999	-2.485	-2.667	-2.658
	(3.036)	(2.616)	(2.581)	(2.606)
N	2461	2461	2441	2441
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.4 Falsification Test: Considering Firearm Fatalities as a Public Health Outcome

In order to check the validity of the results of regressing nonattainment on respiratory mortality rates, I consider deaths due to firearms as an outcome for a falsification test. The majority of fatalities in the U.S. due to firearms are the result of suicides (60%) while the rest are due to homicides (37%). In February 2019, more than 45 medical, legal and injury-prevention organizations came together to form a summit on firearm injury prevention. An overall consensus was reached in order to recognize firearm violence and its resulting deaths as a public health crisis and to support a public health approach in order to solve it. I consider firearm fatalities as an outcome for a falsification test because while firearm fatalities are associated with health behaviours (such as mental illness, poor health leading to depressive thoughts, etc.) they are not feasibly associated with pollution prevention efforts such as the nonattainment designation created by the Clean Air Act.

Tables 1.17 and 1.18 show the results of regressing nonattainment designations on firearm mortality rates. Table 19 shows the results of regressing ozone nonattainment on mortality rates, with a negative relationship between nonattainment and mortality rates shown in every specification. However, with the exception of specification (1) that includes only time trends, none of these are statistically significant. Table 20 shows results for particulate matter nonattainment, with a positive relationship between nonattainment designation and firearm mortality rates being present in every specification. However, once again, these results are not statistically significant. The above results indicate that respiratory mortality is unlikely to be affected by potentially confounding factors that are unrelated to air pollution.

Table 1.17: Regression of Ozone Nonattainment on Firearm-Related Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	-1.513***	-0.507	-0.518	-0.519
	(0.325)	(0.382)	(0.378)	(0.374)
N	7045	7045	7020	7020
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Table 1.18: Regression of PM-2.5 Nonattainment on Firearm-related Mortality Rates

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1990)$	0.614*	-0.233	-0.221	-0.246
	(0.329)	(0.190)	(0.191)	(0.189)
N	5408	5408	5374	5374
Time FE	YES	YES	YES	YES
County FE	NO	YES	YES	YES
Socioeconomic controls	NO	NO	YES	YES
Demographic controls	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. Column (1) includes year fixed effects while column (2) includes county fixed effects. Column (3) controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line. Column (4) includes demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.5 Robustness Checks: Controlling for Lung Cancer

In this paper I consider respiratory mortality - or mortality due to diseases of the respiratory system. It is possible however that some of the effects on mortality shown above are in fact due to the ameliorating effects of the 1990 Amendment on fatality rates due to lung cancer. To see if the treatment effects discussed so far are due to effects resulting from lung cancer I explicitly control for lung cancer mortality rates in the regressions. Table 1.19 shows the estimated effects when lung cancer fatalities are controlled for. In the case of ozone nonattainment, the resulting treatment is reduced (though still highly significant) when lung cancer mortality is controlled for, with a reduction of 10.6% - 8.72 deaths per 100,000 people (compared to a reduction of 11.66 per 100,000 in the mortality rates). The treatment effect is smaller, but not as reduced in the case of $PM_{2.5}$ nonattainment designation, with a reduction of 5.39 per 100,000 individuals, a reduction of 6.5%. In both cases we can therefore see that the treatment effect on respiratory mortality is reduced compared to the original estimates, but the effects are still significant for ozone and particulate matter.

Table 1.19: Robustness Checks: Controlling for Lung Cancer Mortality

	(1) Ozone	(2) PM2.5
$Nonattainment \times 1(\tau > 1990)$	-8.720***	-5.398**
	(1.305)	(2.232)
N	8466	7306
Time FE	YES	YES
County FE	YES	YES
Socioeconomic controls	YES	YES
Demographic controls	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.6 Robustness Checks: Sample Restrictions

In Tables 1.20 and 1.21 I consider various sample restrictions in order to check for the robustness of the primary results. I exclude the five most populous states one by one in order to check whether the treatment effect is maintained in the presence of the exclusion. Table 1.20 considers sample restrictions for ozone nonattainment or attainment designations. Column (1) represents the baseline effect. Column (2) estimates the difference-in-difference model without California. The treatment effect is reduced, but still statistically significant, suggesting that California is a somewhat important factor driving the results. Column (3) runs the regression without the state of Texas while column (4) estimates the model by dropping New York. Column (5) estimates the treatment effect without including Florida while column (6) runs the regression on mortality rates without including Illinois. In all specifications the results remain statistically significant at 1%. Tables 1.21 performs similar calculations. In the case of PM nonattainment designation dropping Florida has no effect on the baseline results, while dropping New York increases the mortality rate. All in all, the results show that while the estimates vary slightly, the effects are reasonably robust to these sample restrictions.

Table 1.20: Robustness Checks Via Sample Restrictions for Ozone

	(1) Baseline	(2) W/O California	(3) W/O Texas	(4) W/O New York	(5) W/O Florida	(6) W/O Illinois
$Nonattainment \times 1(\tau > 1990)$	-11.66***	-10.05***	-11.82***	-11.46***	-11.73***	-11.85***
	(1.369)	(1.331)	(1.424)	(1.444)	(1.375)	(1.422)
N	8572	7705	8010	8113	8544	8220
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

Table 1.21: Robustness Checks Via Sample Restrictions for Particulate Matter

	(1) Baseline	(2) W/O California	(3) W/O Texas	(4) W/O New York	(5) W/O Florida	(6) W/O Illinois
$Nonattainment \times 1(\tau > 1990)$	-7.664***	-6.897***	-7.761***	-8.014***	-7.664***	-7.960***
	(2.314)	(2.369)	(2.353)	(2.334)	(2.314)	(2.458)
N	7466	6711	7437	7192	7466	7115
Time FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age.

1.7.7 Additional Robustness Checks

Tables 1.22 and 1.23 show additional robustness checks. In all three tables, Column (1) represents the baseline estimates. Column (2) includes a lag of the dependent variable. Column (3) includes a second period lag of the dependent variable. Column (4) includes quadratic time trends. Column (5) uses the natural log of the adjusted mortality rate as the dependent variable.

Table 1.22 shows that including the lags, be they first period or second, of the dependent variable has little effect on the treatment effect. Including the quadratic time trends reduces the mortality rate, but the effect remains highly statistically significant. Using the log of the dependent variable does not alter the significance, but increases the estimated effect of ozone nonattainment designation to 15.1%. Similarly, Table 1.23 shows that including the first and second period lags has little effect on the baseline estimate, while including quadratic trends reduces the effect. Using the log of the adjusted mortality rate leads to a 8.55% effect, which is lower than the effect obtained in any of the previous specifications.

Table 1.22: Robustness Checks For Ozone Designations

	(1)	(2)	(3)	(4)	(5)
$Nonattainment \times 1(\tau > 1990)$	-11.66***	-11.64***	-11.66***	-6.658***	-0.151***
	(1.369)	(1.369)	(1.369)	(1.334)	(0.0167)
N	8572	8572	8572	8572	8572
Time FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) represents the baseline estimates. Column (2) includes a lag of the dependent variable. Column (3) includes a second period lag of the dependent variable. Column (4) includes quadratic time trends. Column (5) uses the natural log of the adjusted mortality rate as the dependent variable.

Table 1.23: Robustness Checks For Particulate Matter Designations

	(1)	(2)	(3)	(4)	(5)
$Nonattainment \times 1(\tau > 1990)$	-7.664***	-7.645***	-7.660***	-6.615***	-0.0855***
	(2.314)	(2.302)	(2.314)	(2.305)	(0.0252)
N	7466	7466	7466	7466	7466
Time FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
Socioeconomic controls	YES	YES	YES	YES	YES
Demographic controls	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Outcome is age-adjusted mortality rate. All columns (1) include year fixed effects while column (2) include county fixed effects (3) control for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line and (4) include demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) represents the baseline estimates. Column (2) includes a lag of the dependent variable. Column (3) includes a second period lag of the dependent variable. Column (4) includes quadratic time trends. Column (5) uses the natural log of the adjusted mortality rate as the dependent variable.

1.7.8 Alternative Control Groups

The preceding analysis uses data from the E.P.A.'s *Green Book*, which describes the history of all counties that were ever in nonattainment. This is in keeping with previous literature, which uses *Green Book* data to analyse the impact of nonattainment designation on mortality. However the *Green Book* data describes the history of counties that are essentially "switchers": counties shifting in and out of nonattainment over time. It is worthwhile to understand what the effects of the 1990 CAAA are when counties that are not switchers, i.e. always-in-attainment, are included in the analysis. Counties that are always in nonattainment also belong to the group of counties that are not switchers. However over the 3 decades of study in this analysis no county is always in nonattainment for either ozone or particulate matter. Therefore the set of "non-switchers" is restricted to counties that are always in attainment.

Tables 1.24 and 1.25 compare the difference-in-difference results when the control group is restricted to counties that are always-in-attainment versus when the the analysis is restricted to the counties that comprise switchers. Table 1.24 shows how when the control group is restricted to always-in-attainment counties for ozone the treatment effect shows a reduction in the age-adjusted mortality rate of 15.52 per 100,000 versus 11.66 per 100,000 when the analysis is restricted to switchers. In Table 1.25 we can see that for particulate matter, with an always-in-attainment control group the reduction in mortality rate is 20.14 per 100,000 versus 7.66 per 100,000. In both cases we can see that restricting the control group to always-in-attainment counties raises the treatment effect.

1.7.9 Additional Robustness Checks

Tables 1.26 and 1.27 describes the treatment effects from the 1990 CAAA on adult mortality when controls are added for the other criteria air pollutant NAAQS: sulfur dioxide, lead,

Table 1.24: Difference-in-difference regression of Ozone Nonattainment on Mortality Rates

	(1) Always-In-Attainment Control	(2) Switchers
$Nonattainment \times 1(\tau > 1990)$	-15.52***	-11.66***
	(1.157)	(1.369)
N	52264	8620

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The above regressions include controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line as well as demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) has always-in-attainment counties as the control group while Column (2) includes only the counties that are ever-in-nonattainment with attainment counties being designated as the control group.

Table 1.25: Difference-in-difference regression of Particulate Matter Nonattainment on Mortality Rates

	(1) Always-In-Attainment Control	(2) Switchers
$Nonattainment \times 1(\tau > 1990)$	-20.14***	-7.664***
	(2.507)	(2.116)
N	52264	7466

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The above regressions include controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line as well as demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) has always-in-attainment counties as the control group while Column (2) includes only the counties that are ever-in-nonattainment with attainment counties being designated as the control group.

carbon monoxide and nitrogen dioxide. In both tables the above regressions include controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line as well as demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) includes an indicator for sulfur dioxide NAAQS while Column (2) has an indicator for lead NAAQS. Column (3) includes an indicator for carbon monoxide NAAQS while Column (4) includes an indicator for nitrogen dioxide NAAQS. Column (5) includes a full set of NAAQS indicators. When the full set of controls are added the treatment effects falls to 6.67 per 100,000 for ozone and 5.97 per 100,000 for particulate matter. This means that the reduction in mortality rate is 8.2% for ozone and 7.3% for particulate matter.

Table 1.26: Robustness Checks for Ozone: Different NAAQS

	(1) SO2	(2) Lead	(3) CO	(4) NO2	(5) All
$Nonattainment \times 1(\tau > 1990)$	-10.33***	-7.457***	-10.56***	-6.767***	-6.674***
	(1.383)	(1.327)	(1.398)	(1.318)	(1.327)
N	8572	8572	8572	8572	8572

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The above regressions include controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line as well as demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) includes an indicator for sulfur dioxide NAAQS while Column (2) has an indicator for lead NAAQS. Column (3) includes an indicator for carbon monoxide NAAQS while Column (4) includes an indicator for nitrogen dioxide NAAQS. Column (5) includes a full set of NAAQS indicators.

Table 1.27: Robustness Checks for Particulate Matter: Different NAAQS

	(1)	(2)	(3)	(4)	(5)
	SO2	Lead	CO2	NO2	All
$Nonattainment \times 1(\tau > 1990)$	-7.122***	-5.911***	-7.330***	-6.834***	-5.978***
	(2.268)	(2.219)	(2.282)	(2.246)	(2.202)
N	7466	7466	7466	7466	7466

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The above regressions include controls for socioeconomic variables such as annual income, number of hours worked per week, number of quarters worked per year, income from unemployment insurance and percentage of the population below the poverty line as well as demographic variables such as percentage of county population that is African American, percentage of county population that is Asian, percentage of county population that is married, percentage of county population that has a high school diploma, percentage of county population that has completed a Bachelor's degree, percentage of county population that has a Master's degree and average county age. Column (1) includes an indicator for sulfur dioxide NAAQS while Column (2) has an indicator for lead NAAQS. Column (3) includes an indicator for carbon monoxide NAAQS while Column (4) includes an indicator for nitrogen dioxide NAAQS. Column (5) includes a full set of NAAQS indicators.

1.8 Conclusion

This paper takes a look at how the Clean Air Act Amendment of 1990 affected adult mortality rates in the three decades since the Amendment. The results show that nonattainment designation at the county level had an appreciable, statistically significant effect on mortality rates. These results are robust to a variety of specifications and robustness checks. These results support the contention of the Second Prospective Study conducted by the EPA examining the benefits and costs of the 1990 Clean Act Amendment. The report attributed 230,000 deaths prevented due to reduced exposure to particulate matter to the 1990 Amendment. The results in this paper suggest that with an average U.S. population of 300 million an estimated 31,800 fewer deaths due to ozone exposure occurred. Similar calculations show that 19,500 fewer deaths occurred due to particulate matter exposure thanks to the 1990 Amendment. With a value of statistical life of \$10 million, this suggests \$513 billion saved as a result of just the regulations regarding ozone and particular matter. However this should be considered an upper bound, as it is not clear whether the effects of air pollutants on mortality are additive across air pollutants or not. A reasonable lower bound would be \$195 billion, accruing from the number of particulate matter deaths avoided. The E.P.A. study used an average value of statistical life of \$7.4 million which, combined with 230,000 deaths avoided, resulted in gains of \$1.7 trillion. Even using the upper bound of \$513 billion this would be less than a third of the benefits hypothesized by the E.P.A. However the scope of this paper runs to nonattainment designation alone. An avenue of further research is to examine the health benefits accruing from other pollution prevention measures.

One might wonder why no similar results were obtained for sulfur dioxide. The answer may lie in the impact of the Clean Air Act on sulfur dioxide reductions in general. A 2004 paper by Michael Greenstone found that the nonattainment designation legislated by the Clean Air Act Amendment of 1970 had a modest, if any, impact on the dramatic reductions in sulfur dioxide concentrations over the 30 years succeeding the Amendment. This is suggested by the results in this paper, where the 1990 Amendment has no impact on adult mortality rates in the 3 decades since the Amendment. Since identification of the impact on mortality rates depends crucially on an appreciable reduction in sulfur dioxide concentrations associated with nonattainment designation, it is not surprising that a lack of impact on sulfur dioxide levels translates to a lack of effect on mortality rates.

It is worthwhile to ask what the results of this paper means for environmental policies in the context of the current U.S. Administration. The Trump administration has actively rolled back environmental regulations in the interest of manufacturing and industry growth. In 2017 the E.P.A. delayed an Obama-era requirement for states to submit measurements of the levels of ozone by 2017. The 2015 regulation would have required the oil-refining industry to install expensive equipment to remove ozone-creating chemicals from gasoline and other fuels. The decision to delay the designation of areas of the country that met new ozone standards was reversed by the E.P.A. after 16 state attorneys general filed a lawsuit challenging the delay with the United States Court of Appeals for the District of Columbia. While the results of this paper suggests that the health benefits of the ozone and particulate matter designations is lower than previously hypothesized, they are still rather substantial. With costs of compliance of $5.1 billion associated with ozone and particulate matter NAAQS as hypothesized by the 2011 E.P.A. study a cost-benefit analysis of nonattainment designation for these two criteria air pollutants would suggest that the benefits exceed the costs by several orders of magnitude. Given the association of ozone and particulate matter with asthma, respiratory disease and cardiovascular disease this alone would suggest that the payout to the 1990 Amendment is worth it.

A current proposal by the Trump administration is aiming at significantly limiting the research that the government can use to determine public health regulations (Friedman (2019)). The proposal would require that scientists and researchers disclose all of their raw data, including confidential medical data, before the agency could consider an academic study's conclusions. If passed the proposal would erect significant challenges to enact new clean air rules because many studies detailing the impact of regulations use confidential medical data. This paper, by using publicly available medical data, suggests that the Clean Air Act has made significant inroads into gains in public health resulting from air pollution regulation.

Chapter 2: The Impact of the 1990 Clean Air Act Amendment on Employment and Wages: A Case Study of the Pharmaceutical Industry

2.1 Introduction

On October 27th, 1948 an air inversion caused a wall of smog to build up in Donora, Pennsylvania. The following day, many residents of the community experienced coughing and other symptoms of respiratory illness. Approximately 7,000 of the town's 14,000 population were affected and 20 people died as a result of the smog which lasted until October 31st when rainfall dispersed the phenomenon. The culprits were toxic air emissions from neighbouring zinc and steel plants. Mortality rates in Donora were found to be significantly higher than that in nearby towns even 10 years after the fact.

The above event is just one example of how air pollution can have a significant impact on human health and well-being. Federal efforts to control air pollution in the United States culminated in the Clean Air Act of 1963 which required research into methods to monitor and control air pollution. Detailed federal and state regulations were required by the 1970 Amendment to the Clean Air Act, which required that both stationary industrial pollution sources as well as mobile pollution sources be regulated. The 1990 CAA Amendment was an even more drastic expansion of the federal mandate, which increased the number of regulated toxic chemicals from 7 to 189, representing a dramatic increase in EPA authority in implementing and enforcing regulations reducing toxic air emissions.

Prior research work has mainly focused on the impact of criteria air pollutants (CAPs), specifically, carbon monoxide, sulfur dioxide, ozone and particulate matter covered by the Clean Air Act which divided counties into attainment and nonattainment counties based on performance standards for these pollutants. This paper is complementary to prior work by examining hazardous air pollutants (HAPs) instead of CAPs. It greatly widens the scope of pollutants analyzed to include 189 regulated toxic chemicals in terms of their impact on labour market and health outcomes. Isen et al. (2017) was the first paper to show that exposure to air pollution *in utero* or in the first year of birth has an impact on later-in-life outcomes. They found that the 1970 Clean Air Act Amendment, by reducing exposure to air pollution, led to an increase in earnings and annual quarters worked 30 years later. This study builds on the same idea by studying whether reduced exposure to air toxics over time led to improvements in earnings and employment measures.

This study is the first paper to study the effect of air toxics regulation on economic measures such as earnings, weekly hours and annual quarters worked. The regulatory field of air toxics involves a complicated set of standards, intended to govern both emissions as well as technology. These standards are sometimes promulgated for a single air toxic chemical and sometimes for an entire industry. I study the pharmaceutical industry in particular, which is a subset of the chemical manufacturing industry. The pharmaceutical industry provides an attractive candidate for study because the emissions limits that govern the pharmaceutical industry are overall limits that cover a wide range of chemicals. Most industry sources governed under the air toxics regulation have specific limits set for individual chemicals that are usually couched in flow terms. This makes comparing actual emissions with standards rather difficult due to lack of data regarding the emissions flow capacities of individual firms. The most widely available data on toxic emissions is provided by the Toxics Release Inventory, which expresses yearly emissions in pounds per year. The pharmaceutical industry's emissions limits are also expressed in annual pounds per year, making it possible to study the impact of he Clean Air Act on emissions, and via emissions, other measures such as earnings that are indirectly related to health benefits from the air regulation.

I leverage emissions data from the TRI to study whether the Clean Air Act Amendment of 1990, which was the first piece of legislation to cover all hazardous air chemicals under its purview, had a noticeable impact on measures such as earnings and employment via health benefits accruing from reduced exposure to air toxics. I find that earnings increased as a result of the regulation (which went into effect in 1998); the results on employment measures such as weekly hours worked and number of annual quarters worked is mixed, with certain groups benefiting from the regulation while others remained unaffected.

The remaining sections of the paper are as follows: Section 2.2 provides an overview of the toxics profile for the pharmaceutical industry. Section 2.3 gives a history of the Clean Air Act while Section 2.4 provides a brief review of the related literature. Section 2.5 describes the data and its limitations. Section 2.6 gives an outline of the research design while Section 2.7 provides the empirical framework. Section 2.8 discusses the results while Section 2.9 concludes.

2.2 Toxic Release Inventory Profile for the Pharmaceutical Industry

From all the facilities reporting 2833 or 2834 as the primary SIC code, around 200 facilities reported to the Toxic Release inventory in 1995 out of the 916 pharmaceutical facilities reported by the *1992 Census of Manufactures*. All firms can deal with toxic emissions in one of two ways: (1) release to the environment (air, water and land) without treatment and (2) transfers off-site. In 1995, of the pharmaceutical industry's TRI releases, 57% were air releases, with the prevalence of volatile chemicals explaining the air intensive chemical loading of the pharmaceutical industry. Six of the ten most commonly emitted toxic chemicals are highly volatile: methanol, dichloromethane, toluene, ethylene glycol, N,N-Dimethylformamide and acetonitrile. These chemicals are primarily used to extract active ingredients and for cleaning equipment. The primary method of release to the environment are from fugitive air and point sources.

While any hazardous chemical released by a pharmaceutical firm is included in the pharmaceutical NESHAP, methanol, methylene chloride and toluene are specifically mentioned by the regulation. Methanol is easily absorbed by the respiratory tract and is toxic to humans in moderate to high doses. Observed toxic effects at high dose levels include central nervous system damage and blindness. Short-term exposure to methylene chloride is associated with central nervous system effects such as giddiness, stupor, irritability, headaches, numbness and tingling in the limbs. These effects become more severe with long-term exposure, due to increased carbon monoxide in the blood from the breakdown of methylene chloride. Occupational exposure to methylene chloride has been linked to increased incidence of spontaneous abortions in women. Acute damage to the eyes and upper respiratory tract, unconsciousness and death were reported in workers exposed to high concentrations of methylene chloride, which has been reported as a probable human carcinogen. Inhalation of toluene can cause headaches, confusion, weakness and memory loss, while also affecting liver and kidney function. In addition, reactions of toluene in the atmosphere contribute to the formation of ozone in the lower atmosphere. Ozone is known to affect the respiratory system, especially in vulnerable individuals who suffer from asthma or allergies.

When one compares the reported pounds released per facility, the pharmaceutical industry is above average in its pollutant releases per facility. Of the 20 manufacturing SIC codes listed in the TRI database, the average level of pollutant release per facility (including pharmaceutical plants) was approximately 101,000 pounds.The TRI releases of the average pharmaceutical facility were 150,000 pounds, making the industry 1.5 times higher in per facility releases than for other industries. Most pharmaceutical substances are manufactured utilizing "batch" processes, wherein products are manufactured in small batches. The batch nature and large volumes of raw materials used to produce the relatively small amounts of high purity pharmaceutical products may account for the higher rate released by the pharmaceutical industry.

The pharmaceutical industry is a small part of the larger industry chemical manufacturing. While chemical manufacturing sources have their own NESHAP the emissions limits for chemical firms are mainly couched in flow terms, making the availability of data difficult. The TRI requires that firms report their toxic releases in lbs. per year, and the pharmaceutical industry NESHAP places limits on emissions in terms of lbs. per year, making it possible to directly study the impact of toxic emissions on wages and employment.

2.3 The Clean Air Act and the 1990 Amendment

The Clean Air Act of 1963 expanded federal role in the fight against air pollution by requiring federal authorities to establish air quality criteria. This role was later formalized in the 1970 Amendment to the Act by requiring the newly created EPA to carry out the Act's provisions. The 1970 Amendment not only directed the EPA to establish national air quality standards, it required states to develop implementation plans to establish limits for individual sources of emissions. The role of the EPA in regulating air pollution has been steadily expanded in further amendments to the Act. The 1990 Amendment dealt with the subject of air toxics by establishing a list of 189 regulated hazardous air pollutants. The EPA was required to establish standards for major sources, which are defined as those with the potential to emit 10 tons per year of any single hazardous pollutant or 25 tons of any combination of air pollutants.

In addition the EPA was required to establish technology-based emission standards, called Maximum Achievable Control Technology (MACT standards) and to specify categories of sources subject to these emission standards. The EPA is to revise standards periodically (at least every 8 years). The MACT standards for new sources "shall not be less stringnt than the most stringent emissions level that is achieved in practice by the best controlled similar source." The standards for existing sources may be less stringent than those for new sources, and are given 3 years following the promulgation of standards to achieve compliance.

In addition to major sources of hazardous air pollution, the 1990 Amendment also requires the EPA to establish standards for stationary "area sources" determined to produce the threat of adverse effects to human health or the environment. The provision requires the EPA to regulate the stationary area sources responsible for 90% of the emissions of the 30 hazardous air pollutants that present the greatest risk to public health in the largest number of urban areas. These standards are known as the National Emission Standards for Hazardous Air Pollutants.

2.4 Literature Review

There have been relatively few studies on the effect of environmental regulation on wages. Hollenbeck (1979) analyzes an interindustry production model with endogeneous price and wage determination. This model studies the impact of stationary source air pollution regulation on the level and distribution of employment and earnings. Specifically, the model examines the effects of the restrictions on permissible emissions levels from stationary sources as determined by the 1970 Clean Air Act Amendment. This Amendment requires specific industries to build new plants or modify existing plants to accommodate the best available pollution control technology, equipment and processes. The model considers only the cost side of the issue because the benefits of pollution regulations are likely to be intangible These intangibles include the reduced incidence of disease, reduced damage to the atmosphere and vegetation, which are difficult to value, unlike the costs of clean air which are likely to affect economic activity directly. Hollenbeck (1979) likens air pollution regulation to a factor tax on selective industries, which in turn leads to effects on relative product prices. The regulation of capital investments made by specific industries will lead to substitution effects within these industries. A 3-factor of production model, where the facts are pollution abatement capital, other capital and labour, the substitution effects can be hypothesized to relatively favour the former factor.To the extent that regulated industries pass on increased costs of production to consumers, relative prices will change affecting consumer demand, production and employment. The two key results are that (i) some pollution intensive sectors actually end up better off as a result of the policy while some sectors that are most adversely affected had no pollution abatement expenditures at all and (ii) the earnings differential after the regulation tend to be regressive.

Duffy-Deno (1992) examines the question of whether environmental regulations repress economic activity. He uses the bias against new sources of pollution created by regulations imposed by the 1970 and 1977 Amendments to the U.S. Clean Air Act. This bias is hypothesized to have several effects. As new firms face higher compliance costs, this bias protects existing firms from competition, allows them to earn positive economic profits and increases their value. This bias also provides firms with the incentive to increase the operation time of facilities before retirement because under the CAA regulations any new facility within an existing plants is considered a new source. As older facilities tend to generate higher levels of pollution perverse incentives can be created to delay the achievement of environmental goals by delaying the closure of these older plants. In addition, since the bias against new sources of environmental pollution increases the cost of entry or expansion into regulated industries, there may be a negative impact on regional economic activity. Differences in local regulations and corresponding enforcement effects may account partially for differences in compliance costs.

Duffy-Deno (1992) provides empirical evidence of the relationship between per unit pollution abatement costs and regional employment and earnings levels. Since more stringent regulations lead to higher per unit compliance costs, regions characterized by higher compliance costs may also be characterized by relatively lower levels of employment and earnings. The results show that the manufacturing sector has been negatively affected from 1974 to 1982. The total cost of pollution however does not have a statistically significant association with either total employment or earnings levels. The implication is that employment and earnings gains in one sector may exactly offset the losses in other sectors. The fact that earnings levels are not affected suggests that the reduction in labor demand may be exactly offset by a reduction in labor supply.

Mishra and Smyth (2011) look at the extent to which firms in China pass on the costs of environmental regulation in the form of lower wages to workers. The hypothesis is that if firms pass the cost of pollution abatement on to workers we can expect a negative relationship between pollution abatement and wages. On the other hand, there is also a compensating wage differential argument, where workers could demand higher wages for working in a dirty firm. The results imply a reduction in the average hourly wage between 13.8% and 18.8% for individuals in firms which reported implementing measures to control pollution. The results are consistent with abating firms passing on the costs of abatement to workers in the form of lower wages, rather than the existence of a compensating wage differential where workers in high polluting firms demand higher wages.

Walker (2013) uses confidential Longitudinal Employer Household Dynamics (LEHD) data from the U.S. Census Bureau to follow workers across their jobs over time in order to study the wage costs borne by workers who remain in the newly regulated (and therefore less productive) sector under the U.S. Clean Air Act and the long-run earnings losses for those who leave the sector. The results show that workers in the regulated sector had average earnings decline by more than 5% in the 3 years after the regulation. The average worker in a regulated sector experienced a total earnings loss equivalent to 20% of their preregulatory earnings. An aggregate estimate of the total forgone wage bill associated with the regulation-induced sector shift in production is around $5.4 billion (in 1990 dollars). Isen et al. (2017) goes in a slightly different direction by examining how in-utero exposure to air pollution affects later-in-life employment and earnings outcomes. They find that individuals who were in utero or born in counties that were regulated under the Clean Air Act work on average 0.020 quarters more annually, and enjoy annual earnings that are 1% higher than cohorts that are born into more polluted counties.

Prior empirical work has shown mixed evidence on the effect of environmental regulation (including the Clean Air Act) on employment. A study on the effect of particulate matter by Kahn (1997) finds that high levels of TSP were associated with slowing business growth. Henderson (1996) finds (using county employment data) that the nonattainment designation by the EPA was responsible for the exit of plants from a county. Both Becker and Henderson (1997) and List and McHone (2000) show that the birth of new firms in counties subject to ozone regulation were adversely affected due to the movement of polluting firms to attainment areas.

Greenstone (2002) finds that the 1970 and 1977 Amendments to the CAA caused a loss of jobs, capital stock as well as output in polluting industries. In addition, the CAA Amendments caused a significant retardation to the growth of polluting manufacturers in nonattainment counties. However Greenstone (2002) looks at four criteria air pollutants – ozone, carbon monoxide, sulfur dioxide and total suspended particulates (TSPs)- and does not examine toxic chemicals.

Morgenstern et al. (2002) find that environmental regulation did not lead to a significant change in employment, with a small but significant increase in employment detected in some sectors. Berman and Bui(2001) find a positive relationship between air quality regulation and firm labour demand.

Walker (2011) looks at the impact of the CAAA on labour reallocation and finds that firms respond to environmental regulatory pressure by destroying jobs rather than reducing hiring rates. He considers plant-level regulatory status and details how these plants respond to changes in environmental regulation. Walker designates counties that are in nonattainment to be more highly regulated than counties that are in attainment of emissions standards. He finds there is a persistent relationship between being highly regulated and sector-level employment. The increased stringency of regulations due to the 1990 Amendment caused the polluting sector to reduce employment by 15 percent in the 10 years following the regulation. Overall the literature shows a negative relationship between employment and the presence of environmental regulation in the form of the CAA.

2.5 Data

The primary data for this paper are from the Toxics Release Inventory from the Envirofacts database made publicly available by the Environmental Protection Agency. Data on income, employment, and individual characteristics are from the IPUMS Current Population Survey. These data sources are described in further detail below.

3.1 Toxics Release Inventory Under the Emergency Planning and Community Right-to-Know Act of 1986 a plant must file a report with the EPA if that plant has ten or more employees and produces or uses quantities of toxic chemicals above a certain threshold. This is true for each of the nearly 650 chemicals covered in the Toxics Release Inventory. A plant's releases and transfers of a chemical are broken down by the TRI form which details where the toxic chemical ends up: air, land, underground injection, surface water, public sewage, or off-site transfer (mainly to storage or disposal facilities). Ever since its debut in 1989 the

TRI has become a well-known measure of a plant or company's environmental performance.

3.2 Current Population Survey The Current Population Survey (CPS) is a U.S. household survey conducted by both the U.S. Census Bureau and the Bureau of Labour Statistics. The Current Population Survey is administered monthly by the Census Bureau to over 65,000 households, though over the past 15 years the sample size has been closer to 75,000. The survey gathers information on educational indicators, labour force status, demographics, housing data and other characteristics of the U.S. population. This survey data is used extensively by economists, demographers, sociologists and other researchers.

The basic monthly CPS is a battery of labour force and demographic questions. Over the years supplemental questions on special topics have been added for specific months. Among these, the March Annual Social and Economic Supplement (ASEC) is the most widely used by social scientists and policymakers. The IPUMS data makes specific use of the ASEC for annual data. Despite the usefulness of the CPS, the CPS files from the U.S. Census Bureau are inconvenient to use. There are many issues related to forming a time series by piecing together surveys from many different years. There are changes in location and length of variables over time, requiring many different program formats to obtain a given set of variables across many years. There are subtle changes in variable coding, as well as the questionnaire questions from which the variables are derived. For instance, the values at which monetary variables are top-coded change over time, in ways that are sometimes not specified in the survey documentation.

The IPUMS CPS is an integrated dataset on individuals and households from the Current Population Survey from 1962 onward. To enable cross-time comparisons using the CPS data , variables in IPUMS CPS are coded identically, or "harmonized." The IPUMS CPS project was carried out by the Minnesota Population Center in collaboration with Unicon Research

Table 2.1: Summary Statistics for CPS and QCEW Data

Variable	CPS	QCEW
Demographic variables		
% African American	8.98	
% Asian	2.32	
% Married	69.54	
% Female	47.84	
% Completed High School	32.71	
% Completed Bachelors	32.98	
% Completed Masters	13.94	
Age	40.99	
Socioeconomic variables		
Annual Wages	$53,875.55	$92, 297.54
Quarters Worked Per Year	3.85	
Income from Unemployment Insurance	$191.82	
Annual Number of Employees		15,520.72
Annual Number of Establishments		127.73
Average Weekly Wage		$1,787.94

Corporation. Major funding comes from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, in addition to supplementary funding from the National Science Foundation program in Social Science Infrastructure and the Robert Wood Johnson Foundation.

The IPUMS CPS integrated dataset has information on weekly and hourly earnings by occupational status, detailed demographic groups, age, education, union status and full-time and part-time employment status. I use usual hours worked in the past week as a proxy for employment. I merge the data from the TRI database together with the CPS data to gain industry-state-year cells for the individual. The observations span nearly three decades, from 1987 to 2016. I then collapse wage and employment data to county-level averages. The final model is a regression of county-level measures of wage and employment on the treatment.

3.3 Quarterly Census of Employment and Wages I also utilize a second dataset on employment and wages provided by the Quarterly Census of Employment and Wages (QCEW) published by the Bureau of Labour Statistics. The program originated in the 1930s, and was known as the ES-202 program until 2003 when the current QCEW name was adopted. The primary economic product is the tabulation of employment and wages of establishments which report to the Unemployment Insurance (UI) programs of the United States. Employment covered by these UI programs represents about 97% of all wage and salary civilian employment in the country.

In general, QCEW monthly employment data represent the number of covered workers who worked during, or received pay for, the pay period that included the 12th day of the month. Virtually all workers are reported in the state in which their jobs are located. Covered private-industry employment includes most corporate officials, executives, supervisory personnel, professionals, clerical workers, wage earners, piece-workers, and part-time workers. Persons on paid sick leave, paid holiday, paid vacation, and the like are also included. Persons on the payroll of more than one firm during the period are counted by each UI-subject employer, if they meet the employment definition noted previously. Workers are counted even though, in the latter months of the year, their wages may not be subject to UI tax. It excludes proprietors, the unincorporated self-employed, unpaid family members, and certain farm and domestic workers. The employment count also excludes workers who earned no wages during the entire applicable pay period because of work stoppages, temporary layoffs, illness, or unpaid vacations.

Average annual wages per employee for any given industry are computed by dividing total annual wages by annual average employment. A further division by 52 yields average weekly wages per employee. Annual pay data only approximate annual earnings, because an individual may not be employed by the same employer all year or may work for more than one employer at a time (*Employment and Wages Online*, U.S. Bureau of Labour Statistics (2010)).

I also utilize the number of pharmaceutical establishments in a state as an outcome of interest. An establishment is an economic unit, such as a farm, mine, factory, or store that produces goods or provides services. It is typically at a single physical location and engaged in one, or predominantly one, type of economic activity for which a single industrial classification may be applied. Occasionally, a single physical location encompasses two or more distinct and significant activities. Each activity is reported as a separate establishment, if separate records are kept, and the various activities are classified under different NAICS industries.

Most employers have only one establishment; the establishment is the predominant reporting unit or statistical entity for reporting employment and wage data. Most employers who operate more than one establishment in a state file a Multiple Worksite Report (MWR) each quarter. The MWR form is used to collect separate employment and wage data for each of the employer's establishments. Some employers with two or more very small establishments do not file an MWR. If the total employment in an employer's secondary establishments (all establishments other than the largest) is 10 or less, the employer generally files a consolidated report for all establishments. Also, some employers either cannot, or will not, report at the establishment level and, thus, aggregate establishments into one consolidated unit, or possibly several units, though not at the establishment level.

Before 1991, employers provided covered employment and wage data on a reporting unit basis. Reporting unit data typically furnished detail only for different county locations or industrial operations within a state. A nonstandard form, similar in concept to the MWR and called the Statistical Supplement, was used by States to collect these county industry data. Although reporting units were, for the most part, individual establishments, employers could provide a summary of their employment and wage data for multiple establishments within a county that were conducting the same type of industrial activity. For example, a fast-food business might have submitted a single report that covered all of its operations within a county prior to 1991; on the MWR, the employer reports employment and wage data for each location. The MWR substantially enhanced the accuracy of the QCEW data after 1991 and allowed the QCEW data to be a better sample frame for other programs (*Employment and Wages Online*, U.S. Bureau of Labour Statistics (2010)).

The Current Population Survey (CPS) has some differences from the Quarterly Census of Employment and Wages data. The Current Population Survey (CPS) is published monthly by the BLS and Census Bureau. CPS employment data are estimated from a survey of about 60,000 U.S. households, while QCEW employment data are summarized from quarterly reports submitted by 10.0 million U.S. establishments. The CPS counts employed persons, whereas the QCEW program counts covered workers who earned wages during the pay period that includes the 12th of the month. Consequently, the CPS includes persons 'with a job but not at work' who earn no wages, for example, workers on extended unpaid leaves of absence. QCEW data, by contrast, exclude unpaid workers. QCEW data count separately each job held by multiple jobholders. While the CPS counts such workers once, in the job at which they worked the most hours, the CPS does have some multiple jobholder data. The CPS counts employed persons at their place of residence; the QCEW program counts jobs at the place of work. CPS also differs from the QCEW program, in that it includes self-employed persons; unpaid family workers employed 15 or more hours during the survey period; and a greater proportion of agricultural and domestic workers. CPS data exclude persons under age 16, while the QCEW program counts all covered workers, regardless of age (*Employment and Wages Online*, U.S. Bureau of Labour Statistics (2010)).

In addition to the above differences, the QCEW sample I utilize is different from the CPS in three important ways. The CPS data I use are from 1987 to 2016 whereas the QCEW data is from 2001 to 2016. This difference is mainly because I restrict myself to public-use datasets and the BLS makes QCEW data publicly available only from 2001 onwards. The second difference is that the CPS data are microdata that I collapse to county-level averages whereas the QCEW data I collect are state-level data. There are two reasons for this difference: the first is a time constraint imposed by the way in which the QCEW county level data are published. The BLS publishes the data for each county separately. If there are 4 variables of interest and roughly 3,000 counties in the sample, building the dataset would entail compiling around 12,000 data tables by hand, which is outside the feasible time period of my study. To make the dataset-building more manageable I restrict the analysis to the state level. The second reason is that at the county-level there are serious discrepancies in the publishing of QCEW data, as in order to maintain confidentiality data are frequently missing or unreported. In addition because the scope of my study is restricted to the pharmaceutical industry, the number of counties for which employment and wage data are missing goes up dramatically. In order to have a more complete dataset, therefore, I restrict the level of the dataset to the state level. The third difference between the two datasets is in the employment-related measures made available by both. I use the numbers of weekly hours worked and the number of annual quarters worked as the two employment measures from the CPS. For the QCEW data I use the number of establishments and the number of employees as measures of employment.

There are advantages and disadvantages associated with using both datasets. The CPS data, because it is a household-level dataset, allow me to see how regulation of a firm affects changes in the working behaviour and earnings of individuals located in the same county as that firm. I can conduct a micro-level analysis of the effects of environmental regulation on individuals. However, the drawback of using such a dataset is that I cannot determine how aggregate trends in employment and wages are affected by firm-level regulation aimed at improving the environment. Given that the firm-level downsizing sometimes created by pollution control policies in one sector is frequently offset by hiring increases in other sectors, the research on the aggregate impacts of environmental regulation in the U.S. is not always clear. While I do not study any sector other than the pharmaceutical industry I attempt to address this question by looking at state-level differences in employment and wages due to the regulation. Utilizing an aggregate dataset such as the QCEW however means that micro-level (in this case at the county level) changes in employment and wages can be washed out in the econometric analysis. In a sense, therefore, the implications of both datasets are complementary to each other, with one level of analysis at the county level, and the other at the state level.

3.4 Limitations of the data My dataset has two limitations. The first is that the Toxic Release Inventory data is self-reported data. Firms are required to complete forms detailing their annual emissions, which forms the basis of the inspections and other compliance-related activities by enforcement authorities. This is arguably a source of measurement error, and if emissions are underreported the estimates of the impact of the regulation are likely to be biased. However this problem is likely to be inevitable since data collection for toxic releases is very different from that of criteria air pollutants. As part of measures to combat CAPs monitoring stations are placed at various locations within counties to take daily (and hourly) measurements of ambient air pollution. Hazardous air pollutants (HAPs) on the other hand are so numerous (189 regulated hazardous air chemicals listed in the Clean Air Act to just 6 criteria air pollutants) that to deploy state-sponsored instruments to measure emissions is simply infeasible given the variation in industry emission standards. It may also be that hazardous emissions may have to be measured at point sources (which in most cases is at the firm level) as opposed to being measured by way of overall ambient concentrations. For these reasons firms are required to formally report the level of emissions themselves, making measurement error an unavoidable reality of working with TRI data.

The second limitation of the dataset comes from the way non-attainment status is assigned. I assign a firm to be in non-attainment if that firm in a county exceeds 2000 lbs per year of HAP emissions. This definition only takes into account the emissions limits and whether a firm operates within these limits. However emissions standards for hazardous air pollutants not only delineate the emissions limit to which a firm is subject, but also technological standards that firms belonging to the industry source category are expected to fulfill. In this sense the assignment mechanism I use is useful as a first pass for assigning non-attainment status but is not completely definitive, as it is theoretically possible for a firm to meet the emissions limit and yet fail to implement the technological standards governing that industry source. The 2000 lbs/year limit is therefore a necessary condition for non-attainment status, but not sufficient.

2.6 Research Design

The ideal estimation of the impact of a regulation aimed at the firm level requires the identification of two groups of firms that are identical in all characteristics apart from the application of the regulatory standard. However the characteristics of firms that are major polluters differ from those of non-polluters in appreciable ways. Firms that produce significant levels of emissions tend to be larger in size. Becker and Henderson (2000) show that plants in CAAA-regulated counties tend to be 25-69% larger than plants in unregulated counties, though this effect tends to diminish with the age of the plant. Polluting firms also tend to be older and suffer slower growth rates (Walker (2011)). A simple comparison of wages between polluting and non-polluting firms that does not take into account these observable (and unobservable) differences is therefore likely to yield biased estimates. The framework suggested by the Clean Air Act provides a potential way to make such a comparison by basing identification on a federally mandated emissions limit.

Variation in this framework occurs across space and time. Firms are considered 'treated' if they meet the emissions cutoff for the applicability of the regulatory standard at any point in time. In the 1998 sample, 98 pharmaceutical firms were regulated while 44 firms were left unregulated because their total HAP emissions did not meet the emissions cutoff for the regulation to be applicable. Such cross-sectional variation means that I can control for the separate identification of county-specific shocks and the regulation treatment effects. There is also variation in time as firms are regulated according to their current emissions limits so it is possible for a firm to be regulated in one year and then to be unregulated in the next. Pre/post comparisons are therefore possible within counties and firms and time-invariant unobservable group characteristics can be controlled for by including group fixed effects. The effect of the regulation is therefore isolated from changes at the group level other than the change in regulation.

An issue with estimating the impact of regulation on firms emitting air toxics is the correlation between pollution and economic activity. Grossman and Krueger(1995) demonstrate the presence of an inverted U-shaped relationship between environmental degradation and income, with initial deterioration in environmental quality at lower income levels followed by improvements in environmental indicators at higher levels of income. Walker (2013) shows that air pollution had a depressive effect on county level wages. As a result of this correlation pollution is likely to enter as an endogeneous variable in any direct estimation of the impact of air pollution on outcomes such as wages, household income and employment.

I attempt to circumvent this endogeneity issue by using the 1998 Clean Air Act NESHAP for the pharmaceutical industry as an instrument for air pollution. The national emissions standard for air toxics for this industry is federally mandated and so can be considered independent of county-level movements in tastes, preferences, demographics or underlying economic conditions. Changes in wages or hours worked can thus be considered orthogonal to the federal standard, except through its effect on air pollution. The Clean Air Act-mandated standard can therefore be considered as a valid instrument for air pollution, as the application of the regulatory standard to firms is a discrete function of the level of air toxic emissions by firms.

2.7 Empirical Framework

I adapt the empirical model used in Walker et al. (2017) to judge two related issues: (i) the impact of pollution on wages, hours worked and quarters worked and (ii) the direct impact of air pollution regulation on wages, hours worked and quarters worked. Walker et al (2014) assign treatment at the county level, where a county is said to be in nonattainment status if the average concentration of the air pollutant across all monitor observations exceeds the national ambient air quality standard. Here treatment is at the firm level, where a firm is said to be in nonattainment if the total HAP emissions per year exceeds the federal limits imposed by the regulation. Variation in this empirical framework is thus on two fronts: firm non-attainment status and time. Firm non-attainment status (f) is an indicator variable that takes on a value of 1 if the firm is designated to be in non-attainment of the emission limits. There are two time periods that represent the "pre" and "post" of the regulatory change (t): for pharmaceutical manufacturing the regulatory policy goes into effect in 1998.

The basic economic model takes the following form:

$$y_{ct} = \alpha + \beta.HAP_f + X'_{ct}.\gamma + \lambda_f + \mu_t + \tau_{st} + \epsilon_{ct} \tag{2.1}$$

y_{ct} is the outcome variable which is either average annual wages in county c in year t or average number of hours worked per week or average number of quarters worked per year. HAP is the total level of HAP emissions by a firm measured in $lbs/year$. X_{ct} is a vector of time-varying socio-economic and demographic county characteristics that may possibly affect the outcome variable. They include percent of county population that is female, percent of county population that is married, African American, Asian, has completed a high school, bachelors or masters education, percent of county that is below the poverty line, percent that is unemployed, average total income and average income from unemployment insurance. μ_t captures the yearly time trends in the data while τ_{st} captures time-varying determinants of the outcome variable that are common to all firms operating withing a given state x year. ϵ_{ct} represents unobserved shocks to the outcome variables in a county in a given year.

The OLS model is likely to provide biased estimates due to substantial omitted variables bias. In addition, any unobserved shocks that affect both pollution as well as employment and earnings measures will lead to biased estimates. I therefore use an instrumental variables approach, where the first stage leverages the variation provided by the 1998 regulation as an instrument for air pollution. The first-stage regression in a two-stage least-squares regression framework is therefore as follows:

$$HAP_{ct} = \alpha.Nonattainment \times 1(\tau > 1998) + X'_{ct}\rho + \gamma_c + \mu_{st} + v_{ct} \tag{2.2}$$

The first stage regresses nonattainment of emissions standards of firms on total HAP emissions interacted with an indicator equal to 1 for the years after the CAAA regulation went into effect on total HAP emissions. α provides a difference-in-difference estimate of the impact of the regulation on emissions. In the second stage, I use the predicted HAP emissions instead of actual HAP emissions in equation (1):

$$y_{ct} = \alpha_0 + \alpha_1 \widehat{HAP}_{ct} + X'_{ct}\kappa + \gamma_c + \epsilon_{ct} \tag{2.3}$$

As mentioned in Isen et al. (2017), it is possible for the CAAA to affect counties in ways other than pollution. Some studies have shown that the CAA has led to declining economic conditions in regulated counties (Walker(2011), Walker(2013)) in which case the exclusion restriction will be violated. In such a situation the 2SLS estimates will be biased. For this reason, I directly estimate the impact of the CAAA on earnings and employment measures by running the following difference-in-difference regression:

$$y_{ct} = \alpha.Nonattainment \times 1(\tau > 1998) + X'_{ct}\rho + \gamma_c + \mu_{st} + \epsilon_{ct} \tag{2.4}$$

α here represents the direct impact of the 1998 regulation on outcome y_{ct} which may either be earnings or weekly hours worked or annual quarters worked.

2.8 Results

2.8.1 Current Population Survey data

OLS results

The OLS results are presented in Tables 2.2, 2.3 and 2.4. Table 2.2 shows the effect of toxic air pollution on earnings. No statistically significant effect of pollution on earnings is found in any model. Table 2.3 shows the regression of average hours worked per week on total emissions and finds that the effects are not statistically significant from zero. Table 2.4 shows a similar result for number of annual quarters worked. The model with the full set of controls (Column (5)) show that the effect of pollution is zero.

The results from the OLS regressions suggest that air pollution has no impact on either earnings or employment. However OLS regressions are likely subject to omitted variables bias. For example, pollution tends to be correlated with poverty rates and individuals who live in poorer counties will have a lower capacity to earn higher earnings (Isen et al.(2017)). Therefore the results of these models are unlikely to indicate the true relationship between pollution and earnings or employment. I therefore use an instrumental variable approach to study the relationship between air pollution and earnings and employment.

Table 2.2: OLS regression of Total Emissions on Wages

	(1)	(2)	(3)	(4)	(5)
Total emissions	-0.00531**	0.000588	-0.000100	-0.000287	-0.000200
	(0.00207)	(0.00257)	(0.000229)	(0.000342)	(0.000425)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.3: OLS regression of Total Emissions on Hours Worked

	(1)	(2)	(3)	(4)	(5)
Total emissions	-0.000000732**	-0.000000701**	6.88e-08	9.17e-08	4.83e-08
	(0.000000301)	(0.000000334)	(4.27e-08)	(8.48e-08)	(7.63e-08)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.4: OLS regression of Total Emissions on Quarters Worked

	(1)	(2)	(3)	(4)	(5)
Total emissions	-6.32e-08	-5.33e-08	5.20e-09*	4.35e-09	5.57e-09*
	(7.37e-08)	(8.74e-08)	(3.13e-09)	(2.73e-09)	(3.19e-09)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

IV 2SLS estimates

I instrument for air pollution using implementation of the 1990 Clean Air Act Amendment. The 1990 Amendment had a significant impact on air pollution. Because the Amendment is a regulatory decision at the federal level, the passage of the Amendment is unlikely to be correlated with earnings or employment and therefore satisfies the exclusion restriction. Table 2.5 presents the first-stage regression of total emissions on the policy. In every specification the impact of the 1990 Amendment on total emissions is highly significant, suggesting that the first stage is strong.

Table 2.6 presents the results of the second stage IV regression of earnings on predicted emissions and control variables. Column (5) employs a full set of controls and shows that air pollution has a statistically significant negative impact on earnings. A one unit increase in total emissions reduces earnings by 0.024. This result is similar to the results in Isen et al. (2017). Tables 2.7 and 2.8 show the IV results for weekly hours worked and annual quarters worked. Toxic emissions had zero impact on both measures, though the results for quarters worked are mixed, but not statistically significant.

However, it is possible for the 1990 Amendment to affect counties in ways beyond air pollution. Greenstone (2003), Walker (2011) and Walker (2013) show that the passage of the Clean Air Act affected areas that were regulated by having a regressive impact on both earnings and employment. In this case the 2SLS estimates will be biased, and so I run the difference-in-difference regressions to find out the direct impact of the 1990 Amendment.

Table 2.5: IV regression on Total Emissions

	(1)	(2)	(3)	(4)	(5)
$Nonattainment \times 1(\tau > 1998)$	-211352.7***	-222148.3***	-155322.4***	-154807.6***	-143477.6***
	(58803.7)	(59513.9)	(28544.7)	(28597.8)	(34756.6)
N	16634	16634	16634	16634	16634
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Difference-in-difference results

Table 2.9 shows the results of the earnings difference-in-difference regressions. In all specifications the effects are positive, indicating that the passage of the regulatory requirements

Table 2.6: IV regression of Total Emissions on Wages

	(1)	(2)	(3)	(4)	(5)
Predicted emissions	-0.00928***	0.00110	-0.000206	-0.0217***	-0.0243**
	(0.00293)	(0.00264)	(0.000973)	(0.00835)	(0.0105)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.7: IV regression of Total Emissions on Hours Worked

	(1)	(2)	(3)	(4)	(5)
Predicted emissions	-0.00000137***	-0.00000147***	-1.05e-08	-0.00000214*	-0.00000259
	(0.000000441)	(0.000000455)	(0.000000120)	(0.00000126)	(0.00000168)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.8: IV regression of Total Emissions on Quarters Worked

	(1)	(2)	(3)	(4)	(5)
Predicted emissions	-0.000000114	-0.000000108	6.74e-09	1.90e-08	3.17e-08
	(7.36e-08)	(9.16e-08)	(6.32e-09)	(8.14e-08)	(0.000000106)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

in 1998 increased earnings by $3,423.5. Compared to average annual earnings of $57,475.17, this represents an increase of 5.95%. Table 2.10 shows the impact of the 1998 policy on average weekly hours worked, and indicates a positive effect in all specifications. Table 2.11 shows the effect on average annual quarters worked and finds a negative but statistically insignificant impact. Figure 2.1 and 2.2 show the difference-in-difference estimates in an event study-type graph. While the estimates appear to be noisy, the effects are mostly positive over the period of study. In addition the estimates prior to the regulation appear to be close to zero, providing further evidence to the validity of the difference-in-difference regressions.

Tables 2.10 and 2.11 show similar regressions for weekly hours worked and annual quarters worked. The effects on weekly hours worked shows that when county fixed effects are included, individuals work 0.331 more hours per week as a result of the regulation. This translates to $457.31 additional earnings per year [1]. The results for annual quarters worked show that the effects of the 1998 regulation are negative, but not statistically significant at traditional significance levels.

Table 2.9: Difference-in-difference regression on Earnings

	(1)	(2)	(3)	(4)	(5)
$Nonattainment \times 1(\tau > 1998)$	115.7	3225.2	2185.0*	3363.2**	3423.5**
	(3210.0)	(2695.1)	(1199.5)	(1303.2)	(1475.4)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

[1] This calculation is obtained by considering that the average annual earnings is $57,475.17 and that workers work an average of 40 hours per week for 50 weeks every year, implying that workers earn $27.63 in hourly earnings. 0.331 extra hours per week then translates to additional annual earnings of $0.0331 \times 50 \times \$27.63 = \$457.31$

Table 2.10: Difference-in-difference regression on Weekly Hours Worked

	(1)	(2)	(3)	(4)
$Nonattainment \times 1(\tau > 1998)$	0.330	0.206	0.237	0.331^{*}
	(0.503)	(0.476)	(0.190)	(0.195)
N	16500	16500	16500	16500
TIME FE	YES	YES	YES	YES
STATE FE	NO	YES	YES	YES
STATE X YEAR FE	NO	NO	YES	YES
COUNTY FE	NO	NO	NO	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

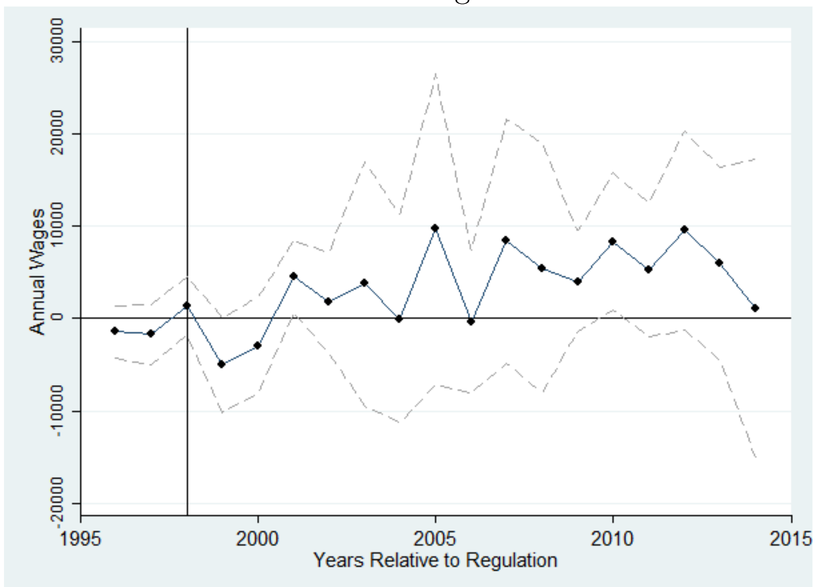
Table 2.11: Difference-in-difference regression on Annual Quarters Worked

	(1)	(2)	(3)	(4)	(5)
$Nonattainment \times 1(\tau > 1998)$	-0.0140	-0.00674	-0.0148	-0.00294	-0.00302
	(0.0405)	(0.0353)	(0.0124)	(0.0125)	(0.0159)
N	16500	16500	16500	16500	16500
Time FE	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	YES
State FE	NO	YES	YES	YES	YES
State X Year FE	NO	NO	YES	YES	YES
County FE	NO	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 2.1: Difference-in-difference Regression Estimates on Earnings



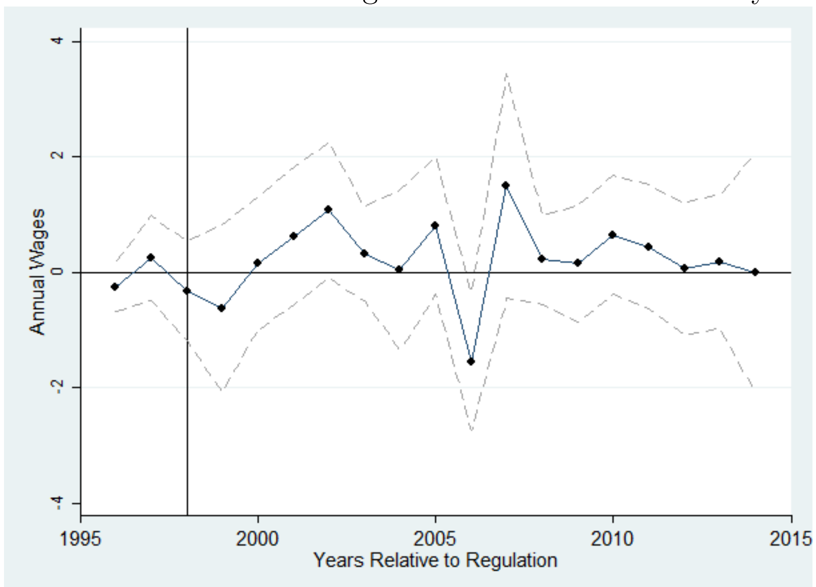
Treatment Heterogeneity

Non-linearity in the Dose-Response Relationship

The model specifications in Tables 2.2-2.10 have assumed that exposure to toxic air emissions has a linear relationship with health, and by extension, outcomes such as earnings or number of weekly hours or annual quarters worked. However non-linearity in the functional form of the dose-response relationship between exposure and health would lead to the underestimation or overestimation of the effects of pollution on outcomes in a linear model. Currie and Neidell (2005) suggest that the possibility that pollution has visible effects only past some threshold.

To counter this objection I estimate a difference-in-difference-in-difference model where treatment is interacted with the level of annual toxic emissions by a firm. The standard DID model thus becomes:

Figure 2.2: Difference-in-difference Regression Estimates on Weekly Hours Worked



$$y_{ct} = \alpha + \beta_1.Regulation \times 1(\tau > 1998) \times Emissions + \beta_2.Regulation \times 1(\tau > 1998)$$
$$+\beta_3.Regulation \times Emissions + \beta_4.Emissions \times 1(\tau > 1998) + \beta_5.Regulation$$
$$+\beta_6.Emissions + \beta_7.1(\tau > 1998) + X'_{ct} + \mu_{st} + \gamma_c + \epsilon_{ct}$$

β_1 represents the coefficient on the triple-difference estimator: the interaction between the regulation indicator, the post-1998 cohort indicator and the level of annual toxic emissions summed over all hazardous air pollutants emitted by a firm. β_2 is the coefficient on the standard difference-in-difference estimator. β_3 is the interaction between the treatment indicator and the level of annual HAP emissions. β_4 is the interaction between annual emissions and the post-regulation indicator.

If β_1 is zero, this would imply that the effect of the Clean Air Act Amendment does not vary linearly in toxic emissions. If, however, β_1 is positive then this implies that the impact of the 1990 Amendment is greater the higher the level of pollution and would suggest that pollution has a greater impact on outcomes in areas with higher than average pollution. As cautioned in Isen et al. (2017) the problem with this test is that even if there is evidence of treatment heterogeneity, it is possible for such heterogeneity to be attributable to health factors other than pollution. For instance some counties may lack ready access to healthcare, which may make the population particularly vulnerable to health conditions and affect their earnings potential and willingness to work more hours and days. In this case the greater responses of individuals to changes in pollution may be a result of these underlying health conditions rather than the magnitude of the level of pollution. I partially address this issue by including county fixed effects in the model but it is possible for there to be other unobserved factors driving any possible treatment heterogeneity. Table 2.12 suggests that the impact of the regulation is diminishing in the level of pollution, though none of the effects are statistically significant. This result suggests that in particularly polluted areas, state or county-level pollution policies may be better equipped to deal with toxic emissions.

Table 2.12: Difference-in-difference Treatment Heterogeneity with Level of Emissions

	(1) Earnings	(2) Hours Worked	(3) Quarters Worked
$Nonattainment \times 1(\tau > 1998) \times Emissions$	-1.062	-0.000362	-0.00000760
	(1.686)	(0.000247)	(0.0000191)
$Nonattainment \times 1(\tau > 1998)$	3794.2**	0.521*	-0.0000735
	(1678.8)	(0.281)	(0.0169)
N	16500	16500	16500
R^2	0.907	0.919	0.933

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Differences by Sex

I check for treatment heterogeneity by dividing the overall sample into subsamples based on sex. Tables 2.13 and 2.14 describe the difference-in-difference estimates by gender. The treatment effect for wages is positive for both men and women. Though the coefficients on treatment differ by gender, this is not statistically significant.

Table 2.13: Difference-in-difference Treatment Heterogeneity for Males

	(1) Earnings	(2) Hours Worked	(3) Quarters Worked
$Nonattainment \times 1(\tau > 1998)$	1852.7	0.777	0.0543**
	(3317.8)	(0.547)	(0.0223)
N	13189	13189	13189
R^2	0.825	0.874	0.874

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.14: Difference-in-difference Treatment Heterogeneity for Females

	(1) Earnings	(2) Hours Worked	(3) Quarters Worked
$Nonattainment \times 1(\tau > 1998)$	2132.5	-0.307	-0.0107
	(2408.0)	(0.366)	(0.0388)
N	12569	12569	12569
R^2	0.900	0.870	0.855

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

When it comes to weekly hours worked, the impact of the CAA Amendment is insignificant for men and women. When it comes to number of annual quarters worked. For women, the treatment effect is negative, though this is not significant at traditional significance levels. For men there is a positive, statistically significant effect, implying that as a result of the regulation men on average work 0.054 quarters more. This implies additional earnings of \$873.09 per year. [2]

Differences by Age Group

I also check for heterogeneity by age group. For annual earnings I have microdata for individuals aged 15 to 60, and so I divide the county-by-year earnings data into the following age

[2] This number is calculated as follows: the average male annual earnings in the pharmaceutical industry is \$64674.94, which translates to average daily earnings of \$177.18. One annual quarter translates to 91.25 days so 0.054 quarters translates into earnings of $0.054 \times 91.25 \times \$177.18 = \$873.05$.

groups: less than 20 years, 20-30, 30-40, 40-50 and 50-60. For employment-based measures (annual quarters worked and weekly hours worked) I have microdata for individuals from age 18 to 65. I divide the county-level aggregates into: less than 25 years, 25-35, 35-45, 45-55 and 55-65 year age groups.

Table 2.15 describes the heterogeneity of annual earnings by age group. We see a positive impact of the Clean Air Act Amendment at all age groups, though the difference-in-difference estimates differ across age groups in levels and significance. Workers aged 20-30 enjoy on average an increase of \$5,131, an increase of 8.9% in annual earnings.

Estimates of the effect on weekly hours worked vary in sign and significance across age groups as evidenced in Table 2.16. For workers below the age of 25 this effect is negative and statistically significant t: on average workers of this age group work 3.051 fewer hours per week. Given an average of 42.84 hours worked per week, this represents a 7.1% decrease in the number of hours worked per week. Workers in the 55 to 65 year age group work 1.07 more hours per week as a result of the regulation. Gains from the policy appear to be highest for older workers. Table 2.17 looks at the results for annual quarters worked which are mixed. There is a positive, statistically significant effect on workers aged 25 to 35 years, who work 0.086 annual quarters more. This translates to a gain of roughly \$1,390 more per year in annual earnings.

Table 2.15: Difference-in-difference Wage Heterogeneity for Different Age Groups

	(1) Less than 20 years	(2) 20 to 30 years	(3) 30 to 40 years	(4) 40 to 50 years	(5) 50 to 60 years
$Nonattainment \times 1(\tau > 1998)$	447.0	5131.3*	9447.9	6039.3	14536.5
	(2644.9)	(2975.4)	(5953.3)	(7603.5)	(9544.1)
N	7462	10551	10411	7900	3043
R^2	0.890	0.862	0.826	0.901	0.974

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.16: Difference-in-difference Hours Heterogeneity for Different Age Groups

	(1) Less than 25 years	(2) 25 to 35 years	(3) 35 to 45 years	(4) 45 to 55 years	(5) 55 to 65 years
$Nonattainment \times 1(\tau > 1998)$	-3.051**	-0.874	0.433	1.255	1.070**
	(1.212)	(0.676)	(0.541)	(0.904)	(0.540)
N	2931	9750	10992	8971	5819
R^2	0.953	0.832	0.840	0.887	0.922

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.17: Difference-in-difference Heterogeneity in Effects on Annual Quarters Worked for Different Age Groups

	(1) Less than 25 years	(2) 25 to 35 years	(3) 35 to 45 years	(4) 45 to 55 years	(5) 55 to 65 years
$Nonattainment \times 1(\tau > 1998)$	-0.297	0.0861*	0.0325	0.0217	-0.0251
	(0.220)	(0.0504)	(0.0390)	(0.0336)	(0.0292)
N	2931	9750	10992	8971	5819
R^2	0.920	0.861	0.843	0.913	0.834

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Differences by Race

Table 2.18, 2.19 and 2.20 contain the difference-in-difference estimates separated by race. The overall result appears to be primarily driven by whites, who earned an additional $3,361.2 annually as a result of the regulation. The effect for blacks however appears to be negative, but not statistically significant. The effects on weekly hours worked and annual quarters worked are positive, but not statistically significant.

Table 2.18: Difference-in-difference Treatment Heterogeneity for Whites

	(1) Earnings	(2) Hours Worked	(3) Quarters Worked
did_pharm_firm	3361.2*	0.278	0.000605
	(1755.0)	(0.278)	(0.0162)
N	13842	13842	13842
R^2	0.907	0.922	0.953

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.19: Difference-in-difference Treatment Heterogeneity for Blacks

	(1) Earnings	(2) Hours Worked	(3) Quarters Worked
did_pharm_firm	-4700.2	0.334	0.0339
	(4069.3)	(1.611)	(0.0306)
N	1377	1377	1377
R^2	0.921	0.925	0.875

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Conclusion

I find that the Clean Air Act Amendment of 1990 not only had a significant impact on toxic air emissions, but also had an impact on economic outcomes. The gains from the regulation appear to be concentrated on workers in the mid-prime of their working lives. The results suggest that apart from the direct effect of reducing pollution, air quality regulations can improve socioeconomic outcomes such as earnings. These indirect benefits may be due

Table 2.20: Difference-in-difference Treatment Heterogeneity for Asians

	(1)	(2)	(3)
	Earnings	Hours Worked	Quarters Worked
did_pharm_firm	1010.9	-3.404	0.0320
	(15572.3)	(2.348)	(0.173)
N	312	312	312
R^2	0.972	0.976	0.858

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

to the health benefits of working in a less polluted environment. Further study is needed to see whether the results for the pharmaceutical industry also hold true for other industries.

2.8.2 Using the Quarterly Census of Employment and Wages data

Empirical Framework

I adapt the empirical model used in Walker et al. (2017) to judge how the regulation affects wages as well as the number of employees and firm establishments in a state. The following is the full empirical specification:

$$y_{st} = \alpha + \beta_1.Regulation + \beta_2 X_{st} + \mu_s + \gamma_t + \eta_{st} + \lambda_f + \epsilon_{st}$$

y_{st} is the outcome variable which can be either annual wages, average weekly wage, number of employees or number of establishments. β_1 is the coefficient on the regulation variable which takes a value of 1 if the total toxic emissions of the firm exceeds 2,000 lbs. per year and 0 otherwise. X_{st} is a vector of state demographic characteristics such as percentage of the population White, African-American, Asian, married, female, and so forth. μ_s represents state fixed effects, γ_t represents year fixed effects and η_{st} are state by year fixed effects. Finally, λ_f represents firm fixed effects and ϵ_{st} is the error term.

Results

Tables 2.21, 2.22, 2.23 and 2.24 show the results for the regression of annual wages, average weekly wage, total number of employees and number of firm establishments on the regulation. In Table 2.21, when only year fixed effects are included, the regulation reduces annual wages in the pharmaceutical industry by \$2,420.7. This effect falls to \$166 when state fixed effects are included, though not statistically significant. When state by year fixed effects, and later firm fixed effects are included the magnitude falls to essentially zero. The latter results are highly statistically significant, showing a precisely estimated zero effect of the regulation on state-level wages.

Table 2.22 shows the same regressions performed on average weekly wage. Once again, when only year fixed effects are included the toxics regulation reduces weekly wages by \$77.92, though this is not statistically significant. But when state by year and firm fixed effects are included, we once again have a precisely estimated zero effect of the regulation on wage at the state-level.

Table 2.23 regresses the total number of employees employed in the pharmaceutical sector in a state on toxics regulation aimed at the industry. It is interesting to note that the coefficients on the regulation variable when only year and state effects are accounted for are negative but not statistically significant, suggesting a depressive effect of environmental regulation on employment. However when state by year and firm fixed effects are included we obtain a statistically significant zero effect of the regulation on the total number of employees.

Table 2.24 regresses the total number of pharmaceutical establishments in a state on the regulation. Once again, when year and state fixed effects are included in the model the effect on the number of firms is negative, suggesting that firms are likely to go out of business as a result of the air toxics regulation. When state by year and firm fixed effects are included we have a statistically significant zero effect on the number of firms in a state.

Table 2.21: Regression of Annual Wage on Regulation

	(1)	(2)	(3)	(4)
	annual_wage	annual_wage	annual_wage	annual_wage
treatment	-2420.7	-166.0	-6.34e-10***	7.52e-10***
	(7624.8)	(1006.6)	(1.71e-10)	(2.27e-10)
N	11562	11332	11332	11332
Time FE	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES
State FE	NO	YES	YES	YES
State X Year FE	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.22: Regression of Average Weekly Wage on Regulation

	(1) weekly_wage	(2) weekly_wage	(3) weekly_wage	(4) weekly_wage
treatment	-77.92	-3.157	1.90e-11***	-5.74e-12***
	(147.3)	(19.37)	(5.10e-12)	(1.74e-12)
N	11332	11332	11332	11332
Time FE	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES
State FE	NO	YES	YES	YES
State X Year FE	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.23: Regression of Total Number of Employees on Regulation

	(1) number_employees	(2) number_employees	(3) number_employees	(4) number_employees
treatment	-5570.8	-298.8	6.17e-10***	-1.05e-11***
	(5729.3)	(375.7)	(1.68e-10)	(3.24e-12)
N	11188	11188	11188	11188
Time FE	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES
State FE	NO	YES	YES	YES
State X Year FE	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.24: Regression of Number of Establishments on Regulation

	(1) number_establishments	(2) number_establishments	(3) number_establishments	(4) number_establishments
treatment	-74.58	-0.777	-1.32e-12***	-3.28e-13***
	(60.69)	(2.958)	(3.52e-13)	(9.82e-14)
N	11332	11332	11332	11332
Time FE	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES
State FE	NO	YES	YES	YES
State X Year FE	NO	NO	YES	YES

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Conclusion

Prior literature on the impact of the Clean Air Act on wages and employment have been decidedly mixed, with the effects ranging from negative to positive at the micro level. The results of this paper suggest that in the case of the pharmaceutical industry, at a more aggregate level, the impact of environmental regulation on wages and employment is negligible. Indeed, the results show that the effect of air toxics regulation is a very precisely estimated zero.

2.9 Discussion

In this paper I explore the impact of environmental regulations on labour market outcomes. I employ a quasi-experimental approach to study how the regulation of toxic chemicals in the pharmaceutical industry as set out by the Clean Air Act Amendment of 1990 affect employment and earnings in that sector. Utilizing the micro-level data in the Current Population Survey I find that the pharmaceutical industry saw an increase in annual wages as a result of the environmental regulation that was implemented in 1998.

The question becomes whether this result can be generalized to other sectors. There are some indications as to why this may not be the case for other industries. The pharmaceutical industry is highly capital intensive and has a much higher than average per-facility emissions rate compared to other sectors. It is plausible that as a result of the regulation pharmaceutical firms were required to invest heavily in pollution control technologies and saw an increase in the demand for skilled labour capable of operating this technology. It is also worth keeping in mind that the QCEW results show that at the state level the regulation has had zero effects on the number of establishments or wages. This may indicate that labour market trends in one state may be offset by those in others, so that the overall impact of the regulation washes out to zero.

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