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

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Abstract

In this paper, I 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 state implements a strict plan for reducing the concentrations of precursors to ozone which are volatile organic compounds (VOCs) and nitrogen oxides (NO_x). 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. 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.

Keywords: Toxics Release Inventory; Nonattainment; Spillovers; Regulation; Pollution

JEL classification: Q53

1 Introduction

In this paper, 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 uses 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, this paper also examines 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 examine 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 can 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 paper is the first to address these air quality regulatory spillovers and thus report such findings.

The paper is organized as follows. Section 2 provides a background of the regulatory process as well as a review of related previous literature. Section 3 lays out the conceptual framework. Section 4 describes the data. Section 5 specifies the empirical framework and identification strategy and section 6 summarizes the estimation results. Finally, Section 7 concludes.

2 Background

2.1 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 heatlh or welfare. Criterial 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].

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 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. The designation of nonattainment status is one possible and commonly used proxy for regulatory stringency, because according to Becker & Henderson [6], new and existing

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

plants are subject to much stricter controls in nonattainment areas, relative to attainment areas. Henderson [14] 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.

2.2 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 firms' choice of emission levels and the extensive margin is firms' location choice. Different measures or proxies for regulatory stringency that have been used in previous 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.

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

2.2.1 Intensive Margin

The intensive margin is firms' 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 [14] 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 [13] finds that SO_2 nonattainment status is associated with modest reductions in SO_2 concentrations. Chay and Greenstone [9] and [10] find striking evidence that TSP levels fell substantially more in TSP nonattainment counties than attainment counties. Aufhammer et al. [4] 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. [3] 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 [18] 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 [5] 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.

2.2.2 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 [6] 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 [16] 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 [12] 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 [11] 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 [15] 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.

3 Conceptual Framework

Henderson's [14] analysis suggests that a switch in county attainment status to nonattainment induces a greater regulatory effort and results in cleaner air. In this paper, 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, 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 intended consequence of air quality regulation is to reduce 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, which would lower total emissions in nonattainment counties, but increase total 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 pounds 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 the paper 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 is necessary 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 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 emissions such as carbon dioxide to see if there are additional spillover effects from ozone regulation. 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,

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

or carbon dioxide) then I conclude that the tighter regulatory environment is leading to the reduction of other emissions besides those related to ozone.

4 Data

The data for county nonattainment status is publicly available through the EPA's website [1]. 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. I focus on the nonattainment status for 1-hour ozone because there is greater variation of counties moving in 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).

The Toxics Release Inventory (TRI) is a publicly available database that can be obtained directly from the EPA. The data was retrieved using the EPAs Risk Screening and Environmental Indicators (RSEI) program version 2.1.2 (August 2004) [2]. 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 includes 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 paper 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 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 1: Top 10 TRI Chemicals

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%	

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 of fertilizers and pesticides. The measure of CO_2 used here is the total of both on-site and off-site emissions. Units are Megagram C for CO_2 estimates. These data span the years 1990-2004 [8].

Per capita income data were obtained from the Bureau of Economic Analysis [17] and population density data were obtained jointly from the U.S. Census Bureau [7] and the EPA's Risk-Screening Environmental Indicators [**?**]. 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.

5 Empirical Specifications

5.1 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 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 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.

Using an ordinary least squares fixed-effects framework I estimate the parameters of the following regression equation

$$TRI_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{5.1}$$

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, containing 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.

I use the second part of this model, which combines two specifications, to analyze the effect of changes in nonattainment status 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 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 or lower per facility emissions, I estimate the parameters of the following two equations

$$Facilities_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{5.2}$$

$$\left(\frac{Emissions}{Facility}\right)_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1989_t + \ldots + \delta_{14} d2002_t + \gamma_i + \epsilon_{it} \tag{5.3}$$

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. $\mathbf{Nonattain}_{it}$ 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. $d1989_t$,...,$d2002_t$ 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.

5.2 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 same federal standards as the criteria pollutants.

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.

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.

$$IndividualTRI_{jit} = \alpha_j + \mathbf{Nonattain}_{it}\boldsymbol{\phi}_j + \mathbf{X}_{it}\boldsymbol{\beta}_j + \delta_{j1}d1989_t + \ldots + \delta_{j14}d2002_t + \gamma_i + \epsilon_{jit} \quad (5.4)$$

$IndividualTRI_{jit}$ 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.

5.3 Model 3: Unregulated greenhouse gas emissions

I use this model to estimate the effect of ozone nonattainment on the unregulated greenhouse gas carbon dioxide, specifically carbon dioxide from cropland production. 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

$$CarbonDioxide_{it} = \alpha + \mathbf{Nonattain}_{it}\boldsymbol{\phi} + \mathbf{X}_{it}\boldsymbol{\beta} + \delta_1 d1991_t + \ldots + \delta_{12} d2002_t + \gamma_i + \epsilon_{it} \quad (5.5)$$

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, containing 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.

5.4 Identification Strategy

Table 2 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: 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).

Looking at 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 ammendments of 1990. On July 1, 1987, the EPA revised the NAAQS for particulate matter, replacing total supsended 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). 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 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 paper 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.

Since all counties that make switches in attainment 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 3 and 5, 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

$$H_0 \quad : \quad Residuals = 0 \tag{5.6}$$

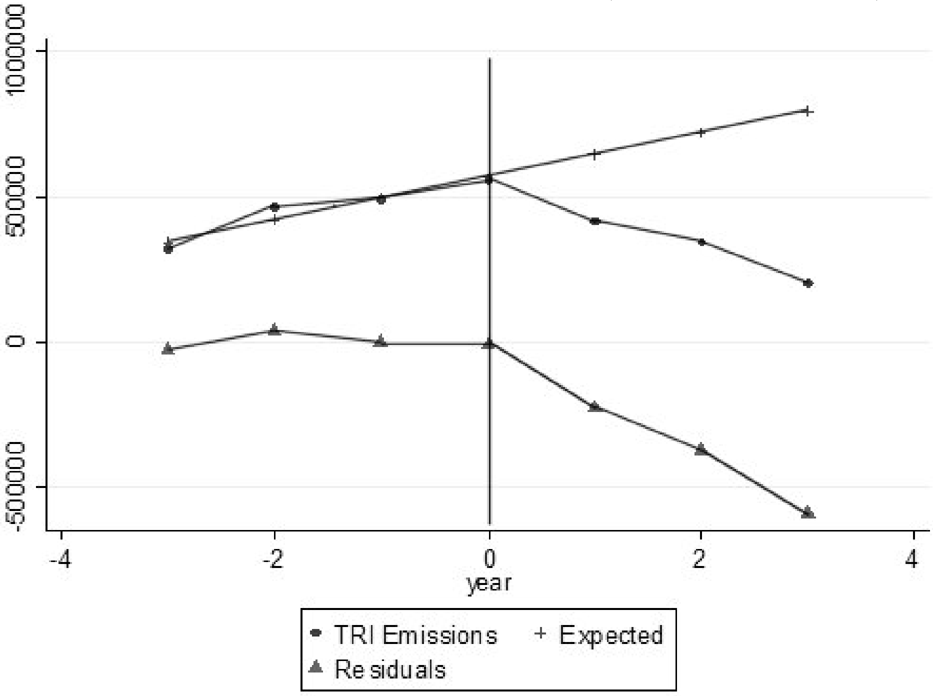
$$H_A \quad : \quad Residuals \neq 0 \tag{5.7}$$

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 4 and Table 5. An example of a significant break from the pre-switch trend is Sussex County, Delaware (depicted in Figure 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 3 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 3: 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 1: Attainment to Nonattainment (Sussex County, DE)



6 Results

The estimation of the first model achieves two objectives. The first is to examine the effect of additional years on nonaatainment on TRI emissions. Emissions are expected to decline because of a tighter regulatory climate. The second objective is to determine using the second and third specifications of the model whether TRI emissions are declining because of a decrease in TRI reporting facilities or because individual facilites are reducing emissions. The estimation results are summarized in Table 6.

Estimation of the first 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 1% level. Generally speaking, for each additional year a county is in nonattainment for ozone overall TRI emissions per county are reduced by 17,926 pounds. Given the average emissions per county in a given year are 897,266 pounds, this is a modest reduction (2% 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.

The second part of the model decomposes the extensive margin and the intensive margins. From the estimation of the second specification the number of TRI reporting facilities are declining as a result of ozone nonattainment. The coefficient on 'Years of Nonattainment' is negative and significant at the 1% level. This translates into one less facility for every four years a county is in nonattainment (.26 fewer facilities for each year). 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. This conclusion is consistent with many of the studies on firm location decisions which find that strict environmental regulation induces firms to locate in or shift production to less stringent counties. Unfortunately, given the data is only number of TRI reporting facilities, it is not possible to know whether the facilities simply shut down or whether they relocated.

Estimation of the first model show that TRI emissions are declining as a result of ozone nonattainment. Using the 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, methyly ethyl ketone, and dichloromethane. These ten releases are all regulated, but methanol, toluene, xylene, carbon disulfide, methyle 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 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 avergage 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 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.

As a final check for spillover effects using the third model, I test whether ozone nonattainment has an effect on unregulated emissions. Carbon dioxide emissions from cropland production are used for this final test as the dependent variable of interest. The results from parameter estimation are summarized in Table 8.

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.

7 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. 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 paper 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.

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Table 4: 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 5: 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

Table 6: Model 1 - Fixed Effects OLS Estimation Results

	Total TRI Pounds	Number of TRI Facilities	TRI Pounds (Per Facility)
Nonattainment for Ozone	205,266.8*	3.455637**	2,736.137
	[90,318.47]	[.2225217]	[38,833.61]
Years of Ozone nonattainment	-17,926.11**	-.2601651**	676.9745
	[5,737.05]	[.0141346]	[2,466.72]
Per capita Income	-13.24731	-.0003008**	5.663459
	[8.570039]	[.0000211]	[3.6848]
Population Density	-1,085.744**	-.0024368**	85.0186
	[369.4252]	[.0009102]	[158.8392]
Constant	1,443,415**	12.87216**	110,654.3
	[131,614]	[.3242634]	[56,589.17]
Observations	23,505	23,505	23,505
R^2	0.0135	0.0543	0.0029

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

Table 7: Model 2 - Fixed Effects OLS Estimation Results

	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	-19234.73**	-8064.645**	-31448.09**	-7266.497**	-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

Table 8: Model 3 - Fixed Effects OLS Estimation Results

	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

Table 9: Summary Statistics

Top 50% of Emitting Counties (1988-2002)

Variable	Obs	Mean	Std. Dev.	Min	Max
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
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
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

All Counties (1988-2002)

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