Air Quality Regulation and the Reduction of Toxic and Greenhouse Gases

by

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B.A., Western Michigan University, 2004

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A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Department of Economics

2011

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Air Quality Regulation and the Reduction of Toxic and Greenhouse Gases
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Air Quality Regulation and the Reduction of Toxic and Greenhouse Gases

Thesis directed by Prof. Nicholas Flores

The focus of this dissertation is to examine the effect of county-level air quality regulatory status on polluting behavior across counties. Ozone is regulated subject to the National Ambient Air Quality Standards (NAAQS) of the Clean Air Act. When a county is out of compliance (or out of attainment) for the ozone standard, the county implements a strict plan for reducing the concentrations of precursors to ozone which are volatile organic compounds (VOCs) and nitrogen oxides (NOx). I use county-level attainment status for 1-hour ozone as a proxy for air quality regulatory regime. Regulation of ozone creates a tighter regulatory climate that could spill over and lead to reduced emissions of a large range of pollutants (both regulated and unregulated), primarily those tracked by the EPA's Toxics Release Inventory. From estimation using panel data in a fixed-effects framework, the results provide support for the existence of spillovers as evidenced by the reduction of non-VOC emissions associated with non-attainment status of 1-hour ozone and by the reduction of unregulated industrial carbon dioxide emissions.

I also use county-level measures of pro-environment voting from the U.S.House of Representatives as a proxy for regional heterogeneity in preferences of citizens for more or less regulation in order to estimate their effect on toxic air emissions at a local level. Even though constructing county-level voting scores from congressional district scores requires a degree of approximation in counties that lie partially in multiple districts, the fact that county lines do not change with the decennial Census allows for measures of emissions activity in specific locations over time when using panel data spanning more than ten years. From estimation using panel data in a fixed-effects framework, the results suggest that allowing for regional heterogeneity in preferences at the county level can explain within-state variation in toxic emissions where state-level aggregates fail to identify such a relationship.

Dedication

To my family: my mother Nancy; my father Carl; and my sisters Kara and Whitney.

Acknowledgements

I am ever so grateful to my advisor, Nicholas Flores for all of his guidance with this work. I also acknowledge that much of this work began under the counsel of Randall Walsh. I have received many helpful comments, criticisms, and suggestions from Terra McKinnish, Robert McNown, Scott Savage, and Jana Milford. Scott Holladay has also been instrumental in the progress of this work. Additional thanks to my classmates Karen Maguire, Jessica Vechbanyongratana, and Andy Meyer for their help and comments. Parts of this dissertation have been presented at the Occasional California Workshop at UC Santa Barabara, the Annual Summer Meetings of the Association of Environmental and Resource Economists in Orlando, and the University of Colorado Environmental Workshop. I received many helpful comments and questions from participants at these workshops. Especially helpful were conversations with Dietrich Earnhart.

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Chapter 1

Introduction

The focus of this dissertation is to examine the effect of county-level air quality regulatory status on polluting behavior across counties. The general approach I use in order to analyze this problem is to first consider the overall effect regulation has on county-level emissions and then I attempt to identify two separate effects that could lead to higher or lower emissions within a county. These two separate effects occur along the extensive and intensive margins. The extensive margin includes firm location and shut-down decisions, while the intensive margin includes facilities reducing their individual emissions. A tighter regulatory climate could create incentives for firms to respond along either of these margins in order to maximize profit, depending on whether it is less costly to relocate in order to avoid imposed costs associated with regulation or whether it is in the firms best interest to reduce output or to install more efficient technology. Firm response along the extensive margin likely leads only to a redistribution outcome, but response along the intensive margin could lead to lower per facility emissions which would lower emissions in one county without leading to an increase in emissions in another county.

When addressing this problem of the effect of a tighter regulatory climate on emission levels, one of the main difficulties is finding a measure to describe regulatory stringency since no direct measure exists. Researchers are then forced to rely on proxies and make certain assumptions to justify their use. In this dissertation I use two different proxies. The first proxy I use is a somewhat direct measure of regulatory stringency even though certain assumptions still need to be made. Nonattainment status is a proxy for regulation that is commonly used in the literature. The second proxy I use is an indirect measure of regulatory stringency that has been used in the literature, but has only been used in analyses that do so at the state level. Pro-environment voting scores from the League of Conservation Voters works as a proxy indirectly through citizen preferences for more or less regulation. For this research I create county-level measures for this proxy, which, to the best of my knowledge, have not been previously used in the literature.

In chapter 2, I use county-level attainment status for 1-hour ozone as a proxy for air quality regulatory regime and estimate the effect it has on both regulated and unregulated toxic emissions as well as on unregulated carbon dioxide from cropland production. Ozone is regulated subject to the National Ambient Air Quality Standards (NAAQS) of the Clean Air Act. When a county is out of attainment (or out of compliance) for the ozone standard, the state implements a strict plan for reducing the concentrations of precursors to ozone which are volatile organic compounds (VOCs) and nitrogen oxides (NO_x). Regulation of ozone creates a tighter regulatory climate that could spill over and lead to reduced emissions for a large range of pollutants (both regulated and unregulated), primarily those tracked by the EPA's Toxics Release Inventory. The results provide support for the existence of spillovers as evidenced by the reduction of non-VOC emissions associated with nonattainment status of 1-hour ozone.

In chapter 3, I extend the analysis from chapter 2 to take a closer look at the effect of ozone nonattainment status on industrial carbon dioxide before it was regulated, since the U.S. Environmental Protection Agency is currently in the initial phase of regulating stationary sources of industrial carbon dioxide emissions. Permit requirements for construction of new and modified sources are now in place for the largest emitters; operating permits for these largest emitters will be required later this year; and the EPA is currently in the review process for setting national performance standards for carbon dioxide. Expanding on previous findings of regulatory spillover effects that involve reductions of VOCs and non-VOCs in nonattainment areas for the National Ambient Air Quality Standards for ozone, the results suggest that a tighter regulatory climate (proxied by ozone nonattainment) leads to reductions in unregulated greenhouse gas emissions.

In chapter 4, I use county-level measures of pro-environment voting from the U.S. House of Representatives as a proxy for regional heterogeneity in preferences of citizens for more or less regulation in order to estimate their effect on toxic air emissions at a local level. I use data on voting records provided by the League of Conservation Voters. Even though constructing county-level voting scores from congressional district scores requires a degree of approximation in counties that lie partially in multiple districts, the fact that county lines do not change with the decennial Census allows for measures of emissions activity in specific locations over time when using panel data spanning more than ten years. The results suggest that allowing for regional heterogeneity in preferences at the county level can explain within-state variation in toxic emissions where state-level aggregates fail to identify such a relationship.

The main contributions of this dissertation to the literature include: disaggregation of the Toxics Release Inventory to look specifically at the effect of ozone nonattainment on VOCs and non-VOCs separately to identify regulatory spillover effects in chapter 2; the use of measures of industrial carbon dioxide to further test for spillover effects in chapter 3; and creating county-level meausures of League of Conservation Voting Scores to identify the effect of pro-environment voting on emissions at a more localized level than states in chapter 4.

Chapter 2

Identifying Spillover Effects from Enforcement of the National Ambient Air Quality Standards

In this chapter, I examine the effect of county-level air quality regulatory status on polluting behavior across counties. Two often analyzed responses of firms to regulations are their choice of emissions levels and firm location decisions. The emissions data used here capture both behaviors. I separately examine what is happening at the extensive (facility numbers) and intensive (emission levels) margins. For the analysis, I use attainment status as a proxy for air quality regulatory regime where regulation of ozone creates a tighter regulatory climate that could spill over and lead to reduced emissions of a large range of pollutants.

Ozone is regulated subject to the National Ambient Air Quality Standards (NAAQS) of the Clean Air Act (CAA). To identify spillover effects, I use the EPA's Toxics Release Inventory (TRI), which reports emissions of multiple hazardous air pollutants (HAPs) including precursors for ozone. When a county is out of compliance (or also referred to as being out of attainment) for ozone, the state implements a strict plan for reducing the precursors to ozone which are volatile organic compounds (VOCs) and nitrogen oxides (NO_x). Since the TRI contains VOCs as well as non-VOCs, a reduction in VOCs is expected, which consequently would lower the overall TRI measure. By disaggregating the TRI data, I also examine what happens to non-VOCs due to ozone nonattainment. Since non-VOC hazardous air pollutants are regulated, although not under the NAAQS, as a final test for spillovers I estimate the effect of ozone nonattainment on unregulated greenhouse gas emissions from a combination of on-site and off-site cropland production.

Previous studies have made a link between nonattainment status for criteria pollutants subject to the NAAQS of the Clean Air Act and emission levels for those specific pollutants. There have been no attempts in the existing literature to identify these spillovers. This is important because not accounting for these spillovers could lead policy-makers to significantly underestimate the potential benefits (in terms of reduced pollution levels) associated with the NAAQS.

The results provide support for the existence of spillovers as evidenced by the reduction of non-VOC emissions associated with nonattainment status of 1-hour ozone. The reduction of overall TRI emissions is caused by reductions of both VOCs and non-VOCs. Since the number of TRI reporting facilities is decreasing and there is a lack of a statistically significant relationship between ozone nonattainment and pounds of emissions per facility, I conclude that the exodus of facilities is the primary reason for decreased emissions. The reduction of unregulated carbon dioxide emissions associated with cropland production due to ozone nonattainment is further evidence of spillover effects. This work is the first to address these air quality regulatory spillovers and thus report such findings.

2.1 Background

2.1.1 The Regulatory Process

The U.S. Environmental Protection Agency has identified the following six pollutants as criteria pollutants: carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter (PM_{10} and $PM_{2.5}$), and lead (Pb). A measure of TSPs (or total suspended particulates) was used for particulate matter until 1991. Criteria pollutants are those pollutants which have been determined to endanger public health or welfare. Criteria pollutants fall under the laws outlined in sections 108-110 of the Clean Air Act[1] which defines the National Ambient Air Quality Standards (NAAQS) and Title 40 of the Code of Federal Regulations sets of maximum allowable concentrations for each of the six criteria pollutants[2] .

[1] 42 USC §7408-7410 (the same as CAA §108-110)
[2] 40 CFR §50

Every year, counties in violation of these standards are designated as nonattainment counties. Nonattainment areas must have and implement a plan to meet the standard or risk losing some forms of federal assistance. The standard for 1-hour ozone under the NAAQS stipulates as long as the highest hourly reading does not exceed 0.12 parts per million (ppm) on more than one day per year in a county, then a county is in attainment. The standard can also be described as the second-highest daily maximum or the single-highest hourly reading over all hours and days of the year, except for the first day with the highest annual hourly reading. The designation of nonattainment status is one possible and commonly used proxy for regulatory stringency, because according to Becker and Henderson [10], new and existing plants are subject to much stricter controls in nonattainment areas, relative to attainment areas. Henderson [35] explains that all firms in nonattainment counties are more likely to be closely monitored and subject to greater enforcement efforts.

In addition to the NAAQS criteria pollutants, the EPA and local environmental agencies monitor and regulate a wide range of other pollutants often referred to as hazardous air pollutants (HAPs). Currently no federal standards exist limiting the amount of ambient air concentrations of these pollutants, however, there are regulations in place under Section 112 of the Clean Air Act[3] requiring industries to reduce these compounds using the maximum available control technology (MACT). There are a number of HAPs that are regulated indirectly for NAAQS, because many HAPs are volatile organic compounds (VOCs) which help form the criteria pollutants ozone and particulate matter.

2.1.2 Firm Response to Regulation

In the literature on firm behavioral response to environmental regulation there are two main categories into which firm behavior can be grouped: the intensive margin and the extensive margin. The intensive margin is the firm's choice of emission levels and the extensive margin is the firm's location choice. Different measures or proxies for regulatory stringency that have been used in pre-

[3] 42 USC §7412 (Law); 40 CFR §61,63 (Implementation)

vious studies include nonattainment status for criteria pollutants subject to NAAQS, air pollution abatement (APA) expenditures such as the Pollution Abatement Costs and Expenditures (PACE) Survey, number of inspections and enforcement activities at facilities, records of green voting in Congress, and right-to-work status of states.

2.1.2.1 Intensive Margin

The intensive margin is the firm's choice of emission levels, which could include reducing output or introducing better technology to meet the emissions standards. The following papers use nonattainment status for NAAQS criteria pollutants as a proxy for regulatory stringency and examine the effect of nonattainment status on the corresponding criteria pollutant. Henderson [35] examines the effects of nonattainment status for 1-hour ozone on levels of ozone. His results suggest that a switch in county attainment status to nonattainment induces a greater regulatory effort and results in cleaner air, particularly a 3-8 percent improvement in ground-level ozone. Greenstone [33] finds that SO_2 nonattainment status is associated with modest reductions in SO_2 concentrations. Chay and Greenstone [16] and [17] find striking evidence that TSP levels fell substantially more in TSP nonattainment counties than attainment counties. Aufhammer et al. [8] examine whether nonattainment status is responsible for the drops in PM_{10} experienced in nonattainment counties. In a spatially disaggregated analysis with the emissions monitor as the unit of observation, monitors that exceed the federal standards experience drops greater than the average of the remaining monitors within the same county. The county nonattainment status does not explain a statistically significant share of the variation in PM_{10} concentrations.

Anton et al. [6] proxy for environmental regulation using inspections and number of superfund sites. They find that stricter regulation induces firms to adopt more environmental management systems (EMSs) and environmental management practices (EMPs), which they show reduce emissions of HAPs. Terry and Yandle [57] use environmental expenditures as a proxy for regulatory action and fail to find a meaningful statistical relationship between expenditures and reductions in toxic releases using a cross sectional analysis. Becker [11] examines the effect that nonattainment status has on air pollution abatement activity at the firm level using the PACE survey. His results suggest that heavy emitters in nonattainment counties were subject to more stringent regulation and therefore had higher APA expenditures.

2.1.2.2 Extensive Margin

Firm location decisions are commonly classified as the extensive margin. The types of location decisions firms make include shifting production across facilities in the case of multi-plant firms, physically relocating existing operations, and choosing where to open new facilities in order to avoid the most stringent regulatory standards. Becker and Henderson [10] suggest that firm births fall dramatically in counties that are in nonattainment for ozone. Using the PACE survey as a measure of regulatory stringency, Levinson [45] reports that there is little evidence that stringent state environmental regulations deter new plants from opening. Focusing on the paper and oil industries, Gray and Shadbegian [29] find that states with stricter regulations have smaller production shares. They use a variety of proxies for state-level environmental regulation including nonattainment status, congressional voting records on environmental legislation, pollution abatement spending, and an index of state environmental laws. Using similar measures of regulatory stringency, Gray [28] finds that states with stricter regulations tend to have lower birth rates of new plants. Even though the impacts are not enormous, according to the paper, these results are similar to explanatory variables such as unionization. Holmes [36] also finds similar results using right-to-work laws (non-unionization) as a measure of regulatory stringency and reports that these state policies do matter for firm location decisions. Using border effects he finds that manufacturing employment increases by about one-third when crossing the border from a non-right-to-work state into a right-to-work (pro-business) state.

2.2 Conceptual Framework

Firm response to regulation is driven by incentives and their objective is to maximize profit by choosing inputs, location, and production techniques which minimize costs. Without regulation firms are not held accountable for the negative externality they create when emitting toxic releases as a byproduct of the production process. Once the firms are expected to internalize the externality through regulation, they need to alter their profit-maximizing decision and determine their best response to the higher costs associated with regulation. This change in profit-maximizing decision could be choosing to relocate in a county with less strict regulation and subsequently lower costs associated with production or, if that is cost prohibitive, update to more efficient technology to lower emissions and avoid fines.

Henderson's [35] analysis suggests that a switch in county attainment status to nonattainment induces a greater regulatory effort and results in cleaner air. I expand on the existing literature to see if ozone nonattainment leads to cleaner air due to lower levels of ozone only or if it leads to lower levels of ozone as well as other air emissions not related to ozone. The first step is to measure the effect of regulatory stringency on overall toxic air releases and then proceed by disaggregating the measures to find if there are separate effects on ozone precursors and those releases that are unrelated to ozone.

Ozone nonattainment in the current year is expected to be associated with higher levels of overall emissions than attainment counties, because higher emissions are the reason that the county is out of attainment. A negative relationship between cumulative number of years a county has been out of attainment and the levels of emissions in the county is the hypothesized result. The underlying reasoning is that counties that are not making progress toward returning to attainment will draw more attention and subsequently stricter enforcement. The higher costs associated with regulation could create incentives for firms to make decisions to either relocate or to install more efficient technology in order to maximize profit.

The intended consequence of air quality regulation is a reduction of emissions below an acceptable safety threshold nationwide which should translate into lower emissions per facility. It is very conceivable that facilities would leave counties with strict regulation and relocate in attainment counties where regulation is less strict. This would lower total emissions in nonattainment counties, but increase total emissions in attainment counties. This case would not necessarily result in a net reduction of emissions, but rather a redistribution of emissions. If facility numbers are increasing, but pounds per facility are decreasing, then firms are emitting less and that is the primary factor leading to reduced emissions. Cleaner facilities entering the county is a possible story consistent with this scenario. The first set of estimations of this chapter tests whether there are lower overall emissions in ozone nonattainment counties and whether these are due to fewer facilities or fewer pounds of emissions per facility.

After estimating the effect of ozone nonattainment status on an overall measure of toxic air releases, if that effect is negative, then it would be informative to examine whether the emissions of ozone precursors are the only factor influencing this decline in total emissions or whether regulation has effects on those emissions that are not ozone precursors. Through this disaggregation I am able to identify spillover effects from the regulation of ozone. Recall that these toxic releases are either indirectly regulated under the NAAQS for the case of VOCs or under Section 112 of the Clean Air Act[4] which requires employment of maximum available control technology (MACT). However, it is also desirable to test unregulated greenhouse gas emissions such as carbon dioxide to see if there are additional spillover effects from tighter regulation (as proxied by ozone nonattainment). If there is a significant negative relationship between years of ozone nonattainment and the levels of the non-VOCs analyzed here (hydrochloric acid, ammonia, sulfuric acid, chlorine, or carbon dioxide) then I conclude that the tighter regulatory environment is leading to the reduction of other emissions besides those related to ozone.

2.3 Data

The data for county nonattainment status is publicly available through the EPA's website [2]. Beginning in 1978 to 2010, every July counties are listed if they are designated as nonattainment (either the whole county or part of the county) for one of the criteria pollutants. Attainment status is used as a proxy for regulatory stringency, because new and existing plants are subject to much stricter controls in nonattainment areas, relative to attainment areas. Counties in nonattainment

[4] 42 USC §7412 (Law); 40 CFR §61,63 (Implementation)

are more likely to be closely monitored and subject to greater enforcement efforts. I focus on the nonattainment status for 1-hour ozone because there is greater variation of counties moving into and out of nonattainment relative to other criteria pollutants. Another reason is that the data for toxic releases includes both VOCs (precursors to ozone) and non-VOCs so I can separately analyze whether nonattainment for ozone is having an effect on VOCs (which I would expect) as well as non-VOCs (which would be unintended benefits of ozone regulation).

Table 2.1 summarizes the variation of counties that go into and out of nonattainment for three criteria pollutants: 1-hour ozone, sulfur dioxide (SO_2), and airborne particulate matter (PM_{10}). The identification of the empirical models comes from switches in regime (attainment status), so ideally I would like to use the data with the most variation so I can tell if switching regimes makes a difference in emission levels.

Table 2.1: Nonattainment county variation

	1-hour Ozone	PM_{10}	SO_2
Number of counties always in attainment	1217	1505	1514
Number of counties never in attainment	168	0	19
Single Change: Nonattainment to attainment	100	0	33
Single Change: Attainment to Nonattainment	35	50	0
Multiple Changes	47	12	1

Sample includes the top 50% of TRI emitting counties (1567).

From the SO_2 nonattainment data, 33 counties make a switch from nonattainment to attainment. These are counties that are already in nonattainment in 1988 and return to attainment status at some point over the next 15-year period. There are no counties in attainment in 1988 that make a single switch to nonattainment. There is only one county that makes multiple switches (nonattainment to attainment and back to nonattainment). Therefore there is not much variation to exploit using the SO_2 nonattainment data.

PM_{10} was initially regulated in 1991 as a result of the Clean Air Act Amendments of 1990. On July 1, 1987, the EPA revised the NAAQS for particulate matter, replacing total suspended particulates (TSPs) as the indicator for particulate matter with a new indicator that included only those particles less than or equal to 10 micrometers in diameter. The switch in standards came from the recognition that particulate matter smaller than 10 micrometers in diameter posed more of a health risk than the larger particles. The standard was again updated in 1997 to focus on $PM_{2.5}$ which is particulate matter smaller than 2.5 micrometers in diameter.

For particulate matter between 1988-2002, 50 counties had a single change from attainment to nonattainment (see Table 2.1). All of these switches occur in 1991 as a result of the change in standards for particulate matter. There are no counties that make a single switch from nonattainment to attainment since there were no counties in nonattainment in 1988 because the PM_{10} standard was not in effect yet. Those counties that experience multiple changes are the ones that made it back into attainment after the initial switch in 1991. Because of this common switch in the PM_{10} nonattainment data, there is much less variation across counties than Table 2.1 would suggest. Even though this uniform switch could be useful in a statistical sense to examine the effect that differences in regime have on toxic emissions, I choose not to use PM_{10} because there are only 62 counties that make any kind of a switch.

For this chapter I use nonattainment for 1-hour ozone, because of all the criteria pollutants it has the most variation. There are counties that switch into attainment, out of attainment, and counties that experience multiple switches. There are 182 counties from the sample that make some kind of switch in regime. There are also no changes in standards for 1-hour ozone between the years 1988-2002.

Congress established the Toxics Release Inventory under the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA)[5] , and later expanded it in the Pollution Prevention Act of 1990[6] . EPCRA Section 313 requires EPA and the States to collect data annually on releases and transfers of certain toxic chemicals from industrial facilities and make the data available to the public through the Toxics Release Inventory (TRI). The TRI database can be obtained directly

[5] 42 USC §116
[6] 42 USC §133

from the EPA. The data for this research were retrieved using the EPA's Risk Screening and Environmental Indicators (RSEI) program version 2.1.2 (August 2004) [1]. This database contains data on point source (stack), fugitive, and direct water emissions as well as off-site transfer of toxic pollutants. Total pounds of emissions are reported, but the data also include hazard and risk scores. Hazard scores are constructed by multiplying the pounds released by the chemicals' toxicity weight. Risk-based scores combine the surrogate dose with toxicity weight and population estimates. The temporal coverage of this data ranges from 1988 to 2002 and is available at the facility level. For the purpose of this research, I use only the pounds of stack air emissions and I aggregate to the county level. The number of TRI reporting facilities is provided by the RSEI program used to obtain data on emissions.

The top ten TRI releases include hydrochloric acid, methanol, ammonia, toluene, xylene, sulfuric acid, chlorine, carbon disulfide, methyl ethyl ketone, and dichloromethane. Six of these ten releases are volatile organic compounds (VOCs) and are indirectly regulated through the NAAQS for ozone. The remaining four are regulated as HAPs, but are not subject to the same federal standards as the criteria pollutants. The top ten TRI releases make up 72% of the overall TRI measure and the top five alone make up 51.3% of the overall measure.

Table 2.2: Top 10 TRI Releases

Chemicals	% TRI Emissions	Volatile Organic Compound
1. Hydrochloric Acid	17.9	No
2. Methanol	12	Yes
3. Ammonia	9	No
4. Toluene	7.2	Yes
5. Xylene	5.2	Yes
6. Sulfuric Acid	4.8	No
7. Chlorine	4.8	No
8. Carbon Disulfide	4.8	Yes
9. Methyl Ethyl Ketone	3.5	Yes
10. Dichloromethane	2.8	Yes
Top 5	51.3%	
Top 10	72%	

Certain characteristics about the TRI data require that the results from this analysis be used with caution. Any facility emitting levels above the currently established threshold are required to report to the TRI. The data are self reported by facilities and not necessarily verified by the EPA. There may exist an incentive for facilties to under-report their emissions and therefore the numbers in the dataset are likely to be biased toward zero. Emission levels are sometimes calculated using technology based engineering estimates rather than actual measurements. These measurement errors are likely to lead to conservative estimates.

Reporting requirements have also changed over time with respect to which releases facilities are required to report, which industries are required to report, and the thresholds for various releases above which firms are required to report their releases. The first chemical expansion occurred in 1993 with the addition of certain chemicals that appear on the Resource Conservation and Recovery Act (RCRA)[7] list of hazardous wastes and certain hydrochlorofluorcarbons (HCFCs) [8] to EPCRA §313. The second expansion was the addition of 286 chemicals[9] and chemical categories on November 30, 1994. The additional chemicals can be characterized as high or moderately high in toxicity, and currently manufactured, processed or otherwise used in the United States. The top ten TRI releases have all been tracked since the beginning of the program in 1987, however thresholds for reporting have changed. SIC codes that have been required to report since 1987 include SIC codes 20-39 (listed in Table 2.3). On May 1, 1997, EPA published a final rule adding seven industry sectors to TRI[10] : metal mining, coal mining, electrical utilities that combust coal and/or oil, hazardous waste treatment and disposal facilities, chemical wholesale distributors, petroleum bulk stations and terminals, and solvent recovery services. Currently a facility must report to TRI if it is in a specific industrial sector required to report (e.g., manufacturing, mining, electric power generation), employs 10 or more full-time equivalent employees, and manufactures or processes over 25,000 pounds of a TRI-listed chemical or otherwise uses greater than 10,000 pounds of a listed

[7] 58 FR 63500
[8] 58 FR 63496
[9] 59 FR 61432
[10] 62 FR 23833

chemical in a given year. According to 40 CFR §372.25, the reporting thresholds upon initiation of TRI program focused on the largest emitters, and over the next two years reduced the thresholds for reporting. In 1987, the threshold was 75,000 pounds of the chemical manufactured or processed for the year. In 1988, the threshold was 50,000 pounds of the chemical manufactured or processed for the year. 1989 and thereafter the threshold was 25,000 pounds of the chemical manufactured or processed for the year.

Table 2.3: Manufacturing Sectors Required to Report to TRI (1988-2002)

SIC code	Industrial Sector	Initial Year
10	Metal Mining	1998
12	Coal Mining	1998
20	Food and Kindred Products	1987
21	Tobacco Products	1987
22	Textile Mill Products	1987
23	Apparel and Other Textile Products	1987
24	Lumber and Wood Products	1987
25	Furniture and Fixtures	1987
26	Paper and Allied Products	1987
27	Printing and Publishing	1987
28	Chemicals and Allied Products	1987
29	Petroleum and Coal Products	1987
30	Rubber and Misc. Plastics Products	1987
31	Leather and Leather Products	1987
32	Stone, Clay, and Glass Products	1987
33	Primary Metal Industries	1987
34	Fabricated Metal Products	1987
35	Industrial Machinery and Equipment	1987
36	Electronic and Other Electric Equipment	1987
37	Transportation Equipment	1987
38	Instruments and Related Products	1987
39	Miscellaneous Manufacturing Industries	1987
4911/4931/4939	Electric Utilities	1998
4953/7389	RCRA/Solvent Recovery	1998
5169	Chemical Wholesalers	1998

The data on carbon dioxide is fossil-fuel CO_2 emissions associated with cropland production in the United States. On-site emissions refer to emissions occurring on the farm. Off-site emissions are those that occur off the farm such as emissions from the production and transport of fertilizers and pesticides. Also included in the off-site measure is the electricity produced that is used on site. The measure of CO_2 used here is the total of both on-site and off-site emissions. The values are estimated (not measured) using a combination of independent survey data, established energy consumption parameters for field scale operation budgets, and CO_2 coefficients based on summation of individual management practices as opposed to national extrapolation estimates. The units are megagram C for CO_2 estimates. These data span the years 1990-2004 [15].

Per capita income data were obtained from the Bureau of Economic Analysis [50] and population density data were obtained jointly from the U.S. Census Bureau [13] and the EPA's Risk-Screening Environmental Indicators [1]. Both were available at the county level annually from 1988 to 2006. There are other variables I wish to obtain, but they are either available annually but at the state level or available at the county level but for only certain years. The variables that I would ideally like to include if available are median age, median income, racial composition, firm concentrations, percent college graduates, percent with children, and percent elderly.

2.4 Estimation and Results

2.4.1 Model 1: TRI emissions, facilities, and per facility emissions

I use the first part of this model to estimate the effect of nonattainment status on overall toxic releases. I construct a 15-year panel data set which includes the years 1988-2002 and includes the top 750 TRI emitting counties, due to the large number of counties with zero emissions (743 counties) over the fifteen-year period. The dependent variable is total pounds of stack air emissions from the TRI. The key explanatory variables are nonattainment status broken up into two measures. The first is an indicator variable which equals 1 if the county is designated as nonattainment for 1-hour ozone (either whole or part) in year t and equals 0 otherwise. The second is the cumulative number of years a county has been in nonattainment. This measure is used because firms that have been in nonattainment longer will have even stricter regulations than counties that have just entered nonattainment status. I control for population density and per capita income. I include county fixed effects to control for factors that are specific to a county that do not change over time. Such factors may be that some states have higher annual exposure to sunlight which is a key factor in ozone formation. I include year fixed effects in an attempt to control for the changing of reporting thresholds and the inclusion of additional industries required to report over time. Using an ordinary least squares fixed-effects framework I estimate the parameters of the following equation

$$TRI_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{2.1}$$

where TRI_{it} represents the measure of total pounds of TRI stack air emissions in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. To control for year effects that affect all counties, I include $d1989_t, \ldots, d2002_t$ as dummy variables for years 1989-2002. The term γ_i is the county fixed effects, which includes all factors within a given county that do not vary over time. To remove γ_i, I use time demeaning which is the fixed-effects transformation model. ϵ_{it} is the idiosyncratic error term. The estimation results are provided in Table 2.4 under the baseline specification.

Estimation of the baseline specification confirms the expectation that the longer a county is in nonattainment for ozone the greater the reduction of TRI emissions since the coefficient on 'Years Nonattainment' is negative and statistically significant at the 5% level. The results suggest that for each additional year a county is in nonattainment for ozone overall TRI emissions per county are reduced by 22,881 pounds. Given the average emissions per county in a given year are 1,723,807 pounds, this is a modest reduction (1.3% of the average). Since TRI consists of 612 releases, it is likely that spillover effects are present, but it is not possible to be sure because VOCs are included in the TRI measure. It is possible that TRI emissions are declining only because of reductions of VOCs. I examine these more closely in the second model when I disaggregate and estimate the effects on individual releases.

A summary of the TRI data reveals that the mean of county-level TRI emissions is 1,723,807 and median level of emissions is 829,290. The maximum observed level of TRI emissions is 119,000,000. From this summary the distribution of TRI pounds of emissions is seemingly very right skewed as shown in Figure 2.1. I re-specify the model by changing the baseline specification

Table 2.4: Results - Effect Of Ozone Nonattainment On TRI Emissions

	Baseline	I	II	III
	TRI Pounds	ln(TRI Pounds)	TRI Pounds	ln(TRI Pounds)
Ozone nonattainment	295,989.70	0.3576258 **	46,855.30	-0.025637
	[166,717.30]	[0.1307793]	[134,250.10]	[0.122415]
Years of ozone nonattainment	-22,881.54 *	-0.0161364 *	-3,092.68	-0.0028827
	[10,334.11]	[0.0081065]	[10,044.05]	[0.0091586]
Per capita income	-21.39821	-0.0000776 **	53.03836 *	0.0000979 **
	[18.13613]	[0.0000142]	[22.73067]	[0.0000207]
Population density	-2,633.81 **	0.0014253 *	708.8642	0.0018964 **
	[849.1724]	[0.0006661]	[810.5987]	[0.0007391]
Constant	2,872,303 **	15.19271 **	1,304,974 **	11.55458 **
	[476,295.80]	[0.3736241]	[346,307.40]	[0.3157779]
County fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
County time trends	No	No	Yes	Yes
Observations	11,250	11,250	11,250	11,250
R^2	0.0254	0.0299	0.6895	0.5824

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

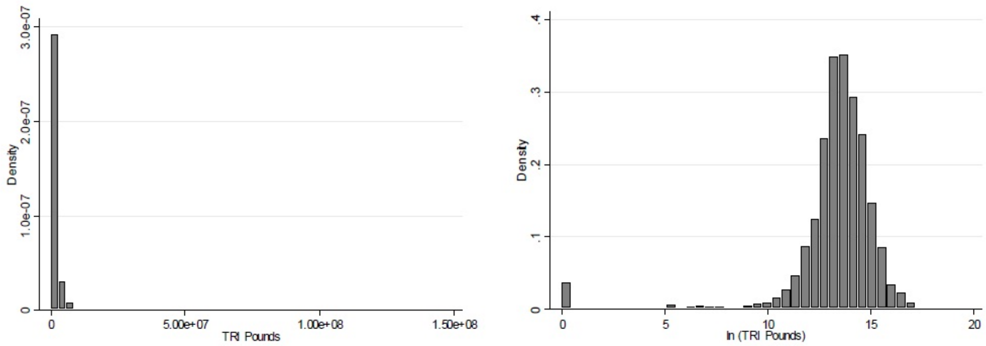
to one which uses the natural logarithm of pounds of TRI emissions as the dependent variable. I estimate the parameters of the following equation.

$$ln(TRI)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \qquad (2.2)$$

The estimation results are provided in Table 2.4 under specification I. From the estimation of Equation 2.2, the coefficient on 'Years Nonattainment' is negative and statistically significant at the 5% level. The coefficient estimate suggests that for each additional year a county is in nonattainment there is a 1.6% reduction in pounds of TRI emissions.

A careful analysis of the emissions data for those counties that make a switch from either attainment to nonattainment or nonattainment to attainment shows that a large number of counties experience a significant deviation from the trend leading up to a switch shortly after the switch has occurred. In an attempt to account for the effects of this break in trend after a switch, I re-specify the model to include county-specific time trends. I estimate the parameters of the re-specified

Figure 2.1: Distribution of County-Level TRI Emissions (Pounds)



model using both level and logged measures of TRI pounds as the dependent variable.

$$TRI_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \mathbf{Y}_{it}\boldsymbol{\rho} + \epsilon_{it} \quad (2.3)$$

$$ln(TRI)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \mathbf{Y}_{it}\boldsymbol{\rho} + \epsilon_{it} \quad (2.4)$$

$\mathbf{Y}_{it}$ is a matrix which includes 750 county-specific time trends. The estimation results are provided in Table 2.4 under specifications II and III. The results still suggest a negative relationship between the number of years a county has been in nonattainment and pounds of TRI emissions when including time trends. The coefficient estimate on 'Years Nonattainment' is no longer statistically significant for either specification.

In general, the results from the estimation of the first part of the model suggest that overall emissions are declining as a result of a tighter regulatory climate as proxied by the number of years a county has been in nonattainment. One concern to be aware of is that due to self-reported nature of the TRI dataset, it is possible that regulation is having an effect on reporting instead of actual emission levels. It is possible that facilities that are close to the reporting requirement threshold may choose not to report, which has the potential to substantially under-report overall emissions in a county.

The objective of the second part of the model is to analyze the effect of regulatory stringency along the extensive margin by estimating the effect of changes in nonattainment status on the number of TRI reporting facilities per county. The panel data set is the same as above using years

1988-2002 and the top 750 TRI emitting counties, however in this specification the dependent variable is number of TRI reporting facilities per county. To find out whether toxic releases are decreasing due to fewer facilities, I estimate the parameters of the following equation

$$Facilities_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{2.5}$$

using an ordinary least squares fixed-effects framework, where $Facilities_{it}$ represents the measure of TRI reporting facilities in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. $d1989_t,\ldots,d2002_t$ are dummy variables for years 1989-2002. The term γ_i is the county fixed effects term and ϵ_{it} is the idiosyncratic error term. The estimation results are provided in Table 2.5 under the baseline specification.

From the estimation of Equation 2.5 the number of TRI reporting facilities are declining as a result of ozone nonattainment. The estimated coefficient on 'Years of Nonattainment' is negative and significant at the 1% level. The results suggest there will be roughly one less facility for every three years a county is in nonattainment (.32 fewer facilities for each year).

The distribution of TRI facilities is such that the median number of facilities in a county is 7, while the mean number of facilities is 13.8. The maximum number of facilities is 486. This suggests that the distribution of TRI facilities per county is also right skewed. Figure 2.2 shows the distribution of both the level measure of TRI facilities and the natural logarithm of TRI facilities. I re-specify the model by changing the baseline specification to one which uses the natural logarithm of TRI facilities as the dependent variable. I estimate the parameters of the following equation.

$$ln(Facilities)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{2.6}$$

The results are provided in Table 2.5 under specification I. From the estimation of Equation 2.6, the estimated coefficient on 'Years Nonattainment' is negative and significant at the 1% level

Table 2.5: Results - Effect of Ozone Nonattainment On TRI Facilities

	Baseline	I	II	III
	TRI Facilities	ln(TRI Facilities)	TRI Facilities	ln(TRI Facilities)
Ozone nonattainment	4.342841 **	0.1409983 **	0.2321296	0.0226638
	[0.3960617]	[0.0165511]	[0.2852234]	[0.0172298]
Years of ozone nonattainment	-0.3283347 **	-0.0085661 **	0.0591175 **	-0.0003802
	[0.0245502]	[0.0010259]	[0.0213393]	[0.0012891]
Per capita income	-0.0005256 **	-0.0000152 **	0.0005828 **	0.0000153 **
	[0.0000431]	[1.80E-06]	[0.0000483]	[2.92E-06]
Population density	-0.0023524	0.0001287	0.0155285 **	0.0005282 **
	[0.0020173]	[0.0000843]	[0.0017222]	[0.000104]
Constant	28.21479 **	2.582038 **	2.618829 **	1.754655 **
	[1.131511]	[0.0472849]	[0.7357534]	[0.0444455]
County fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
County time trends	No	No	Yes	Yes
Observations	11,250	11,250	11,250	11,250
R^2	0.0774	0.06	0.7649	0.4995

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

and suggests that for every additional year a county is in nonattainment, the number of facilities decreases by 0.85%. As an additional test, I again include time trends to take into account any breaks in trend after a switch in nonattainment status. I estimate the parameters of the re-specified model using both level and logged measures of TRI pounds as the dependent variable.

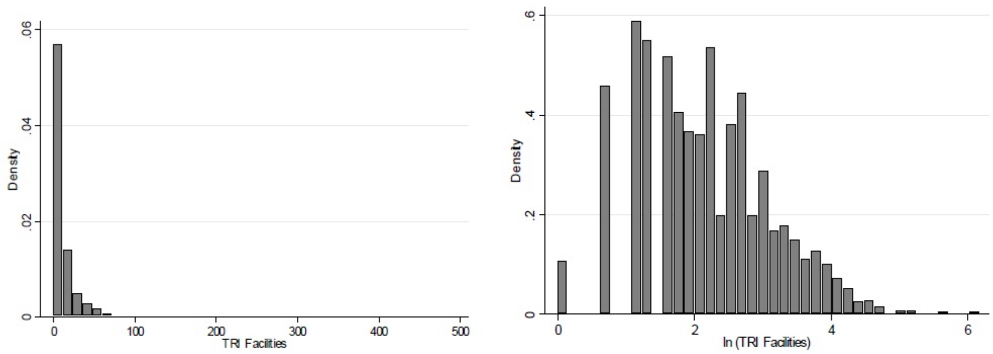
$$Facilities_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \mathbf{Y}_{it}\boldsymbol{\rho} + \epsilon_{it} \quad (2.7)$$

$$ln(Facilities)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \mathbf{Y}_{it}\boldsymbol{\rho} + \epsilon_{it} \quad (2.8)$$

$\mathbf{Y}_{it}$ is a matrix oontaining 750 county-specific time trends. The estimation results are provided in Table 2.5 under specifications II and III.

The number of facilities in nonattainment counties could be declining for three different reasons. First, facilities could shut down because of greater regulatory stringency. Second, facilities could exit the county and relocate in a county with lower regulatory stringency. Third, the facilities

Figure 2.2: Distribution of TRI Facilities



may no longer be reporting any TRI emissions because they have dropped below the threshold above which reporting is required. For the third case to be true, given that reporting thresholds have been lowered over time, per facility emissions should be declining. A decline in per facility emissions would be the desired effect, where simply relocating facilities would be a redistribution effect and not lead to an overall reduction in emissions.

The objective of the third part of the model is to analyze the effect of regulatory stringency along the intensive margin by estimating the effect of changes in nonattainment status on TRI emissions per facility. The panel data set is the same as above using years 1988-2002 and the top 750 TRI emitting counties, however in this specification the dependent variables are number of TRI reporting facilities per county. To find out whether toxic releases are decreasing due to lower per facility emissions, I estimate the parameters of the following equation

$$\left(\frac{Emissions}{Facility}\right)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{2.9}$$

using an ordinary least squares fixed-effects framework, where $\left(\frac{Emissions}{Facility}\right)_{it}$ is per-facility emissions in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. $d1989_t, \ldots, d2002_t$ are dummy variables for years 1989-2002. The term γ_i is the county fixed effects term and ϵ_{it} is the idiosyncratic error term. The estimation results are provided in Table 2.6 under the baseline specification.

Table 2.6: Results - Effect Of Ozone Nonattainment On Per Facility TRI Emissions

	Baseline	I	II	III
	TRI/Fac	ln(TRI/Fac)	TRI/Fac	ln(TRI/Fac)
Ozone nonattainment	22,827.93	0.1907996	-12,437.97	-0.0578584
	[71,872.04]	[0.1267743]	[82,467.69]	[0.1192821]
Years of ozone nonattainment	169.5844	-0.0064942	1,656.07	-0.0024157
	[4,455.05]	[0.0078582]	[6,169.90]	[0.0089242]
Per capita income	8.809753	-0.0000623 **	20.65682	0.0000837 **
	[7.818508]	[0.0000138]	[13.96308]	[0.0000202]
Population density	259.7924	0.0013455 *	167.8011	0.0014002
	[366.0793]	[0.0006457]	[497.9378]	[0.0007202]
Constant	64,796.41	12.77874 **	41662.55	9.984105 **
	[205,331.70]	[0.3621823]	[212,731.10]	[0.3076964]
County fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
County time trends	No	No	Yes	Yes
Observations	11,250	11,250	11,250	11,250
R^2	0.0049	0.0252	0.3563	0.576

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

From the estimation of the third specification, the lack of statistical significance suggests that nonattainment has almost no effect on per facility TRI emissions. It appears that firm exodus is the cause of the reduced emissions. Re-specifying the model to include the natural log of the dependent variable, county-specific time trends, or both (results shown in Table 2.6 under specifications I-III) also fails to show a statistically significant relationship between the number of years a county has been in nonattainment and per facility TRI emissions. The relationship between 'Years Nonattainment' is positive when using level measures of per facility emissions, but becomes negative when using the logged measure. Based on these results, it seems plausible that facilities are not simply reporting fewer emissions which would allow them to drop below the reporting threshold. If a facility were right at the threshold at which a marginal decrease in the amount of emissions reported would cause the number of facilities to decrease, the change in overall emissions would be negligible, which is not what the results from Table 2.4 would suggest. It seems reasonable to conclude that facilities are decreasing because they either shut down or relocate because of a tighter regulatory climate. This conclusion is consistent with many of the studies on firm location decisions which find that strict environmental regulation leads firms to locate in or shift production to less stringent counties. Unfortunately, given the data only offers a count of TRI reporting facilities, it is not possible to know whether the facilities simply shut down or whether they relocated.

2.4.2 Model 2: NAAQS and non-NAAQS effects

I use this model to differentiate between the effects of nonattainment status on VOCs and non-VOCs. The top ten TRI releases include hydrochloric acid, methanol, ammonia, toluene, xylene, sulfuric acid, chlorine, carbon disulfide, methyl ethyl ketone, and dichloromethane. Six of these ten releases are volatile organic compounds (VOCs) and are indirectly regulated through the NAAQS for ozone. The remaining four are regulated as HAPs, but are not subject to the same federal standards as the criteria pollutants. All of the top ten releases have been tracked by TRI since 1987. Only the reporting requirement thresholds and which industries are required to report have changed over time.

I construct a 15-year panel data set which includes the years 1988-2002 and includes the top fifty percent of TRI emitting counties. The dependent variables are each of the top ten TRI stack air releases from the TRI. The explanatory variables are nonattainment status for ozone and cumulative number of years a county has been in nonattainment. I control for population density and per capita income. I include year fixed effects to control for the changing of reporting thresholds because the changing of reporting thresholds will affect all counties in the same way.

To differentiate between the effects on VOCs and non-VOCs I estimate the parameters of the following equation for each of the top ten TRI releases using an ordinary least squares fixed-effects framework.

$$IndividualTRI_{jit} = \alpha_j + \mathbf{Nonattain}_{it}\boldsymbol{\phi}_j + \mathbf{X}_{it}\boldsymbol{\beta}_j + \delta_{j1}d1989_t + \ldots + \delta_{j14}d2002_t + \gamma_i + \epsilon_{jit} \quad (2.10)$$

$IndividualTRI_{jit}$ is pounds of individual toxic release j for county i in year t, where j represents each of the top ten TRI releases. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. $d1989_t,\ldots,d2002_t$ are dummy variables for years 1989-2002. The term γ_i is the county fixed effects term and ϵ_{it} is the idiosyncratic error term.

Estimation of the first model shows that TRI emissions are declining as a result of ozone nonattainment. Using this second model, I test whether ozone nonattainment only affects VOCs included in the TRI or if other releases are affected as well. Of the top five TRI releases three are VOCs and six of the top ten releases in the TRI are VOCs. The top ten are hydrochloric acid, methanol, ammonia, toluene, and xylene, sulfuric acid, chlorine, carbon disulfide, methyl ethyl ketone, and dichloromethane. These ten releases are all regulated, but methanol, toluene, xylene, carbon disulfide, methyl ethyl ketone, and dichloromethane are VOCs which are indirectly regulated for ozone under the NAAQS. Hydrochloric acid, ammonia, sulfuric acid, and chlorine are regulated, but not under the same federal standard as ozone. Only the results of the estimation of the top five are reported in Table 2.7. I simply mention results of the remaining five.

Estimation of the fixed-effects model for each of the top ten TRI releases reveals that emissions of non-VOCs are declining as a result of ozone nonattainment with the exception of chlorine. There is a significant reduction of hydrochloric acid which makes up the largest percentage (17.9%) of aggregate TRI releases. Ammonia, the third largest percentage (9%), is also significantly reduced as a result of nonattainment. An additional year of ozone nonattainment is associated with a 19,234 pound reduction of hydrochloric acid and a 31,448 pound reduction of ammonia. The average of emissions of hydrochloric acid and ammonia are 270,837 and 203,501 pounds respectively. A change of 19,234 pounds of hydrochloric acid is 7.1% of the average and a change of 31,448 pounds of ammonia is 15.5% of the average, which is a fairly substantial reduction. Sulfuric acid decreases with additional years on nonattainment, however is not statistically significant. This is evidence

Table 2.7: Results - Effect of Ozone Nonattainment On Top 10 Individual TRI Releases

	Hydrochloric Acid (Pounds)	Methanol (Pounds)	Ammonia (Pounds)	Toluene (Pounds)	Xylene (Pounds)
		VOC		VOC	VOC
Nonattainment for Ozone	283,925.6*	-6,806.946	646,118.6**	-7,776.762	-124,720.6**
	[111,986]	[34,733.35]	[65,156.09]	[26,466.83]	[28,439.36]
Years of Ozone nonattainment	-19,234.73**	-8,064.645**	-31,448.09**	-7,266.497**	-503.488
	[7,113.375]	[2,206.27]	[4,138.73]	[1,681.179]	[1,806.474]
Per capita Income	-9.055343	4.428319	1.661112	-2.533499	3.948436
	[10.626]	[3.295739]	[6.182458]	[2.511355]	[2.698522]
Population Density	-517.143	58.68236	644.4223*	-137.7969	4.334822
	[458.0508]	[142.0681]	[266.5047]	[108.256]	[116.3241]
Constant	557,032**	258,426.2**	69,589.83	298,447.3**	91,644*
	[163,188.4]	[50,614.17]	[94,946.84]	[38,568.04]	[41,442.44]
Observations	23,505	23,505	23,505	23,505	23,505
R^2	0.0059	0.0018	0.0131	0.0052	0.0032

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

of spillovers since these non-VOCs are not regulated under the National Ambient Air Quality Standards. VOCs are indirectly regulated under the NAAQS and those VOCs examined here, with the exception of carbon disulfide, are lower as expected as a result of ozone nonattainment because they are precursors to ozone formation.

2.4.3 Model 3: Unregulated greenhouse gas emissions

As an additional test for spillover effects from the enforcement of the NAAQS, I use this model to estimate the effect of ozone nonattainment on the unregulated greenhouse gas carbon dioxide, specifically carbon dioxide from cropland production. Under-reporting of carbon dioxide measures is not as much of a concern with this dataset since they are not measured, but rather estimated. There will still be some error in the estimation of the data, but it is a consistent calculation procedure (see Nelson et al. [48] for details). I construct a panel data set using all counties and the years 1990-2002. To find out the effect that ozone nonattainment has on unregulated greenhouse gases, I estimate parameters for the following equation

$$CarbonDioxide_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1991_t + \ldots + \delta_{12} d2002_t + \gamma_i + \epsilon_{it} \qquad (2.11)$$

where $CarbonDioxide_{it}$ represents megagrams or metric tons of carbon from cropland production in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. To control for year effects that affect all counties, I include $d1991_t, \ldots, d2002_t$ as dummy variables for years 1991-2002. The term γ_i is the county fixed effects, which includes all factors within a given county that do not vary over time. To remove γ_i, I use time demeaning which is the fixed-effects transformation model. ϵ_{it} is the idiosyncratic error term. The results from parameter estimation are summarized in Table 2.8.

Table 2.8: Results - Effect of Ozone Nonattainment On Cropland Carbon Dioxide

	Carbon Dioxide from Cropland Production (Megagram C)
Nonattainment for Ozone	627.085**
	[71.48741]
Years of Ozone nonattainment	-24.09921**
	[4.47217]
Per capita Income	-.0049505
	[.0043196]
Population Density	-.5547635*
	[.2225101]
Constant	7,113.848**
	[69.85546]
Observations	40,703
R^2	0.0243

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

The coefficient on ‘Years of Nonattainment’ is negative and statistically significant at the 1% level which implies that an additional year of ozone nonattainment leads to a 24 megagram reduction of carbon dioxide from cropland production. However, with a mean emissions level of 7,178 megagrams, this change, which is 0.3% of the average, seems to be only a very modest reduction. Ozone nonattainment not only has a significant negative effect on toxic releases (both

VOCs and non-VOCs), but also leads to lower unregulated greenhouse gas emissions such as carbon dioxide.

2.5 Conclusion

The results provide support for the existence of spillovers as evidenced by the reduction of non-VOC emissions associated with nonattainment status of 1-hour ozone. The reduction of overall TRI emissions is caused by reductions of both VOCs and non-VOCs. Since the number of TRI reporting facilities is decreasing and there is a lack of a statistically significant relationship between ozone nonattainment and pounds of emissions per facility, it seems reasonable to conclude that the exodus of facilities is the primary reason for decreased emissions. Since the TRI reports a count of facilities in a county, it is important to recognize that declining facility numbers does not necessarily mean that facilities shut down or moved to a new county. If facility numbers decrease, it is possible that emission levels at some facilities dropped below the required threshold for reporting, thereby causing the number of facilities to drop. However, given the results found in this work, that explanation seems unlikely. The reduction of unregulated carbon dioxide emissions associated with cropland production due to ozone nonattainment is further evidence of spillover effects.

To the best of my knowledge, this work is the first to address these air quality regulatory spillovers and thus report such findings. Important implications of these findings would be that not accounting for these spillovers could lead policy-makers to significantly underestimate the potential benefits (in terms of reduced pollution levels) associated with the NAAQS. Also this analysis provides additional credibility for the use of nonattainment status as a proxy for regulatory stringency.

Table 2.9: Summary Statistics

Top 750 Emitting Counties (1988-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
TRI pounds (stack air)	11,250	1,723,807	3,775,368	0	1.19e+08
TRI reporting facilities	11,250	13.849	24.953	0	486
Per facility emissions	11,250	322,987.8	1,348,453	0	6.50e+07
Years of nonattainment for ozone	11,250	3.795	7.285	0	25
Nonattainment for ozone	11,250	.2426667	.4287142	0	1
Per capita income	11,250	20,805.19	5,858.492	7677	61759
Population density	11,250	189.7784	602.6435	0	13582

Top 50% of Emitting Counties (1988-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
Hydrochoric Acid	23,505	270,837	2,185,927	0	1.53e+08
Ammonia	23,505	203,501.4	1,482,101	0	6.03e+07
Toluene	23,505	185,820	680,646.2	0	2.70e+07
Methanol	23,505	297,848.2	1,221,581	0	3.08e+07
Xylene	23,505	133,017.2	694,400.7	0	4.86e+07
Dichloromethane	23,505	56,019.37	310,548.4	0	1.05e+07
Carbon disulfide	23,505	45,282.74	977,027.9	0	4.62e+07
Methyl ehtyl ketone	23,505	91,752.37	385,377.6	0	1.82e+07
Chlorine	23,505	46,947.11	1,652,505	0	1.10e+08
Sulfuric acid	23,505	248,979.8	4,077,513	0	2.57e+08
Years of nonattainment for ozone	23,505	2.66237	6.332302	0	25
Nonattainment for ozone	23,505	.1732823	.3784992	0	1
Per capita income	23,505	19,923.31	5,601.505	7380	61759
Population density	23,505	132.4999	555.7981	0	13582

All Counties (1990-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
Cropland CO_2 (Megagrams)	40,703	7,178.088	8,246.035	0	70,678.95
Years of nonattainment for ozone	40,703	1.62192	5.20538	0	25
Per capita income	40,703	19,620.89	5,554.011	0	85,984
Population density	40,703	87.87008	562.2077	0	21,354
Nonattainment for ozone	40,703	.1032602	.3043022	0	1

Chapter 3

The Effects of Ozone Regulation On Unregulated Industrial Carbon Dioxide Emissions

On April 2, 2007, the Supreme Court ruled that greenhouse gases (GHGs), including carbon dioxide, fit the definition of air pollutants under the Clean Air Act (CAA)[1] , and required the U.S. Environmental Protection Agency (EPA) to determine whether or not greenhouse gas emissions from new motor vehicles present a danger to public health. On December 7, 2009, the EPA issued an endangerment finding and a cause and contribute finding regarding greenhouse gases for mobile sources under section 202(a) of the Clean Air Act. The endangerment finding stated that current and projected concentrations of the six primary well-mixed greenhouse gases carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF_6) in the atmosphere threaten the public health and welfare of current and future generations. The cause and contribute finding stated that the combined emissions of these well-mixed greenhouse gases from new motor vehicles and new motor vehicle engines contribute to the greenhouse gas pollution which threatens public health and welfare. On December 15, 2009, the final findings were published in the Federal Register[2] and the final rule became effective January 14, 2010[3] .

The regulation of CO_2 from mobile sources also prompted the EPA to consider regulation of stationary sources of carbon dioxide and other greenhouse gases. On January 2nd, 2011, the largest

[1] *Massachusetts v. EPA*, 549 U.S. 497 (2007)
[2] Docket ID [EPA-HQ-OAR-2009-0171; FRL-9091-8]
[3] http://epa.gov/climatechange/endangerment.html

stationary sources of carbon dioxide emissions were required to obtain construction permits (New Source Review) for any new sources or for any major modifications to existing facilities. Operating permits (Title V) will be required of these sources beginning July 1, 2011. The EPA is currently in the process of setting guidelines for New Source Performance Standards for carbon dioxide and other greenhouse gases for natural gas, oil and coal-fired energy generating units. Based on a recent signing agreement, the EPA is committed to issuing proposed regulation by July 26, 2011.

Previous studies have made a link between nonattainment status for criteria pollutants subject to the National Ambient Air Quality Standards of the Clean Air Act and emission levels for those specific pollutants. This research expands on previous findings of regulatory spillover effects and analyzes the effect of ozone regulation on industrial releases of carbon dioxide before greenhouse gases were regulated. The results suggest that some spillover effects from the regulation of ozone exist which lead to a slight reduction of carbon dioxide emissions, but most importantly a reduction in per facility emissions. This is likely due to updating production methods or installing new technology, which reduces emissions of a wide range of pollutants. These results are significant because they show that it may not be necessary to directly regulate every pollutant.

3.1 Air Quality Regulation Background

The Clean Air Act (CAA) of 1970 is the law detailed in the United States Code under Air Pollution Prevention and Control (Title 42, Chapter 85)[4] . The enforcement of the Clean Air Act is detailed under Title 40 of the Federal Code of Regulation: Protection of Environment (administered by the United States Environmental Protection Agency). The CAA regulatory programs proceed as follows. First the EPA identifies emissions of a pollutant from a set of sources: stationary[5] and mobile[6] . Then the EPA undertakes an analysis of whether these emissions present a danger to the public health or welfare and, if it is the case, issues an endangerment finding. An endangerment

[4] Titles in the Clean Air Act correspond to subchapters in the U.S. Code.

[5] Stationary sources include electric generating units (EGUs), large industrial boilers, pulp and paper, cement, iron and steel industry, refineries, nitric acid plants.

[6] Mobile sources include airplanes, automobiles, lawn and garden equipment, locomotives, marine engines, motorcycles, trucks and buses.

finding is a necessary and sufficient condition for regulation. Once an endangerment finding has been issued, the EPA cannot refuse to regulate although they retain some discretion over how to regulate.

The regulation of stationary sources of emissions is broken down into three different forms: air quality standards, technology standards, and permit programs for new and modified sources. The citations of laws governing these three types of regulations are summarized in Table 3.1.

Table 3.1: Summary of Stationary Source Regulation - Laws and Implementation

	Law		Implementation
	United States Code	Clean Air Act	Code of Federal Regulations
Air Quality Standards:			
National Ambient Air Quality Standards	42 USC §7408-7410	CAA §108-110	40 CFR §50
- State Implementation Plans	42 USC §7410,7502	CAA §110,172	40 CFR §51-52
Technology Standards:			
New Source Performance Standards	42 USC §7411	CAA §111	40 CFR §60
Hazardous Air Pollutants	42 USC §7412	CAA §112	40 CFR §61,63
Permit Programs:			
New Source Review (Construction)	42 USC §7470-7479,7503	CAA §160-169,173	40 CFR §51-52
- PSD	42 USC §7470-7479	CAA §160-169	40 CFR §52
- NAA	42 USC §7503	CAA §173	40 CFR §51
Title V (Operating)	42 USC §7661a-7661f	CAA §501-506	40 CFR §70-71

3.1.1 Air Quality Standards

3.1.1.1 National Ambient Air Quality Standards (NAAQS)

The regulatory process of the National Ambient Air Quality Standards begins with the EPA determining whether a given pollutant endangers public health or welfare. Those pollutants which have been determined to endanger public health or welfare are then listed as criteria pollutants. The EPA has identified the following six pollutants as criteria pollutants: carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulate matter (PM_{10} and $PM_{2.5}$), and lead (Pb). A measure of TSPs (or total suspended particulates) was used for particulate matter until 1991. The agency must then determine what air quality standard is necessary to protect public health (primary standard) and welfare (secondary standard). Title 40 of the Code of Federal

Regulations lists the maximum allowable concentrations for each of the six criteria pollutants. The EPA has oversight, but the states are responsible for compliance in what is referred to as cooperative federalism.

Every year counties in violation of these standards are designated as nonattainment counties. The standard for 1-hour ozone under the NAAQS is as long as the highest hourly reading does not exceed 0.12 parts per million (ppm) on more than one day per year in a county, then that county is in attainment. The standard can also be described as the second-highest daily maximum or the single-highest hourly reading over all hours and days of the year, except for the first day with the highest annual hourly reading. For counties designated as nonattainment, the state must formulate a state implementation plan outlining how they plan to return any nonattainment counties back to attainment status.

3.1.1.2 State Implementation Plans (SIP)

The goal of NAAQS regulation is to ensure that areas which fail to attain these standards are brought back into compliance and that those areas currently meeting standards continue to do so in the future. State Implementation Plans[7] are the regulations and other materials for meeting clean air standards and associated Clean Air Act requirements. SIPs include state regulations that EPA has approved; state-issued, EPA-approved orders requiring pollution control at individual companies; planning documents such as area-specific compilations of emissions estimates and computer simulations (modeling analyses) demonstrating that the regulatory limits assure that the air will meet air quality standards, and federally promulgated regulations, designated as FIP (federal implementation plan). Each state must illustrate how an area will come into compliance with primary (health) standards[8] within five years. In nonattainment areas, states are required to impose reasonably available control technology[9] (RACT) on emitters. States that fail to adequately plan are subject to sanctions,[10] including potential loss of federal highway funding.

[7] http://www.epa.gov/reg5oair/sips/
[8] CAA §110
[9] CAA §172
[10] CAA §179

3.1.2 Technology Standards

3.1.2.1 New Source Performance Standards (NSPS)

New Source Performance Standards[11] are national emission standards that are progressively tightened over time to achieve a steady rate of air quality improvement without unreasonable economic disruption. The NSPS imposes uniform requirements on new and modified sources through the nation. It could be a numerical emission limit, a design standard, an equipment standard, or a work practice standard. These standards are based on the best demonstrated technology (BDT). Any new source of air pollution must install the best control system currently in use within that industry. Standards typically need to be reviewed and possibly updated about every eight years.

Primary enforcement responsibility of the NSPS rests with EPA, but this authority can be delegated to the states. States can adopt an NSPS or impose limitations of their own as long as the state requirements are as stringent as the federal requirements. The states have to be certain that any new source will not adversely affect their SIP. For this reason all new sources must undergo a review process known as the New Source Review.

3.1.2.2 Hazardous Air Pollutants (HAPs)

In addition to the NAAQS criteria pollutants, the EPA and local environmental agencies monitor and regulate a wide range of other pollutants often referred to as hazardous air pollutants[12] (HAPs) under section 112 of the CAA. The CAA of 1970 required the EPA to identify and list all air pollutants (not already identified as criteria pollutants) that may reasonably be anticipated to result in an increase in mortality or an increase in serious irreversible or incapacitating reversible illness. For each pollutant identified[13] , the EPA was to then establish national emissions standards for hazardous air pollutants (NESHAPs) at levels that would ensure the protection of the public

[11] http://www.epa.gov/apti/course422/apc4c.html
[12] http://www.epa.gov/apti/course422/apc4e.html
[13] The current list includes 188 compounds. Examples of toxic air pollutants include benzene, which is found in gasoline; perchlorethlyene, which is emitted from some dry cleaning facilities; and methylene chloride, which is used as a solvent and paint stripper by a number of industries. Examples of other listed air toxics include dioxin, asbestos, toluene, and metals such as cadmium, mercury, chromium, and lead compounds. The majority of the HAPs are volatile organic compounds (VOCs)

health. They found it very difficult to establish these standards because of the uncertainty in assessing health risk.

In the first phase of the HAPs program, the CAA defines two types of emissions standards: maximum achievable control technologies (MACTs) and generally available control technologies (GACTs). MACTs[14] are emission standards that achieve "the maximum degree of reduction in emissions of the hazardous air pollutants" taking into consideration the cost of achieving such emission reduction, and any non-air quality health and environmental impacts and energy requirements. GACTs are less stringent emission standards based on the use of more standard technologies and work practices. In the second phase of the HAPs program, the EPA has to assess and report on the residual risk due to HAPs that is likely to remain after attainment of the MACT and GACT standards. Based on this assessment, EPA may implement additional standards to address any significant remaining, or residual, health or environmental risks.

3.1.3 Permit Programs

The process of permitting for new or modified sources takes two forms: construction permits and operating permits. Constructions permits are referred to as New Source Review Permits. NSR permits are broken down into two subcategories: PSD permits which are specific to sources in attainment areas and NAA permits which are specific to sources in nonattainment areas. Operating permits are referred to as Title V permits and are either state/locally-issued or EPA-issued.

3.1.3.1 New Source Review (NSR) - Construction Permits

The New Source Review[15] (NSR) permitting program established as part of the 1977 Clean Air Act Amendments is a construction permitting program. NSR permits are legal documents that specify what construction is allowed, what emission limits must be met, and often how the emissions source must be operated. The primary objective of these permits is to ensure that air

[14] MACT is determined differently for new and existing sources of HAPs. For new sources, MACT is equivalent to the best controlled similar source in a given industry. For existing sources, MACT represents the average emission limit achieved by the best performing 12 percent of the existing sources for which EPA has information.

[15] http://www.epa.gov/NSR/

quality is not significantly degraded by adding new factories and modifying existing facilities such as power plants. In areas with clean air, NSR assures that new emissions do not significantly worsen air quality, where in areas with poor air quality, such as nonattainment areas, NSR assures that allowing new emissions from new sources or modifications does not prevent progress toward improving air quality. They also want to make sure that advances in pollution control do not significantly prevent industrial expansion.

Prevention of Significant Deterioration[16] (PSD) is the NSR permitting program that applies to new sources or modifications that occur within attainment areas or areas which are unclassifiable with the NAAQS. The purpose of PSD permits is to protect public health and welfare; preserve or enhance air quality in areas of special national or regional interest such as natural, recreational, scenic, or historic sites; guarantee that economic growth is consistent with maintaining clean air quality; and assure that any decision to permit increased air pollution is made only after careful evaluation of all the consequences and involves public participation in the decision making process. It requires the installation of the "Best Available Control Technology" (BACT), an air quality analysis, an additional impacts analysis, and public involvement. BACT is an emissions limitation which is based on the maximum degree of control that can be achieved. This includes fuel cleaning or treatment and innovative fuel combustion techniques. BACT may be a design, equipment, work practice, or operational standard if imposition of an emissions standard is infeasible.

Nonattainment (NAA) NSR[17] is the permitting program that applies to new sources or modifications at existing facilities located specifically in nonattainment areas. The requirements are customized for the nonattainment area. All nonattainment NSR programs require the lowest achievable emission rate (LAER), emission offsets, and opportunity for public involvement. LAER is either the most stringent emission limitation contained in the implementation plan of any state or the most stringent emission limitation achieved in practice. Offsets are emission reductions that must offset the emissions increase from the new source or modification and provide a net

[16] http://www.epa.gov/NSR/psd.html
[17] http://www.epa.gov/NSR/naa.html

improvement in air quality. The purpose for offsets is to allow a nonattainment area to move towards attainment of the NAAQS while still allowing some industrial growth.

3.1.3.2 Title V - Operating Permits

Title V permits[18] are required by most large sources and some smaller sources for operation. Permitting authorities issue these legally enforceable operating permits to different air pollution sources once operation has started[19]. Title V permits are typically issued by state and local permitting authorities and are referred to as part 70 permits because the corresponding regulations are found in Title 40 of the Code of Federal Regulations under part 70. EPA-issued permits are referred to as part 71 permits.

3.2 Conceptual Framework

Results from chapter 2 suggest evidence of spillover effects from the enforcement of the NAAQS for ozone on both VOCs and non-VOCs, both of which are regulated. In this chapter, I analyze whether ozone nonattainment has an effect on industrial stationary sources of carbon dioxide. CO_2 was unregulated before just recently, with the exception of the reporting requirements under the Acid Rain Program.

The Acid Rain Program[20] (ARP) instituted a system of continuous emissions monitoring[21] (CEM) to ensure that the mandated reductions of SO_2 and NO_x are achieved. CEM is the continuous measurement of pollutants specifically related to the formation of acid rain, which are released through industrial processes in the form of exhaust gases from combustion. The ARP requires the continuous monitoring of SO_2, NO_x, volumetric flow, and diluent gas[22]. Under this program, CO_2 monitoring and estimation procedures are detailed as well.

[18] CAA §501-507; 42 USC §7661-7661f

[19] http://www.epa.gov/oaqps001/permits/

[20] CAA §401-416

[21] http://www.epa.gov/airmarkt/emissions/continuous-factsheet.html

[22] A gas of known quality introduced for analytical purposes so that it quantitatively lowers the concentration of the components of a gaseous sample; this may also be the complementary gas. [IUPAC Compendium of Chemical Terminology, 2nd Edition (1997)]

Since NO_x is monitored by the ARP and is also a precursor to ozone, if a county is in nonattainment for ozone, local regulators will be imposing stricter enforcement in order to reduce NO_x and VOCs and bring the county back into attainment. If better technology is installed, this may reduce other emissions besides NO_x and VOCs such as CO_2. County-level carbon dioxide could also be reduced by firms leaving the county.

The intended consequence of air quality regulation is to reduce emissions below an acceptable safety threshold nationwide which translates into lower emissions per facility. It is very conceivable that facilities would leave counties with strict regulation, which would lower emissions in nonattainment counties, but increase emissions in attainment counties where regulation is relatively less stringent. This case would not necessarily result in a net reduction of emissions, but rather a redistribution of emissions. If facility numbers are increasing, but emissions per facility are decreasing, then firms are emitting less and that is the primary factor causing the reduced emissions. Cleaner facilities entering the county is a possible story consistent with this scenario. The first set of estimations of this chapter tests whether there are lower overall emissions in ozone nonattainment counties and the second set of estimations tests whether lower overall emissions are due to fewer facilities or lower emissions per facility.

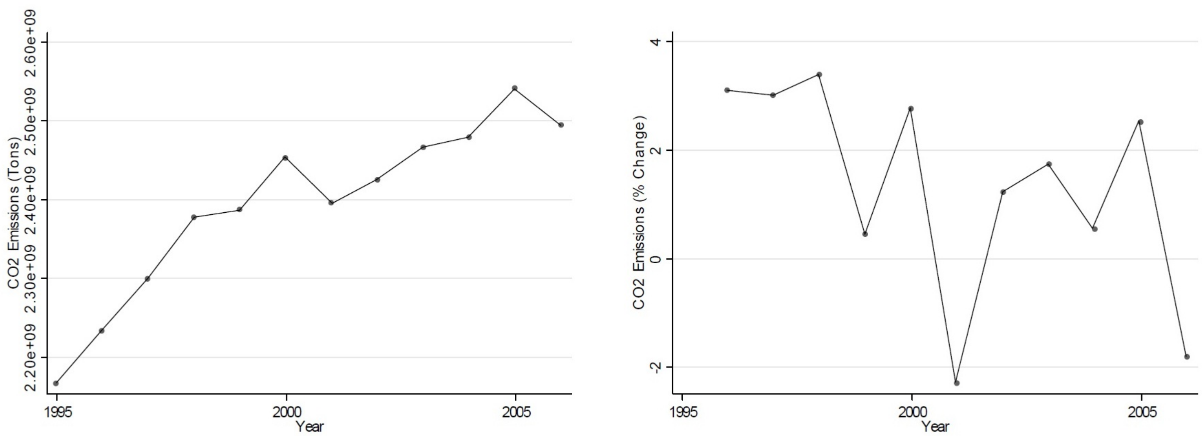
3.3 Data

The industrial carbon dioxide emissions data come from the Clean Air Markets Division[23] (CAMD) of the EPA. The data were extracted at the facility level and then aggregated to the county level. The data are available from 1995-2008. The Part 75 Continuous Emissions Monitoring Rule[24] provides details about applicability and reporting requirements for industrial facilities to report carbon dioxide. The rule was originally published in January 1993 and established continuous emission monitoring (CEM) and reporting requirements under EPAs Acid Rain Program[25] (ARP). The ARP regulates electric generating units (EGUs) that burn fossil fuels such as coal, oil and

[23] http://www.epa.gov/airmarkets/
[24] 40 CFR §75.2,75.10,75.13
[25] CAA §410-416

natural gas and that serve a generator greater than 25 megawatts. For these units Part 75 requires continuous monitoring and reporting of sulfur dioxide (SO_2) mass emissions, carbon dioxide (CO_2) mass emissions, nitrogen oxides (NO_X) emission rate, and heat input[26] .

Figure 3.1: National Trend of Industrial Carbon Dioxide Emissions Reported

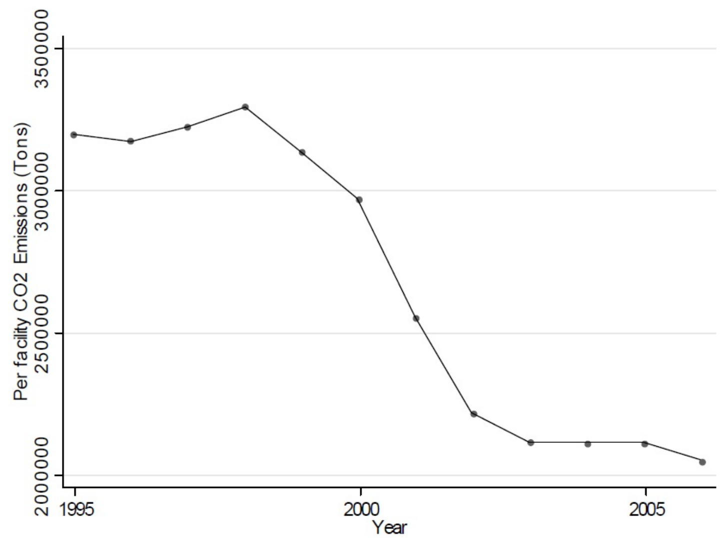


The data for county nonattainment status is publicly available through the EPA's website [2]. Beginning in 1978 to 2009, every July counties are listed if they are designated as nonattainment (either the whole county or part of the county) for one of the criteria pollutants. Attainment status is used as a proxy for regulatory stringency, because new and existing plants are subject to much stricter controls in nonattainment areas, relative to attainment areas. Counties in nonattainment are more likely to be closely monitored and subject to greater enforcement efforts. The research in this chapter focuses on the effect of nonattainment status for 1-hour and 8-hour ozone because there is greater variation of counties moving in and out of nonattainment relative to other criteria pollutants.

The data have 1-hour and 8-hour ozone nonattainment listed separately. There are counties listed as nonattainment for 1-hour ozone up until 2004. There are no counties listed as being in nonattainment for 8-hour ozone before 2004. Only a one-year overlap of these two standards exists. In 2004, there are 214 counties that are listed as nonattainment for both 1-hour and 8-hour ozone. For the purpose of this analysis, I define nonattainment status for ozone as being out of attainment

[26] http://www.epa.gov/airmarkets/emissions/docs/plain_english_guide_part75_rule.pdf

Figure 3.2: National Trend of Per Facility Industrial Carbon Dioxide



for either the 1-hour standard or the 8-hour standard. Combining these two standards I create an indicator variable that equals 1 if the county is out of attainment for either standard and equals 0 otherwise. From this I construct a variable for the cumulative number of years since the county was last in attainment (for both standards) for ozone.

3.4 Empirical Specifications

The primary objective of the empirical model is to examine what effect ozone nonattainment has on unregulated industrial CO_2 emissions. If CO_2 emissions are declining in ozone nonattainment counties, the second objective of the model is then to identify whether it is due to facilities leaving the county or shutting down because of increased regulatory stringency (extensive margin) or whether firms reduce their emissions by decreasing production or installing or upgrading abatement technology because of increased regulatory stringency (intensive margin).

The advantage of panel data is that time-invariant variables can be time demeaned using a fixed effects model, which greatly reduces the required number of variables for estimation, while not leading to omitted variable bias. With the movement of people in the U.S. to the sunbelt states, it would be expected that there would be increased levels of ozone. By including fixed effects, I control for areas with high annual levels of sunshine which is key for ozone formation, but does not change from year to year. The increased population numbers are controlled for by including a measure of population density.

Ozone nonattainment in the current year is expected to be associated with higher levels of overall emissions, because higher emissions are the reason that the county is out of attainment. A negative relationship between cumulative number of years a county has been out of attainment and the levels of emissions in the county is the hypothesized result. The underlying reasoning is that counties that are not making progress toward returning to attainment will draw more attention and subsequently stricter enforcement.

The first objective of the empirical model is to estimate the effect of ozone regulation on unregulated industrial carbon dioxide. I construct a 12-year panel data set which includes the years 1995-2006. The dependent variable is total tons of county-level industrial CO_2 emissions. The key explanatory variable is the cumulative number of years a county has been in nonattainment for ozone. Using an ordinary least squares fixed-effects framework, I estimate the parameters of the following equation

$$(IndustCO_2)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1996_t + \ldots + \delta_{11} d2006_t + \gamma_i + \epsilon_{it} \tag{3.1}$$

where $IndustCO_2$ represents the measure of total tons of industrial carbon dioxide emissions in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. To control for year effects that affect all counties, I include $d1996_t$,$\ldots$,$d2006_t$ as dummy variables for years 1996-2006. The term γ_i is the county fixed effects, which includes all factors within a given county that do not vary over time. To remove γ_i, I use time demeaning which is the fixed-effects transformation model. ϵ_{it} is the idiosyncratic error term.

The second objective of the empirical model is to decompose the effects of ozone nonattainment on carbon dioxide at the extensive and intensive margins. The extensive margin is the effect of ozone regulation on the number of industrial facilities reporting carbon dioxide. The intensive margin is the effect of ozone regulation on per facility emissions. For this part of the model, I combine two specifications in which the dependent variables are number of facilities reporting CO_2 and the tons of CO_2 emissions per facility. The panel data set is the same as above using years 1995-2006. To estimate the extensive and intensive marginal effects, I obtain parameter estimates of the following equations using an ordinary least squares fixed-effects framework.

$$Facilities_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1996_t + \ldots + \delta_{11} d2006_t + \gamma_i + \epsilon_{it} \tag{3.2}$$

$$\left(\frac{IndustCO_2}{Facility}\right)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1996_t + \ldots + \delta_{11} d2006_t + \gamma_i + \epsilon_{it} \tag{3.3}$$

$Facilities_{it}$ is a count of the number of industrial facilities reporting carbon dioxide emissions in county i in year t. $\left(\frac{IndustCO_2}{Facility}\right)_{it}$ is a measure of the per facility industrial carbon dioxide emissions reported in county i in year t. $\mathbf{Nonattain}_{it}$ is a matrix of nonattainment variables which includes a dummy variable for whether county i is designated as nonattainment for ozone in year t and a variable for the cumulative number of years since county i was last in attainment for ozone. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. $d1996_t, \ldots, d2006_t$ are dummy variables for years 1996-2006. The term γ_i is the county fixed effects term and ϵ_{it} is the idiosyncratic error term.

3.5 Results

Estimation results for the panel including all U.S. counties are provided in Table 3.2. The key explanatory variable of interest is the cumulative number of years since a county was last in attainment for ozone. Estimation of Equation 3.1 reveals that for each additional year of nonattainment industrial CO_2 would be reduced by 3,652 tons per year (TPY). This coefficient is statistically significant at the 1% level, however, with a county-level average of 776,514 TPY, this seems to be a very small change (0.4 % of the average). It is important to note that only 725 out of the 3,132 counties had any reported CO_2 emissions from 1995-2006. With that in mind, I repeat the parameter estimation of Equation 3.1 using only those 725 counties and found that for each additional year of nonattainment, CO_2 levels decreased by 9,783 TPY (results in Table 3.2). This result was again statistically significant at the 1% level, however, by removing all of the counties that had zero emissions reported, the mean level of emissions per county increased to 3,290,278 TPY. The absolute change of 9,783 is only 0.2 % of the average level. Considering the average number of years a county is in nonattainment for the 725 counties that reported CO_2 emissions is 4.37, the yearly reduction might be closer to 1% of the average emissions level, which is small, however meaningful given that it is an unintended consequence.

Table 3.2: Results - Effect of Ozone Nonattainment On Industrial Carbon Dioxide

				725 CO2 Emitting Counties		
	Industry CO2 (Tons)	Number of CO2 Facilities	CO2 Tons (Per Facility)	Industry CO2 (Tons)	Number of CO2 Facilities	CO2 Tons (Per Facility)
Ozone Nonattainment	68,804.8 ** [18,636.64]	-0.0663488 ** [0.0137432]	48,222.68 ** [17919.98]	154,748.5 ** [59,575.2]	-.1751139 ** [.0397648]	102,649.2 [57,850.17]
Years of ozone nonattainment	-3,652.866 ** [1,317.545]	0.0169608 ** [0.0009716]	-7,594.787 ** [1266.88]	-9,783.234 ** [3,730.987]	.0280914 ** [.0024903]	-13,966.76 ** [3,622.954]
Population density	493.1804 ** [91.53177]	0.0019034 ** [0.0000675]	-186.2589 * [88.01197]	275.6349 [194.1021]	.0013197 ** [.0001296]	-72.65834 [188.4817]
Per capita income	2.238978 [1.320901]	8.68E-06 ** [9.74E-07]	-2.20752 [1.270106]	-7.350619 [5.971306]	2.73e-06 [3.99e-06]	-7.76108 [5.798404]
Constant	620,945.3 ** [25,505.95]	-0.1117118 ** [0.0188088]	616,030.1 ** [24,525.14]	3,060,504 ** [124,971.6]	.5044627 ** [.0834152]	2,546,422 ** [121,352.9]
Observations	36,864	36,864	36,864	8,700	8,700	8,700
R^2	0.0101	0.0982	0.0042	0.0389	0.2660	0.0139

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

The estimation of Equation 3.2 suggests a positive and statistically significant relationship between the number of years of ozone nonattainment and CO_2 reporting facilities (Table 3.2). Although the magnitude of 0.02 additional facilities for each additional year of ozone nonattainment is rather small, the maximum change in facilities in a single year is an increase of six facilities. Most counties see no change in facilities or only an increase of a single facility in a single year. However, the general trend in reporting facilities is increasing, especially in the 725 counties that report CO_2

emissions. This suggests that along the extensive margin, firms are not leaving counties due to increased regulatory stringency.

The estimation of Equation 3.3 provides a key result at the intensive margin. The coefficient on 'Years Nonattainment' is negative and statistically significant at the 1% level. The magnitude of the coefficient suggests an even larger reduction in per facility emissions than at the county level as a whole. For each additional year of ozone nonattainment, per facility CO_2 emissions are declining by 13,966 TPY (Table 3.2). Since the overall county-level decline in CO_2 emissions was 9,783 TPY, the per facility reductions seem to be offset by the increase in the number of facilities.

Figure 3.2 shows the significant decline in per facility emissions at the national level. This reduction is even more significant in nonattainment counties as evidenced by the results of this section, which suggests evidence of spillover effects from the regulation of ozone. Since all nonattainment NSR programs require the lowest achievable emissions rate and the best available technology, it seems that this is likely to reduce emissions of a wide range of pollutants.

3.6 Conclusion

Previous studies have made a link between nonattainment status for criteria pollutants subject to the NAAQS of the Clean Air Act and emission levels for those specific pollutants. This research expands on previous findings of regulatory spillover effects and analyzes the effect of ozone regulation on industrial releases of carbon dioxide before carbon dioxide was regulated. The results suggest that some spillover effects from the regulation of ozone exist which lead to a slight reduction of carbon dioxide emissions. Since facility numbers are increasing, but emissions per facility are decreasing, then firms are emitting less and that is the primary factor causing the reduced emissions. Cleaner facilities entering the county is a possible story consistent with this scenario. This is likely due to updating production methods or installing new technology as required by the New Source Review permit program for any new facilities in nonattainment counties, which should reduce a wide range of pollutants. These results are significant because they show that it may not be necessary to directly regulate every pollutant.

Table 3.3: Summary Statistics

All Counties (1995-2006)

	Obs	Mean	Std. Dev.	Min	Max
Industrial CO_2 (Tons)	36,864	776,514.2	2,806,313	0	3.16e+07
CO_2 Reporting Facilities	36,864	0.3027886	0.786146	0	15
CO_2 per Facilities (Tons)	36,864	573,051.2	2,129,445	0	2.57e+07
Nonattainment for ozone	36,864	0.1005588	0.3007477	0	1
Years of nonattainment for ozone	36,864	1.725966	5.897527	0	29
Per capita income	36,864	23,286.07	6,457.488	451	119,141
Population density	36,864	84.14475	577.8102	0	21,926.87
Δ CO_2	33,792	9,799.591	342,047.2	-1.66e+07	6,790,776
Δ Reporting Facilities	33,792	0.0160097	0.1711951	-3	6

725 Counties Which Reported Positive Amounts of CO_2 (1995-2006)

	Obs	Mean	Std. Dev.	Min	Max
Industrial CO_2 (Tons)	8,700	3,290,278	5,010,083	0	3.16e+07
CO_2 Reporting Facilities	8,700	1.273103	1.172309	0	15
CO_2 per Facilities (Tons)	8,700	2,428,156	3,835,442	0	2.57e+07
Nonattainment for ozone	8,700	0.2374713	0.4255578	0	1
Years of nonattainment for ozone	8,700	4.37046	8.854737	0	29
Per capita income	8,700	25,336.41	7,349.169	10451	111,346
Population density	8,700	242.367	1,159.433	.53	21,926.87
Δ CO_2	7,975	41,523.23	703,186.8	-1.66e+07	6,790,776
Δ Reporting Facilities	7,975	0.0654545	0.3425792	-3	6

Table 3.4: List of Acronyms

Acronym	Meaning
APA	Air Pollution Abatement
ARP	Acid Rain Program
BACT	Best Available Control Technology
CAA (1970)	Clean Air Act (of 1970)
CAAA (1977 & 1990)	Clean Air Act Amendments (of 1977 & 1990)
CAMD	Clean Air Markets Division
CEM	Continuous Emissions Monitoring
CFR	Code of Federal Regulations
EGUs	Energy Generating Units
EMSs	Environmental Management Systems
EMPs	Environmental Management Practices
EPA	U.S. Environmental Protection Agency
GHGs	Greenhouse Gases
HAPs	Hazardous Air Pollutants
LAER	Lowest Achievable Emissions Rate
MACT	Maximum Available Control Technology
NAAQS	National Ambient Air Quality Standards
NESHAPs	National Emission Standards for Hazardous Air Pollutants
NSPS	New Source Performance Standards
NSR	New Source Review
PACE	Pollution Abatement Costs and Expenditures
PSD	Prevention of Significant Deterioration
RACT	Reasonably Available Control Technology
SIP	State Implementation Plan
TPY	Tons Per Year (unit of emissions)
TSP	Total Suspended Particulates
USC	United States Code
VOCs	Volatile Organic Compounds

Chapter 4

Regional Heterogeneity In Preferences For Air Quality Regulation and the Effect of Pro-Environment Voting On Toxic Emissions

The structure of the air quality regulatory environment in the United States is such that minimum federal standards are set by the Environmental Protection Agency. Federal standards could include maximum allowable ambient concentration of certain pollutants or requirements of the technology that must be employed by new or existing firms. Over time the enforcement of federal standards has become the responsibility of local enforcement agencies. Hence, at the local level there exists heterogeneity in the degree of enforcement of these federal standards. Sometimes heterogeneity is imposed on specific areas because of non-compliance of federal standards. It can also exist because citizens have a preference for a cleaner environment and those who cannot afford it themselves will prefer greater regulatory stringency at the local level in order to obtain it. The primary objective of this chapter is to investigate the effect of citizen preferred greater regulatory stringency on the level of emissions within counties using pro-environment voting at the national level as a proxy for these attitudes.

One of the challenges researchers face when analyzing the effects of environmental regulation on air emissions is the choice of measurement used to describe the regulatory environment. The absence of direct measures of regulation forces researchers to rely on proxies and certain assumptions to describe regulatory stringency. One indirect measure that has been used is congressional voting records on environmental issues which, assuming that votes in Congress reflect attitudes of constituents, acts as a proxy for citizen attitudes towards a tighter regulatory climate. Common practice in the literature is to use state averages of votes from the U.S. House of Representatives or U.S. Senate as a proxy for community attitudes. It seems reasonable to assume that a county-level voting score would be a better proxy for the local regulatory environment than voting scores at the state level, because aggregation at the state level fails to identify which communities in the state are pro-environment. This is important because within each state there are "green" counties and counties that care comparatively little about the environment. An independent organization known as the League of Conservation Voters (LCV) keeps scorecard records on pro-environmental voting behavior of both U.S. Representatives and U.S. Senators. Using these scores provides a measure of how each politician voted and is assumed to proxy how much each community or county values the environment, regardless of how many pro-environment bills are actually passed at the national level.

Several studies have attempted to link measures of citizen attitudes toward pollution to regulatory stringency and its impact on firm behavior. For example, Henderson [35] considers state attitudes toward pollution as measured by the fixed-effect term from a fixed-effects regression with pollution abatement expenditures as the dependent variable. This fixed effect measures the degree to which states either "over spend" or "under spend" on abatement activity with overspending being associated with pro-environment attitudes. He identifies measures of time-invariant attitudes toward pollution and finds that a 1-percent increase in abatement expenditures leads to a 0.04-0.05 percent improvement in air quality measures. Gray and Shadbegian [29] evaluate temporal and cross-sectional variation in state-level aggregates of League of Conservation Voting (LCV) records and find that the share of a firm's production arising at the state level is negatively related to LCV scores. Gray [28] also uses state-level aggregates of LCV scores as a measure of attitudes towards pollution and finds that firm births across states are negatively related to LCV scores. Terry and Yandel [57] link TRI and LCV scores in a 50-state cross-sectional analysis in which they examine the effect of 1988 average LCV rating for each state's two senators on the 1992 level of stack air emissions reported by the TRI. They find a negative, but insignificant coefficient on the LCV score variable.

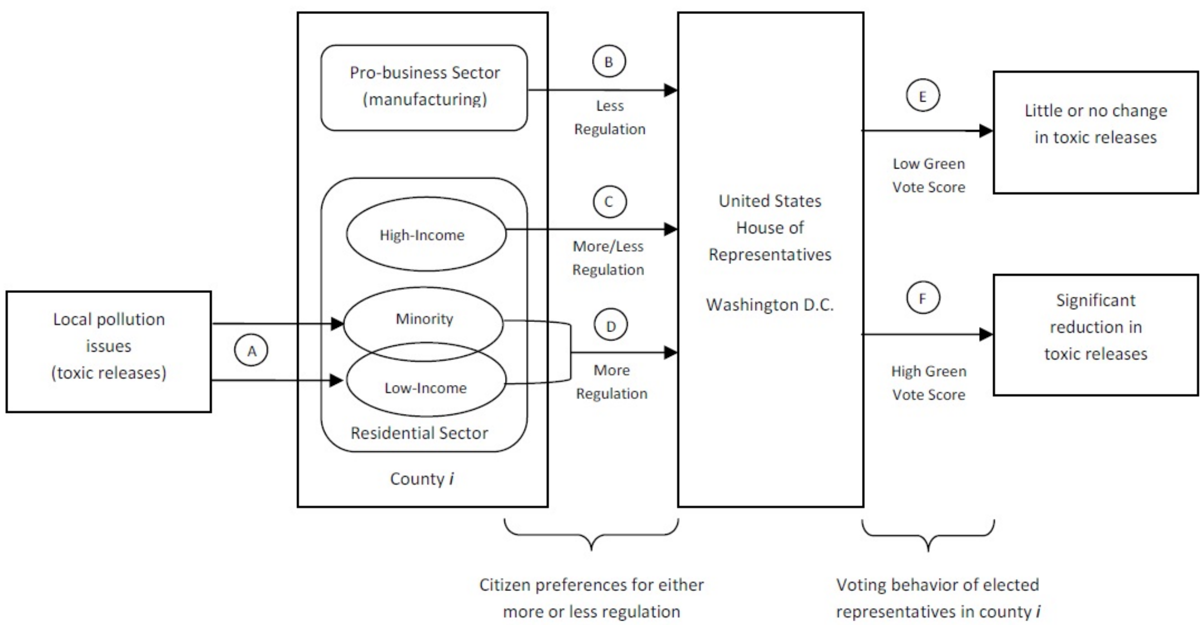
While findings from the previous studies that measure attitudes at the state level have been consistent, to my knowledge, no study has used LCV scores from the U.S. House of Representatives to explore the impact of voter attitudes at the county level. This research is the first to create county-level scores for pro-environment voting by mapping congressional district scores to the county level and creating weighted scores for counties that partially lie in multiple districts. The results suggest that allowing for regional heterogeneity in preferences at the county level can explain within-state variation in toxic emissions where state-level aggregates fail to identify such a relationship. Voting behavior appears to take between one and three years to have an effect on emissions.

4.1 Conceptual Framework

When firms release toxic emissions as a byproduct of the production process, this creates what is referred to in economics as a negative externality. Negative externalities are costs imposed on nearby residents that are not taken into account in the production decisions of firms. These types of costs lead to an output level that is not socially efficient. Coase bargaining [18] is generally not a possible solution since the number of affected individuals is typically large. Collective action against firms responsible for the negative externalities created by toxic releases could be considered a public good. Many individuals desire better air quality, but few are willing to provide the socially optimal level themselves due to the free-rider problem. According to the basic economic theory on public goods, the marginal private benefits of contributing to collective action are much less than the marginal social benefits at the point where the marginal private costs and benefits are equal, leading to under-provision of the public good. Recognizing that clean air benefits society and that it will not be provided by individuals, the government must choose the appropriate level of air quality and provide it by regulating emissions.

In order to make the connection between citizen preferences for regulation and voting patterns as a proxy for regulation and ultimately the effect on toxic releases, I construct a model and explain key links with findings from previous studies. The model links four fundamental questions relating how citizen attitudes or preferences for more or less regulation are translated into environmental outcomes through congressional voting. The four questions are 1.) Which groups are most affected by pollution? 2.) Which groups prefer more regulation? 3.) How do legislators decide which way to vote on environmental policy? and 4.) Do voting outcomes lead to reductions in emissions? The purpose of looking at these four questions separately will help show that shirking is less of a concern when using U.S. Representatives' voting as a proxy for citizen preferences at the county level. Also, it is not as simple as assuming that votes either reflect citizen preferences or legislator ideologies, since within counties there are different preferences for or against increased regulation that need to be considered by the legislator. Figure 4.1 summarizes the key features of the model and I have identified important links which I will refer to as links $A,\ldots,F$.

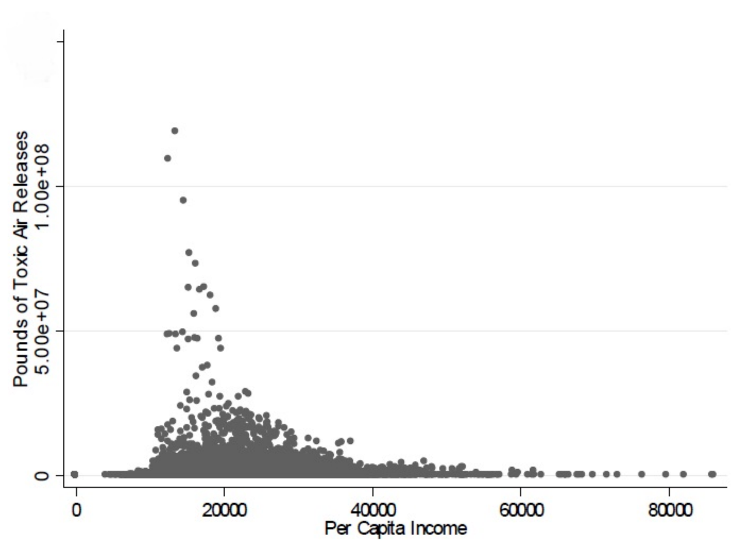
Figure 4.1: Conceptual Framework



I consider four groups of individuals whose attitudes or preferences for more or less regulation are likely to influence decisions. These four individual groups are categorized into two larger groups: pro-business sector and residential sector. The residential sector is divided into low-income, high-income, and minority households. It is likely that minority communities are a subset of the low-income classification, but at the very least there is a large intersection of the two groups. The pro-business sector represents anyone who is employed in one of the polluting industries.

The model suggests that the adverse effects of pollution will be primarily present in lower income and minority communities. The designation of high versus low income is somewhat arbitrary and is slightly unclear from the literature what the exact distinction should be regarding who is most affected by pollution. The poverty line could be chosen as the specific means of separating low from high income designation within counties, but it seems at the county level from Figure 4.2 that the counties most negatively affected by toxic releases are counties with a per capita income slightly higher than the poverty line. Per capita income is sensitive to high income outliers and income distributions are usually right-skewed, which would suggest that those most affected by the pollution are those who may be below the poverty line. Link A in Figure 4.1 shows that pollution affects lower income and minority populations.

Figure 4.2: Distribution of Toxic Air Emissions (TRI) by County Per capita Income



Preferences for more or less regulation vary by group. Those individuals closely associated with business interest will prefer less regulation (link B) since more regulation leads to higher costs of production and lower profit for business owners as well as potential job loss for workers employed in polluting industries. Because business owners do not directly benefit from cleaner air quality, their net benefits will be negative. Most individuals who live in low-income neighborhoods will prefer more regulation (link D in Figure 4.1) because regulation yields a positive net benefit. They receive the benefits of cleaner air quality, which likely outweigh the costs of slightly higher taxes [1] . The exception to this assumption would be those individuals who live in low-income neighborhoods, but who are employed in the polluting industry. It is assumed that these individuals would prefer job security to more regulation. According to this model, these individuals' preferences would be represented by link B in Figure 4.1. The preferences of the individuals who live in high-income neighborhoods are uncertain. It is reasonable to assume that these individuals place a high value on environmental quality, but it is unclear whether they prefer regulation as a means of obtaining higher environmental quality. The most likely outcome will be that those who can afford to move to locations with higher environmental quality will self-select into cleaner neighborhoods rather than relying on the government to provide it for them. On the other hand, there may be individuals who prefer a cleaner environment for society as a whole for altruistic reasons and they realize that regulation is one possible means of achieving that objective. These individuals are generally the more educated and realize that better air quality is a public good that is likely to be under produced. Therefore, it is possible that the high-income households could prefer either more or less regulation (link C in Figure 4.1), even though individuals acting in their own self-interest would simply move to cleaner locations.

Three likely objectives of career politicians are re-election (do whatever it takes to keep their job), altruism (place high priority on doing what is in their constituents' interests), and contribute their own ideologies to the decision making process (regardless of what constituents want). For those whose main priority is re-election, in order to maximize the likelihood of being re-elected, politicians must be aware of their constituents' interests on various issues. When deciding how to vote, the representative for county i takes into account the preferences of all four groups (shown by links B,C,D in Figure 4.1), even though they may not all be equally represented. One would

[1] The increase in costs of regulatory enforcement would be publicly financed through higher taxes, although, given the marginal tax structure, the increase in taxes on low-income households would not be as great as the increase for high-income households

expect those groups who are the most organized to communicate their preferences most clearly. Often the most organized are those representing business interests and are frequently found in Washington D.C. lobbying for less regulation. Communities that are less homogeneous, such as minority communities, are less likely to form collective action against polluting industries. The longer the terms of elected representatives, the greater is the likelihood of shirking from their constituents' interests, because they are most likely to take into account constituent interests when they are close to re-election. The term length of U.S. Representatives is two years which makes them more accountable to their constituencies than U.S. Senators whose term lengths are six years.

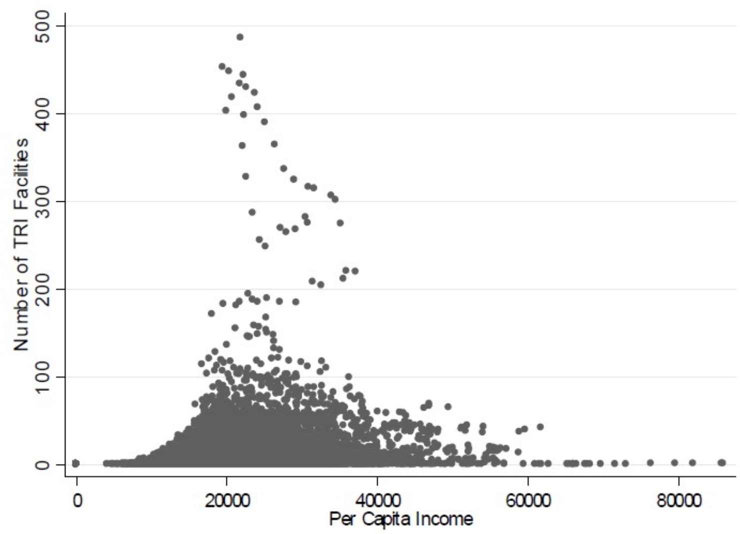
The primary focus of this chapter analyzes how voting behavior of U.S. Representatives affects the level of county-level toxic air releases (links *E,F* in Figure 4.1). The theory would predict that the more pro-environment the representative's vote the greater the reduction of toxic releases (link *F*) will be. The argument is that if there is pro-environment voting at the national level, then there must be overwhelming support for more regulation at the county level, especially since the ones most likely to support more regulation are the ones whose voices are least likely to be heard.

4.1.1 Which groups are most affected by pollution?

There exists a wide body of literature dealing with the question of how community characteristics influence environmental outcomes. Generally, all studies have arrived at the conclusion that the two groups most affected by pollution are low-income communities and minority communities, although most studies argue in favor of either one or the other. The distribution of county-level toxic emissions in Figure 4.2 shows that there is a very high concentration of toxic releases in counties in which the per capita income level is below $25,000, where Figure 4.3 shows TRI facilities are generally located in counties with a per capita income level of $30,000 or below.

A number of studies have analyzed within-county variation in community characteristics to try to identify which groups are the most disproportionally exposed to toxic releases. The following studies have conducted zip code-level analyses and have arrived at varying conclusions: Banzhaf and Walsh [9], Brooks and Sethi [12], Ringquist [54], Arora and Cason [7]. Link *A* is based on the

Figure 4.3: Distribution of Number of TRI Facilities by County Per capita Income



findings of these papers. For this model, I assume that both low-income and minorities are affected by toxic releases.

According to Banzhaf and Walsh [9], low-income families are the most negatively affected. They conduct an empirical test of the Tiebout [58] hypothesis that individuals sort into communities with optimal bundles of taxes and public goods. Assuming firm location to be exogenous, they find that the presence of TRI facilities causes the composition of a community to become poorer over time. This is a result of composition effects suggesting that pollution leads to out-migration by the wealthier households and/or in-migration of poorer households and is consistent with the Tiebout hypothesis. They find that racial composition effects are weak. Arora and Cason [7] find evidence of greater releases in poverty stricken neighborhoods, but also find that race is a significant determinant of toxic releases in the nonurban south, but not elsewhere in the country. Kriesel et al [44] find that minorities are not disproportionally exposed to toxic releases, but find some evidence that poor communities are disproportionally exposed to toxic releases. Additional studies from Gray and Shadbegian [30] and Videras [59] draw similar conclusions. Gray and Shadbegian [30] have found evidence that plants in low income communities pollute more, however not in minority communities. Videras [59] also finds that low-income households are more likely to be exposed to environmental hazards and are more likely to benefit from the provision of a cleaner environment.

Ringquist [54] evaluates the claim that TRI facilities are located in poor and minority communities and, after controlling for a variety of background factors, finds that TRI facilities and pollution are concentrated in zip codes with large minority representation. Brooks and Sethi [12] find that minority (or specifically more ethnically diverse) communities are more likely to be affected by pollution due to the lower likelihood of collective action. They also find that only for the highest income groups with annual incomes exceeding $67,000 per year does higher median income imply lower exposure to emissions. It could be that specific groups are targeted when firms emitting hazardous waste make decisions to locate, for instance, because of the perception that certain types of communities will be less willing and able to engage in costly collective action against the firms.

4.1.2 Which groups prefer more regulation?

In this section, a distinction must be made between preferences for cleaner environment and preferences for more regulation. It is generally accepted that most people recognize the health benefits of a clean environment and that it contributes positively to the value of outdoor recreation. Those with the means of affording it will obtain higher environmental quality through such examples as the purchase of homes in the foothills of the mountains, private golf memberships, or eco-tourism. They are likely to prefer less regulation because the benefits do not directly affect them. They will likely face higher taxes as a result and possibly experience a reduction in home values as previously undesirable areas become more attractive. Those who cannot afford a clean environment for themselves will have to rely on the government to regulate and protect their health.

Fischel [23] finds that income, occupation, and education are robust determinants of preferences for environmental quality and that voting on environmental quality is divided along economic and social class lines. Some studies have used referendum data in an attempt to identify how different groups within a region differ in their preferences for regulation. Kahn and Matsusaka [38] using data from sixteen California Initiatives find that environmental goods, such as parks, appear to be normal goods for people with the mean income level and inferior goods for people with high income.

Their findings support the claim that the wealthy can purchase these goods privately and therefore do not prefer public provision of environmental quality which would be provided through higher taxes. Kahn [37] focuses on how changing demographics affect the perceived benefits and costs of regulation, and finds that minorities, youths, the more educated, and those who do not work in polluting industries are more likely to support environmental regulation. Elliot et al [22], using aggregate level determinants of support for environmental protection over a span of two decades, find that as real per capita income increases, support for additional spending on environmental policy increases as well. They obtain public opinion data from both the National Opinions Research Center (NORC) and the Roper Surveys that solicit respondents' views on environmental spending

One concern is, even if individual group preferences are known, the line of communication between the low-income and minority populations and their legislators is unclear. It has been argued that minorities are less likely to form collective action [12] and are therefore less likely to convey their concerns. Because different groups are less likely to bond with members of another minority group, this is even more of a concern when the composition of minority communities is heterogeneous. It is also important to consider the opportunity cost of each individual group's time. Lower income families do not have the luxury of much free time for collective action. Lower paying jobs require more hours of labor to earn money necessary for survival. Therefore, the opportunity cost of lobbying politicians is much higher for low-income families than for those with higher incomes and more free time.

4.1.3 How do legislators decide which way to vote?

To consider which way a legislator will vote, one must first identify the incentives facing the individual. The incentives will be very different based upon the position of government under consideration. If many of these public officials have chosen this as their career of choice, then it seems reasonable to assume that they would have a strict preference to be re-elected so that they might continue in this line of work. There is also the possibility that certain individuals would like to work their way up to a legislative decision-making position offering them a chance to make their own political ideologies heard. Another possible incentive would be to do whatever is best for constituents, making constituent interest a priority.

Peltzman [51] starts with a basic framework in which voting patterns are a function of ideology of the legislator and the interest of the constituents. Fort et al [24] add in a time-path component to the model which addresses the sensitivity of shirking behavior near re-election time. Since ideology and citizen preferences are not directly observable, all studies that try to estimate these effects on voting patterns have to rely on various proxies. Common proxies for citizen preferences are community economic and social characteristics assumed to be correlated with preferences. For legislator ideology, a number of studies have used either some measure of party affiliation, such as whether they are republican or democrat [2] or voting records by a group such as the Americans for Democratic Action (ADA) [51]. Fort et al [24] treat ideology as an error term which would be the part of the model not explained by community characteristics.

The following equation summarizes the primary factors that influence the way legislators vote on environmental policies and builds upon the models of Peltzman [51] and Fort et al [24].

$$VOTE = f(I, \eta \times P_j) \tag{4.1}$$

$$\eta = \frac{T - \tau}{T} + \psi \tag{4.2}$$

for $j \in$ {B, H, L, M}. I represents specific ideology of the representative. P is a vector of preferences for either more or less regulation of group j, where B represents business interests, H represents high-income neighborhood residents, L represents low-income neighborhood residents, M represents minority neighborhood residents. In Equation 4.2, η is a measure of how much constituent preferences figure in to the legislator's voting decision. T is term length where $T = 6$ for U.S. Senators and $T = 2$ for U.S. Representatives. τ is the number of years before the legislator is up for re-election and decreases with time[3] . Fort et al [24] argue that closer scrutiny at re-election time is expected to tighten the principle-agent relationship, so $\frac{\partial \eta}{\partial \tau} < 0$ implies the closer

[2] With the assumption that the more liberal the party affiliation, the more likely they will be to vote pro-environment

[3] $\tau = 0$ in a re-election year

the representative is to a re-election year, the more closely they would be expected to take into account constituent preferences. ψ is a measure of altruism which is on the interval $[0, 1]$, where 1 means that the legislator cares a lot about doing what is best for their constituents, regardless of whether they are up for re-election or not, and 0 means they do not care at all except for the purpose of being re-elected. η should approach $1 + \psi$ as the legislator gets closer to an election year.

The six-year term length of U.S. Senators makes them less accountable to their constituents, at least for the first three to four years of their term, compared to U.S. Representatives who serve only two-year terms and are more dependent on keeping constituents satisfied for frequent re-elections. Therefore, U.S. Representatives should echo the voices of their constituents much more closely than U.S. senators. The key assumption here about the link between LCV scores and regulatory behavior is that if counties are putting pressure on their politicians at the national level, then they are most likely putting equal, if not greater, pressure on their local politicians and regulators to implement stricter regulations.

The question of shirking has been addressed by a number of papers in the literature. Peltzman [51] argues that shirking should not be a concern. Liberals and conservatives tend to appeal to voters with certain incomes, education, and occupations, and draw contributions from different interest groups. Because of these systematic differences, rationalizing voting patterns does not require relying on explanations that involve shirking. Only on social policy issues (abortion, school prayer, and so on) did ideology play a prominent role. Kalt and Zupan (1984) [39] find that both constituent interests and legislator ideology are important factors. They find evidence that within a principal-agent relationship legislators operate with enough slack to vote according to their own ideological tastes. Kalt and Zupan (1990) [40] use an ideological residual which is consistent with a liberal-conservative ideological spectrum and that is shown to respond to slack in the principle-agent relationship. Hamilton [34] concludes that the theory of rational political ignorance can help explain legislator preferences for policy instruments to control pollution. Legislators from districts with more toxic emissions face trade-offs in support within their districts, because proposed environmental policies often increase the costs of polluting industries, but reduce the risks to residents from exposure to hazardous chemicals. Gilligan and Matsusaka's [25] findings provide support for the hypothesis that logrolling leads representatives to spend more than their constituents would like. Durden et al [20] find that legislators may be viewed as representing strong, well organized interest groups' preferences in exchange for direct and indirect political currency. Goff and Grier [26] believe the question of whether legislators fail to represent their constituencies is currently unanswered by the literature, and cannot be answered by models making cross-sectional comparisons of the voting behavior of U.S. Senators.

4.1.4 Do voting outcomes lead to reductions in emissions?

Once the votes in Congress have been passed, the question of what effect they have on environmental outcomes naturally arises. It should be understood that their effect is really not a direct effect, but rather a proxy for increased regulatory stringency at the local level based upon the preferences of the citizens for a tighter regulatory climate. A limited number of studies have analyzed the effect of voting on environmental outcomes, but have only done so at the state-level. There is naturally room for further investigation if the study attempts to analyze this question at a more localized unit observation, which is the primary objective of this chapter.

Gray and Shadbegian [29] use state-level aggregates of League of Conservation Voters (LCV) records to find that the share of a firm's production arising at the state level is negatively related to LCV scores. They use LCV scores as their principle index of regulatory stringency because of the time-series variation. Gray [28] also uses state-level aggregates of LCV scores as a measure of attitudes towards pollution and finds that firm births across states are negatively related to LCV scores. Terry and Yandel [57] link TRI and LCV scores in a 50-state cross-sectional analysis in which they examine the effect of 1988 average LCV rating for each state's two senators on the 1992 level of stack air emissions reported by the TRI. They find a negative, but insignificant coefficient on the LCV score variable. Shadbegian and Gray [56] conduct a study which examines plant-level economic and environmental performance for three industries. Using a Seemingly Unrelated

Regressions (SUR) framework they find a negative and statistically significant relationship between state-level LCV scores (average of U.S. Representatives) and toxic releases for the oil and paper industries.

4.2 Data

4.2.1 League of Conservation Voters

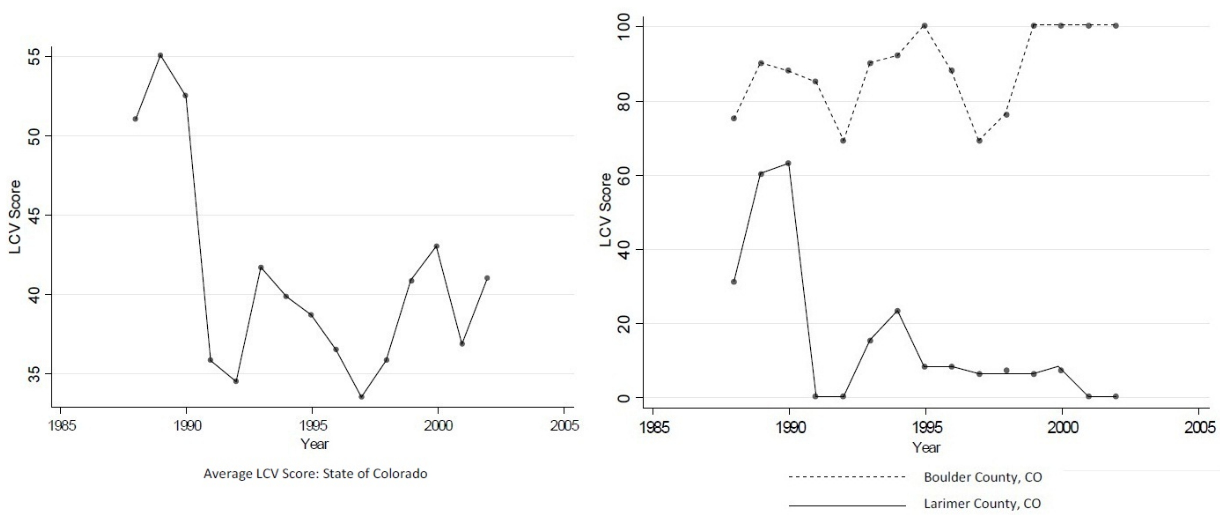
The League of Conservation Voters [49] is an independent organization which tracks congressional voting records on environmental issues. The annual scorecards report the percentage of pro-environment votes cast by each legislator in a given year. Voting in favor of all possible environmental policies would earn a score of 100 and voting against all policies would earn a score of 0. There are scores reported for both U.S. Representatives and U.S. Senators. Every year there are roughly seven different votes cast by Senators on such topics as Gulf drilling and farm conservation funding. For Representatives there are somewhere between twelve and sixteen votes cast each year on such topics as EPA enforcement, Arctic drilling, fuel economy, and energy efficiency. Each representative is given a score from 0 to 100 with 100 being the most pro-environment. To identify variation in standards at the county level I use the LCV scores of U.S. Representatives.

The League of Conservation Voters issues scorecards on a yearly basis starting in 1970. The scorecards previous to 1989 become slightly problematic because they are calculated bi-annually. Therefore, 1987 and 1988 would share the same score. Another issue with the data is that the Speaker of the House votes at his or her discretion, so there are no votes recorded for those districts that are represented by the current Speaker of the House. Michigan's District 3 is missing voting scores in 1993 because Rep. Paul Henry was ill for part of this session of Congress and passed away. His replacement, Rep. Vern Ehlers, was elected to Congress on December 8th, 1993. The LCV reports no score for District 3 in 1993. New Jersey's District 1 is also missing a score in 1990 because Rep. Jim Florio was elected Governor in 1989 and his House seat was not filled until November 1990. The missing observations are summarized in Table B.4 of the appendix. Table B.5 lists the four Speakers of the House from 1988 to 2002, the years they served, and which state/district they represented.

4.2.2 County level versus state or congressional district level

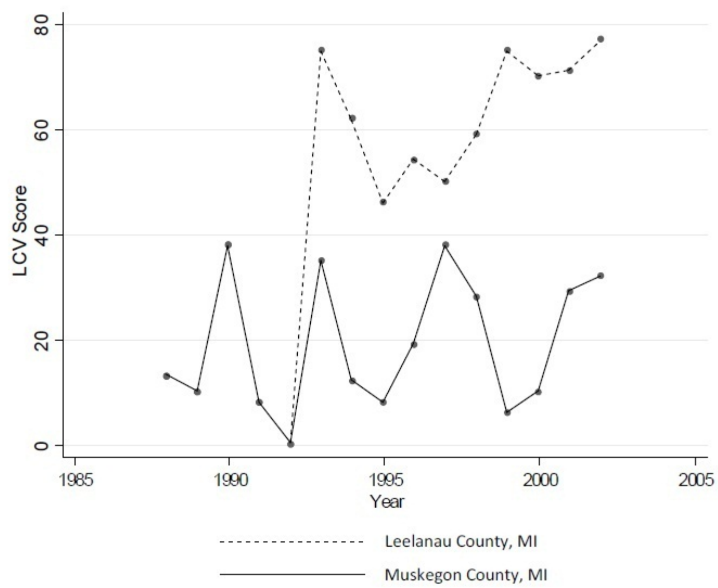
Due to the nature of aggregation, using state averages of U.S. House or Senate voting as a proxy for community standards fails to identify which communities in the state are pro-environment, because within each state there are pro-environment counties and counties that care very little about the environment. For example, Figure 4.4 shows the average LCV score for the state of Colorado from 1988 to 2002. Based on this trend it appears that Colorado is not very pro-environment. However, Figure 4.4 also shows two counties in Colorado that are quite different: Boulder County which is very pro-environment and Larimer County which is not.

Figure 4.4: Time Trend of Colorado LCV Scores



While congressional districts are a more localized unit of observation than state-level, one thing is problematic when using them in a panel data set. Congressional district lines are redrawn every decennial Census. Figure 4.5 shows the LCV scores for two Michigan counties, Leelanau County and Muskegon County, from 1988-2002. Both counties are in Congressional District 9 from 1988-1992 based on the 1980 Census, but after district lines are redrawn for the 1990 Census, Leelanau County is designated as District 1 and Muskegon is designated as District 2 from 1993-2002. In Figure 4.5, when Leelanau County was in the same district as Muskegon County, the LCV scores were relatively low compared to the LCV scores after the switch to District 1. Any county can experience this same drastic variation as preferences change or when new legislators are elected who may have significantly different environmental goals relative to their predecessor. The key objective is to find a more localized unit of observation that does not change boundaries over times (or at least very rarely in the case of county lines).

Figure 4.5: LCV Trends for Leelanau and Muskegon Counties, MI

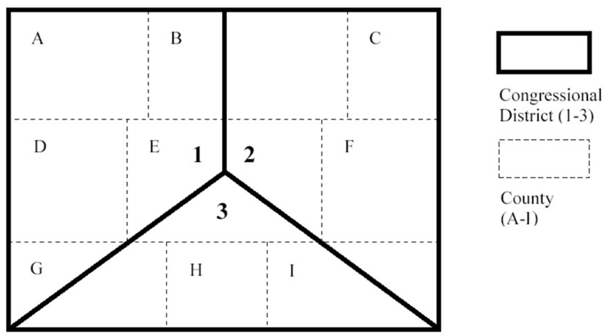


4.2.3 Constructing county-level measures

When constructing county-level measures of LCV scores for the U.S. House of Representatives, which are available at the congressional district level, two challenges arise: district lines are redrawn every ten years based on the decennial Census and a number of counties lie partially in multiple districts. The Census lists each congressional district and which counties are represented by that district. Most counties are completely contained within a single district, but there are 454 counties which belong to multiple districts. To illustrate, consider the hypothetical state in Figure

4.6 which has nine counties (A-I) and three congressional districts (1-3). Counties A, C, D, F, and H all lie within a single district, while counties B, G, and I lie in two districts, and county E lies in all three districts.

Figure 4.6: Congressional District to County Mapping



The Census provides the population of each county in a congressional district. Making a list of all counties, I record which districts are in each county and calculate what percentage of the county's population is in each district. Therefore, for counties that resemble county E in Figure 4.6, I construct a weighted LCV score for each county that lies in multiple districts by multiplying the LCV score from each district by its percentage of the county. Counties that are completely contained within a district simply assume the score of that district. This procedure must be done for every ten-year Census period. I construct a panel of county-level LCV scores from 1988 to 2002 based on the 1980 Census (for years 1988-1992) and the 1990 Census (for years 1993-2002).

4.3 Empirical Specifications

The primary objective of the empirical model is to examine what effect congressional voting on environmental policies has on toxic emissions at a local level. With that focus in mind, if toxic releases are to decrease, the second objective of the model is then to identify whether it is due to facilities leaving the county or shutting down because of increased regulatory stringency (extensive margin) or whether firms reduce their emissions by decreasing production or installing or upgrading abatement technology because of increased regulatory stringency (intensive margin).

The third objective of the model is to run the same empirical analysis using both county-level and state-level data to compare the results in order to see if anything is to be gained from taking advantage of within-state variation.

The most similar empirical specification to this study is the one used by Terry and Yandle (T-Y) [57] in an attempt to identify a relationship between LCV scores and toxic releases (TRI). However, there are key differences between the two studies[4] . T-Y conduct their study at the state level while this study is conducted at the county level. T-Y use the average voting records of the two U.S. Senators in each state and this study uses voting records from U.S. Representatives constructed at the county level. The T-Y study is a cross-sectional analysis and this study takes advantage of panel data. While T-Y have a larger number of control variables than I do in this study, it is necessary when conducting a cross-sectional analysis to include as many relevant variables (time-variant and time-invariant) as possible, otherwise the estimation will suffer from omitted variable bias. The advantage of panel data is that time-invariant variables can be differenced out using a first-differences model or time demeaned using a fixed-effects model, which greatly reduces the required number of variables for estimation, while not leading to omitted variable bias. That being said, there are still time-variant variables that I feel would be relevant to this study, but I was unable to obtain at this time.

One concern with estimation is the potential endogeneity between LCV and TRI emissions. While it is possible that a higher LCV score will lead to a reduction in emissions, it also seems reasonable to assume that higher emissions levels could cause greater concerns about pollution and, therefore, higher LCV scores. T-Y also recognize this potential identification issue and they use the 1988 average of Senators LCV scores to explain TRI in 1992 (a four-year lag). In an attempt to identify the relationship between LCV scores (or more precisely the standards for which they proxy) and pollution, I treat previous years' LCV scores as the independent variable to test whether there is an effect on the current level of pollution, since current pollution should not have any effect on

[4] Terry and Yandle use LCV scores as one of a number of key explanatory variables. Their study does not place the primary focus on LCV scores

LCV scores in years prior to the current time period. Following that line of reasoning, I construct one- to five-year lagged LCV scores for at least 10 years in order to explain the effect of these scores on TRI emissions as well as how long before these policies would be effective. I construct a 15-year panel data set which includes the years 1988-2002 and includes the top fifty percent of TRI emitting counties, due to the large number of counties with zero emissions (743 counties) over the fifteen year period. The dependent variable is total pounds of stack air emissions from the TRI. The key explanatory variable is the county-level measure of LCV scores, which has been constructed as previously described.

To estimate the effect of pro-environment voting on overall toxic releases using an ordinary least squares fixed-effects framework, I estimate the parameters of the following equation

$$TRI_{it} = \alpha_0 + \alpha_1 LCV_{it-l} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{4.3}$$

where TRI_{it} represents the measure of total pounds of TRI stack air emissions in county i in year t. LCV_{it-l} is the pro-environment voting score for county i in year $t-l$ where $l \in \{1, \ldots, 5\}$ denotes the year lag. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. To control for year effects that affect all counties, I include $d1989_t, \ldots, d2002_t$ as dummy variables for years 1989-2002. The term γ_i is the county fixed effects, which includes all factors within a given county that do not vary over time. To remove γ_i, I use time demeaning which is the fixed-effects transformation model. ϵ_{it} is the idiosyncratic error term.

If toxic releases are decreasing as a result of higher LCV scores, the second objective of the empirical model is to identify whether this decrease is due to facilities leaving the county or shutting down because of increased regulatory stringency (extensive margin) or whether firms reduce their emissions by decreasing production or installing or upgrading abatement technology because of increased regulatory stringency (intensive margin). The second part of the model combines two specifications to analyze the effect of pro-environment voting on the number of TRI reporting facilities per county as well as per facility emissions. The panel data set is the same as above using years 1988-2002 and the top fifty percent of TRI emitting counties, however, in these specifications the dependent variables are the number of TRI reporting facilities per county and pounds of TRI stack air emissions per facility per county. To find out whether toxic releases are decreasing due to fewer facilities (extensive margin) or lower per-facility emissions (intensive margin), I estimate the parameters of the following two equations

$$Facilities_{it} = \alpha_0 + \alpha_1 LCV_{it-l} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{4.4}$$

$$Emissions/Facility_{it} = \alpha_0 + \alpha_1 LCV_{it-l} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{4.5}$$

using an ordinary least squares fixed-effects framework where $Facilities_{it}$ represents the measure of TRI reporting facilities in county i in year t. $Emissions/Facility_{it}$ is per-facility emissions in county i in year t. LCV_{it-l} is the pro-environment voting score for county i in year $t-l$ where $l \in \{1,\ldots,5\}$ denotes the year lag. $\mathbf{X}_{it}$ is a matrix of control variables which includes population density and per capita income. $d1989_t, \ldots, d2002_t$ are dummy variables for years 1989-2002. The term γ_i is the county fixed effects term and ϵ_{it} is the idiosyncratic error term.

To address the third objective of comparing the county-level results to the state-level results, I repeat the estimation of Equations 4.3, 4.4, and 4.5 using the state-level aggregates of the variables used in the county-level analysis. The state-level TRI measure (TRI_{jt}) is total pounds of TRI stack air emissions in state j in year t. The state-level TRI facilities measure ($Facilities_{jt}$) is the sum of all TRI reporting facilities in state j in year t. The state-level per-facility emissions ($Emissions/Facility_{jt}$) is total pounds of TRI stack air emissions in state j in year t divided by the total number of reporting facilities for that state in year t. The state-level LCV score (LCV_{jt-l}) is the average of the voting scores of the Representatives from all Congressional Districts in the state for each of $l \in \{1,\ldots,5\}$ lags. Also included are the dummy variables for years 1989-2002 and the γ_j state fixed effects term. ϵ_{jt} is the idiosyncratic error term.

4.4 Results

The objectives of the empirical model are 1.) to estimate the effect of pro-environment voting on toxic emissions at a local level, 2.) to identify whether emissions are decreasing due to firm exodus (extensive margin) or a reduction in per-facility emissions (intensive margin), and 3.) to compare the results from county-level analysis and state-level analysis. The estimation results of Equation 4.3 for both county- and state-level measures are summarized in Table 4.1 for the one- to three-year lags (Table B.1 for the four- to five-year lags).

Table 4.1: Results - Effect of LCV Scores On TRI Emissions

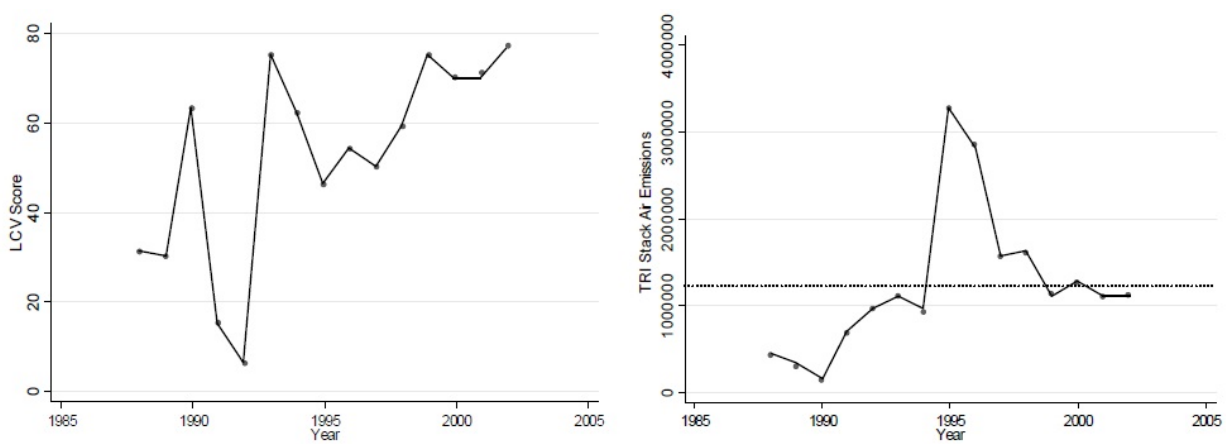
	Total Pounds (County)	Total Pounds (State)	Total Pounds (County)	Total Pounds (State)	Total Pounds (County)	Total Pounds (State)
LCV_{t-1}	-1,280.308*	-31,085.81				
	[553.131]	[42,501.11]				
LCV_{t-2}			-1,281.848*	-19,852.57		
			[545.846]	[44,346.65]		
LCV_{t-3}					-1,161.952*	-52,967.85
					[549.995]	[46,287.1]
Population	-1,128.57**	770,888.9**	-1,059.464**	775,656.2**	-926.332**	799,375.8**
Density	[360.507]	[152,557.4]	[346.569]	[160,789.6]	[346.055]	[174,099]
Per Capita	-10.277	-2,055.13**	-2.546	-2,019.077**	-0.179	-1,997.423**
Income	[8.496]	[605.2238]	[8.424]	[623.136]	[8.670]	[656.638]
Constant	1,357,457**	2.20e+07*	1,149,401**	1.87e+07	1,030,528	1.59e+07
	[216,740]	[1.11e+07]	[214,809]	[1.17e+07]	[148,060]	[1.25e+07]
Observations	21,883	700	20,322	650	18,761	600
R^2	0.0133	0.1938	0.0144	0.1927	0.0159	0.1997

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

Parameter estimation of Equation 4.3 confirms the expectation that higher LCV scores at the county-level lead to a slight reduction of TRI emissions since the coefficient on LCV_{it-l} is negative and statistically significant at the 5% level for $l \in \{1,2,3\}$. The model predicts that a 1-point increase in LCV score would lead to an overall decrease of TRI emissions per county by roughly 1,200 pounds. Even though this is statistically significant, with an average level of emissions in a county 897,266 pounds, this does not seem to be a very significant effect unless the voter score increased by a very significant amount. An increase in LCV score from 0 to 100 would be expected to decrease toxic releases by 120,000 pounds within one to three years.

With a closer look at the data, I identify counties that experience an increase of at least 50 LCV points to see if the model's prediction would hold true. Three different Michigan counties that fit the criteria offer some verification. A look at the emissions levels of Alpena County shows that it is one of the high-emission counties in the state with an average of 1,222,064 pounds of toxic emissions per year. Figure 4.7 shows two time trends for Alpena County: LCV scores and the level of TRI emissions over the fifteen-year period. Alpena County experienced a significant increase in LCV score of 69 points from 1992 to 1993 when the 1990 Census lines were redrawn and Alpena switched from District 11 to District 1. The model would predict that an increase in LCV score of 69 points would lead to a decrease of 82,800 TRI pounds within one to three years. From 1995 to 1996, three years after the LCV increase, Alpena County saw a decrease in emissions from 3,260,926 pounds to 2,846,030 pounds (an absolute change of 414,896 for a 12% decrease), which is a fairly substantial change. One year after that change, there was an even larger decrease from 2,846,030 in 1996 to 1,555,671 in 1997 (an absolute change of -1,290,359 for a 45.3% decrease), which is a very significant reduction in emissions.

Figure 4.7: LCV and TRI Trends for Alpena County, MI



Other Michigan counties that experienced a significant increase in LCV scores from 1992 to 1993 were Antrim and Delta Counties. Antrim County, with an average level of toxic emissions around 12,758 pounds per year, is a county with a much lower level of toxic emissions than Alpena County. The 69-point increase in LCV score from 1992 to 1993 lead to a decrease in TRI from 15,600 pounds in 1994 to 10,000 pounds in 1995. This absolute change of 5,600 is much less than the model predicts, but, given the relatively low level of emissions, is a 35.8% decrease, which is a significant reduction in emissions. Delta County with average emissions per year equal to 640,650 pounds also experienced a 69-point increase in LCV score from 1992 to 1993 which lead to a decrease in TRI from 687,850 pounds in 1996 to 538,840 pounds in 1997. This was a 21.6% decrease in emissions.

The coefficient estimates of LCV_{jt-l} from Equation 4.3 using state-level measures are not statistically significant, so it seems that county-level measures provide more accurate measures of citizen preferences for regulation. Significance at the county level but not at the state level would suggest that changes are taking place in emissions within states and across counties rather than across states because the LCV scores represent local preferences and not preferences for the state as a whole. From the summary statistics in Table 4.4, aggregation to the state level smooths out the variability such that the maximum absolute change in LCV scores is 53 points, where at the county level the maximum absolute change is 92 points.

The second part of the model decomposes the extensive and intensive margins. From the parameter estimation of Equation 4.4, the number of TRI reporting facilities is predicted to decline as a result of higher LCV scores. From Table 4.2, the coefficients of LCV_{it-l} for the county-level data are negative and statistically significant at the 1% level for $l \in \{1,2\}$ which would suggest that firms are exiting the counties or shutting down because of increased regulatory stringency. However, the magnitude of the coefficients suggests that LCV is not enough of a factor to cause facilities to exit or shut down at the county level. A one-point increase in LCV score leads to 0.006 fewer facilities at the county level and 0.27 fewer facilities at the state level. This does not seem to have a significant effect at the county level since the maximum increase in LCV score from 0 to 100 would only lead to a 0.6 facility decrease. This is not too surprising given that LCV is an indirect measure of regulatory stringency. Also, the average number of facilities in a county is about 8 and the average change in facilities is -0.006. At the state level there seems to be a small meaningful effect on facility numbers since the coefficient on LCV_{jt-l} is negative and statistically significant at the 5% level for $l = 1$. The model predicts that the maximum increase in LCV score from 0 to 100 in state j would lead to a decrease of 27 facilities.

Table 4.2: Results - Effect of LCV Scores On TRI Facilities

	Facilities (County)	Facilities (State)	Facilities (County)	Facilities (State)	Facilities (County)	Facilities (State)
LCV_{t-1}	-.00661**	-.273*				
	[.00141]	[.139]				
LCV_{t-2}			-.00415**	-.110		
			[.00143]	[.141]		
LCV_{t-3}					-.000792	.0330
					[.00131]	[.129]
Population	-.00357**	-1.408**	-.00323**	-1.162*	-.00172*	-.688
Density	[.000921]	[.499]	[.000908]	[.511]	[.000827]	[.486]
Per Capita	-.000385**	-.0101**	-.00036**	-.00956**	-.000320**	-.00883**
Income	[.0000217]	[.00198]	[.0000221]	[.00198]	[.0000208]	[.00183]
Constant	18.774**	579.225**	18.014**	573.584**	14.831**	518.125**
	[.553]	[36.428]	[.563]	[37.356]	[.354]	[35.007]
Observations	21,883	700	20,322	650	18,761	600
R^2	0.0422	0.2636	0.0426	0.2723	0.0407	0.2691

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

From the parameter estimation of Equation 4.5, the lack of statistical significance with the exception of the two-year lag on LCV suggests that votes have an effect on per facility TRI emissions and that it takes about two years for these to take effect (Table 4.3). It appears that firm exodus is the cause of the reduced emissions at the state level, but at the county level very few firms are exiting as a result of the voting pattern. This conclusion of firm exodus at the state level is consistent with many of the studies on firm location decisions which find that strict environmental regulation induces firms to locate in or shift in production to less stringent counties. Given the limitations on firm data it is not possible to identify whether the facilities simply shut down or whether they relocated since only the number of TRI reporting facilities is used. At the county level it may be an indication that there is actual reduction of emissions taking place and not simply a redistribution.

Table 4.3: Results - Effect of LCV Scores On Per Facility TRI Emissions

	Pounds Per Facility (County)	Pounds Per Facility (State)	Pounds Per Facility (County)	Pounds Per Facility (State)	Pounds Per Facility (County)	Pounds Per Facility (State)
LCV_{t-1}	-287.040	216.4225				
	[252.461]	[286.3277]				
LCV_{t-2}			-580.626*	351.4873		
			[271.706]	[270.2497]		
LCV_{t-3}					-560.332	521.3212
					[289.0204]	[268.7568]
Population	74.672	4,930.769**	74.242	4,664.9**	77.896	4,346.673**
Density	[164.543]	[1,027.771]	[172.512]	[979.8565]	[181.851]	[1,010.871]
Per Capita	6.445	-2.362428	7.419	-3.423442	7.656	-4.132459
Income	[3.878]	[4.07736]	[4.193]	[3.797407]	[4.556]	[3.812638]
Constant	32,049.64	-126,538.2	16,280.02	-124,621.8	43,169.71	-115,091.2
	[98,924.89]	[75,067.35]	[106,925.8]	[71,589.29]	[77,804.93]	[72,799.67]
Observations	21,883	700	20,322	650	18,761	600
R^2	0.0030	0.0958	0.0033	0.0882	0.0034	0.0906

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

4.5 Conclusion

The primary objective of this chapter is to examine what effect congressional voting on environmental policies has on toxic emissions at a local level. If toxic releases are decreasing, the second objective of the model is then to identify whether it is due to facilities leaving the county or shutting down because of increased regulatory stringency (extensive margin) or whether firms reduce their emissions by decreasing production or installing or upgrading abatement technology because of increased regulatory stringency (intensive margin). The third objective of the model is to run the same empirical analysis using both county-level and state-level data to compare the results in order to see if anything is to be gained from taking advantage of within-state variation.

I use county-level measures of pro-environment voting from the U.S. House of Representatives as a proxy for regional heterogeneity in preferences of citizens for more or less regulation. U.S. Representatives are more accountable to their constituents because of the frequency of re-election and because they represent a smaller geographical region. Even though constructing county-level measures of voting scores requires a degree of approximation in counties that lie partially in multiple districts, the fact that county lines do not change with the decennial Census allows for measures of emissions activity in specific locations over time using panel data spanning more than ten years.

People living in low-income and minority communities are the most directly affected by toxic releases and prefer more regulation since they cannot afford to self-select into cleaner neighborhoods. They are also the groups that are least likely to engage in collective action against polluters or to lobby politicians to make their voices heard. Assuming that legislators take different groups preferences into account when deciding how to vote on different policies, if they are voting more pro-environment at the national level, this indicates that there is overwhelming pressure from those groups at the local as well.

The results show that pro-environment voting scores at the county level are associated with a reduction in TRI emissions within one to three years after the voting has occurred. Significance at the county level but not at the state level would suggest that changes are taking place in emissions across counties within states rather than across states because LCV scores represent local preferences and not preferences for the state as a whole. It appears that firm exodus is the cause of the reduced emissions at the state level, but at the county level very few firms are exiting as a result of the voting pattern. This conclusion of firm exodus at the state level is consistent with many of the studies on firm location decisions which find that strict environmental regulation induces firms to locate in or shift in production to less stringent counties. At the county level it may be an indication that there is actual reduction of emissions taking place and not simply a redistribution. To the best of my knowledge, this research is the first to construct county-level measures of pro-environmental voting from the U.S. House of Representatives and use them as a proxy for citizen preferences for regulation to determine their effect on toxic releases at a local level.

Table 4.4: Summary Statistics

Top 50% of Emitting Counties (1988-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
LCV score	23,444	36.89369	29.06418	0	100
TRI pounds (stack air)	23,505	897,266	2,731,773	0	1.19e+08
TRI reporting facilities	23,505	8.5612	18.1613	0	486
Per-facility emissions	23,505	182,606.3	945,129.4	0	6.50e+07
Per-capita income	23,505	19,923.31	5,601.505	7,380	61,759
Population density	23,505	132.4999	555.7981	0	13,582
Δ LCV score	21,866	-.9736862	17.65127	-92	92
Δ TRI pounds	21,938	-15,957.49	892,607.9	-3.39e+07	2.35e+07
Δ TRI facilities	21,938	-.0062905	1.828708	-53	39

States (1988-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
LCV score (U.S House average)	750	46.30506	24.27527	0	100
TRI pounds (stack air)	750	2.83e+07	2.90e+07	37,296	1.44e+08
TRI reporting facilities	750	284.128	272.5141	3	1252
Per-facility emissions	750	118,420.4	152,150	2,491.004	1,691,254
Per-capita income	750	22,809.8	5,385.068	11,561.27	42,920.69
Population density	750	66.80337	92.02104	.5229201	446.4016
Δ LCV Score	700	-.637406	10.86083	-56	43
Δ TRI pounds	700	-501241.2	8,516,750	-4.12e+07	9.38e+07
Δ TRI facilities	700	.1542857	22.13909	-119	131

Chapter 5

Dissertation Conclusion

The results from chapter 2 provide support for the existence of spillovers as evidenced by the reduction of non-VOC emissions associated with nonattainment status of 1-hour ozone. The reduction of overall TRI emissions is caused by reductions of both VOCs and non-VOCs. Since the number of TRI reporting facilities is decreasing and there is a lack of a statistically significant relationship between ozone nonattainment and pounds of emissions per facility, it seems reasonable to conclude that the exodus of facilities is the primary reason for decreased emissions. The reduction of unregulated carbon dioxide emissions associated with cropland production due to ozone nonattainment is further evidence of spillover effects.

The results from chapter 3 suggest that some spillover effects from the regulation of ozone exist which lead to a slight reduction of carbon dioxide emissions. Since facility numbers are increasing, but emissions per facility are decreasing, then firms are emitting less and that is the primary factor causing the reduced emissions. Cleaner facilities entering the county is a possible story consistent with this scenario. This is likely due to updating production methods or installing new technology as required by the New Source Review permit program for any new facilities in nonattainment counties, which should reduce a wide range of pollutants. These results are significant because they show that it may not be necessary to directly regulate every pollutant.

To the best of my knowledge, this work is the first to address these air quality regulatory spillovers and thus report such findings. Important implications of these findings would be that not accounting for these spillovers could lead policy-makers to significantly underestimate the potential benefits (in terms of reduced pollution levels) associated with the NAAQS. Also this analysis provides additional credibility for the use of nonattainment status as a proxy for regulatory stringency.

The results from chapter 4 show that pro-environment voting scores at the county level are associated with a reduction in TRI emissions within one to three years after the voting has occurred. Significance at the county level but not at the state level would suggest that changes are taking place in emissions across counties within states rather than across states because LCV scores represent local preferences and not preferences for the state as a whole. It appears that firm exodus is the cause of the reduced emissions at the state level, but at the county level very few firms are exiting as a result of the voting pattern. This conclusion of firm exodus at the state level is consistent with many of the studies on firm location decisions which find that strict environmental regulation induces firms to locate in or shift in production to less stringent counties. At the county level it may be an indication that there is actual reduction of emissions taking place and not simply a redistribution. To the best of my knowledge, this research is the first to construct county-level measures of pro-environmental voting from the U.S. House of Representatives and use them as a proxy for citizen preferences for regulation to determine their effect on toxic releases at a local level.

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Appendix A

Trend Analysis Around Time of Switch In Nonattainment Status

The counties that make a switch in attainment status for ozone do so in different years. The first step is to standardize the counties in order to compare them. I treat switches from nonattainment to attainment and switches from attainment to nonattainment separately. First, I group all counties that make a switch from nonattainment to attainment. There are 147 counties that made this switch. For each county, I define the year of the switch from nonattainment to attainment as year 0 (or $t = 0$). The year before the switch is redefined as year -1 (or $t = -1$) and the year after the switch is redefined as year 1 (or $t = 1$). So if county i was redesignated as attainment in 1993, 1994 would be year 1 and 1992 would be year -1. I am concerned about overall TRI emissions between the span of three years prior to a switch and three years after a switch. All of the counties are then lined up in the data set according to year 0, so that each has seven time periods ($t = -3, -2, -1, 0, 1, 2, 3$). One problem occurs with this group of counties. Since the temporal span of the data ends with 2002, any switches that occur in 2002 will have no observations post-switch. Likewise, any switches after 1999 will have some missing observations due to the temporal limits of the data set. There are 24 counties for which this is the case and are not included in this analysis. Therefore in Tables A.1 and A.3, there are 123 counties instead of 147 that are used to examine the switch from nonattainment to attainment. I repeat this process for those 82 counties that make a switch from attainment to nonattainment.

Once the counties are lined up according to year of the switch, I then construct predicted values by fitting a regression line to the first four time periods for each county (years $t = -3, -2, -1, 0$).

The predicted values for all seven time periods are based on the trend leading up to the switch. I extend the regression line to the last three time periods ($t = 1, 2, 3$) assuming that the switch from nonattainment to attainment will not change the trend leading up to a switch. I construct the residuals for each county by subtracting the predicted emissions levels from the observed emissions levels ($TRI_{observed}$ - $TRI_{predicted}$). If there is no change in trend, the residuals should equal zero. If there is a significant break in trend due to the switch from nonattainment to attainment or attainment to nonattainment, then the residuals should be statistically significantly different from zero. For each county I keep the residuals from years $t = 1, 2, 3$ and test the following hypothesis

$$H_0 \quad : \quad Residuals = 0 \tag{A.1}$$

$$H_A \quad : \quad Residuals \neq 0 \tag{A.2}$$

using a t-test with 2 degrees of freedom. This is done for both types if regime switches. The results of these t-tests are given in Table A.2 and Table A.3. An example of a significant break from the pre-switch trend is Sussex County, Delaware (depicted in Figure A.1) which switched from attainment to nonattainment in 1991. In Sussex County before the switch TRI emissions are increasing and after the switch TRI emissions are decreasing. If there is a significant break in trend, then the switch in attainment status matters in a statistical sense. Table A.1 summarizes the t-test results and 53 out of 123 counties that make the switch from nonattainment to attainment experience a significant break in trend, where 31 out of 82 counties that make a switch from attainment to nonattainment experience a significant break in trend.

Table A.1: T-test Results (Summary)

Nonattainment to Attainment				Attainment to Nonattainment			
Significance	Counties	Trend	Counties	Significance	Counties	Trend	Counties
10% Level	24	Pos/Pos	1	10% Level	9	Pos/Pos	1
5% Level	24	Pos/Neg	23	5% Level	16	Pos/Neg	10
1% Level	5	Neg/Neg	3	1% Level	6	Neg/Neg	7
		Neg/Pos	26			Neg/Pos	13
Total $\leq$ 10%		53		Total $\leq$ 10%		31	
Total Counties		123		Total Counties		82	

Figure A.1: Attainment to Nonattainment (Sussex County, DE)

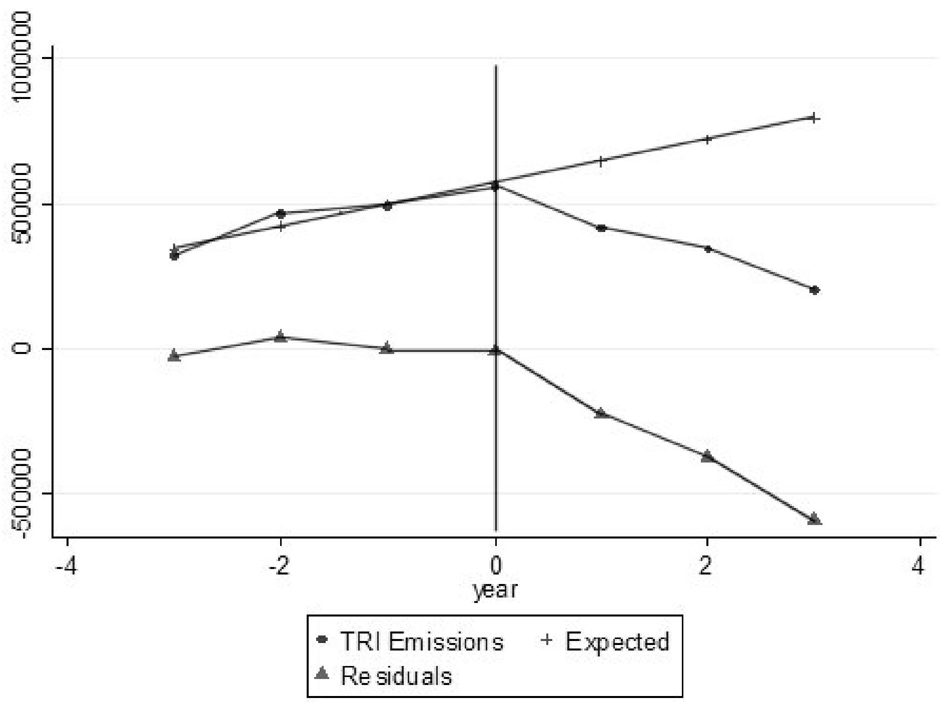

Table A.2: T-test Results By County (Switch from Attainment to Nonattainment)

County	P-value	Significance	County (cont)	P-value	Significance
AL.SHELBY	0.5435		NY.SARATOGA	0.0121	**
CA.ALAMEDA	0.5963		NY.SCHENECTADY	0.0883	*
CA.CONTRA COSTA	0.084	*	OH.DELAWARE	0.4351	
CA.SAN MATEO	0.0332	**	OH.FRANKLIN	0.3505	
CA.SANTA CLARA	0.4521		OH.LICKING	0.0115	**
DE.KENT	0.0636	*	OH.MEDINA	0.0926	*
DE.SUSSEX	0.3762		OH.WOOD	0.6862	
GA.CHEROKEE	0.0022	***	PA.BLAIR	0.1498	
IL.GRUNDY	0.0948	*	PA.CAMBRIA	0.0302	**
IL.KENDALL	0.0806	*	PA.MERCER	0.2635	
IL.MC HENRY	0.1909		PA.SOMERSET	0.3846	
IL.WILL	0.3507		SC.CHEROKEE	0.0079	***
IN.VANDERBURGH	0.1137		TN.KNOX	0.8988	
KY.DAVIESS	0.2463		TX.CHAMBERS	0.1012	
KY.FAYETTE	0.1405		TX.COLLIN	0.3366	
KY.GREENUP	0.161		TX.DENTON	0.2453	
KY.HANCOCK	0.359		TX.FORT BEND	0.0946	*
KY.MARSHALL	0.2701		TX.HARDIN	0.1075	
KY.OLDHAM	0.2433		TX.MONTGOMERY	0.2875	
KY.SCOTT	0.0322	**	VA.CHESAPEAKE CTY	0.2518	
MD.CECIL	0.151		VA.COLONIAL HTS CTY	0.0457	**
MD.CHARLES	0.3236		VA.HAMPTON CTY	0.0854	*
MD.FREDERICK	0.0578	*	VA.HANOVER	0.0039	***
ME.HANCOCK	0.3491		VA.HOPEWELL CTY	0.3733	
NC.DAVIDSON	0.0281	**	VA.JAMES CTY	0.2663	
NC.DAVIE	0.038	**	VA.NEWPORT NEWS CTY	0.2059	
NC.DURHAM	0.4124		VA.NORFOLK CTY	0.1151	
NC.FORSYTH	0.9078		VA.PORTSMOUTH CTY	0.0146	**
NC.GASTON	0.5652		VA.SMYTH	0.9576	
NC.GRANVILLE	0.1049		WA.KING	0.2193	
NC.GUILFORD	0.549		WA.PIERCE	0.1378	
NC.WAKE	0.0472	**	WA.SNOHOMISH	0.0089	***
NY.DUTCHESS	0.1441		WI.KEWAUNEE	0.9336	
NY.ERIE	0.5978		WI.MANITOWOC	0.0233	**
NY.ESSEX	0.0263	**	WI.WALWORTH	0.1112	
NY.GREENE	0.2195		WI.WASHINGTON	0.1063	
NY.JEFFERSON	0.0206	**	WV.CABELL	0.1025	
NY.MONTGOMERY	0.0435	**	WV.KANAWHA	0.0267	**
NY.NIAGARA	0.1685		WV.PUTNAM	0.0316	**
NY.ORANGE	0.0026	***	WV.WAYNE	0.1324	
NY.RENSSELAER	0.0051	***	WV.WOOD	0.3469	

* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table A.3: T-test Results By County (Switch from Nonattainment to Attainment)

County	P-value	Significance	County (cont)	P-value	Significance	County (cont)	P-value	Significance
CA.ALAMEDA	0.1992		MI.OTTAWA	0.1898		OR.CLACKAMAS	0.0727	*
CA.CONTRA COSTA	0.4945		MI.ST CLAIR	0.3019		OR.MULTNOMAH	0.0533	*
CA.SAN MATEO	0.5043		MI.WASHTENAW	0.0601	*	OR.WASHINGTON	0.4541	
CA.SANTA CLARA	0.0345	**	MI.WAYNE	0.0179	**	PA.BERKS	0.0151	**
CA.SANTA CRUZ	0.1238		MO.CLAY	0.5294		SC.CHEROKEE	0.0419	**
FL.BROWARD	0.0951	*	MO.JACKSON	0.0927	*	TN.BRADLEY	0.041	**
FL.DADE	0.0808	*	MO.PLATTE	0.0564	*	TN.DAVIDSON	0.0244	**
FL.DUVAL	0.471		NC.DAVIDSON	0.1055		TN.HAMILTON	0.068	*
FL.HILLSBOROUGH	0.1651		NC.DAVIE	0.5811		TN.KNOX	0.0279	**
FL.PALM BEACH	0.2907		NC.DURHAM	0.0976	*	TN.ROANE	0.5608	
FL.PINELLAS	0.1694		NC.FORSYTH	0.5296		TN.RUTHERFORD	0.0603	*
IN.ELKHART	0.4618		NC.GASTON	0.2439		TN.SHELBY	0.9364	
IN.MARION	0.4697		NC.GRANVILLE	0.0045	***	TN.SUMNER	0.0254	**
IN.ST JOSEPH	0.1719		NC.GUILFORD	0.0769	*	TN.WILLIAMSON	0.2442	
IN.VANDERBURGH	0.0685	*	NC.MECKLENBURG	0.1985		TX.GREGG	0.0281	**
KS.JOHNSON	0.0086	***	NC.WAKE	0.0272	**	TX.VICTORIA	0.0541	*
KS.WYANDOTTE	0.0001	***	OH.ASHTABULA	0.0472		UT.DAVIS	0.1628	
KY.BOYD	0.202		OH.CLARK	0.1055		UT.SALT LAKE	0.473	
KY.DAVIESS	0.6021		OH.CLINTON	0.2851		VA.CHESAPEAKE CTY	0.3188	
KY.FAYETTE	0.0125	**	OH.COLUMBIANA	0.0333	**	VA.CHESTERFIELD	0.2468	
KY.GREENUP	0.2725		OH.CUYAHOGA	0.7185		VA.COLONIAL HTS CTY	0.0825	*
KY.HANCOCK	0.166		OH.DELAWARE	0.2564		VA.HAMPTON CTY	0.7112	
KY.MARSHALL	0.0723	*	OH.FRANKLIN	0.044	**	VA.HANOVER	0.066	*
KY.SCOTT	0.0436	**	OH.GEAUGA	0.1893		VA.HENRICO	0.0925	*
LA.BEAUREGARD	0.0472	**	OH.GREENE	0.1991		VA.HOPEWELL CTY	0.0705	*
LA.CADDO	0.0252	**	OH.JEFFERSON	0.422		VA.JAMES CTY	0.2024	
LA.CALCASIEU	0.1102		OH.LAKE	0.1636		VA.NEWPORT NEWS CTY	0.0198	**
LA.GRANT	0.1837		OH.LICKING	0.0744	*	VA.NORFOLK CTY	0.2361	
LA.JEFFERSON	0.533		OH.LORAIN	0.2106		VA.PORTSMOUTH CTY	0.2572	
LA.ORLEANS	0.0388	**	OH.LUCAS	0.3025		VA.RICHMOND CTY	0.0945	*
LA.ST BERNARD	0.0039	***	OH.MAHONING	0.0275	**	WA.CLARK	0.0946	*
LA.ST CHARLES	0.0169	**	OH.MEDINA	0.9395		WA.KING	0.2112	
LA.ST JAMES	0.1583		OH.MIAMI	0.4241		WA.PIERCE	0.2034	
LA.ST JOHN BAPT	0.508		OH.MONTGOMERY	0.1334		WA.SNOHOMISH	0.2337	
LA.ST MARY	0.0039	***	OH.PORTAGE	0.0615	*	WI.SHEBOYGAN	0.0426	**
ME.HANCOCK	0.4011		OH.PREBLE	0.0284	**	WI.WALWORTH	0.191	
MI.KENT	0.0472		OH.STARK	0.039	**	WV.CABELL	0.1442	
MI.LIVINGSTON	0.0794	*	OH.SUMMIT	0.1691		WV.KANAWHA	0.2956	
MI.MACOMB	0.0138	**	OH.TRUMBULL	0.1762		WV.PUTNAM	0.423	
MI.MONROE	0.599		OH.WOOD	0.622		WV.WAYNE	0.1006	
MI.OAKLAND	0.0917	*	OK.TULSA	0.378		WV.WOOD	0.1504	

* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Appendix B

Additional Tables

Additional tables from Chapter 4.

Table B.1: Results - Effect of LCV Scores On TRI Emissions (4-5 Year Lags)

	Total Pounds (County)	Total Pounds (State)	Total Pounds (County)	Total Pounds (State)
LCV_{t-4}	-296.375	-39,842.36		
	[580.554]	[50,135.78]		
LCV_{t-5}			353.516	-24,848.22
			[603.925]	[53,974.59]
Population	-820.504*	784,209.4**	-649.692	742,870**
Density	[358.372]	[190,156.6]	[367.621]	[205,022.7]
Per Capita	2.935	-2,003.081**	7.031	-1,917.258*
Income	[9.374]	[716.7342]	[10.012]	[781.702]
Constant	883,966.9**	3.31e+07	792,556.1**	1.49e+07
	[167,818.8]	[1.93e+07]	[255,684.8]	[1.55e+07]
Observations	17,200	550	15,638	500
R^2	0.0170	0.2052	0.0191	0.2120

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

Table B.2: Results - Effect of LCV Scores On TRI Facilities (4-5 Year Lags)

	Facilities (County)	Facilities (State)	Facilities (County)	Facilities (State)
LCV_{t-4}	.00145	.12702		
	[.00124]	[.12247]		
LCV_{t-5}			.00139	.12368
			[.00115]	[.11247]
Population	-.000649	-.47191	.000281	-.21172
Density	[.000768]	[.46449]	[.000701]	[.42723]
Per Capita	-.000258**	-.0069915	-.000174**	-.0050948**
Income	[.0000201]	[.0017508]	[.0000191]	[.0016289]
Constant	13.656**	513.7995**	12.613**	406.6307**
	[.360]	[47.07535]	[.487]	[32.31146]
Observations	17,200	550	15,638	500
R^2	0.0364	0.2644	0.0312	0.2646

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

Table B.3: Results - Effect of LCV Scores On Per Facility TRI Emissions (4-5 Year Lags)

	Pounds Per Facility (County)	Pounds Per Facility (State)	Pounds Per Facility (County)	Pounds Per Facility (State)
LCV_{t-4}	-190.105	570.0449*		
	[314.0902]	[287.9047]		
LCV_{t-5}			-5.5005	2 66.4511
			[337.755]	[294.6373]
Population	75.204	4,139.443**	78.808	4,069.3**
Density	[193.886]	[1091.974]	[205.598]	[1119.181]
Per Capita	9.0334	-4.136407	9.441	-4.20574
Income	[5.0713]	[4.115846]	[5.599147]	[4.267167]
Constant	5,783.291	-101,459.6	-54,302.31	-96,950.68
	[90,793.06]	[110669]	[142,995.7]	[84643.15]
Observations	17,200	550	15,638	500
R^2	0.0032	0.0909	0.0033	0.0907

Standard errors in brackets
* significant at 5% level; ** significant at 1% level

Table B.4: Missing Values of LCV Scores and Sample Size Determinants

	LCV		Δ LCV		LCV_{t-1}		LCV_{t-2}		LCV_{t-3}		LCV_{t-4}		LCV_{t-5}	
County	Years	Total	Years	Total	Years	Total	Years	Total	Years	Total	Years	Total	Years	Total
GA.CHEROKEE	1995-1998	4	1995-1999	5	1996-1999	4	1997-2000	4	1998-2001	4	1999-2002	4	2000-2002	3
GA.COBB	1995-1998	4	1995-1999	5	1996-1999	4	1997-2000	4	1998-2001	4	1999-2002	4	2000-2002	3
GA.DE KALB	1995-1998	4	1995-1999	5	1996-1999	4	1997-2000	4	1998-2001	4	1999-2002	4	2000-2002	3
GA.FULTON	1995-1998	4	1995-1999	5	1996-1999	4	1997-2000	4	1998-2001	4	1999-2002	4	2000-2002	3
GA.GWINNETT	1995-1998	4	1995-1999	5	1996-1999	4	1997-2000	4	1998-2001	4	1999-2002	4	2000-2002	3
IL.DE KALB	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
IL.DU PAGE	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
IL.KANE	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
IL.KENDALL	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
IL.LA SALLE	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
IL.LEE	1999-2002	4	1999-2002	4	2000-2002	3	2001-2002	2	2002	1				
MI.BARRY	1993	1	1993-1994	2	1994	1	1995	1	1996	1	1997	1	1998	1
MI.IONIA	1993	1	1993-1994	2	1994	1	1995	1	1996	1	1997	1	1998	1
MI.KENT	1993	1	1993-1994	2	1994	1	1995	1	1996	1	1997	1	1998	1
NJ.GLOUCESTER	1990	1	1990-1991	2	1991	1	1992	1	1993	1	1994	1	1995	1
TX.TARRANT	1988	1	1989	1	1989	1	1990	1	1991	1	1992	1	1993	1
WA.SPOKANE	1989-1994	6	1989-1995	7	1990-1995	6	1991-1996	6	1992-1997	6	1993-1998	6	1994-1999	6
WA.WALLA WALLA	1989-1994	6	1989-1995	7	1990-1995	6	1991-1996	6	1992-1997	6	1993-1998	6	1994-1999	6
Missing Observations		61		72		55		49		43		37		32
Remaining Observations	23,505-61 = 23,444		23,505-(1567+72) = 21,866		23,505-(1567+55) = 21,833		23,505-(2*1567+49) = 20,322		23,505-(3*1567+43) = 18,761		23,505-(4*1567+37) = 17,200		23,505-(5*1567+32) = 15,638	

* Maximum possible observations: 23,505 = 1,567 counties (top 50% of emitting counties) × 15 years

* Each lag eliminates 1,567 observations. Since 1988 is the first year of the panel, maximum number of observations for the 1-year lag is 23,505 - 1,567 = 21,938

1. Michigan District 3 is missing observations in 1993 because Rep. Paul Henry was ill for part of this session of Congress and passed away. Rep. Vern Ehlers was elected to Congress December 8, 1993.

2. New Jersey District 1 is missing voting scores for 1990 because Rep. Jim Florio was elected Governor in 1989 and his House seat was not filled until Nov. 1990

3. The remaining missing observations are due to Speakers of the House voting at their own discretion. See Table B.5.

Table B.5: Speakers of the House from 1988-2002

Speaker	Party	State	District	Years
Jim Wright	Democrat	Texas	12	1988 - 1989
Tom Foley	Democrat	Washington	5	1989 - 1995
Newt Gingrich	Republican	Georgia	6	1995 - 1999
Dennis Hastert	Republican	Illinois	14	1999 - 2002

* In 1989, Jim Wright (Texas) stepped down as Speaker of the House. Tom Foley (Washington) was elected to replace him.

* These districts will be missing votes in the dataset since Speakers of the House vote at their own discretion.