The Effects of the Clean Air Act on Local Industrial Wages In the Presence of Wage Spillover

Kijin Kim

Department of Economics, University of Illinois at Urbana-Champaign
kkim96@illinois.edu

April 2013

Selected Paper prepared for presentation at the 6th Annual Midwest Graduate Student Conference on Regional and Applied Economics (CRAE), Columbus, Ohio, 5-6 April 2013

The Effects of the Clean Air Act on Local Industrial Wages In the Presence of Wage Spillover

Kijin Kim

Department of Economics, University of Illinois at Urbana-Champaign

April 2013

Abstract Since the beginning of the Clean Air Act, firms operating in regulated counties have faced with higher costs, which consequently had an impact on local labor markets. This paper investigates the effects of the air quality regulation on local manufacturing wages. Taking into account wage spillover explicitly into the model distinguishes this paper from existing studies in which spillover was ignored or was not a major focus. Using the 1982-2007 Census of Manufactures and the historical pollutant-specific nonattainment status for all counties, I construct the wage model with fixed effects partly based on the model specification in Greenstone (2002). I find the wage reduction in emitters induced by the regulations ranging from 2% to 10% depending on the pollutant, which in the 2005 dollar amount are equivalent to loss of roughly \$800~\$4,000 a year. I also find that the regulation effects are not uniform across industries: petroleum & coal, chemical & allied products and paper & allied products are influenced most among emitters. I find an evidence of the existence of spillover, but it is not so evident in the preferred fixed effects model.

Key Words: Wage, Spillover, Clean Air Act, Spatial Panel, Spatial 2SLS

1 Introduction

Since the onset of the Clean Air Act (CAA) of 1970, the Environmental Protection Agency (EPA) was authorized to designate all counties in the US as either nonattainment or attainment determined by whether an area or a county meets the national air quality criteria. Polluting firms in a county designated as nonattainment status have been imposed stricter restriction on emitting pollutants than emitters in attainment counties while non-emitters (or clean industries) are not regulated in counties with either of designations. Against this backdrop, the effects of the environmental regulation on labor markets, especially employment which is an important consideration by local policy makers, have been a center of debate for decades in the US. Along with the effects on employment, the effects on business location also have drawn many researchers' attention. Some of these studies argue that the restriction has had a significant negative impact on the employment of polluting manufacturing sectors in nonattainment counties, and that pollution-intensive industries are more likely to be located in counties with lax regulation.

This paper examines the policy effects on one of the most important labor market outcomes: wages. One of the simplest mechanisms of environmental regulations (e.g. pollution tax) on local labor markets suggests that when the regulation is imposed, in a new equilibrium employment is determined by the relative responsiveness of local labor demand and supply, local wages are likely to fall.[1] If the regulation puts downward pressure on wages in polluting sectors, it might be one of the supporting evidences that polluting firms pass on the cost of alleviating pollution in the form of lower wages given the firms' profits are maximized.

Using the 1982-2007 Census of Manufactures and the historical pollutant-specific nonattainment status for all counties, I construct the wage model with fixed effects partially based on the model specification in Greenstone (2002). This model exploits the inter-industry, cross-county, and temporal variation to estimate the effects of the CAA on polluting industries during the sample periods. First, I estimate average regulation effects by pollutant on wages in the entire polluting industries and test for equality of policy effects across pollutant. Then, I identify the policy effects on affected industries in a more detailed level, using a modified fixed effects model. Further I investigate if the effects on a given industry vary by pollutant and if the effects of a given pollutant-specific regulation vary across industry.

Taking into account wage spillover explicitly into the models distinguishes this study from existing studies in which spillover was ignored or was not a major focus. Wage spillover documented in various studies (Babcock et al., 2005; Budd, 1992, 1995, 1997; Ready, 1990; Drewes, 1987) suggests that estimated policy effects without considering spillover could be biased. Implementing the methods in spatial econometrics, I estimate the measure of spillover effects. Major findings show that emitters in nonattainment counties experience significant wage loss of 2-10% relative to emitters in attainment counties, and that there exists differential impact of the regulations across emitters. I find an evidence of wage spillover, but its magnitude substantially decreases with the inclusion of fixed effects.

This paper proceeds as follows. Section 2 describes costs hike in affected manufacturing sectors and a brief history of the Clean Air Act. Section 3 contains literature review on the effects of environmental policy on the labor market outcomes. The models and estimation methods are specified in section 4. Section 5 describes the data and section 6 presents the empirical results. Section 7 concludes the paper.

[1] A rise in production cost due to a pollution tax reduces demand for labor. Meanwhile, improved air quality attracts new labor forces into the region with the regulation, increasing supply for labor. When a relative movement to the left in the labor demand curve is smaller (larger) than a shift to the right in the labor supply curve, wages fall and employment rises (fall). (O'sullivan, Chapter 5, 2007) See also Figure A1. Even when labor demand shifts to the right, for example, as abatement activities require more labor, wage could fall if labor supply increases even more than the amount of the shift in labor demand.

2 Backgrounds

2.1 **A History of the Clean Air Act**[2]

After passed as the first legislation regarding air pollution in 1963, the Clean Air Act of 1970 introduced a fundamental roadmap to control air pollution from mobile sources (e.g. cars) and stationary sources (e.g. industry). One of the major features of the 1970 CAA is the establishment of the Environmental Protection Agency (EPA). To ensure public health and welfare, the EPA set the air quality criteria, the National Ambient Air Quality Standards (NAAQS) for six pollutants, i.e., carbon monoxide (CO), ozone (O_3), lead (Pb), nitrogen dioxide (NO_2), particulate matter (PM), and sulfur dioxide (SO_2).[3] The 1970 CAA required each state to submit to the EPA for approval the State Implementation Plans (SIPs) including procedures to comply with the standards, and thus to have responsibilities to keep their own air clean. State agencies could directly control major sources of regulated pollutants or indirectly attempt to reduce air pollution through transportation planning. State plans have authority to "require owners or operators of stationary sources to install, maintain, and use emission monitoring devices and to make periodic reports to the State on the nature and amounts of emissions from such stationary sources."[4]

One of the major changes in the 1977 Amendment was for the EPA to designate areas as nonattainment or attainment based on the "design values" of the NAAQS. Nonattainment areas are where the air quality does not meet the national standards, thus more stringent measures to reduce air pollution is required.

The Clean Air Act Amendments of 1990 adopted major changes such as the introduction of permit program (Title V) for 189 toxic pollutants, while the 1990 Amendments expanded the regulatory power of the EPA by authorizing the EPA to impose penalty in areas which failed to submit or implement the SIPs, and modified the air quality standards to reflect current scientific findings. Under the Title V, major sources of regulated pollutants were required to apply for permits issued by state and local air pollution control agencies. Permits are valid for five years and should be renewed when expired. In nonattainment areas, tighter permit requirement is applied, for example, permits are required for factories in

---

[2] The history of the CAA in this section is mostly based on Davison and Norbeck (2012), McCarthy et al. (2011) and the EPA webpage (www.epa.gov/air/caa/caa_history.html).

[3] A list of regulated particulate matter includes total suspended particulate (TSP), particulate matter up to 10 micrometers (μm) in size (PM10), and particulate matter up to 2.5 micrometers (μm) in size (PM2.5). Since 1990, the EPA switched its focus of regulating particulate matter from TSP to PM10 and PM2.5. Starting in 1990 PM10 has been regulated so far. The EPA also started to regulate PM2.5 from 2005 onwards. These changes are based on "current scientific knowledge and uncertainties" concerning public health (Air Quality Criteria for Particulate Matter, EPA, 1996 & 2006). The list of regulated pollutants as of 2011 is presented in Table A1.

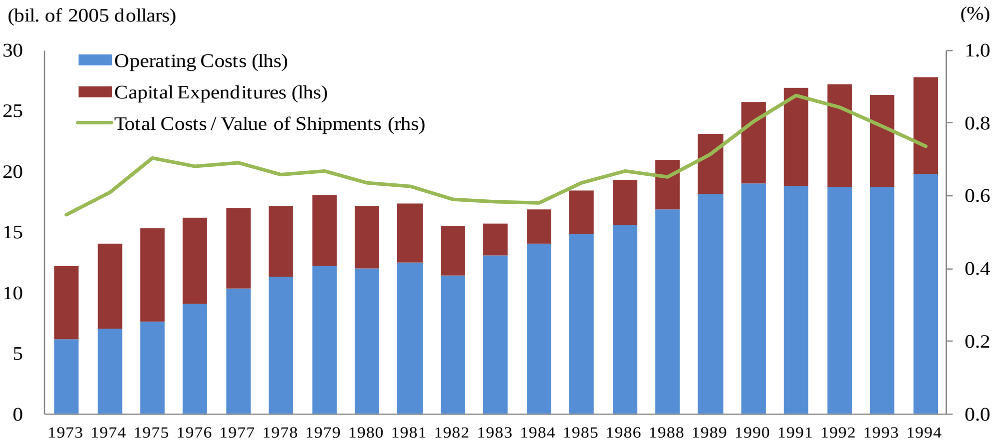
[4] 40 CFR 51.230 (1986)

nonattainment areas emitting more than 50 tons of a pollutant per while the corresponding threshold in attainment areas is 100 tons per year.

2.1 **Pollution Abatement Costs in Manufacturing Sectors**

Although the CAA was not intended to directly influence specific industries that emit pollutants, firms operating in nonattainment counties have faced with higher costs[5], which consequently had an impact on labor demand and supply. For the entire manufacturing sector, total costs of pollution abatement including capital expenditures (e.g. baghouses, scrubbers, and absorbers) and operating costs (e.g. labor costs, costs of materials, and maintenance) have been gradually increasing since early 1970s, except for the periods of early 1980s during which the second oil shock in 1979 deterred economic growth (Figure 1).

Figure 1. Cost of Compliance with Pollution Control for Manufacturers[6]



Source: Pollution Abatement Costs and Expenditures Survey (PACE), the Census Bureau

Immediate cost increase in capital expenditure, operation, and research and development to comply with the air quality standards was enough to cause industry criticisms while a number of firms in most affected industries eventually recognized the implications of the policy and reflected environment protection aspects into their business objectives such as sustainable growths in the future.[7] As an example of direct cost hike, costs of Title V program, which requires permits for major emitters, were thought by representatives for

[5] Becker (2005) finds that emitters of regulated pollutants in nonattainment counties are faced with higher pollution abatement costs (operating costs and capital expenditures) than those in attainment counties.

[6] Since 1994 the PACE survey was conducted only twice, in 1995 and 2005. The data show an increase from 1995 to 2005 in pollution abatement costs for manufacturers. However, it is difficult to compare these figures and the previous surveys due to the fundamental change in the scope and meaning of pollution abatement.

[7] Davidson and Norbeck (2012) take examples of major companies such as Ford Motor Company, Dupont, Rhom and Haas, Exxon Mobil, Texas Instruments, 3M Corporation, P&G and Boeing, and describe the extent of cost increase and how they combined environmental issues with their operating goals.

industries to significantly exceed what federal and local environment agencies anticipated at the beginning of regulation layouts. The Alliance of Automobile Manufacturers estimated costs for assembly plants from application to issuance to be $170,000 with ongoing administrative cost of $150,000 per year, while the EPA's estimates are $55,000 for permit issuance plus $8,100 for administration. Estimates for issuance from the American Chemistry Council ranged from $35,000 to $3.3 million, which were compared to $30,000-$55,000 estimated by the EPA.[8] Furthermore major sources of pollutants operating in nonattainment counties were subject to more stringent thresholds for pollution level, which might have required Title V permit that would have not been necessary if they had been located in attainment counties.

3 Literature Review

Many of past empirical studies have shown somewhat mixed results about the effects of the CAA (or environmental regulations in general) on employment and business location. Several studies among them focus on a single pollutant, either CO, O_3, or TSP. Using panel regression with particulate data from the EPA, Kahn (1997) concludes positive correlation between high TSP level and slow business activities. Henderson (1996) examines the O_3 regulation effects on plants using county employment data and argues that the designation of nonattainment led plants to exit a county. Becker and Henderson (1997) and List and McHone (2000) similarly find that firm births in the areas with the O_3 regulation are negatively affected due to a shift of polluting activities to cleaner attainment areas. Meanwhile, for multiple policy effects, Greenstone (2002) uses firm-level microdata and four pollutants (CO, O_3, SO_2, and TSP), and finds an evidence that the CAA substantially retarded the growth of polluting manufactures in nonattainment counties. Kahn and Mansur (2010) explore the effects of regulations with respect to labor union status and energy-intensity as well as air quality regulation. They show that pollution-intensive industries are likely to locate in lax environmental regulation. On the other hand, using plant-level data for four heavily polluting industries, Morgenstern et al. (2002) find that there are no significant change in employment due to the environmental regulation, and a small but significant increase in employment is detected in some sectors. Berman and Bui (2001b) also note positive effects of air quality regulation on the U.S. refineries' labor demand. Bartik (1988), McConnell and Schwab (1990), and Levinson (1996) find less evidence that plant location is associated with environmental policy.

The CAA effects on public health, housing markets, and pollution level are also popular

[8] Title V Task Force, "Final Report to the Clean Air Act Advisory Committee: Title V Implementation Experience" (April 2006)

subjects. Chay and Greenstone (2003) examine the effects of TSP on infant mortality using county attainment status as an instrument for TSP level within the framework of regression discontinuity design. They find that reduction in TSP resulted in significant decline in infant mortality at county level. Chay et al. (2003) focuses on adult mortality, but finds little evidence of a decrease in adult mortality associated with TSP reduction. Chay and Greenstone (2005) employ hedonic model of housing prices using the similar identification strategy as in Chay and Greenstone (2003), and find that the elasticity of housing values with respect to TSPs ranges from -0.20 to -0.35. Greenstone (2004) explores the impact of SO_2 nonattainment status on the level of SO_2 pollution using propensity score matching. He finds that nonattainment designation played a minor role in the dramatic reduction in SO_2 concentrations.

There are just a few empirical studies on the effects of environmental policies including the CAA on labor income. Hollenbeck (1978) investigates the effects of the 1970 CAA using computable generable equilibrium model and finds regressive effects on earnings. Bartel and Thomas (1985) find that the regulatory effect of the Occupational Safety and Health Administration (OSHA) and the EPA on industry wages could become negative for less unionized and smaller firms. Using the data for 63 Standard Metropolitan Statistical Areas (SMSAs) Duffy-Deno (1992) finds that higher pollution abatement costs are weakly associated with earnings loss. Walker (2012) examines how the 1990 Clean Air Act Amendments (CAAA) affected workers' earnings, using employer-worker matched micro-datasets from the Longitudinal Employer Household Dynamics (LEHD). He argues that workers in newly regulated plants lost a total of $9 billion earnings during the post-regulation periods. In Mishra and Smyth (2012), they also use matched worker-firm dataset and investigate the effects of pollution regulation on wages in Shanghai, China. They find that firms passed back the cost of regulation to workers in the form of lower wages.

Theories on the regulation effects on either labor demand or labor supply show ambiguous results on the employment in the new equilibrium. However, the effects on local wages are to some degree consistent when major findings on labor demand and supply are combined. Demand for labor is likely to be reduced if the activity for pollution abatement under the environmental regulation requires more capital than labor. If the air quality improves in regulated regions[9], which will attract more labor force, then the shift in labor supply in those regions might be positive or small, depending on migration costs. The effects on employment cannot be determined uniformly and this is consistent with mixed empirical results. However, in any case of the shifts in labor supply and demand curves, the predicted

[9] Studies on the effects of the CAA on air quality show mixed results that differ by pollutant. Henderson (1996) and Chay et al. (2003) find regulatory status is associated with the reduction of O3 and TSP levels. On the other hand, Greenstone (2003) argues that nonattainment designation played a minor role in the decline in SO2 level.

effects of the regulation on wages are unambiguously not positive.[10]

Morgenstern et al. (2002) note that regulation raises production costs and demand for goods produced by polluting firms decrease, and consequently less labor is required for decreased production. They also point out that employment could increase when environmental activities are labor-intensive. Applying the partial static equilibrium model, Berman and Bui (2001) also argues that theory does not predict precisely which direction labor demand under environmental regulations would move. It is dependent upon whether abatement activity and labor are complements or substitutes. However, the measures for pollution abatement that the regulation requires seem rather capital-intensive.[11] To comply with the standards, emitters are often required to implement up-to-date pollution control technology and even develop advanced technology.

Past research in labor and regional economics examines labor supply associated with environmental policy by focusing on the relationships between air quality and migration or health effects. Ostro (1983) and Hausman et al. (1984) find empirical evidences of significant positive association between air pollution and lost work days. Examining the effects of air quality improvement in Mexico on labor supply (working hours), Hanna and Oliva (2011) find the evidence of increase in labor mainly induced by reduced absenteeism to work due to health problem. They use a partial equilibrium model where individuals value air quality in their utility function and better air quality reduces disutility of work. A simple spatial general equilibrium model in Roback (1982) suggests that wages should be lower in more amenable places (e.g. cites with clean air) to reflect the value of amenity. However, Bayer et al. (2009) point out that when migration is costly, the change in wages due to the cleaner air should be small since the benefits from moving to places with the cleaner air should compensate for migration cost as well as earnings loss (and higher rents). Meanwhile, in an attempt to evaluate the *macroeconomic* impacts of the Clean Air and Clean Water acts, the econometric general equilibrium model in Hazilla and Kopp (1990) suggests that household labor supply declines due to the price increase in consumption relative to leisure under the regulation.

[10] The preceding arguments are associated with spatial variation in pollution control, which causes inter-regional movement of factors. There also exist a number of studies on migrating factors between polluting and nonpolluting sectors within space. Yohe (1979) explores the backward incidence of pollution control in a two sector general equilibrium where labor and capital are perfectly mobile. His model suggests that more stringent pollution control have a backward incidence onto factors of production. Since Yohe, the theory has been extensively studied with different assumptions. Their main points are that the effects of pollution control vary mainly by factor mobility, factor intensity, and wage rigidity. See also Yu and Ingene (1982), Foster (1984), and Wang (1990).

[11] According to the 2005 PACE Survey, total manufacturers spent $4,096 million for labor and $5,908 million for capital expenditures associated with pollution abatement activities. The ratio of capital expenditures to labor costs in manufacturing is 1.44 and increases to 2.14 when the depreciation is added to capital expenditures. The most capital-intensive manufacturing sector based on this ratio is petroleum and coal producers (NAICS: 324) and the least is leather and allied products manufacturers (NAICS: 316). See Table A2 for more detail.

4 Models

4.1 Panel Model

Each panel is consisted of county by industry by year. Following Greenstone (2002) in a similar fashion, the basic model is given by

$$
\begin{aligned}
E_{cit} = \beta_0 + \beta_1 X_{cit-5} &+ \beta_{21}\, EmitCO_{it-5} + \beta_{22}\, EmitO3_{it-5} + \beta_{23}\, EmitSO2_{it-5} + \beta_{24}\, EmitPM_{it-5} \qquad (1)\\
&+ \beta_{31}\, NonattainCO_{ct-5} + \beta_{32}\, NonattainO3_{ct-5}\\
&+ \beta_{33}\, NonattainSO2_{ct-5} + \beta_{34}\, NonattainPM_{ct-5}\\
&+ \beta_4\, 1(EmitCO = 1\ \&\ NonattainCO = 1)_{cit-5}\\
&+ \beta_5\, 1(EmitO3 = 1\ \&\ NonattainO3 = 1)_{cit-5}\\
&+ \beta_6\, 1(EmitSO2 = 1\ \&\ NonattainSO2 = 1)_{cit-5}\\
&+ \beta_7\, 1(EmitPM = 1\ \&\ NonattainPM = 1)_{cit-5} + \varepsilon_{cit}
\end{aligned}
$$

where $\varepsilon_{cit} = \delta_c + \gamma_t + u_{cit}$ or $\varepsilon_{cit} = \alpha_{ci} + \gamma_t + u_{cit}$

The subscripts, *c*, *i*, and *t* refer to county, industry, and year respectively. The dependent variable is payroll per employee in sub-manufacturing sectors with 2-digit standard industrial classification (SIC). All explanatory variables have the time subscript *t-5* so that they are predetermined for causality. Payroll is deflated by the personal consumption expenditure (PCE) index (2005=100) compiled by the Bureau of Economic Analysis and then is taken logarithm. A vector of covariates, *X*, contains value of shipment as a measure of industry size[12] and the number of employees in other polluting (clean) industries within the same county and county population as a measure of agglomeration effects. Apparently it is crucial to take into account the characteristics on individuals residing in counties to control for heterogeneity of counties. Thus, *X* also includes: %Male, %Age 19 and below, %Age 20-34, %Age 35-54, %Age 55-64, %Age 65-84, %Black, %Hispanic, %Bachelor's degree and above (and squared of it), %Never married, %Veteran, poverty rate, and unemployment rate. *EmitPollutant* is a dummy variable indicating an industry that emits a specific pollutant and β_{2i} (i=1,2,3,4) captures wage differences between emitters and nonemitters with all else being equal. *NonattainPollutant* is a dummy representing if a county is designated as nonattainment by the standards of four regulated pollutants. i.e, CO, O_3, SO_2, and PM.[13] β_{3i} (i=1,2,3,4) shows the difference in wages between attainment counties and counties with pollutant-specific nonattainment status holding other variables constant. The coefficients, β_4-β_7, on pollutant-specific interaction terms between emitter and nonattainment represent estimates of

[12] Controlling for industry size is essential in capturing the regulation effects. Bartel and Thomas (1985) point out that the regulation effects depend on economies of scale, i.e., smaller firms suffer a larger unit-cost effect and so they are more disadvantaged.

[13] The dummy variable PM includes TSP from 1978 to 1990, PM10 from 1990 onwards and PM2.5 from 2005 onwards. When a county is nonattainment for either of TSP, PM10 or PM2.5, PM is assigned a value of one, zero otherwise.

policy effects for each pollutant. The policy effect is captured by comparing the difference between emitters and non-emitters within nonattainment counties with the difference between emitters and non-emitters within attainment counties. For example, the CO regulation effects on CO emitter are represented by

$$\begin{aligned}\beta_4 = \{&\mathrm{E}[\mathrm{E}_{cit}|\mathrm{Z}, \mathrm{EmitCO}_{it-5} = 1, \mathrm{NonattainCO}_{ct-5} = 1] \\ &- \mathrm{E}[\mathrm{E}_{cit}|\mathrm{Z}, \mathrm{EmitCO}_{it-5} = 0, \mathrm{NonattainCO}_{ct-5} = 1]\} \\ &- \{\mathrm{E}[\mathrm{E}_{cit}|\mathrm{Z}, \mathrm{EmitCO}_{it-5} = 1, \mathrm{NonattainCO}_{ct-5} = 0] \\ &- \mathrm{E}[\mathrm{E}_{cit}|\mathrm{Z}, \mathrm{EmitCO}_{it-5} = 0, \mathrm{NonattainCO}_{ct-5} = 0]\}\end{aligned}$$

where Z includes all of the covariates and fixed effects excluding EmitCO_{it-5} and $\mathrm{NonattainCO}_{ct-5}$. The error term includes unobserved county or individual (i.e., county by industry) fixed effects to control for time-invariant or permanent wage determinants unique to each county or each local industry. The fixed effects models are useful to ensure consistency of estimates in case that nonattainment status covaries with unobserved county or local industry characteristics: for example, labor force in nonattainment counties might have higher skills than those in attainment ones, or local industries are probably more likely to be located in nonattainment counties due to location advantages. Each observation is weighted by average number of employees in the current and previous periods to take into account of cell size.

4.2 Wage Spillover

Economic variables in geographical units are generally known to be spatially correlated: for example, wages in a region are likely to be high when wages in surrounding regions are high (positive spatial autocorrelation). In the presence of wage spillover, estimated regulation effects in the model where spillover is not taken into account can be biased so that the alternatives such as spatial autoregressive lags and/or spatial error models can address the problem with spatial dependence (Lacombe, 2003). A number of empirical studies find the existence of positive wage spillover. One possible explanation of wage spillover in Drewes (1986) is that a credible threat of quit from employees to employers who are faced with high costs of turnover, e.g., hiring and training costs, could directly link high wages in a region to high wages in others regions. Also, wage spillover can take place through pattern bargaining (Ready, 1990; Budd, 1992, 1995, 1997), where the union starts wage negotiation with an employer, then implements a similar strategy to other employers in the industry, or social comparisons (Babcock et al., 2005), where both union and employers refer to wages negotiated in other firms as a benchmark.

I define the spatial dependence in terms of geographical proximity, which implies that local industrial wages are more dependent upon industrial wages in the closer regions. As illustrated in Figure A2, spatial dependence measured by Moran scatter plot suggests that real wages in a county are significantly correlated with real wages in neighboring counties.[14] The slopes in the regressions of mean wages in neighboring counties on local mean wages range approximately from 0.3 to 0.6, varying by year. According to Anselin (2005), a reduced form in cross-sectional data when there are no priori to limit spillover to either explanatory variables or the error term follows as

$$\mathbf{y} = (\mathbf{I} - \boldsymbol{\lambda}\mathbf{W})^{-1}\mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \boldsymbol{\lambda}\mathbf{W})^{-1}\mathbf{u} \tag{2}$$

$$= \left(X\beta + \lambda WX\beta + \lambda^2 W^2 X\beta + \cdots\right) + (u + \lambda Wu + \lambda^2 W^2 u + \cdots) \tag{3}$$

where $u \sim N(0, \sigma^2 I)$. Equation (3) can be derived from equation (2) under the conditions that $|\lambda| < 0$ and the element of W is less than one. The terms in the first (second) parenthesis in equation (3) represent spillover from explanatory variables (the error). Specifically, β indicates the direct effects from a change in X, and $\lambda\beta$ represents the indirect effects from a change in X in neighboring regions (WX : first-order contiguity). The higher-order terms describe the induced effects from a change in X in farther neighbors ($W^2X, W^3X, \cdots$). Hence, λ measures the sign and magnitude of spillover effects. Premultiplying equation (2) by $(I - \lambda W)$ and rearranging the terms for y yields

$$y = \lambda Wy + X\beta + u$$

, which turns out to be a spatial lag or spatial autoregressive model (SAR). A more general form could have two different weight matrices, one for explanatory variables and the other for the errors.

Assuming that wage spillover stems from contiguous regions, a spatial lag model with fixed effects is presented as follows[15]:

$$E = X\boldsymbol{\beta_1} + EM\,\boldsymbol{\beta_2} + NT\,\boldsymbol{\beta_3} + EM \circ NT\,\boldsymbol{\gamma} + \lambda WE + \epsilon \tag{4}$$

where ϵ contains county fixed effects or county by industry fixed effects; $X =$ a matrix of

[14] Moran scatter plot represents relationships between any variable of interest in a region (y) and the same variables in surrounding regions (Wy). W is a spatial weight matrix in which diagonal elements are zero and off-diagonal elements represent the extent of "closeness" between two regions. The W matrix used in this paper is based on Queen's contiguity. By the criterion of Queen-based contiguity, geographical units are determined as neighbors when they share any point in common, including common boundaries and corners. On the other hand, Rook criterion treat regions as neighbors only when they share common boundaries. See Appendix A for how the W matrix is constructed.

[15] See Babcock et al. (2005) for the model of wage spillover using the spatial econometrics technique.

covariates and a constant as in equation (1); $\mathrm{EM} =$ a matrix comprising column vectors of pollutant-specific emitter indicator, i.e., $(\mathrm{EmitCO}, \mathrm{EmitO3}, \mathrm{EmitSO2}, \mathrm{EmitPM})$; $\mathrm{NT} =$ a matrix containing column vectors of pollutant-specific nonattainment designation for counties, i.e., $(\mathrm{NonattainCO}, \mathrm{NonattainO3}, \mathrm{NonattainSO2}, \mathrm{NonattainPM})$; $\mathrm{EM} \circ \mathrm{NT} =$ the Hadamard (element-wise) product of EM and NT; $\boldsymbol{\beta_1}$, $\boldsymbol{\beta_2}$, $\boldsymbol{\beta_3}$, and $\boldsymbol{\gamma}$ = coefficient vectors; W = the row-standardized Queen-based spatial weight matrix. Therefore, WE indicates neighboring counties' mean wages and ρ represent the strength of spillover across counties. A reduced form of equation (4) is provided by

$$\begin{aligned} \mathrm{E} &= (\mathrm{I} - \lambda \mathrm{W})^{-1}(\mathrm{X}\boldsymbol{\beta_1} + \mathrm{EM}\,\boldsymbol{\beta_2} + \mathrm{NT}\,\boldsymbol{\beta_3} + \mathrm{EM} \circ \mathrm{NT}\,\boldsymbol{\gamma} + \epsilon) \qquad (5) \\ &= \left(\mathrm{X}\boldsymbol{\beta_1} + \lambda \mathrm{WX}\boldsymbol{\beta_1} + \lambda^2 \mathrm{W}^2 \mathrm{X}\boldsymbol{\beta_1} + \cdots\right) \\ &+ \left(\mathrm{EM}\,\boldsymbol{\beta_2} + \lambda \mathrm{W}\,\mathrm{EM}\,\boldsymbol{\beta_2} + \lambda^2 \mathrm{W}^2\,\mathrm{EM}\,\boldsymbol{\beta_2} + \cdots\right) \\ &+ \left(\mathrm{NT}\,\boldsymbol{\beta_3} + \lambda \mathrm{W}\,\mathrm{NT}\,\boldsymbol{\beta_3} + \lambda^2 \mathrm{W}^2\,\mathrm{NT}\,\boldsymbol{\beta_3} + \cdots\right) \\ &+ \left(\mathrm{EM} \circ \mathrm{NT}\,\boldsymbol{\gamma} + \lambda \mathrm{W}\,(\mathrm{EM} \circ \mathrm{NT})\boldsymbol{\gamma} + \lambda^2 \mathrm{W}^2\,(\mathrm{EM} \circ \mathrm{NT})\,\boldsymbol{\gamma} + \cdots\right) \\ &+ \left(\epsilon + \lambda \mathrm{W}\,\epsilon + \lambda^2 \mathrm{W}^2\,\epsilon + \cdots\right) \qquad (6) \end{aligned}$$

Deriving equation (6) from equation (5) holds under the condition that $|\lambda| < 0$ and the element of W is less than one. In the fourth line of equation (6), $\boldsymbol{\gamma}$ represents *direct* policy effects on emitters in nonattainment counties, $\lambda\boldsymbol{\gamma}$ represents *spillover* effects from *immediate* neighbors because $\mathrm{W}\,(\mathrm{EM} \circ \mathrm{NT})$ measures the number of emitters in neighboring nonattainment counties. Similarly, $\lambda^2\boldsymbol{\gamma}$ and higher order coefficients represent *spillover* effects from *the second-order and higher* neighbors. Hence, as long as λ is not zero, overall policy effects on emitters in nonattainment counties is $\left(1 + \lambda + \lambda^2 + \cdots\right)\boldsymbol{\gamma} = 1/(1-\lambda)\boldsymbol{\gamma}$, where $1/(1-\lambda)$ is the spillover multiplier. When λ is zero, equation (6) is identical to equation (1). Based on past studies, I expect λ to be positive and less than one.

Spatial models are generally estimated by maximum likelihood for consistency of estimates while the OLS estimates are not consistent because the disturbance term is correlated with the spatial lagged dependent variable. However, when the sample size is large, it is hard to implement maximum likelihood method due to computational difficulties. Furthermore, the fact that the data in this analysis have sparsely missing panel units in particular years makes maximum likelihood more impracticable because many of currently available statistical softwares do not support unbalanced spatial panel. As an alternative, Kelejian and Prucha (1998) propose spatial two-stage least squares (S2SLS) method for cross-sectional data, which produces consistent estimators. For a panel model with fixed effects, Baltagi and Liu (2011) suggest the fixed effects spatial 2SLS (FE-S2SLS)[16]. Thus, I use FE-S2SLS to estimate equation (4). In the first stage, it is required to generate the fitted values for the spatial lag term ($\widehat{\mathrm{WE}}$) by using instrumental variables (IVs) which include Z,

[16] Brief matrix algebra for FE-S2SLS with the spatial lagged dependent variable is provided in Appendix B.

WZ, and W^2Z where Z contains all explanatory variables. In the second stage, the fitted values generated in the first stage replace their original values in equation (4). Then, the same estimation procedure as for equation (1) is conducted.

5 Data

Historical nonattainment status for counties is obtained from the EPA[17]. These data indicate whether a whole or a part of county is nonattainment for each regulated pollutant. Carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), and particulate matters (TSP, PM_{10} and $PM_{2.5}$) are chosen for analysis among all regulated pollutants.[18] Greenstone (2002) classifies sub-manufacturing sectors with SIC 2- to 4-digit levels which are highly likely to be affected by the CAA by four pollutants as shown in Table 1.[19]

The main sources of industrial wages are the 1982, 1987, 1992, 1997, 2002, and 2007 Census of Manufactures (CM)[20]. The CM also contains other characteristics of sub-manufacturing sectors such as the number of firms and employees, value added, cost of material, value of shipments, etc. It is important to note the difference in level of observations and industrial classification between this paper and Greenstone (2002). This paper uses the CM that is publicly available while Greenstone (2002) uses firm-level microdata samples based on the CM, which enables him to classify every firm in the sample into 4-digit SIC level. Classification to 3- to 4-digit SIC levels using the public dataset, however, significantly reduces the number of samples available due to data confidentiality (see Table A3). Thus, when the emitter's SIC suggested by Greenstone are 3 or 4 digits, I use the higher level, i.e., 2 digit (Table 1). As such, all the analysis hereafter are based on 2-digit SIC levels[21].

[17] Source: http://www.epa.gov/airquality/greenbook/datadownload.html.

[18] The list of regulated pollutants includes nitrogen dioxide (NO_2) and lead (Pb) as well. The two pollutants are excluded in the analysis. The reactions of volatile organic compounds (VOC) and nitrogen dioxide (NO_2) form ozone (O_3). During the periods of analysis, there are only four counties with NO_2 nonattainment and twelve counties with Pb nonattainment, which makes meaningful statistical inference infeasible.

[19] Polluting sub-manufacturing sectors by pollutant are determined on the basis of the extent of how much pollutant they emit relative to total industry. Greenstone (2002) classifies an industry as pollutant-specific emitter if the fraction of pollution that the industry produces relative to the whole industries is larger than seven percent.

[20] The periods of samples in Greenstone (2002) are 1967, 1972, 1977, 1982 and 1987. During those periods, TSP was the only targeted particulate matter, but PM_{10} and $PM_{2.5}$ were also in place as well as TSP during the sample periods in this study.

[21] List and McHone (2000) also used sub-manufacturing sectors with 2-digit SIC to identify O_3 emitters.

Table 1. Classification of Emitters

2-digit SIC	Description	Emittes in Greenstone (2002)					
		SIC up to 4-digit	Description	CO	O3	SO2	TSPs
24	Lumber &wood	24	Lumber&Wood				Y
26	Paper&allied	2611-31	Pulp&Paper	Y	Y	Y	Y
27	Printing&publishing	2711-89	Printing		Y		
28	Chem.&allied	2861-9	Organic Chem		Y		
		2812-9	Inorganic Chem.			Y	
29	Petroleum&coal	2911	Petrol. Refin.	Y	Y	Y	
30	Rubber&misc. plastic	30	Rubber&Rubber		Y		
32	Stone,clay&glass	32	Stone, Clay, Glass		Y	Y	Y
33	Primary metal	3312-3, 3321-5	Iron&Steel	Y	Y	Y	Y
		333-4	Non-ferrous Metals	Y		Y	
34	Fabricated metal	34	Fabric. Metals		Y		
37	Transportaion equip.	371	Motor Vehicle		Y		

Data availability in terms of county-level is depicted in Figure A3 and Figure A4. In Figure A3, nonattainment status for all counties in all states except for Alaska and Hawaii is mapped by pollutant. A county is marked if it has been designated at least once as pollutant-specific nonattainment during the Census years (1982, 1987, 1992, 1997, 2002, 2007). The maps show that nonattainment counties are mostly located in the northeastern and pacific states in the US, which suggests that it is likely that this geographic concentration causes spatial dependence in wages across regulated counties. Figure A4 indicates that for this analysis there are many missing counties where 2-digit manufacturing wages during the CM years are unavailable or incomplete due to data confidentiality. Fortunately, the numbers of available counties with pollutant-specific nonattainment are not remarkably reduced while total number of available counties is relatively small[22]. Majority of the counties in the Mountain West do not have sub-manufacturing wage in the publicly available CMs because the size of manufacturing firms are fairly small or there are counties in those regions where manufacturing sectors do not exit (thus, most counties in those regions are attainment) so that releasing those data do not meet standards for data dissemination.

One of the concerns about the missing data is associated with selection bias. Since missing counties in the data are not randomly scattered, estimates of (say, negative) policy effects might be downward (upward) biased if wages in the missing counties used as controls are lower (higher) than wages in non-missing attainment counties. However, it might be not unreasonable to exclude counties in the Mountain West from samples. Nonattainment counties used as controls existing in the sample and missing counties are not expected to be comparable since the extent of observable and unobservable heterogeneity in missing areas is high and decision on business location by manufacturing firms located in the Mountain West could be distinct relatively from firms in other areas. Therefore, subsequent analysis is conducted with the currently available dataset.

[22] In only 1,448 out of 3,109 counties, 2-digit manufacturing wages are available. However, 160 (448, 54, 326) out of 170 (548, 75, 443) CO (O3, SO2, PM) nonattainment counties contain available wage data.

Since 1997, industrial classification in the Census of Manufactures was changed to National American Industry Classification System (NAICS) from Standard Industrial System (SIC). Sub-manufacturing sectors with 3-digit NAICS in the 1997, 2002, and 2007 CM are matched with 2-digit SIC sectors for consistency of industrial classification (see Table A4).

Observable characteristics on county demographics are obtained from the 1990 and 2000 Census of Population (CM). Major characteristics of counties extracted from the 1990 and 2000 CM are provided in Table A5. It seems apparent that several characteristics are associated with nonattainment status: Population in nonattainment counties is approximately 8-9 times larger than that in attainment counties. Those who live in nonattainment counties earn higher income and they are more likely to be non-white, Hispanic, more educated and single[23]. This suggests that to ensure the consistency of estimates for regulation effects, it is necessary to control for observable county characteristics while unobservable ones should be filtered out through fixed effects.

6 Empirical Results

6.1 Fixed Effects Models

Estimates from wage model in equation (1) are provided in Table 2. The effects of SO_2 and PM regulations on wages are consistently negative across all specifications though their statistical significance differs by inclusion of fixed effects. Meanwhile CO and O_3 regulations show mixed signs of results, largely not different from zero effect.

Specifically, estimates from the pooled OLS model in column (1) and (2) suggest that regulation effects on wages are negative although its effects do not appear strong across all pollutants. For example, in column (1) O_3 and SO_2 regulation put in place five years ago appear to decrease wages in O_3 and SO_2 emitters by 9.8% and 5.1% respectively. However, these results are not so convincing because unobserved characteristic of county or local industry might be associated with nonattainment designation.

In fixed effect models, SO_2 and PM regulations probably play a role in decreasing wages in emitters of the corresponding pollutants. Moreover, no substantial changes in coefficients between column (3) and (4), and between (5) and (6) suggest that county (or county by industry) fixed effects appropriately take into account county characteristics including observed ones. The model with county and time fixed effects in column (4) suggests that PM regulation effects are significant at 10% level. However, PM regulation effects disappear and

[23] Since variables for county characteristic are only available from the decennial Census (1990 and 2000) and changes in variation of those variables are quite small over time, county characteristics from the 1990 Census of Population are repeatedly used for the periods of 1982, 1987 and 1992. The 2000 Census is used for the rest of the periods.

SO_2 regulation effects become highly significant in individual and time fixed effect models in column (5) and (6). Estimates from the preferred model, in which the most detailed level of the unobservable is controlled, indicate that SO_2 emitters in SO_2 nonattainment counties have lower wages on average by 8% relative to SO_2 emitters in SO_2 attainment counties (when the controls are non-SO_2 emitters), while the other pollutant-specific regulations did not exert strong influence. Furthermore, the hypothesis in column (6) that regulation effects for all pollutants are equal, H_0: $\beta_4=\beta_5=\beta_6=\beta_7$, is rejected at the 5% level. In sum, these findings indicate that regulation effects on emitters' wages range from -10% to -2% depending on pollutant-specific regulation.

Table 2. Wage Model - Equation (1)

	(1)	(2)	(3)	(4)	(5)	(6)
CO regulation effect	-0.004	0.007	0.017	0.015	0.004	-0.002
	(0.017)	(0.016)	(0.015)	(0.015)	(0.014)	(0.015)
O3 regulation effect	-0.098***	-0.047***	0.000	0.001	0.008	0.003
	(0.016)	(0.015)	(0.015)	(0.014)	(0.011)	(0.010)
SO2 regulation effect	-0.051***	-0.021	-0.005	-0.004	-0.077***	-0.080***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.027)	(0.027)
PM regulation effect	-0.008	-0.018	-0.021	-0.021*	-0.008	-0.009
	(0.015)	(0.014)	(0.013)	(0.012)	(0.008)	(0.008)
R-squared	0.393	0.505	0.620	0.621	0.937	0.938
County Characteristics		Yes		Yes		Yes
Year FE			Yes	Yes	Yes	Yes
County FE			Yes	Yes		
County x Industry FE					Yes	Yes
Equality of Reg. Effects	9.16	2.16	1.16	1.06	2.77	2.73
(F-stat & p-value)	(0.000)	(0.090)	(0.325)	(0.367)	(0.040)	(0.042)
#obs	13,127	13,127	13,127	13,127	13,127	13,127

Notes: Dependent variable = log(real payroll). Robust standard errors in parentheses. Each observation is weighted by average number of employees in the current and previous periods. Samples from the 1982, 1987, 1992, 1997, 2002, 2007 CM are used. Covariates common across specifications are value of shipments, number of employees in other polluting (clean) industries within the same county, and county population. Variables for county characteristics include %Male, %Age 19 and below, %Age 20-34, %Age 35-54, %Age 55-64, %Age 65-84, %Black, %Hispanic, %Bachelor's degree and above (and squared of it), %Never married, %Veteran, Poverty rate, and Unemployment rate. *** p<0.001, ** p<0.05, * p<0.1

The model specification in Greenstone (2002) assumes that an industry is a pollutant-specific emitter if the industry accounts for 7% or more of industrial sector emissions of that pollutant[24]. This assumption does not take into account the magnitude of the emission: for example, the policy effects on outcome are treated to be the same whether an industry emits 7% or 37% of a pollutant. It also assumes that any industry that emits a pollutant below 7% is classified as "clean" industries, but there exists a chance that the "clean" industries that emit

[24] See table A2 in Greenstone (2002).

less than the cutoff might be affected. Further, the 7% assignment rule is not based on any scientific evidence and is not relevant to designation process.[25]

To develop these findings into the question of which industries are affected by specific pollutants, a modified model is constructed by keeping the entire set of polluting sectors and assuming that any emitter could be affected by any of pollutant-specific nonattainment status. The modified wage model is given by

$$\begin{aligned} E_{cit} = \beta_0 + \beta_1 X_{cit-5} + \beta_2 Ind_i + \beta_{31} NonattainCO_{ct-5} + \beta_{32} NonattainO3_{ct-5} \\ + \beta_{33} NonattainSO2_{ct-5} + \beta_{34} NonattainPM_{ct-5} \\ + \beta_4 Ind_i * NonattainCO_{ct-5} \\ + \beta_5 Ind_i * NonattainO3_{ct-5} \\ + \beta_6 Ind_i * NonattainSO2_{ct-5} \\ + \beta_7 Ind_i * NonattainPM_{ct-5} + \varepsilon_{cit} \\ \varepsilon_{cit} = \delta_c + \gamma_t + u_{cit} \text{ or } \varepsilon_{cit} = \alpha_{ci} + \gamma_t + u_{cit} \end{aligned} \tag{7}$$

where *ind* is a vector of dummy variables indicating 2-digit SIC industry (see Table 1) and non-emitters have zeros in all dummy variables; β_4-β_7 are coefficient vectors in which each element corresponds to pollutant-specific regulation effects on each 2-digit SIC industry.

The results from the model with county by industry and time fixed effects are presented in Table 3. Estimation results from the models with county and/or time fixed effects are additionally provided in Table A7. All coefficients are estimated in a single regression described in equation (7). These estimates provide detailed information on not only regulation effects of four pollutants on a particular emitter but regulation effects of a given pollutant across emitters. A shaded cell indicates a sector which emits pollutants in the corresponding column according to the classification suggested by Greenstone (2002). All of the estimates in shaded areas are statistically either zero or negative. Note that there exit several sectors that are not emitters of a particular pollutant by the standards of Greenstone, but are significantly influenced by the pollutant-specific regulation: for example, producers of chemical and allied products are not CO or PM emitters by the classification of Greenstone, but the CO and PM nonattainment designation are shown to reduce the annual industrial wages by 6.9% and 4.9%, respectively. This implies that classifying each industry into pollutant-specific emitters might not appropriate since an industry that emits a specific pollutant is likely to be an emitter of other pollutants as well.

Test for equal effects of a pollutant across industry (the second last row in table 3) suggests that regulation effects of each pollutant on emitters' wages differ by industry. Wages in manufacturing sectors such as chemical & allied products and petroleum & coal products are affected negatively by the CO regulation. The O_3 regulation also has a negative impact on wages in petroleum & coal sector. In particular, the CO and O_3 regulations are responsible

[25] Greenstone (2002) also implements 4.5% and 9% assignment rule for robustness check, but these choices of cutoffs also seem to be made without any scientific basis.

for approximately 24% and 11% of wage reduction in the manufacturing sector of petroleum & coal products. Wage loss of 7% in manufacturers of paper & allied products is attributed to the SO_2 regulation, while the same regulation seems to increase wages by 10% in the sector of fabricated metal. The PM regulation induces wage reduction of 2% and 5% in the sectors of paper & allied products and chemical & allied products respectively. On the contrary, wages in the sector of fabricated metal are shown to increase by 10% and 3% due to the SO_2 and PM regulations. Other than the fabricated metal products industry, each pollutant-specific regulation shows non-positive effects on all emitters as expected. Unexpected wage gain in the sector of fabricated metal induced by the SO2 and PM regulations might be attributed to unobserved characteristics unique to the industry such as distinct factor-intensity of pollution abatement activities, and thus it requires further investigation.

Table 3. Modified Wage Model - Equation (4)

SIC	Industry	CO (β_4)	O3 (β_5)	SO2 (β_6)	PM (β_7)	Equal Effect across Pollutant?
24	Lumber &wood	-0.003	0.001	0.048	0.018	Yes
		(0.025)	(0.021)	(0.058)	(0.015)	
26	Paper&allied	0.015	0.000	-0.065*	-0.022*	Yes
		(0.017)	(0.016)	(0.034)	(0.013)	
27	Printing&publishing	-0.003	-0.019	0.025	0.017	Yes
		(0.022)	(0.014)	(0.033)	(0.017)	
28	Chem.&allied	-0.069**	-0.026	-0.015	-0.049***	Yes
		(0.027)	(0.019)	(0.045)	(0.019)	
29	Petroleum&coal	-0.238***	-0.111***	0.091	0.030	No
		(0.064)	(0.033)	(0.068)	(0.052)	
30	Rubber&misc. plastic	-0.002	0.000	0.010	0.019	Yes
		(0.018)	(0.015)	(0.025)	(0.014)	
32	Stone,clay&glass	0.045*	-0.006	0.011	0.022	Yes
		(0.024)	(0.019)	(0.036)	(0.014)	
33	Primary metal	0.003	-0.018	-0.013	-0.017	Yes
		(0.024)	(0.021)	(0.044)	(0.015)	
34	Fabricated metal	0.008	0.017	0.098**	0.032***	Yes
		(0.015)	(0.014)	(0.039)	(0.012)	
37	Transportaion equip.	-0.030	-0.023	-0.019	0.021	Yes
		(0.033)	(0.028)	(0.064)	(0.031)	
Equal effect across Industry?		No	No	No*	No	
Fixed Effects =Year, County x Indusry ; R-squared = 0.9389 #obs = 13,127						

Notes: Dependent variable = log(real payroll). Equality of regulation effects = “No” if significant at 5% level (*: significant at 10% level). Coefficients from each panel are from a single regression. Shaded cells represent sectors emitting the corresponding pollutant in the top row according to Greenstone (2002). Robust standard errors are used. Each observation is weighted by average number of employees in the current and previous periods. See the notes in Table 2 for the list of covariates. *** p<0.001, ** p<0.05, * p<0.1

The hypothesis that regulation effects on a particular sector are equal across all of the four regulated pollutants (the last column in table 3) is rejected only in the case of the manufacturing sector of petroleum & coal products. The other sectors show equal regulation effects across pollutants.

To sum up, I find from the modified wage model that 1) regulation effects of each pollutant on emitters’ wages differ by industry; 2) Three sectors that are most affected include petroleum & coal, chemical & allied products and paper & allied products. Particularly, wages in the petroleum & coal products industry are down by a total of 35% due to the CO and O_3 regulations. The 2005 PACE survey in the last three columns of Table A2 supports this evidence by showing that total expenditures for pollution abatement in these industries are highest among manufacturing sectors.

6.2 Spatial Two-Stage Least Squares (S2SLS)

As an attempt to separate out spatial dependence and capture spillover across counties, neighboring counties' mean wages are included and estimated, using spatial 2SLS. In the first stage, surrounding counties' wages are regressed on a set of IVs, (Z, WZ, W^2Z) and its fitted values are generated. Z includes shipments, population, nonattainment status by pollutant, %Male, %Age 19 and below, %Age 20-34, %Age 35-54, %Age 55-64, %Age 65-84, %Black, %Hispanic, %Bachelor's degree and above (and squared of it), %Never married, %Veteran, poverty rate, and unemployment rate. Estimation results for the first stage are given in Table A6. Large F statistics with or without the presence of any fixed effects suggest that Z, WZ and W^2Z are valid instruments.[26] Declining AIC and BIC associated with the inclusion of fixed effects is in favor of the fixed effects model. The model with county and time fixed effects, shown in column (6), is chosen to generate fitted values for neighboring counties' mean wages.

The results from the second stage are given in Table 4. Column (1), (3) and (5) are for models without the spatial lag, the same as columns (2), (4) and (6) in Table 2. Note that there are signs of positive spatial dependence in wages and estimates for policy effects are little changed with the presence of the spatial lag. Column (2) suggests that the local wages rise 3.8% when mean wages in neighboring non-polluting counties increase by 10%.[27] The *direct* O3 regulation effects on wages in O3 emitters are -3.1%. Since the coefficient on the spatial lag is 0.38, *spillover* from immediately neighboring O3 emitters in nonattainment counties is -1.2% (= -3.1% * 38%). Taking into account spillover from higher-order neighbors as well, I obtain a total of -5% (= -3.1 * 1/(1-0.038)). Thus, in the presence of wage spillover, the model without the spatial lag in column (1) underestimates the policy effect in absolute term (-4.7% vs. -5.0%). Similarly, the model with the spatial lag as well as county

---

[26] One concern about estimating the first stage is that as the more fixed effects are added, the less the IVs explain the dependent variable. In other words, when individual fixed effects are present, explanatory power mostly come from the fixed effect, not the IVs.

[27] Since wages are log-transformed, the coefficient on spatial lag should be interpreted as elasticity of local wage with respect to *geometric* mean wages in surrounding regions. Suppose that there are three regions that are contiguous each other. A simple spatial lag model for a particular region, e.g. region 1, can be written as $\log(y_1) = \alpha + \beta(0.5(\log(y_2) + \log(y_3)) + \epsilon_1$. Note that $\beta = (dy_1/y_1)/(d\sqrt{y_2 y_3}/\sqrt{y_2 y_3})$. Strictly speaking, the interpreting the coefficient on the spatial lag as a partial regression coefficient is partially correct since the neighboring values depend on the dependent variable. (Anselin, 2003)

and time fixed effects in column (4) results in a total of -2.6% (= -2.1% * 1/(1-0.207)) as PM regulations effects on PM emitters while the model only with county and time fixed effects in column (3) yields PM regulations effects of -2.1%. Test for equal regulation effects across pollutant in the specification with the spatial lag show similar results to the model without the spatial lag.

Table 3. Spatial 2SLS Wage Model

	(1)	(2)	(3)	(4)	(5)	(6)
CO regulation effect	0.007	0.000	0.015	0.015	0.003	-0.003
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
O3 regulation effect	-0.047***	-0.031**	0.001	0.001	0.003	0.005
	(0.015)	(0.015)	(0.014)	(0.014)	(0.010)	(0.010)
SO2 regulation effect	-0.021	-0.006	-0.004	-0.004	-0.080***	-0.080***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.027)	(0.027)
PM regulation effect	-0.018	-0.018	-0.021*	-0.021	-0.009	-0.009
	(0.014)	(0.014)	(0.012)	(0.013)	(0.008)	(0.008)
Mean Wages		0.383***		0.207*		0.066
in neighboring counties		(0.033)		(0.122)		(0.072)
R-squared	0.505	0.518	0.621	0.616	0.938	0.937
County Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes	Yes	Yes	Yes
County FE			Yes	Yes		
County x Industry FE					Yes	Yes
Equality of Reg. Effects	2.16	0.81	1.06	1.04	2.73	2.80
(F-stat & p-value)	(0.090)	(0.486)	(0.367)	(0.375)	(0.042)	(0.038)
#obs	13,127	12,622	13,127	12,622	13,127	12,622

Notes: Dependent variable = log(real payroll). Robust standard errors in parentheses. Each observation is weighted by average number of employees in the current and previous periods. See notes in Table 2 for the list of covariates. *** p<0.001, ** p<0.05, * p<0.1

The measure of spillover, however, seems to be decreasing as more fixed effects are added in the model. In the model with county by industry and time fixed effect, the coefficient on the spatial lag declines to 0.066 and is not statistically different from zero. This occurs since spatial lagged dependent variable (WE) and fixed effects are correlated. In other words, neighboring wages are generally likely to be high when the fixed effects of neighboring counties are high and, in turn the county fixed effect is also high. This can be confirmed by checking the residuals of the model without the spatial lag.

Figure A5 shows the Moran plots of residuals where plot A is for column (1), plot B & C are for column (3), and plot D & E are matched with column (5). In plot C and E, fixed effects are added to the residuals. Plot A, which shows the relationships between a county's residual and its neighbors' residual, depicts significantly positive slope. This positive slope is reflected to the large spatial coefficient in column (2). The Moran plot B of residuals from county and time fixed effects model (column (3)) show flatter slope, but when county fixed effects are considered with the residuals, the spatial dependence becomes stronger. Similar pattern is also true to the Moran plot D & E of residuals from county by industry and time fixed effect model.

Additionally, I assume that any emitter could be affected by any of pollutant-specific nonattainment status while not restricting a particular industry to an emitter of a specific pollutant. Under this assumption, the spatial 2SLS results are provided in Table 5, which shows the estimated model with county by industry and time fixed effects. Estimation results from the models with county and/or time fixed effects are presented in Table A8. The same fitted values of the spatial lag previously generated in the first stage are added in equation (7) to estimate the effects of spatial dependence. Note that wage spillover across counties is not statistically different from zero. This is consistent with the previous results from fixed effects models in column (6), Table 4. *Direct* Regulation effects by pollutant are quite similar to those in Table 3. Tests for equality of regulation effects across industries and pollutants are also unchanged with the inclusion of the spatial lag.

Major findings point out that the presence of wage spillover has the slightest impact on the *direct* policy effect, but the *overall* effects must take into account *spillover*. I find an evidence of the existence of spillover, but it is not so evident in the preferred fixed effects model.

Table 4. S2SLS - Modified Wage Model

SIC	Industry	CO (β_4)	O3 (β_5)	SO2 (β_6)	PM (β_7)	Equal Effect across Pollutant?
24	Lumber &wood	-0.002	0.001	0.047	0.020	Yes
		(0.025)	(0.021)	(0.058)	(0.015)	
26	Paper&allied	0.014	0.001	-0.065*	-0.022*	Yes
		(0.017)	(0.016)	(0.034)	(0.013)	
27	Printing&publishing	-0.002	-0.016	0.030	0.018	Yes
		(0.023)	(0.014)	(0.033)	(0.018)	
28	Chem.&allied	-0.070**	-0.025	-0.013	-0.049**	Yes
		(0.027)	(0.020)	(0.045)	(0.019)	
29	Petroleum&coal	-0.238***	-0.111***	0.084	0.030	No*
		(0.063)	(0.033)	(0.068)	(0.052)	
30	Rubber&misc. plastic	-0.003	0.000	0.011	0.019	Yes
		(0.018)	(0.015)	(0.025)	(0.014)	
32	Stone,clay&glass	0.044*	-0.001	0.011	0.019	Yes
		(0.024)	(0.018)	(0.036)	(0.014)	
33	Primary metal	0.002	-0.018	-0.015	-0.016	Yes
		(0.024)	(0.021)	(0.044)	(0.015)	
34	Fabricated metal	0.009	0.018	0.099**	0.032***	Yes
		(0.015)	(0.014)	(0.040)	(0.012)	
37	Transportaion equip.	-0.030	-0.024	-0.016	0.020	Yes
		(0.033)	(0.029)	(0.065)	(0.031)	
Mean Wages in the Neighborhood			0.065 (0.071)			
Equal effect across Industry?		No	No	No*	No	
Fixed Effects =Year, County x Indusry ; R-squared = 0.9386 ; #obs = 12,622						

Notes: Dependent variable = log(real payroll). Equality of regulation effects = “No” if significant at 5% level (*: significant at 10% level). Coefficients from each panel are from a single regression. Shaded cells represent sectors emitting the corresponding pollutant in the top row according to Greenstone (2002). Robust standard errors are used. Each observation is weighted by average number of employees in the current and previous periods. See the notes in Table 2 for the list of covariates. *** p<0.001, ** p<0.05, * p<0.1

6 Conclusions

This paper estimates the effects of the Clean Air Acts on local wages in polluting industries while taking into account wage spillover across counties. Since there occur the shifts in the labor demand due to induced additional costs to emitters and/or in the labor supply due to improved air quality, I find wage reduction in emitters induced by the regulations ranging from 2% to 10% depending on the pollutant, which in the 2005 dollar amount are equivalent to loss of roughly \$800~\$4,000 a year.[28] These findings of negative impact of environmental regulations on wages are consistent with recent empirical studies such as Walker (2012) and Mishra and Smyth (2012). I also find that the regulation effects are not uniform across industries: petroleum & coal, chemical & allied products and paper & allied products are influenced most among emitters. This finding is associated with the fact that these three emitters pay the highest pollution abatement costs. In particular, the CO and O_3 regulations reduced annual wages in the petroleum & coal products industry by a total of 35%. The CO and PM regulation decreased annual wages in the chemical & allied products industry by 12%. The paper & allied products industry suffered loss of earnings by 9% due to the SO_2 and PM regulations.

In the presence of positive wage spillover, which might occur, for example, in the process of wage negotiation, overall policy effects should take into account spillover from other counties as well as direct policy effects. Using fixed effects spatial 2SLS (Baltagi and Liu, 2011), this paper attempts to capture any possible wage spillover which was not a main focus in or was ignored by previous studies. I find an evidence of the existence of spillover, but unfortunately it is not so evident in the preferred fixed effects model.

It is important to understand that since this study focus only on “direct effects” to affected business, its results should not be extended to “indirect effects”, i.e., asymmetric distribution of regulation effects could provide other firms or workers with relative advantage (Bartel and Thomas, 1985). Moreover estimating *net* regulation effects in terms of overall welfare should require different framework that exhaustively encompasses indirect long-term gain in competitive advantage for firms and human health effects caused by air quality benefit as well as direct costs. Policy makers must remember that environmental policy should be laid out by balancing costs and benefits.

This paper provides room for further applications that could be addressed in future research. This study assumes a simple structure of wage spillover: cross-county spillover based on geographical proximity and no inter-industry interaction. It might be useful to see whether the structure of regional inter-industry interactions described in state input-output tables (or for smaller regions, if available) could be incorporated or whether economic

[28] This calculation is based on the emitters’ 1982-2007 average payroll of \$41,084 in the 2005 dollars.

proximity, for example inter-regional trade-flow-type weight matrix, could better capture wage spillover structure.

References

Anselin, L. 2003. “Spatial externalities, spatial multipliers, and spatial econometrics.” *International Regional Science Review*, *26*(2), 153-166.

Anselin, L., Gallo, J. L., & Jayet, H. 2008. “The Econometrics of Panel Data.” Netherlands: Springer: 625-660.

Babcock, Linda, John Engberg, and Robert Greenbaum. 2005. “Wage spillovers in public sector contract negotiations: the importance of social comparisons.” *Regional Science and Urban Economics* 35(4):395–416.

Baltagi, BH, and L Liu. 2011. “Instrumental variable estimation of a spatial autoregressive panel model with random effects.” *Economics Letters* (127).

Bartel, AP, and LG Thomas. 1987. “Predation through regulation: the wage and profit effects of the Occupational Safety and Health Administration and the Environmental Protection Agency.” *J. Law Econ.* 30 (October), 239–264.

Bartik, T.J., 1988, “The effects of environmental regulation on business location in the United States.” *Growth Change* 19, 22-44

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. 2009. “Migration and hedonic valuation: The case of air quality.” *Journal of Environmental Economics and Management* 58(1):1–14.

Becker, Randy a. 2005. “Air pollution abatement costs under the Clean Air Act: evidence from the PACE survey.” *Journal of Environmental Economics and Management* 50(1):144–169.

Becker, Randy, and Henderson, Vernon. 1997. “Effects of air quality regulation on decisions of Firms in Polluting Industries.” *NBER Working paper.*

Berman, Eli, and Bui, LTM. 2001a. “Environmental regulation and productivity: evidence from oil refineries” *Review of Economics and Statistics*, 83(August):498–510.

_______________________ 2001b. “Environmental regulation and labor demand: evidence from the South Coast Air Basin.” *Journal of Public Economics* 79(2):265–295.

Budd, J.W., 1992. “The determinants and extent of UAW pattern bargaining.” *Industrial and Labor Relations Review* 45, 523–539.

__________ 1995. “The internal union political imperative for UAW pattern bargaining.” *Journal of Labor Research* 16, 43–55.

__________ 1997. “Institutional and market determinants of wage spillovers: evidence from UAW pattern bargaining.” *Industrial Relations* 36, 97–116.

Chay, Kenneth, and Greenstone, Michael. 2003. “The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession.” *The Quarterly Journal of Economics* (August):1121–1168.

Chay, Kenneth, Dobkin, C, and Greenstone, M. 2003. “The Clean Air Act of 1970 and adult mortality.” *Journal of Risk and Uncertainty* 27(3):279–300.

Chay, Kenneth Y, and Greenstone, Michael. 2005. “Does air quality matter? Evidence from the housing market.” *Journal of Political Economy* 113(2).

Davidson, J. M., & Norbeck, J. M. (2012). “An Interactive History of the Clean Air Act: Scientific and Policy Perspectives.” Massachusetts: Elsevier.

Duffy-Deno, KT. 1992. “Pollution Abatement Expenditures and Regional Manufacturing Activity.” *Journal of Regional Science* 32(4):419–436.

Drewes, Torbens. 1987. “Regional Wage Spillover in Canada.” *The Review of Economics and Statistics* 69(2):224–231.

Edwards, J. H., and A. W. F. Edwards. 1984. Approximating the tetrachoric correlation coefficient. Biometrics 40: 563.

Greenstone, Michael. 2002. “The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures.” Journal of Political Economy 110(6):1175–1219.

Greenstone, M. 2004. Did the Clean Air Act cause the remarkable decline in sulfur dioxide concentrations?. *Journal of environmental economics and management*, *47*(3), 585-611.

Forster, B. A. 1984. “The backward incidence of pollution control: A dual approach.” *Journal of environmental economics and management*, *11*(1), 14-17.

Hanna, R., & Oliva, P. 2011. “The Effect of Pollution on Labor Supply: Evidence from a Natural Experiment in Mexico City” (No. w17302). National Bureau of Economic Research.

Hausman, Jerry, Bart Ostro, and David Wise 1984. “Air Pollution and Lost Work.” NBER Working Paper No. 1263

Hazilla, Michael, and RJ Kopp. 1990. “Social cost of environmental quality regulations: A general equilibrium analysis.” *Journal of Political Economy* 98(4):853–873.

Henderson, V. 1996. “Effects of air quality regulation.” *The American Economic Review 86* (September):789–813.

Herberich, David. 2010. “Three quasi-experimental and experimental papers in environmental economics.” PhD Dissertation, University of Maryland

Hollenbeck, Kevin. 1979. “The Employment and Earnings Impacts of the of Stationary Source Air Pollution1.” *Journal of Environmental Economics and Management* (6):208–221.

Kahn, ME. 1997. “Particulate pollution trends in the United States.” *Regional Science and Urban Economics* 27(1):87–107.

Kahn, Matthew E, and Mansur, Erin T. 2010. “How Do Energy Prices , and Labor and Environmental Regulations Affect Local Manufacturing Employment Dynamics ? A Regression Discontinuity Approach.” *NBER Working paper* (November).

Kelejian, HH, and IR Prucha. 1998. “A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances.” *The Journal of Real Estate Finance and Economics* 17:99–121.

Krueger, AB, and Summers, LH. 1988. “Efficiency wages and the inter-industry wage structure.” *Econometrica* 56(2):259–293.

Lacombe, Donald J. 2004. “Does Econometric Methodology Matter? An Analysis of Public Policy Using Spatial Econometric Techniques.” *Geographical Analysis* 36(2).

Levinson A., 1996, “Environmental regulations and manufacturers’ location choices: Evidence from the Census of Manufactures”, *J. Public Econom*. 62, 5–29 (1996).

List, JA, and McHone, WW. 2000. “Measuring the effects of air quality regulations on ‘dirty’ firm births: evidence from the neo-and mature-regulatory periods.” *Papers in Regional Science* 79(2):177–190.

LeSage, James and Pace, R. Kelley. 2009. “Introduction to Spatial Econometrics.” New York, Taylor & Francis Group.

McCarthy, J. E., Copeland, C., Parker, L., & Schierow, L. J., 2011. “Clean Air Act: A Summary of the Act and Its Major Requirements.” Congressional Research Service (CRS)

McConnell V. D. and Schwab R. M., “Impact of environmental regulation on industry location decisions: The motor vehicle industry”, *Land Econom*. 66, 67–81 (1990).

Miguel, E, and M Kremer. 2003. “Worms: identifying impacts on education and health in the presence of treatment externalities.” *Econometrica* 72(1):159–217.

Mishra, Vinod, and Russell Smyth. 2012. “Environmental regulation and wages in China.” *Journal of Environmental Planning and Management* 55(8):1075–1093.

Morgenstern, Richard D., William a. Pizer, and Jhih-Shyang Shih., 2002. “Jobs Versus the Environment: An Industry-Level Perspective.” *Journal of Environmental Economics and Management* 43(3):412–436.

Ostro, B. D. 1983. “The effects of air pollution on work loss and morbidity.” *Journal of Environmental Economics and Management*, *10*(4), 371-382.

O'sullivan, A. 2007. Urban economics. New York, NY: McGraw-Hill/Irwin.

Ready, K., 1990. “Is pattern bargaining dead?” *Industrial and Labor Relations Review* 43, 272–279.

Roback, Jennifer. 1982. “Wages, Rents, and the Quality of Life.” *Journal of Political Economy* 90(6):1257.

Walker, R. 2012. “The Transitional Costs of Sectoral Reallocation: Evidence From the Clean Air Act and the Workforce.” *US Census Bureau Center for Economic Studies Paper* (August).

Wang, L. F. 1990. “Unemployment and the backward incidence of pollution control.” *Journal of environmental economics and management*, *18*(3), 292-298.

Yohe, Gary. 1979. “The Backward Incidence Statics of Pollution in General Equilibrium.” *Journal of environmental economics and management* 6:187–198.

Yu, E. S., & Ingene, C. A. (1982). “The backward incidence of pollution control in a rigid-wage economy.” *Journal of environmental economics and management*, *9*(4), 304-310.

Appendix

Appendix A. How to construct a contiguity-based spatial weight matrix

This appendix illustrates an example in which county 1 & 2 and county 2 & 3 are sharing borders, and one polluter and one nonpolluter are located in each county.

County 1 (Nonattainment) Polluter / Nonpolluter	County 2 (Attainment) Polluter / Nonpolluter
	County 3 (Nonattainment) Polluter / Nonpolluter

Each element in the weight matrix, W, indicates whether an industry (polluter or nonpolluter) is contiguous to other industries in other counties. It is assumed that industries in the same counties are not interacting, in other words, they are not contiguous. The spatial weight matrix based on Rook and Queen contiguity are given by

$$W^R = \begin{array}{c} \begin{array}{cccccc} \multicolumn{2}{c}{C1} & \multicolumn{2}{c}{C2} & \multicolumn{2}{c}{C3} \\ P & N & P & N & P & N \end{array} \\ \begin{pmatrix} 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{cc} P & \multirow{2}{*}{C1} \\ N & \\ P & \multirow{2}{*}{C2} \\ N & \\ P & \multirow{2}{*}{C3} \\ N & \end{array} \qquad W^Q = \begin{array}{c} \begin{array}{cccccc} \multicolumn{2}{c}{C1} & \multicolumn{2}{c}{C2} & \multicolumn{2}{c}{C3} \\ P & N & P & N & P & N \end{array} \\ \begin{pmatrix} 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{cc} P & \multirow{2}{*}{C1} \\ N & \\ P & \multirow{2}{*}{C2} \\ N & \\ P & \multirow{2}{*}{C3} \\ N & \end{array}$$

where only border-sharing counties are neighbors in W^R; county 1 & 3 are also neighbors in W^Q since they are sharing a point of border. For example, the (1,3)-th element in W^R and W^Q indicates that the polluter in county C1 and the polluter in county C2 are neighbors. Row-standardized matrix is constructed by dividing each element by row sum.

Appendix B. Fixed Effects Spatial Two-stage Least Squares Estimator (Baltagi and Lui, 2011)

A spatial lag model with fixed effects are given by

$$y = \lambda(I_T \otimes W_N)y + X\beta + \iota_T \otimes \mu + u \tag{a}$$

where $y = (y_{11}, \ldots, y_{1N}, \ldots, y_{T1}, \ldots, y_{TN})'$; $W_N =$ a N×N spatial weight matrix; $\mu =$ a N×1 vector of individual fixed effects, $\iota_T =$ a T×1 vector of ones; $X =$ a NT×k covariate matrix; $\beta =$ a k×1 vector of coefficients; a NT×1 random vector of u is assumed to be i.i.d. and independent of X and μ. Rearranging equation (a) in a reduced form yields

$$y = A^{-1}(X\beta + \iota_T \otimes \mu + u) \quad \text{where } A = I_{NT} - \lambda(I_T \otimes W_N)$$

Note that the spatial lagged dependent variable $(I_T \otimes W_N)y$ and the disturbance term u are correlated since

$$E[(I_T \otimes W_N)yu'] = E[(I_T \otimes W_N)A^{-1}(X\beta + \iota_T \otimes \mu + u)u'] = (I_T \otimes W_N)A^{-1}\Omega \neq 0$$

where $\Omega = E[uu']$. Let $Q = (I_T \otimes I_N) - (T^{-1}J_T \otimes I_N) = (I_T - T^{-1}J_T) \otimes I_N$ where J_T is a T×T matrix of ones and let $\tilde{y} = Qy$, $\tilde{x} = Qx$, and $\tilde{u} = Qu$. Demeaning the panel data by premultiplying equation (a) by Q removes time-invariant fixed effects and yields

$$\tilde{y} = \lambda(I_T \otimes W_N)\tilde{y} + \tilde{X}\beta + \tilde{u} \tag{b}$$

Note that $Q(I_T \otimes W_N) = \left((I_T - T^{-1}J_T) \otimes I_N\right)(I_T \otimes W_N) = (I_T \otimes W_N)\left((I_T - T^{-1}J_T) \otimes I_N\right) = (I_T \otimes W_N)Q$. Let a matrix of instruments for spatial lagged dependent variable be $H = (X, WX, W^2X)$, in which higher orders of W times X could be included, and let $Z = ((I_T \otimes W_N)y, X)$, $\tilde{Z} = QZ$, and $\delta = (\lambda, \beta)'$. Then, equation (b) can be rewritten as $\tilde{y} = \tilde{Z}\delta + \tilde{u}$. Finally, the estimator for fixed effects spatial 2SLS is given by

$$\hat{\delta}_{FE-S2SLS} = \left(\tilde{Z}' P_{\tilde{H}} \tilde{Z}\right)^{-1} \tilde{Z}' P_{\tilde{H}} \tilde{y}$$

where $P_{\tilde{H}} = \tilde{H}\left(\tilde{H}'\tilde{H}\right)^{-1}\tilde{H}'$, $\tilde{H} = \left(\tilde{X}, W\tilde{X}, W^2\tilde{X}\right) = (QX, QWX, QW^2X) = QH$

Table A1. National Ambient Air Quality Standards (NAAQS) as of 2011

Pollutant		Primary/ Secondary	Averaging Time	Level	Form
Carbon Monoxide		primary	8-hour	9 ppm	Not to be exceeded more than once per year
			1-hour	35 ppm	
Lead		primary and secondary	Rolling 3 month average	0.15 $\mu g/m^3$	Not to be exceeded
Nitrogen Dioxide		primary	1-hour	100 ppb	98th percentile, averaged over 3 years
		primary and secondary	Annual	53 ppb	Annual Mean
Ozone		primary and secondary	8-hour	0.075 ppm	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
Particle Pollution	$PM_{2.5}$	primary	Annual	12 $\mu g/m^3$	annual mean, averaged over 3 years
		secondary	Annual	15 $\mu g/m^3$	annual mean, averaged over 3 years
		primary and secondary	24-hour	35 $\mu g/m^3$	98th percentile, averaged over 3 years
	PM_{10}	primary and secondary	24-hour	150 $\mu g/m^3$	Not to be exceeded more than once per year on average over 3 years
Sulfur Dioxide		primary	1-hour	75 ppb	99th percentile of 1-hour daily maximum concentrations, averaged over 3 years
		secondary	3-hour	0.5 ppm	Not to be exceeded more than once per year

Source: http://www.epa.gov/air/criteria.html

Table A2. Costs for Pollution Abatement by Industry

(Million Dollars)

NAICS	Description	Value of shipments	Operating Cost Total	Operating Cost Labor	Operating Cost Depreciation	Capital Exp. Total	CapEx. / Labor cost	(CapEx.+depr.) / Labor cost	Total Costs / Ship. (%)	(Rank)	Oper.Cost / Ship. (%)	CapEx. / Ship. (%)
	ALL INDUSTRIES	**4,735,383.7**	**20,677.6**	**4,095.9**	**2,848.4**	**5,907.8**	**1.44**	**2.14**	**0.56**		**0.44**	**0.12**
311	Food	534,878.2	1,572.8	256.8	198.7	449.0	1.75	2.52	0.38	(9)	0.29	0.08
312	Beverage&Tabacco	123,635.7	277.6	44.1	34.4	77.6	1.76	2.54	0.29	(13)	0.22	0.06
313	Textile mills	41,149.1	221.1	28.6	14.1	30.9	1.08	1.57	0.61	(8)	0.54	0.08
314	Textile prod. Mills	36,705.6	34.9	7.4	2.2	5.3	0.72	1.01	0.11	(19)	0.10	0.01
316	Leather&allied	6,012.9	51.2	10.3	5.9	1.7	0.17	0.74	0.88	(5)	0.85	0.03
321	Wood	112,017.5	566.6	79.7	94.3	142.2	1.78	2.97	0.63	(7)	0.51	0.13
322	Paper	162,848.2	1,796.2	289.6	345.0	573.3	1.98	3.17	1.46	(1)	1.10	0.35
323	Pringing&related support	97,094.5	238.8	36.0	32.4	67.7	1.88	2.78	0.32	(11)	0.25	0.07
324	Petroleum&coal	476,074.7	3,746.1	616.0	479.1	1,743.0	2.83	3.61	1.15	(3)	0.79	0.37
325	Chemical	604,501.2	5,217.2	1,111.5	807.9	1,271.6	1.14	1.87	1.07	(4)	0.86	0.21
326	Plastic&rubber	200,488.7	503.2	118.7	55.7	94.3	0.79	1.26	0.30	(12)	0.25	0.05
327	Nonmetallic	114,320.7	696.0	134.8	113.5	217.4	1.61	2.45	0.80	(6)	0.61	0.19
331	Primary metal	201,835.5	2,291.1	406.7	305.6	511.9	1.26	2.01	1.39	(2)	1.14	0.25
332	Fabricated metal	288,067.9	763.3	206.9	78.5	168.2	0.81	1.19	0.32	(10)	0.26	0.06
333	Machinery	302,203.6	315.8	94.6	36.0	47.4	0.50	0.88	0.12	(18)	0.10	0.02
334	Computer&electronic	373,931.9	623.8	185.3	65.4	155.9	0.84	1.19	0.21	(15)	0.17	0.04
335	Electrical equip, allliance&component	112,078.0	190.8	58.6	18.7	33.0	0.56	0.88	0.20	(16)	0.17	0.03
336	Transportation equip	687,287.7	1,319.1	338.7	140.2	260.1	0.77	1.18	0.23	(14)	0.19	0.04
337	Furniture&related	84,290.6	133.0	35.5	14.1	30.8	0.87	1.26	0.19	(17)	0.16	0.04
339	Misc.	144,381.8	115.5	35.1	6.6	27.7	0.79	0.98	0.10	(20)	0.08	0.02

Source: the 2005 Pollution Abatement Costs and Expenditure (PACE), the Census Bureau

Table A3. Data Availability in the 1987 Census of Manufactures that is publicly available

2-digit			Up to 4-digit (Greenstone)		
code	Descrpition	NM(%)	code	Descrpition	NM(%)
24	Lumber &wood	72.7	24	Lumber&Wood	62.1
26	Paper&allied	40.2	2611-31	Pulp&Paper	***4.0***
27	Printing&publishing	69.4	2711-89	Printing	22.5
28	Chem.&allied	45.2	2861-9	Organic Chem	***5.5***
			2812-9	Inorganic Chem.	***3.3***
29	Petroleum&coal	23.0	2911	Petrol. Refin.	***3.6***
30	Rubber&misc. plastic	58.0	30	Rubber&Rubber	42.9
32	Stone,clay&glass	61.7	32	Stone, Clay, Glass	41.3
33	Primary metal	36.9	333-4	Non-ferrous Metals	***4.0***
			3312-3, 3321-5	Iron&Steel	***3.9***
34	Fabricated metal	69.9	34	Fabric. Metals	51.0
37	Transportaion equip.	23.9	371	Motor Vehicle	***9.8***

* NM - Non-missing

Other sample periods show similar patterns.

Table A4. SIC versus NAICS

SIC	Description	NAICS	Description	polluting industry
20	Food&kindred	311	Food	
21	Tobacco	312	Beverage&Tabacco	
22	Textile mill	313	Textile mills	
23	Apprel&other textile	314	Textile prod. Mills	
23	Apprel&other textile	315	Apperel	
31	Leather&leather prod.	316	Leather&allied	
24	Lumber&wood	321	Wood	Y
26	Paper&allied	322	Paper	Y
27	Printing&publishing	323	Pringing&related support	Y
29	Petroleum&coal	324	Petroleum&coal	Y
28	Chemicals&allied	325	Chemical	Y
30	Rubber&misc. plastic	326	Plastic&rubber	Y
32	Stone,clay&glass	327	Nonmetallic	Y
33	Primary metal	331	Primary metal	Y
34	Fabricated metal	332	Fabricated metal	Y
35	Industrial machinery&equip	333	Machinery	
38	Instruments&related	334	Computer&electronic	
36	Electronic&other	335	Electrical equip, allliance&component	
37	Transportation equip	336	Transportation equip	Y
25	Furniture&fixture	337	Furniture&related	
39	Misc.	339	Misc.	

Table A5. County Characteristics

The 1990 Census of Population

	Attainment[1)]	Nonattment[2)]	CO	O3	SO2	PM
Population	33,441	302,656	660,187	374,173	233,539	406,728
%Male	48.9	48.7	48.7	48.6	48.2	48.7
%Female	51.1	51.3	51.3	51.4	51.8	51.3
%Age 19 and below	29.5	28.2	27.8	28.1	28.6	28.5
%Age 20-34	23.5	25.8	26.6	25.9	25.1	26.1
%Age 35-54	24.4	25.7	25.6	25.7	24.9	25.2
%Age 55-64	8.9	8.3	8.2	8.3	8.6	8.3
%Age 65-84	12.3	10.8	10.6	10.8	11.6	10.7
%Age 85 and over	1.4	1.2	1.2	1.2	1.3	1.2
%White	84.5	78.0	72.7	76.4	85.3	75.8
%Black	10.8	12.7	14.7	13.9	10.4	12.6
%Other races	4.7	9.3	12.6	9.8	4.3	11.5
%Hispanic	4.8	11.2	14.2	11.9	4.3	14.0
%High school and above	71.5	77.1	77.3	76.7	79.2	75.9
%Bachelor's degree and above	15.4	22.6	24.2	22.8	20.9	21.6
%Never married	23.3	28.1	30.3	28.4	27.5	29.2
%Ever married	76.7	71.9	69.7	71.6	72.5	70.8
%Veteran	15.0	14.0	13.4	13.7	15.0	13.6
Per capita income ($)	11,765	15,882	16,606	16,194	14,310	15,229
Poverty rate (%)	15.1	11.5	11.9	11.4	11.9	12.8
Unemployment rate (%)	6.2	6.0	6.5	6.0	6.0	6.8
%Manufacturing employment	18.7	16.4	16.1	16.4	18.3	17.7
#County	2,604	534	139	373	53	239

The 2000 Census of Population

	Attainment[1)]	Nonattment[2)]	CO	O3	SO2	PM
Population	52,017	411,885	926,674	451,818	285,598	747,806
%Male	49.1	49.0	49.0	48.9	48.5	49.6
%Female	50.9	51.0	51.0	51.1	51.5	50.4
%Age 19 and below	28.4	28.9	29.2	28.8	28.3	30.6
%Age 20-34	20.3	21.6	22.6	21.6	20.0	23.2
%Age 35-54	29.1	29.8	28.9	29.9	28.8	28.0
%Age 55-64	9.0	8.2	8.1	8.2	8.7	7.7
%Age 65-84	11.6	10.2	9.9	10.1	12.6	9.3
%Age 85 and over	1.6	1.4	1.4	1.4	1.7	1.2
%White	80.3	69.6	63.6	68.8	78.6	62.7
%Black	11.9	12.7	11.1	13.2	12.1	7.0
%Other races	7.8	17.7	25.2	18.1	9.2	30.2
%Hispanic	7.9	17.6	27.1	17.9	9.6	34.1
%High school and above	80.1	80.7	77.6	80.5	83.7	76.2
%Bachelor's degree and above	21.0	28.1	27.4	28.4	24.4	25.3
%Never married	25.1	29.3	31.0	29.5	28.0	30.6
%Ever married	74.9	70.7	69.0	70.5	72.0	69.4
%Veteran	13.9	11.4	9.9	11.2	13.8	10.6
Per capita income ($)	19,632	23,704	22,973	23,967	20,794	21,697
Poverty rate (%)	12.5	11.6	14.0	11.6	11.6	15.0
Unemployment rate (%)	5.5	5.9	6.8	5.9	5.8	7.1
%Manufacturing employment	15.5	12.4	11.4	12.5	13.0	11.9
#County	2,813	328	48	278	23	38

Note: 1) Counties without any of four pollutant-specific nonattainment status; 2) Counties with either CO, O_3, SO_2 or PM nonattainment status; 3) Weights used in each cell are as follows: total county population for sex, age, race, income, and poverty rate; population age 25 years old and over for education; population age 15 years old and over for marriage status; population age 16 (for the 1990 CP, 18 for the 2000 CP) years old and over for veteran status; labor force for unemployment rate; total employment for manufacturing employment

Table A6. Spatial 2SLS - the first Stage

	Dependent variable = W E					
	(1)	(2)	(3)	(4)	(5)	(6)
Z	Yes	Yes	Yes	Yes	Yes	Yes
WZ	Yes	Yes	Yes	Yes	Yes	Yes
W^2Z		Yes		Yes		Yes
Year FE			Yes	Yes	Yes	Yes
County FE					Yes	Yes
F-stat	160.37	116.04	153.56	113.55	84.36	63.30
R-squared	0.605	0.624	0.613	0.629	0.852	0.856
AIC	-5220.31	-5407.81	-5313.21	-5462.32	-9705.83	-9814.05
BIC	-4956.63	-5015.51	-5023.80	-5044.29	-9416.43	-9396.02
#obs	4,588	4,588	4,588	4,588	4,588	4,588

Note:

1. The coefficients are omitted due to limited space.
2. Z includes shipments, population, nonattainment status by pollutant, %Male, %Age 19 and below, %Age 20-34, %Age 35-54, %Age 55-64, %Age 65-84, %Black, %Hispanic, %Bachelor's degree and above (and squared of it), %Never married, %Veteran, Poverty rate, and Unemployment rate.
3. W is a row-standardized Queen-based spatial weight matrix.
4. E represents county-wide average wages.
5. Robust standard errors in parentheses.
6. Each observation is weighted by county population.

Table A7. Modified Wage Model

SIC	Industry	CO (β_4)	O3 (β_5)	SO2 (β_6)	PM (β_7)	Equal Effect across Pollutant?
	(A) FE = Year; R-squared = 0.540, #obs = 13,127					
24	Lumber &wood	-0.096***	-0.088***	-0.136***	0.038	No
26	Paper&allied	-0.041*	-0.107***	-0.126***	0.073***	No
27	Printing&publishing	-0.006	-0.026	-0.138***	0.055**	No
28	Chem.&allied	-0.060**	-0.068***	-0.111***	0.021	No
29	Petroleum&coal	-0.181***	-0.223***	-0.144*	0.295***	No
30	Rubber&misc. plastic	-0.017	-0.122***	-0.083***	0.023	No
32	Stone,clay&glass	-0.022	-0.084***	-0.091***	0.056**	No
33	Primary metal	-0.003	-0.095***	-0.006	0.026	No
34	Fabricated metal	-0.046**	-0.082***	-0.079***	0.071***	No
37	Transportaion equip.	0.024	0.015	0.064*	0.079**	Yes
	Equal effect across Industry?	No	No	No	No	
	(B) FE =Year, County; R-squared = 0.650 #obs = 13,127					
24	Lumber &wood	-0.044**	-0.061***	-0.095**	-0.004	Yes
26	Paper&allied	-0.011	-0.065***	-0.091***	0.047**	No
27	Printing&publishing	0.031	-0.001	-0.152***	0.051*	No
28	Chem.&allied	-0.025	-0.061***	-0.100***	0.028	No
29	Petroleum&coal	-0.177***	-0.150***	-0.073	0.342***	No
30	Rubber&misc. plastic	-0.008	-0.082***	-0.073***	0.027	No
32	Stone,clay&glass	0.017	-0.048***	-0.094***	0.043*	No
33	Primary metal	0.026	-0.042*	0.011	0.000	Yes
34	Fabricated metal	-0.011	-0.041***	-0.069***	0.057***	No
37	Transportaion equip.	0.045	0.082***	0.087**	0.067	Yes
	Equal effect across Industry?	No	No	No	No	
	(C) FE =Year, County x Indusry ; R-squared = 0.9389 #obs = 13,127					
24	Lumber &wood	-0.003	0.001	0.048	0.018	Yes
26	Paper&allied	0.015	0.000	-0.065*	-0.022*	Yes
27	Printing&publishing	-0.003	-0.019	0.025	0.017	Yes
28	Chem.&allied	-0.069**	-0.026	-0.015	-0.049***	Yes
29	Petroleum&coal	-0.238***	-0.111***	0.091	0.030	No
30	Rubber&misc. plastic	-0.002	0.000	0.010	0.019	Yes
32	Stone,clay&glass	0.045*	-0.006	0.011	0.022	Yes
33	Primary metal	0.003	-0.018	-0.013	-0.017	Yes
34	Fabricated metal	0.008	0.017	0.098**	0.032***	Yes
37	Transportaion equip.	-0.030	-0.023	-0.019	0.021	Yes
	Equal effect across Industry?	No	No	No	No	

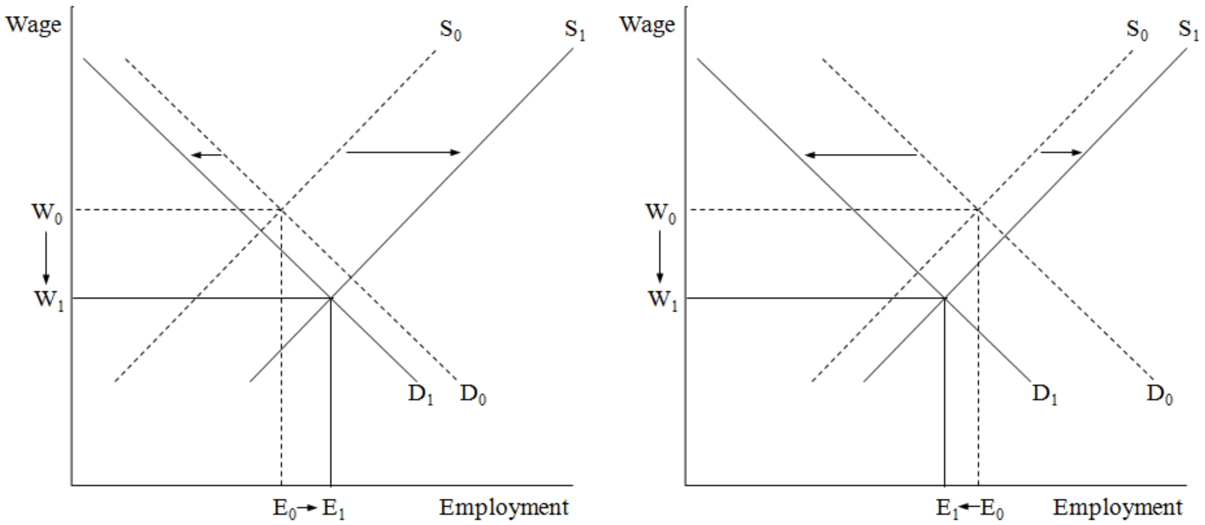
Notes: Dependent variable = log(real payroll). Equality of regulation effects = "No" if significant at 5% level. Coefficients from each panel are from a single regression. Shaded cells represent sectors emitting the corresponding pollutant in the top row according to Greenstone (2002). Robust standard errors are used. Each observation is weighted by average number of employees in the current and previous periods. See the notes in Table 2 for the list of covariates. *** p<0.001, ** p<0.05, * p<0.1

Table A8. Modified Wage Equation - S2SLS

SIC	Industry	CO (β_4)	O3 (β_5)	SO2 (β_6)	PM (β_7)	Equal Effect across Pollutant?
	(A) FE = Year; R-squared = 0.5527, #obs = 12,622					
24	Lumber &wood	-0.096***	-0.080***	-0.056	0.030	No
26	Paper&allied	-0.048**	-0.105***	-0.093***	0.075***	No
27	Printing&publishing	-0.008	-0.022	-0.136***	0.056**	No
28	Chem.&allied	-0.041*	-0.058**	-0.090***	0.016	Yes
29	Petroleum&coal	-0.112***	-0.168***	-0.148*	0.300***	No
30	Rubber&misc. plastic	-0.020	-0.101***	-0.072***	0.026	No
32	Stone,clay&glass	-0.020	-0.064***	-0.079***	0.053**	No
33	Primary metal	-0.011	-0.071***	0.001	0.024	Yes
34	Fabricated metal	-0.042**	-0.067***	-0.070***	0.065***	No
37	Transportaion equip.	0.032	0.032	0.072*	0.081**	Yes
Mean Wages in the Neighborhood			0.415***			
	Equal effect across Industry?	No	No	No	No	
	(B) FE =Year, County; R-squared = 0.6454 #obs = 12,622					
24	Lumber &wood	-0.043*	-0.064***	-0.094*	-0.004	Yes
26	Paper&allied	-0.011	-0.066***	-0.091***	0.048**	No
27	Printing&publishing	0.032	-0.004	-0.153***	0.052*	No
28	Chem.&allied	-0.024	-0.059***	-0.098***	0.029	No
29	Petroleum&coal	-0.184***	-0.163***	-0.077	0.347***	No
30	Rubber&misc. plastic	-0.012	-0.078***	-0.069***	0.026	No
32	Stone,clay&glass	0.016	-0.043**	-0.093***	0.041*	No
33	Primary metal	0.026	-0.041*	0.011	0.001	Yes
34	Fabricated metal	-0.011	-0.039***	-0.069***	0.056***	No
37	Transportaion equip.	0.042	0.082***	0.087**	0.068	Yes
Mean Wages in the Neighborhood			0.161			
	Equal effect across Industry?	No	No	No	No	
	(C) FE =Year, County x Indusry ; R-squared = 0.9386# ; obs = 12,622					
24	Lumber &wood	-0.002	0.001	0.047	0.020	Yes
26	Paper&allied	0.014	0.001	-0.065*	-0.022*	Yes
27	Printing&publishing	-0.002	-0.016	0.030	0.018	Yes
28	Chem.&allied	-0.070**	-0.025	-0.013	-0.049**	Yes
29	Petroleum&coal	-0.238***	-0.111***	0.084	0.030	No*
30	Rubber&misc. plastic	-0.003	0.000	0.011	0.019	Yes
32	Stone,clay&glass	0.044*	-0.001	0.011	0.019	Yes
33	Primary metal	0.002	-0.018	-0.015	-0.016	Yes
34	Fabricated metal	0.009	0.018	0.099**	0.032***	Yes
37	Transportaion equip.	-0.030	-0.024	-0.016	0.020	Yes
Mean Wages in the Neighborhood			0.065			
	Equal effect across Industry?	No	No	No	No	

Notes: Dependent variable = log(real payroll). Equality of regulation effects = “No” if significant at 5% level. Coefficients from each panel are from a single regression. Shaded cells represent sectors emitting the corresponding pollutant in the top row according to Greenstone (2002). Robust standard errors are used. Each observation is weighted by average number of employees in the current and previous periods. See the notes in
Table 2 for the list of covariates. *** p<0.001, ** p<0.05, * p<0.1

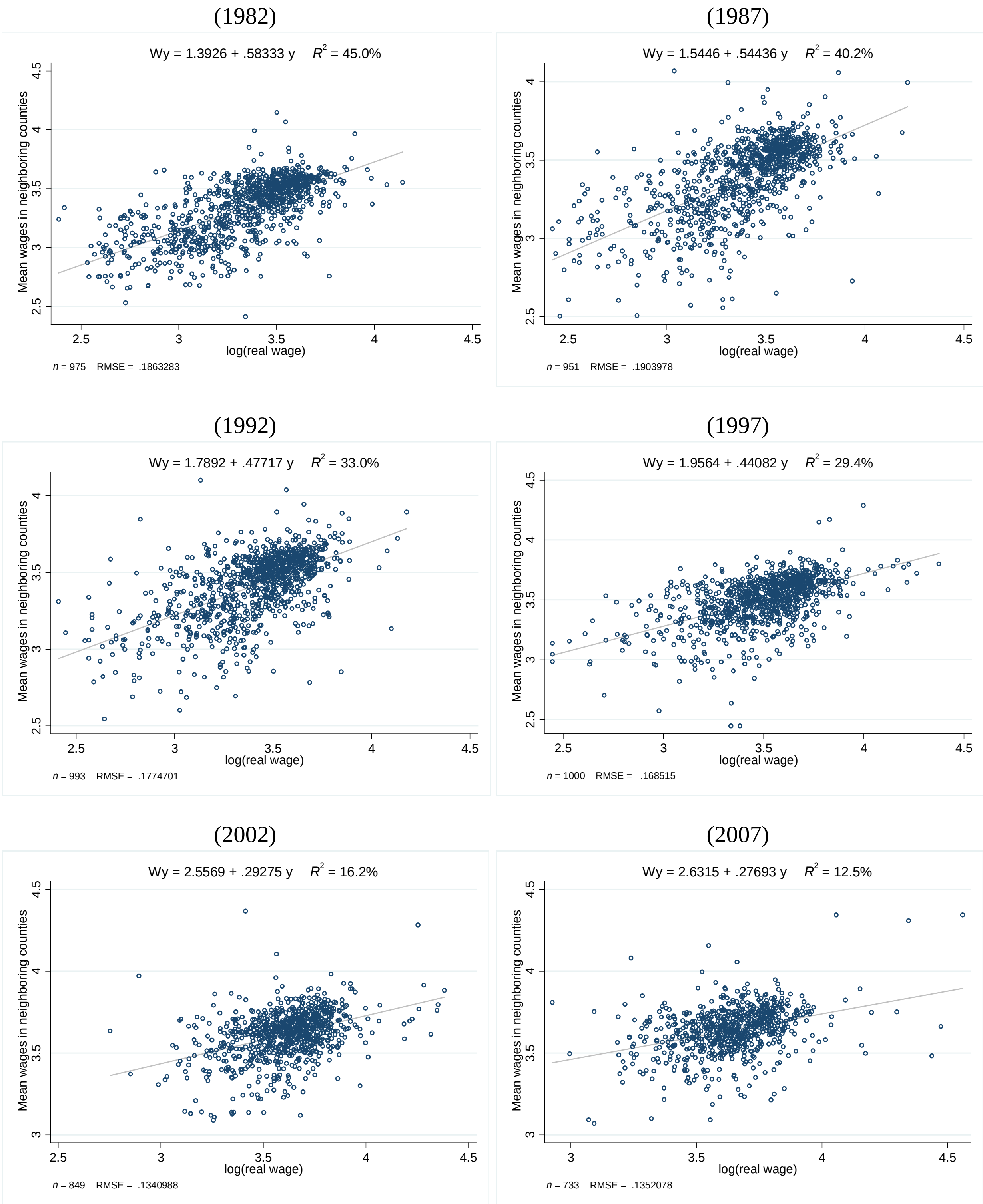
Figure A1. The Effects of the Pollution Tax on Local Labor Markets (O'Sullivan, 2007)



when labor supply is more responsive to the regulation than labor demand

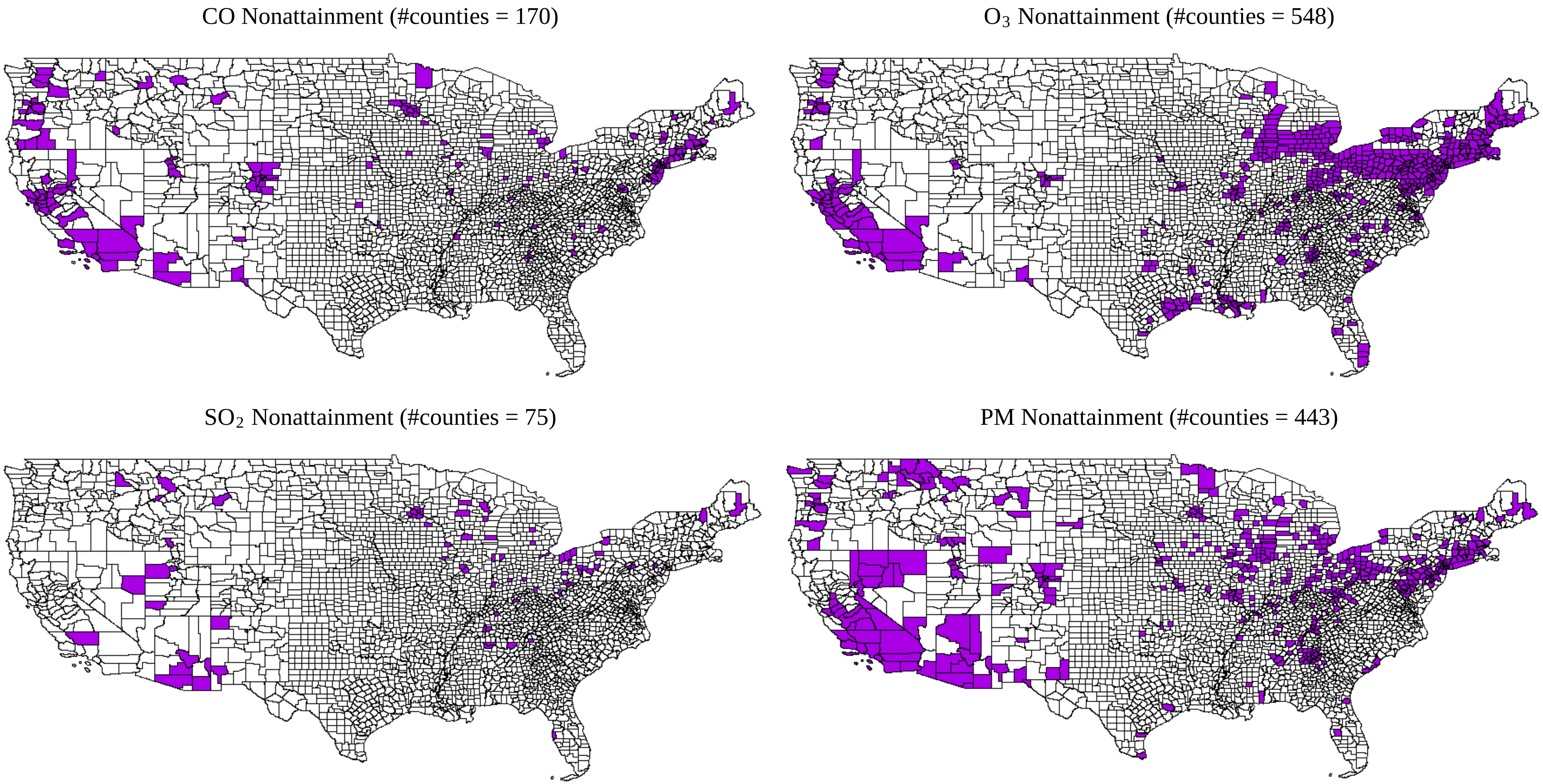
when labor demand is more responsive to the regulation than labor supply

Figure A2. Moran Scatter Plot by Year
(Mean Wages in Neighboring Counties vs. Local Mean Wages)



Note: each dot represents a county.

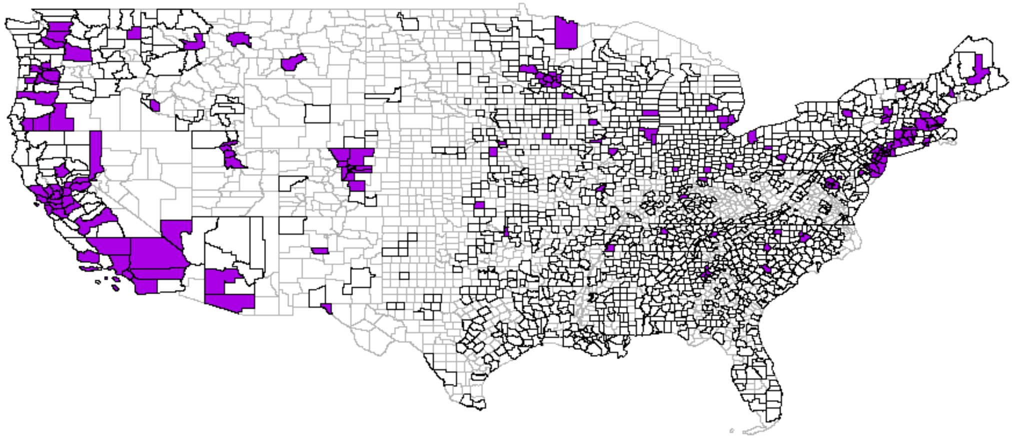
Figure A3. Pollutant-specific nonattainment status for all counties (#total counties = 3,109)



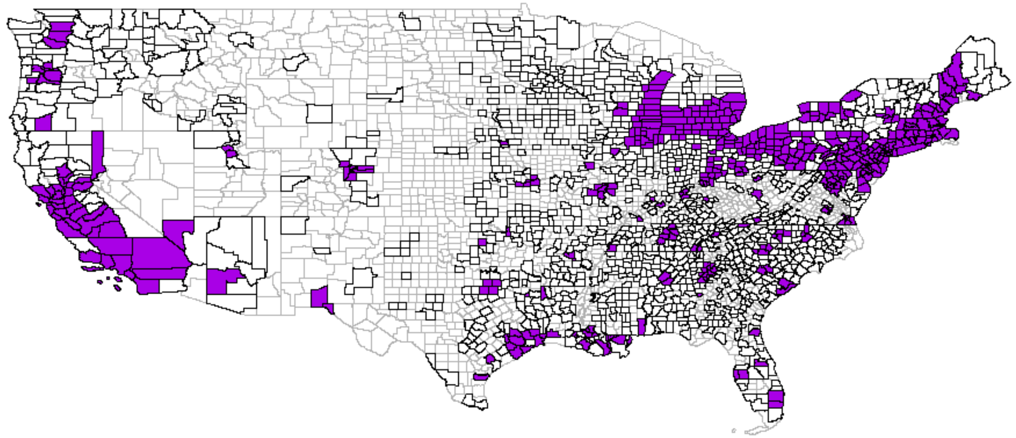
Notes: Black lines represent county borders. All counties in 50 states excepts for Alaska and Hawaii are included. Shaded counties are the ones which have been designated at least once as pollutant-specific nonattainment during the Census years (1982, 1987, 1992, 1997, 2002, and 2007).

Figure A4. Pollutant-specific nonattainment status for counties in the Census samples (#total counties in the Census samples = 1,448)

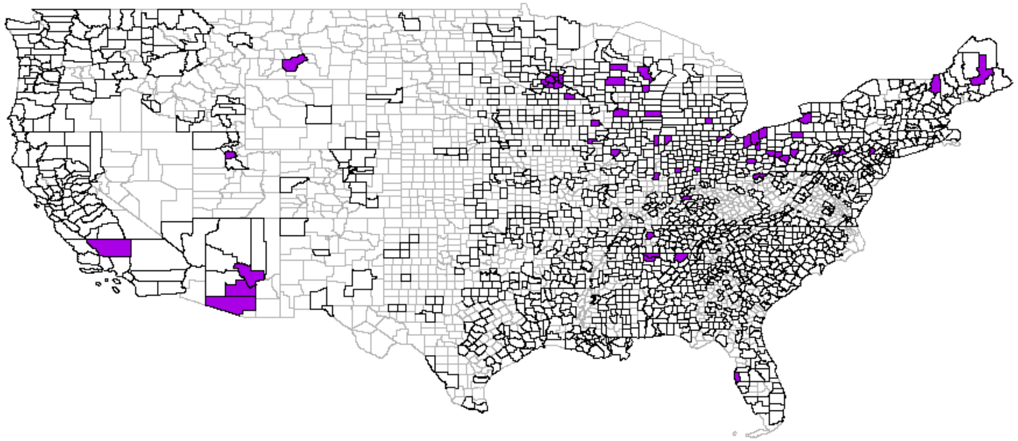
CO Nonattainment (#counties = 161)



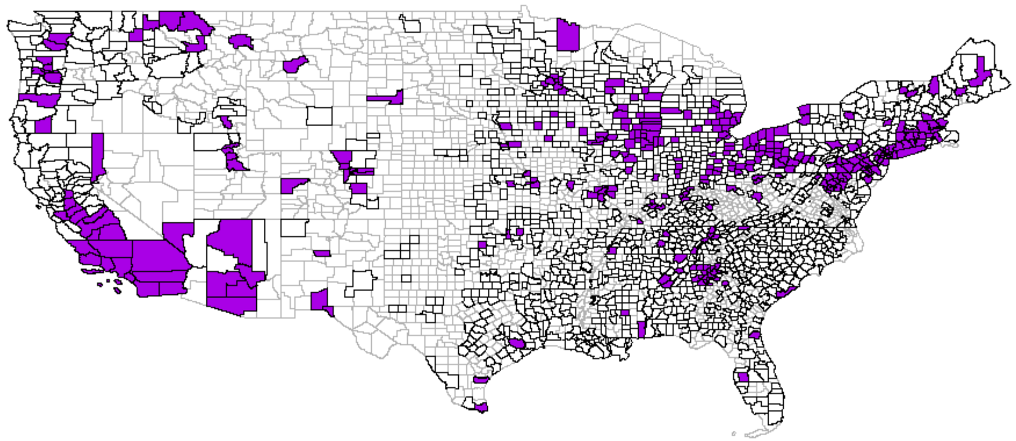
O_3 Nonattainment (#counties = 448)



SO_2 Nonattainment (#counties = 54)



PM Nonattainment (#counties = 326)

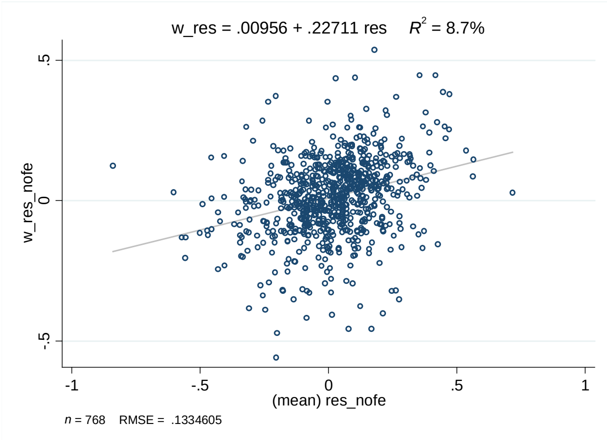


Notes: Grey border lines represent missing counties for the analysis because manufacturing wages in the 1982, 1987, 1992, 1997, 2002, and 2007 Census are unavailable or incomplete due to data confidentiality. Available counties in 50 states excepts for Alaska and Hawaii are included. Shaded counties are the ones which have been designated at least once as pollutant-specific nonattainment during the Census years.

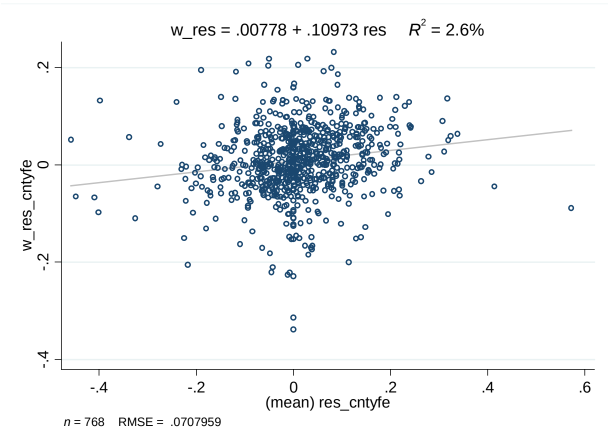
Figure A5. Moran Plot of Residuals (from equation (1))

All plots below are for the year 1987. The other sample years show similar patterns.

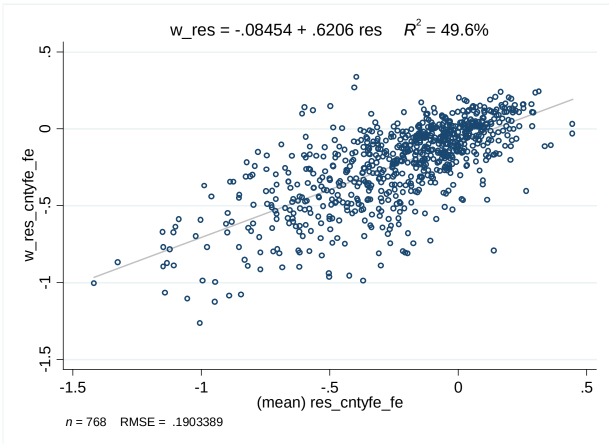
A. Residuals from pooled OLS



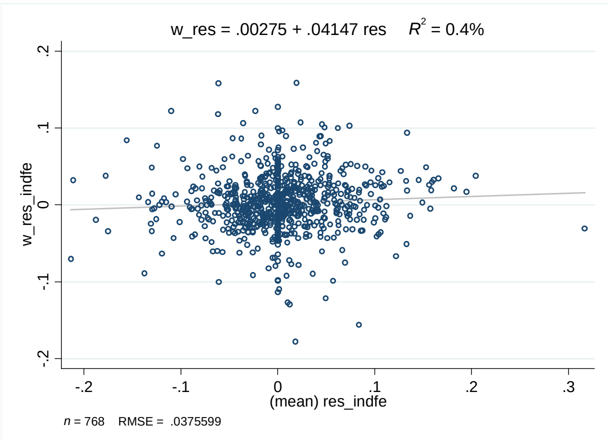
B. Residuals from county FE model



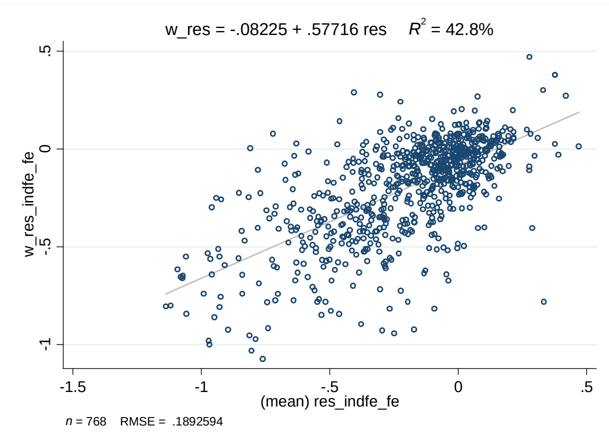
C. County FE + (B)



D. Residuals from county x industry FE model



E. County x industry FE + (D)



Note: each dot represents a county.