Emissions Leakage: Evidence from the U.S. Multi-plant Firms

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Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31 - August 2

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Version May 25, 2016
Incomplete, please do not cite

Abstract

This paper seeks to examine the role of multi-plant's network to determine their affiliated plants' emissions in response to tightened environmental regulations. Polluting plants, which are located across the nation and are exposed to regional environmental pressures, form a network through their affiliated parent company. We investigate whether or not these multi-plant firms, to avoid local environmental compliance, shift pollution emissions from their affiliated plants in regulated counties to those in unregulated ones, thereby leading to emissions leakage. We compile a unique detailed plant-level dataset that pertains to the U.S. manufacturing industry over the period 1990-2008. Taking advantage of the spatial and temporal variations of designated non-attaintment status at county level, we seek to identify the effects of multi-plant firms' network on annual changes in emissions of affiliated plants residing in regulated areas as compared with those in unregulated areas.

Keywords: Clean Air Act Amendments, Air Pollution, Emissions Leakage, Multi-Plants Firm,

JEL Classification: F18, Q56

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1 Introduction

Polluting plants scattering across counties are subject to regional environmental pressures. In response to a stringent local regulatory control, multi-plant firms may shift production (and associated emissions) from affiliated plants located in regulated areas to those siblings in unregulated areas to avoid environmental compliance costs. As a consequence, emissions leakage arise via an unveiled channel, that is, the network of multi-plant firms. While much of existing work has focused on the effects of regulatory control in emissions reductions (Henderson, 1996; Becker and Henderson, 2000; Greenstone, 2004), the literature remains silent about the role of the multi-plant firms' network in the potential emissions leakage due to a lack of detailed data on plants' firm structure.

This paper seeks to examine the role of multi-plant firms' network in affecting their affiliated plants' emissions annual growth rate in response to tightened local environmental regulations. To this end, we compile a detailed plant-level dataset that pertains to the US manufacturing industry over the period 1990-2008. The data cover toxic releases of polluting plants recorded in the Toxic Release Inventory (TRI) of the US Environmental Protection Agency (EPA). We further find other sibling plants affiliated with these dirty emitters from the National Establishment Time Series (NETS) database. To measure plants' exposure to environmental regulation, we further augment the data with county non-attainment designations under the Clean Air Act Amendments (CAAA) legislation of 1990. Taking advantage of the spatial and temporal variations in county-level non-attainment status, we seek to identify the effects of multi-plant firms' network on changes in emissions of affiliated plants located in regulated area as compared with those residing in unregulated areas.

An empirical methodology from Greenstone (2003) is employed and further extended by allowing local regulatory indicator to interact with the multi-plant firm dummy. Specifically, we first investigate whether dirty plants associated with multi-plant firms have lower annual emission growth rates than those affiliated with single-plant firms in response to tightened local environmental controls. Secondly, we construct a measure of the neighborhood headquarters network by summing up the number of affiliated plants in the same industry and located in neighboring counties, which are free from environmental regulations. We then explore how this neighborhood headquarters network in unregulated areas affects annual growth rates of emissions released by dirty polluters affiliated with multi-plant firms. Lastly, we are interested to revisit the hypothesis on the potential unintended consequences of air regulation on pollution in other media (i.e., water), and to unveil the channel of the headquarters regional network in this potential regulation-induced substitution.

The model results generally show that counties with the nonattainment status for a particular pollution category is associated with reduced air emission from plants located there relative to their counterparts in attainment counties when other factors, such as age, industry effects and so on, are controlled. The pressure from air pollution regulation are only found to induce cross media pollution (air-to-water) substitution on Lead-related pollutants. In terms of intra-firm leakage effect, we did not find any strong evidence that a plant within a multi-plant firm located in nonattainment counties have significantly lower total on-site emission relative to a single plant. While, some evidence suggests the local multi-plant network effects may exist, i.e., plants with sibling plants in neighboring attainment counties tend to have lower air-released total on-site TSP-related emission.

This paper contributes to the growing empirical literature that estimates the impact of environmental regulations on firms' site choices within a country or across nations (Henderson, 1996; Becker and Henderson, 2000; Jeppesen et al., 2002; Brunnermeier and Levinson, 2004; List et al., 2003b,a). A closely related work is Hanna (2010), which investigates whether the environmental regulation induces firms to flee the country. She documents robust findings suggesting that the CAAA legislation causes the U.S. based multinational firms in regulated areas to increase their foreign assets and foreign outputs.

This paper is closely related to a line of existing studies that seek to estimate the regulation-induced substitution. Using the TRI data over the period 1987-1997, Greenstone (2003) examines the effects of the county nonattainment designations under the CAAA legislation on annual growth rates of pollution emissions of the iron and steel industry into all media (i.e., air, water, and other). He finds little evidence supporting the unintended consequences of the CAAA on pollution releases into water and ground. A recent study by Gibson (2014) revisits the regulation-induced substitution using the same TRI data over 1987-2010. His paper focuses on the changes in the ratio of water emissions relative to air emissions rather than the levels used in Greenstone (2003). He finds that regulated plants are associated with increases in their ratio of water to air emissions by 44 percent. Moreover, his work also examines the potential spatial leakage through the multi-plan channel, and finds that regulation of an average plant increases air emissions at unregulated plants owned by the same firm by 17 percent. Our results could not support the general conclusion that multi-plant firms reallocated resources from regulated plants to unregulated plants except for TSP-related pollutants. Considering Gibson (2014) checks the leakage effect from the "receiver" side on all emission, if both findings are reliable, it implies that multi-plants firms are allocating "new" production to unregulated plants instead of moving "old" production out from regulated plants in general.

The remaining of this paper is organized as follows: in section 2, we discuss how we construct the variables and present the summary of data set. Estimation results and discussion from a series of modeling strategies are presented in section 3. We conclude in section 4.

2 Data

In this section we summarize data sources, the evolution of TRI emission, and construction of variables.

2.1 Data Source

The data pertain to the US manufacturing industry over the period of 1990-2008. We assemble the data from a variety of sources. The plant-level emission data are from the TRI reported by the US EPA. The information about affiliated plants that share the same headquarters with dirty facilities are obtained from the NETS. The county-level environmental regulation is obtained from the EPA.

The TRI data provide an establishment level record of toxic pollution emission collected by the EPA. Manufacturing establishments that release more than a threshold level of any of approximately 500 toxic chemicals listed by the EPA must report details about how these chemicals are disposed. Specifically, for each toxic chemical, establishments must report the quantity and disposal media (e.g., air, water, landfill, etc.). Most empirical research on emissions rely on pounds of toxic emissions as reported in the Toxic Release Inventory available on the EPA website. Through the efforts made by Greenstone (2003), many of toxic chemicals listed in the TRI can be classified as either lead, TSPs, or VOC, which are three of the six air pollutants regulated by the CAAA.[1] For each of these three pollutants (i.e., lead, TSPs and VOC), we sum up the total releases of all toxic chemicals that are assigned in the pollutant-specific category by each media (i.e., water, air, and ground).

To search affiliated plants sharing the same headquarters with plants recorded in the TRI, we first link the TRI with the NETS. The Dun and Bradstreet by Walls and Associates develops the NETS database through a joint venture. This truly establishment database covers over 300 fields and 40 million unique business establishments on a national basis for every year since 1990. To keep track of each plant, the NETS assigns the Data Universal Numbering System (DUNS) number as a unique identifier. More importantly, for each plant, one could also find its headquarters information from the NETS database. This information provides us headquarters' name, DUNS number, and geographic location. Using the DUNS number recorded in both TRI and NETS databases, we match these recorded polluting plants with those collected in the NETS database. For each matched plant, we then find its related plants within the NETS database through the parent company over the entire study period. We further restrict our search on those in the manufacturing industry.

[1] We thank Michael Greenstone for sharing the data that reports the categorization of toxic chemicals into the lead, TSPs, and VOC.

Furthermore, we merge the plant-level data with pollutant-specific county nonattainment designations under the CAAA legislation. The Green Book Nonattainment Areas for Criteria Pollutants from the EPA indicates whether only part of a county or the whole county is in nonattainment for each criteria air pollutant.[2] For each of three criteria pollutants, i.e., lead, O_3, and TSPs, we assign a county to the nonattainment category, if the whole county or part of the county is designated as nonattainment status.[3]

Figure 1 plots the number of pollutant-specific nonattainment status and the number of counties with changed pollutant-specific nonattainment designations. The data are calculated from the US EPA Green Book. There is a small number of counties that fall into lead nonattainment designations during the study period. For O_3 and TSPs, significant variations in nonattainment designations mainly occur in the post-period of CAAA (i.e., 1990-1996) and the late sample period (i.e., 2002-2008). The latter is due to the new implementation of strict standards associated with these two pollutants. Moreover, during the sample study period of 1990 - 2008 in this paper, there exist substantial variations in county-level nonattainment/attainment designations in both earlier and late sample period, allowing us to identify the causal effects of county-level environmental controls on plant closure decisions.

2.2 Emission Evolution in TRI

Table 1 shows total on-site released pollutants at the industry level. Judged by the total emission, the manufacturing industry, *i.e.* 2-digit SIC codes from 20 to 39, is the biggest emitter. Thus in this study, we will focus on manufacture firms.

Figure 2 shows the trend of total on-site released pollutants during the sample period from the manufacture industry. Each series is normalized by its 1989 value. Although there are some variations in each pollutant category, the overall decreasing trend in each category is

[2] See http://www.epa.gov/air/oaqps/greenbk/index.html.

[3] The formation of ground-level O_3 is a complicated chemical process that involves Volatile Organic Compounds (VOCs) and Oxide of Nitrogen (NO_x) when these two react in the presence of sunlight. We classify a county as nonattainment for O_3 if it is in nonattainment for NO_x and/or O_3, including both 1-hour and 8-hour standards. In the case of TSPs, a county is defined as TSPs-specific nonattainment when it is in nonattainment for PM_{10} and/or $PM_{2.5}$.

clear. Most decrease was seen with the VOC pollutants, closely followed by PM-related and Lead-related pollutants.[4] While at the same time, the total sales has been seen a moderate increase[5]. These trends show that after almost 20 years of 1990 Clean Air Act Amendment, the emission of pollutants reported in TRI has been reduced substantially.

Figure 3 shows the series broken down by firm's multi-plant status. Air emission from both types of plants decreases significantly from the level at the base year with a slightly more reduction for multi-plants firms.

Table 2 shows the air-released pollutant by 2-digit SIC manufacture industries at 1989 and 2008. For major polluters in each category, the decreasing of air-released pollutants is significant except the primary metal product industry (SIC2 = 33) on air-released total suspended particles. Overall, the emission by the whole manufacture industry decreases by 66%, 78% and 74% on Lead-related pollutants, VOC related pollutants and TSP-related pollutants, respectively.

2.3 Variables Construction

We construct outcome variable and other variables of interest that may be influential factors to determine plants' emissions.

Dependent variables of interests are annual growth rates of three different pollutant emissions released by three media. Define Δ_{ipt}^{m} as emission annual growth rates for plant i at time t of pollutant p through media m, where $p \in \{\text{Lead}, \text{O}_3, \text{TSPs}\}$, and $m \in \{\text{water}, \text{air}, \text{total on-site}\}$.

A plant is defined as belonging to a multi-plant firm, if there exists at least one other plant affiliated with the same parent company in terms of sharing the same headquarters' DUNS number at time t; it is a single-plant firm, otherwise. Thus, $Multi_{it}$ denotes the multi-plant firm binary indicator. Note that, the multi-plant affiliation status may vary

[4] There are several missing points in the PM series. The reason is that at those years, the total amount of air-released PM was substantially larger than the amount in other years. A close check shows that the share between air released emission and land-released emission is abnormal. Thus, we will not include this category in the subsequent analysis.

[5] The sales information may not be accurate, the trend of sales presented there should be interpreted with cautions.

with time, due to changes in plant ownership.

The regulatory variable, Reg_{ipt}, measures a plant's environmental regulatory pressure, as proxied by county nonattainment status. The construction of Reg_{ipt} involves with pollutant types. It equals one, if the plant is located in a county that is subject to pollutant p-specific nonattainment at time t, and zero otherwise, where pollutant $p \in \{\text{Lead}, \text{O}_3, \text{TSPs}\}$.

To assess the effects of being associated with multi-plant firms, we create a measure of headquarters network based upon the number of affiliated plants in addition to the multi-plant status dummy variable ($Multi$). If a multi-plan firm would like to reallocate production and associated emissions, it is more likely to shift resources and potential emissions from dirty plants in regulated areas to other affiliated plants in the nearby counties that are free from any environmental compliances. We construct a measure of the headquarters network in neighboring counties, which are not subject to any nonattainment designations. Let $UnRegNbrNum_{ijt}$ denote the number of sibling plants in the same industry j as plant i defined by the 2-digit SIC code and located in neighbor counties, which are free from any nonattainment designations. Alternatively, one could also measure the neighborhood headquarters network with size of affiliated plants accounted for. Define $UnRegNbrEmp_{ijt}$, is the number of total employment of sibling plants from the same parent company in the same 2-digit SIC industry in the neighboring attainment counties. This alternative measure serves as a proxy for total capacity or size of the headquarters network that could absorb potential reallocated resources.

Other plant-level controls include labor employment, value of sales deflated by 2-digit Producer Price Index. Both existing theoretical and empirical studies suggest that plant age plays an important role in determining plant death. We construct plant years of operation as the difference between the current year and the first recorded NETS year, starting from 1990. Plants that are in their first recorded year are given an age of one. As predicted by the Melitz-type trade model (Melitz, 2003), productive plants are more likely to export than those low productive fellows due to the interaction between heterogeneous productivity and fixed costs of exporting. This positive correlation between export decision and productivity has been documented in the empirical trade work (Bernard and Jensen, 2004). In addition, the literature examining heterogenous firms and outsourcing also suggests the causality from high productivity to the outsourcing decisions (Helpman, Melitz, and Yeaple, 2004). To further control unobservable productivity, we include an export indicator and foreign ownership indicator. The former equals one when a plant exports and zero otherwise, while the latter takes a value of one if a plant is owned by a foreign firm and zero otherwise. These two binary variables are time-invariant, as provided in the NETS database.Thus they will be only used in non-fixed effect model specifications.

Finally, to absorb unobservable factors, we include a full set of fixed effects at 2-digit SIC industry, year and county levels.

3 Empirics

3.1 Empirical Models

The empirical model is based on panel-data framework similar as Greenstone (2003). The dependent variables used to represent firms' response to environmental regulations are the growth rate of each type of pollutants, namely, the lead-related pollutants, the VOC related pollutants and the TSPs related pollutants. Our empirical strategy could be summarized as the following multi-variate equation.

$$\Delta_{ipt} = \alpha + \beta_1 Reg_{ipt_0} + \beta_2 Reg_{ipt_0} * Multi_{it} + \gamma ln(sale_{it}) + \delta_x + \epsilon_{ijt} \tag{1}$$

where Δ^m_{ipt} denotes emission growth rate for plant i at time t of pollutant p through media m. We consider three media categories: air-released pollutants and water-released pollutants and the total on-site pollutants.Reg_{ipt_0} represents a plant i's home county's attainment/non-attainment status subject to pollutant p at time t_0. If $t_0 = t$, current status. If $t_0 = t_m$,

m periods lagged county status. We use one-period lagged county status as the proxy for regulation. $Multi_{it}$ is a binary dummy for multi-plant firm status. It takes a value of 1 if the plant i at time t belongs to a multi-plant firm. δ_x controls for effects like fixed effects, industry effects, year effects and county effects. And $\alpha, \gamma, \beta s$ are unknown coefficients.

The parameter β_1 represents the general regulation effects, while the parameter β_2 represents possible intra-firm reallocation effects. If β_2 is negative, it implies the multi-plant firm may reallocate its resources among its child plants to comply with regulation requirements.

Though the dependent variable defined this way can naturally incorporates the "entry" and "exit" of plants. A close look at the raw data from TRI reveals that there are some abnormal records with sudden zero emission in several years, if left there, which can lead to artificial "entry" or "exit" phenomena. For instance, the growth rate at the first year with zero emission will be treated as an "exit" event and Δ equals -200%, while the rate at the last year with zero emission would be thought as an "entry" event and Δ equals +200%. To avoid the impacts of these missing records, we exclude any plant-year samples with either "entry" or "exit" events, *i.e.,* the growth rate is either -200% or +200%. There are many cases where emissions have been recorded for more than two consecutive years, thus the growth rates at middle years are not defined. We exclude these sample points because we are not sure the zero emission represents the true zero emission or just be recorded as zero due to missing information. Treating data this way greatly reduces the sample size and differs from the approach used in Greenstone (2003) and Gamper-Rabindran (2009).[6] Without these samples, our results essentially represent the effects of the non-attainment status on firms when they are operating continuously.

In addition to this main specification, we also use two other multi-plant status measures to replace the dummy variable $Multi$. One measure, denoted by $UnRegNbrNum_{ijt}$, is the number of sibling plants from the same parent company in the same 2-digits SIC industry in the neighboring attainment counties. The other measure, denoted by $UnRegNbrEmp_{ijt}$,

[6] After detailed verification of these records, these samples could be brought back in the analysis.

is the number of total employment of sibling plants from the same parent company in the same 2-digit SIC industry in the neighboring attainment counties.[7] We also applies different set of dummies to control the unobservable factors across specifications.[8]

3.2 Main Results

The empirical models are used to examine two questions of interests: are there any cross-media substitution effects of the regulation? are there any intra-firm leakages among plants affiliated with the same multi-plant firms? The first question could be answered with the coefficient of regulation variables on the growth rate of water-released emission. A positive coefficient implies the possible cross-media substitution happens when the regulation is imposed. The second question could be answered by checking whether the coefficient on multi-plant status measures are negative when the dependent variable is the total on-site emission. Since the pollutants are by-products of the production process, the total on-site emission is a good proxy for the production activities.[9] However, the existence of sibling plants in the neighborhood area can also indicate the local conglomeration effect, which will have positive effect on plants' activities, so does on the emission. The sign of these coefficients represents the combined effects: incentives and possibilities to re-allocate resources to the sibling plants (negative) and the conglomeration effects (positive).[10]

[7] The criteria could also be the plants or employment from the same 4-digit SIC industry. However, if that restriction is used, the number of the plants with positive sibling plants in neighboring countries is greatly reduced.

[8] We report details about which set of unobservables are controlled in each estimation result table.

[9] We also include multi-plant status variables in air-released emission and water-released emission regressions.

[10] Direction measures of conglomeration effects could be found by constructing some variables based on local input-output tables to look at the local demands for the product of the plant from the downstream industries and input support for the plant from upstream industries. Here, we have not constructed these variable yet.

3.3 Lead-relate Pollution

Tables ??, ?? and ?? show the estimation results for air-released, water-released, and total on-site released Lead-related pollutants.[11]

For air-released Lead-related pollutants, the results show that relative to plants located in attainment counties, on average, plants located in nonattainment counties will emit around 13% less Lead-related pollutants. The positive and statistically significant coefficient of the regulation variable in regressions of on-site water-released emission lend support about the possible substitution possibilities between air emission and water emission. However, when more unobservables are controlled for, the coefficients lose statistical significance at any conventional levels. The loss of significance could be attributed to the dramatic drop in sample size. This is because that there are many more zero emissions recorded for water emission than that for air emission. The sample size is about one-quarter of the sample size for air emission. The results from regressions of total on-site emission provide little evidence about the potential intra-firm leakage.

3.4 VOC-relate Pollution

Table??, ?? and ?? show the estimation results for air-released, water-released, and total on-site released VOC-related pollutants.

In general, the results from all specifications agree on the small and negative effects of the nonattainment county designation. However, the fixed effect model fails to deliver the significant results. The model specification I and II, similar to model specifications used in Greenstone (2003); Gamper-Rabindran (2009), do report significant results.

When more unobservables are controlled, the effect of regulation on water-released VOC-related pollutants tends to become negative and significant, a direct contradiction to the cross-media substitution hypothesis. The combined effect on the total on-site VOC-relation

[11] All tables are withdrawn at this point. We will update our results and complete this working paper soon.

emission is likely to be negative. When multi-plant structure is included as a control, there exists a modest intra-firm leakage via the local network, *i.e.,* reallocating production to nearby sibling plans in attainment areas.

3.5 TSP-relate Pollution

Due to the abnormal jump in air-released TSP emission in several years, we do not apply our models to the air-released TSP-related emission in this analysis before we can figure out the causes behind the abnormality. Series of total on-site emission and water-released emissions seems normal and the regression results for these two types of emission are shown in Table **??** and **??**.

The coefficient of TSP designation status on water-released pollutants is statistically insignificant, suggesting no sign of air-to-water substitution. In terms of the intra-firm leakage, the leakage effect is not significant in specification IV. While, coefficients on the local multi-plant network proxies do suggest plants with sibling plants located in nearby attainment counties tend to reduce more on total on-site emission.

3.6 Industry Heterogeneity

To check whether there exist heterogeneous responses to regulation varying with 2-digit SIC industries, we apply our models to plants within 2-digit SIC industries. Since the number of firms and the total emission vary significantly across industries, not all industries appear in regressions of all the three categories (See Table **??** for details).

The results with sub-manufacture industries data generally agree with findings with the manufacture industry data. Regulation on air pollution tends to reduce the air pollution from plants located in non-attainment areas, however, the effects are more likely to be found out not significant due to the greatly reduced sample size. In several industries, such as the *Primary Medal Industries*, there is some evidence on cross media substitution from air to water on Lead-related chemicals. Judging from coefficients of multi-plant status in regressions, there are still no strong evidence to support the existence of intra-firm pollution leakage in general.

4 Conclusion

Using the plant-level emission data from TRI database together with the multi-plant firms structure obtained from the NETS database, we attempt to answer three questions in this paper. Do the CAAA regulation by assigning attainment/nonattainment status to counties have intended impact on plant-level air emission? Are there any cross pollution media substitution such as from air pollution to water pollution? Are there any intra-firm emission leakage effects for multi-plant firms?

The results from our empirical models deliver mixed answers to these questions. Generally, we find intended effects on air pollution reduction, although in some specifications the effect is in the right direction, but is not statistically significant. Secondly, we only find some evidence on the air-to-water substitution for Lead-related emission. We could not find any significant evidence on the intra-firm leakage in general for all the three types of pollutants. However, there may exist the negative effect of local multi-plant network on emission, lending support on the indirect evidence of the possible intra-firm production allocation.

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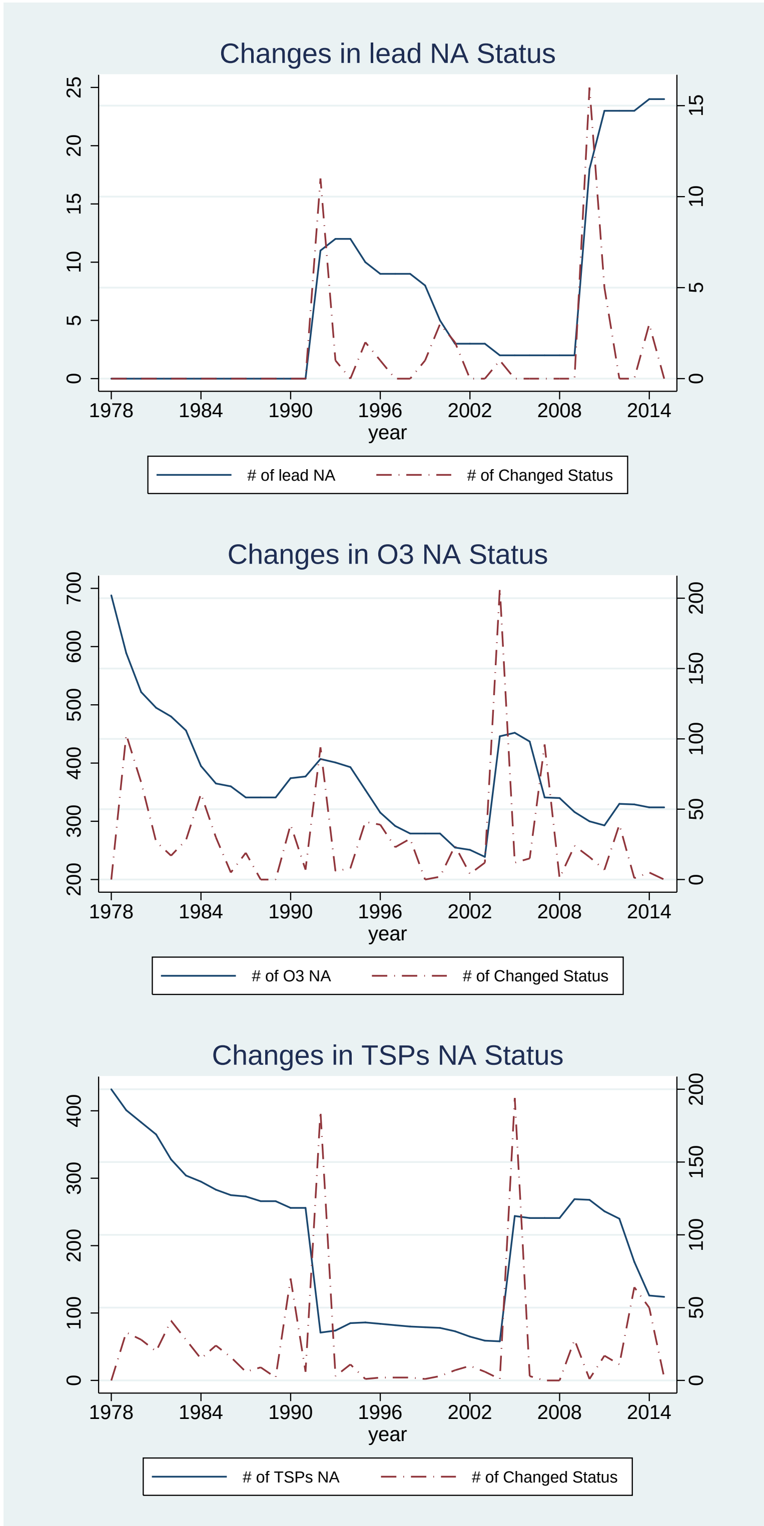

Figure 1: Number of Counties with Nonattainment Status and Number of Counties with Changed Status (Note: the left Y axis is for the number of any NA, while the right Y axis is for the number of changed status.)

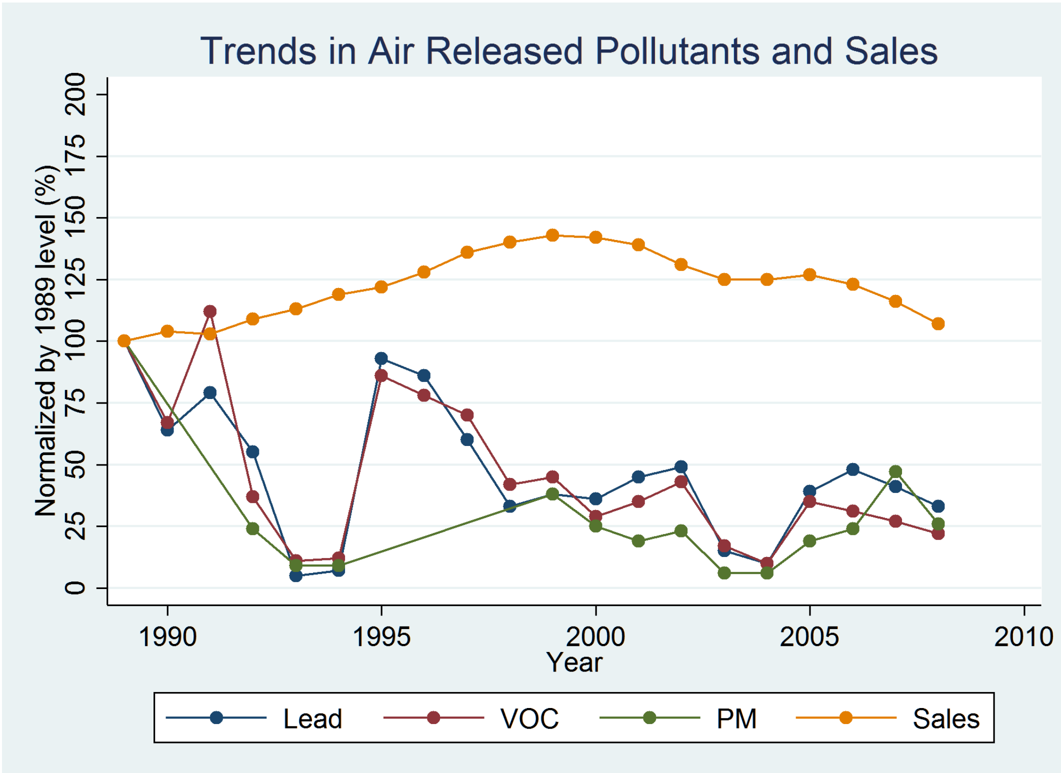

Figure 2: Trends in Air-released Pollutants and Sales

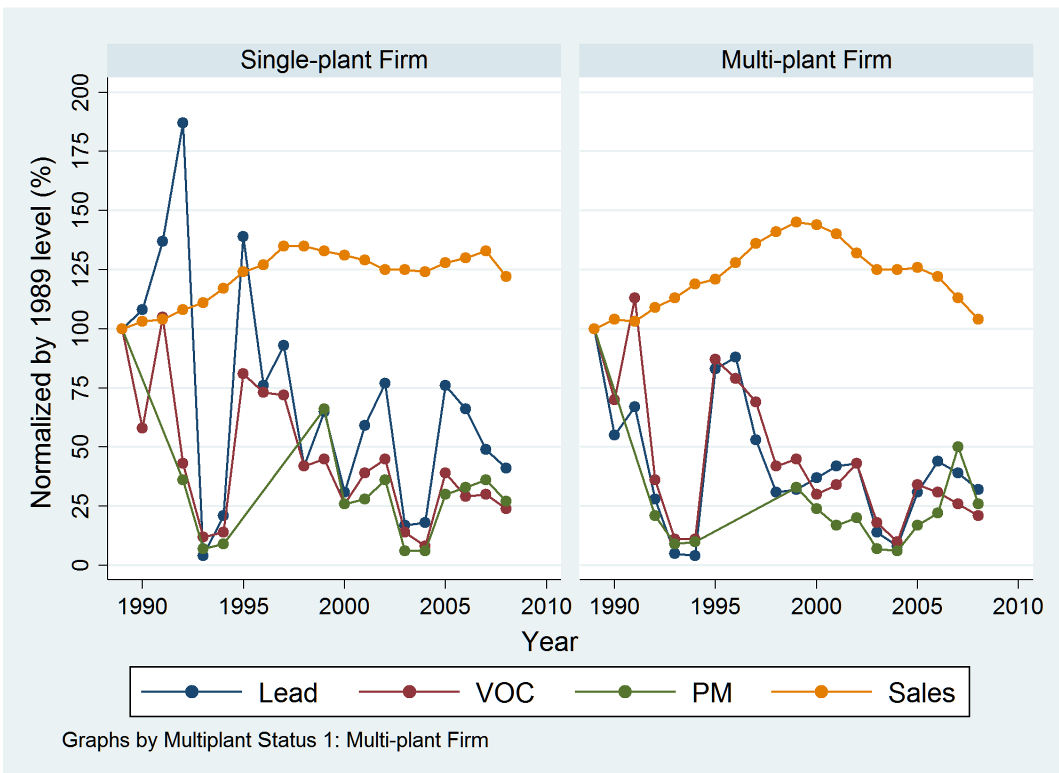

Figure 3: Trends in Air-released Pollutants and Sales by Multi-plant Status

Table 1: Summary of Total On-site Released Pollutants (in:'000lbs)

Industry	2-digit SIC codes	Total On-site Releases of				Rank
		Lead	VOC	TSP	Total	
A. Agriculture, Forestry, Fishing	01-09	0.6	5602.7	39.5	5642.8	8
B. Mining	10-14	2790.7	9676.4	5064	17531.1	7
C. Construction	15-17	6.9	44997.2	889.6	45893.7	4
D. Manufacturing	20-39	10232.9	6990896.6	1195951.9	8197081.4	1
E. Transportation,Public Utilities	40-49	324.3	25445.6	1658.5	27428.4	6
F. Wholesale Trade	50,51	107.7	88200	1888.7	90196.4	2
G. Retail Trade	52-59	6.7	27587.4	69.2	27663.3	5
H. Finance, Insurance, Real Estate	60-67	3.3	4636.2	60.7	4700.2	9
I. Services	70-89	11.4	84284.6	620.6	84916.6	3
J. Public Administration	91-98	0.3	43	2.1	45.4	10
K. Non-classifiable Establishment	99	0	0	0	0	11

Table 2: Total Air-released Pollutant in 2-digit SIC Manufacture Industry (in '000 lbs)

SIC2	Description	Lead			VOC			TSP		
		1989	2008	Chg(%)	1989	2008	Chg(%)	1989	2008	Chg(%)
20	Food, Kindred Products	0	5	N.A	4873	1452	-70	82	118	44
21	Tobacco Products	0	0	N.A	294	50	-83	6	0	-100
22	Textile Mill Products	1	1	0	12600	772	-94	313	6	-98
23	Apparel and Other Textile Products	0	0	N.A	1760	32	-98	4	0	-100
24	Lumber, Wood Products	0	3	N.A	12100	7297	-40	312	5	-98
25	Furniture, Fixtures	0	1	N.A	20500	1433	-93	112	1	-99
26	Paper, Allied Products	0	11	N.A	66900	41100	-39	3368	69	-98
27	Printing, Publishing	0	0	N.A	19700	3134	-84	2	0	-100
28	Chemical, AlliedProducts	97	17	-82.5	196000	33100	-83	8584	712	-92
29	Petroleum, CoalProducts	3	3	0.0	19700	5513	-72	82	8	-90
30	Rubber, Miscellaneous Plastics Products	2	0	-100.0	47100	9539	-80	188	65	-65
31	Leather, Leather Products	0	0	N.A	3104	125	-96	13	0	-100
32	Stone,Clay,GlassProducts	33	10	-69.7	5363	4095	-24	93	193	108
33	Primary Metal Industries	395	105	-73.4	27600	5612	-80	2044	2923	43
34	Fabricated Metal Products	35	12	-65.7	42600	8363	-80	722	175	-76
35	Industrial Machinery and Equipment	10	5	-50.0	27100	2292	-92	280	119	-58
36	Electronic and Other Electric Equipment	113	10	-91.2	44500	1893	-96	695	34	-95
37	Transportation Equipment	26	59	126.9	72300	14600	-80	343	89	-74
38	Instruments and Related Products	17	3	-82.4	33900	1342	-96	137	16	-88
39	Miscellaneous Manufacturing Industries	1	0	-100.0	5412	845	-84	26	4	-85
	total	733	245	-66.6	663406	142589	-78.5	17406	4537	-73.9

All estimation results are very preliminary, we choose not to report Tables and Figures involving these results. Interested readers could contact author for further information.