Pollution Abatement and Environmental Equity: A Dynamic Study*

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Abstract

We study pollution abatement and environmental equity in a dynamic panel model using data for 236 plants in the US pulp and paper industry observed over the period 1985–1997. We suggest a theoretical model for the plant manager who incorporates regulatory pressures into his calculations of optimal amount of pollution. Assuming actual pollution abatement exhibits a sluggish adjustment process, the theoretical model leads to an empirical AR(1) panel model. Using an instrumental variable approach, we estimate our model using both "temporally lagged" and "spatially lagged" economic instruments. We find that children and people below the poverty line are exposed to more pollution, whereas the elderly are exposed to less pollution. These findings confirm the existence of differential treatment based on population characteristics.

Keywords: pollution abatement, environmental equity, dynamic panel, instrumental variable, fixed effects.

1 Introduction

The question of whether disadvantaged population groups, such as racial and socioeconomic minorities, are disproportionately exposed to pollution and whether demographic composition influences the amount of pollutants generated has been studied for roughly two decades. One of the goals of the US Environmental Protection Agency (EPA) is to ensure that "everyone enjoys the same degree of protection from environmental and health hazards and equal access to the decision-making process to have a healthy environment in which to live, learn, and work.[1]" However, while environmental and political groups continue to lobby for "environmental justice," especially with respect to racial and ethnic minorities, the results of economic studies have been ambiguous. There has been no agreement on whether disadvantaged population groups are exposed to more pollution and if so, which of the racial, age, or socioeconomic minorities are more at risk.

This paper studies whether the racial, education, age, and income based population groups are disproportionately exposed to emissions of air pollutants. Specifically, we are interested in whether plants are allowed to emit more air pollutants if their neighborhood has a more disadvantaged population group. From the methodology point of view, this paper is the first to attempt bringing the dynamic panel model into the area of environmental equity studies. We seek to answer this question by examining changes in air pollution emissions for a sample of 236 pulp and paper plants from 1985–1997 and by correlating these changes with changes in the characteristics of communities surrounding the plants. Our results show that neighborhoods with a higher percentage of children and a higher percentage of the population below

[1] Environmental Protection Agency (EPA): http://www.epa.gov/environmentaljustice/

the poverty line are exposed to higher emissions of air pollutants, and that the elderly are exposed to lower emissions of air pollutants. These findings are consistent with the existence of differential treatment based on population characteristics.

The initial study in the literature was produced by the United Church of Christ's Commission (UCC) for Racial Justice (1987). This descriptive study documented that the zip codes which had more pollution as measured by the presence of a treatment, storage, and disposal facility (TSDF), had a higher percentage of minorities (twice that of the areas without TSDFs). They also noted that the relationship between socioeconomic status variables and pollution were not as significant.

Since this seminal study, the quantity and quality of the environmental equity studies has improved remarkably. One area of improvement is the measurement of the dependent variable. Earlier papers (for example, Anderton et al. [1994], Boer et al. [1997], Pollock and Vittas [1995], Oakes, Anderton, and Anderson [1996]) use proximity to nauseous facilities as a proxy for environmental risk, whereas later studies use actual pollution emissions levels (see Brooks and Sethi [1997], Daniels and Friedman [1999], Ringquist [1997], Gray and Shadbegian (2004), Morello-Frosch, Pastor and Sadd [2004]). In this sense, this paper uses actual pollution levels cited at the plant (emissions of particulate matters less than $10\mu m$ [PM10] and emissions of sulfur dioxide [SO_2]) and focuses on the pulp and paper industry dataset which is extended from Gray and Shadbegian (2004).

A second area of improvement has been the attempt to control for alternative explanations and addressing the inherent temporal dimension of environmental equity: assessing the "chicken and the egg" question with respect

to risk exposure and community demographics. Although many studies acknowledge the existence of this issue, most of them are not able to remedy the problem. Ringquist (1997) uses a control variable approach by controlling for housing prices, whereas Gray and Shadbegian (2004) use instrumental variables and control for alternative explanations. This paper addresses this problem through the use of spatially lagged instruments extended to a dynamic model from Gray and Shadbegian (2004).

However, regardless of these improvements, there has been no agreement reached on whether the inequalities with respect to minorities exist. Moreover, there is disagreement in literature reviews as well with respect to what the findings are. Ringquist (2005) provides a fairly good literature review on this subject and a meta study to analyze why conclusions about the existence of environmental inequity differ across studies and attempts to extract a generalizable conclusion. He finds that the differences in the choice of pollution measurement, levels of aggregation, and control factors do not explain away the existence of inequity with respect to race. He also finds that there is less evidence to support inequity with respect to the poor.

We try to add a new angle to the existing literature by addressing the issue of methodology. The contribution of this paper is threefold. The first methodological problem is that the process of pollution abatement is a dynamic process. It is very hard to reduce pollution overnight since it frequently requires changes in equipment and integration with the existing production technology. Hence, pollution abatement may exhibit a sluggish adjustment phenomena. As the empirical literature has so far focused on cross-sectional results, the sluggish adjustment phenomena of pollution abatement is not captured, nor is the delayed response to the dynamic changes in the population

demographic composition. For example, consider a case where the percentage of the poor population in a neighborhood decreased over the last period and there is environmental inequity, so there was high pollution. Because pollution adjusts sluggishly, it did not yet catch onto the change in the composition and remained high in the current period. Regressing current high pollution levels on current decreased percentage of the poor may result in a misleading conclusion that the poor are not more exposed to pollution when in fact they are. This paper deals with inertia in the environmental performance of firms using an instrumental variables partial adjustment model. The second methodological problem is that regressing the pollution amounts on the demographic characteristics introduces an endogeneity problem. The minorities could have self-selected themselves into the more polluted neighborhoods due to the lower housing prices. This paper deals with the endogeneity problem through the use of spatially lagged instruments suggested by Gray and Shadbegian (2004) in their cross-sectional study and extended to a dynamic model. The third methodological problem comes from the inherent difficulty in accounting for the heterogeneity of the firms' production technology and other firm-specific effects. Gray and Shadbegian (2004) used variables such as pulp capacity and paper capacity to control for the plant-specific effects. Although it is better to try controlling for these effects than to leave them unaccounted for, it is hard to control for all of these effects due to a lack of data. Instead, we rely on the methodological advantage of our dynamic panel model. That is, we can bypass the whole issue by first differencing out these fixed effects in a dynamic panel setting.

The rest of this paper is organized as follows: Section 2 proposes a dynamic model of pollution adjustment that allows for a lag in abatement. Section 3

describes the Census and the pulp and paper industry data along with the merging procedures. Section 4 provides a description of the GMM methodology and specifies the choice of instruments for estimating our econometric model. Section 5 discusses results. Section 6 concludes that environmental equity is not met with respect to children and people below the poverty line.

2 Theory: model of dynamic regulation

To model the pollution regulation and compliance within the confines of economic theory, we have two choices in general. The first approach is to model the environmental regulators (such as the EPA and state level regulators) that maximize the total social benefits subject to the total social costs. The optimal level of pollution is reached when the marginal social benefit of pollution abatement equals the marginal social cost. This approach was taken by Gray and Shadbegian (2004). The second approach is to model the firms' behavior under pollution regulation. We choose the second approach in our model.

We construct a simple and intuitive dynamic model for the typical plant whose pollution is under environmental regulation. The plant manager is assumed to be a profit maximizing agent who, in the absence of pollution regulation and in order to maximize his plant's profit, would choose to pollute the environment at such a high level that it becomes unacceptable to the society. The society, through its pollution regulating agencies, is assumed to be the ultimate driving force behind the reduction of pollution. The pollution regulating agencies will interact with the plants through their regulating pressures. The plant manager, under the regulatory environment, fundamentally changes his profit-maximizing calculations to incorporate the regulatory

pressures. When he does that, he arrives at an optimal level of pollution, P^*, which, among other things, depends on the regulatory pressure the plant receives. There are other important factors in determining P^*, the most important one is the plant's existing production technology, out of which the pollution comes as a by-product. For simplicity, we assume that P^* depends on the plant's production technology and the regulatory pressures, as in the following equation:

$$P^* = f(T, R) \tag{1}$$

where T stands for the plant's production technology and R stands for the regulatory pressures the plant faces.

We take the linear expansion of $f(\cdot)$ and assume that the plant's production technology stays relatively fixed through time, denoted T_i. We further assume that the regulatory pressure R consists of two parts: a relatively time-independent regulatory pressure R_i and a relatively time-dependent regulatory pressure R_{it}. Moreover, we assume that the relatively time-dependent regulatory pressure R_{it} itself consists of two parts: an observable part O_{it} and an unobservable part U_{it}. Thus, equation (1) becomes:

$$P^*_{it} = \alpha_i T_i + \beta_1 R_i + \beta_2 O_{it} + \beta_3 U_{it} \tag{2}$$

It is rather self-evident that a plant's pollution emissions depend on its technology, since pollution can be viewed as a by-product of the plant's production process. The assumption that the plant technology stays constant through time seems justifiable: the typical production process is largely dependent on the capital equipment whose life-cycle tends to be long, factory

buildings last a long time once built, and floor plans stay put once the production line is in place. It is particularly justifiable in our case since the pulp and paper industry we study is very capital-equipment intensive. The variable R_i captures the possibility that the heterogeneity among plants may induce regulators to impose plant-specific regulatory pressures. A plant may be considered more politically important by the regulators for various reasons, such as its political visibility, its unionization, its voting district's pro-environmental voting records, etc. In general, both T_i and R_i encompass numerous aspects that are easy to list but hard to account for due to the lack of data. Gray and Shadbegian (2004) attempted to control for at least some of these aspects, such as the pulp and paper capacity, return on assets, and Occupational Health and Safety Administration (OSHA) violations. On the other hand, as one of the methodology advantages we promote, we favor to difference them away rather than controlling for them. Our dynamic panel setting allows us to conveniently difference these fixed effects away and allows us to focus on the main issue of environmental justice.

The decomposition of R_{it} into an observed part O_{it} and an unobservable part U_{it} is done to facilitate our empirical study, which focuses on observable data, such as population demographic characteristics. The unobservable data U_{it} will eventually enter into the error terms of our empirical estimation.

At time t, the plant manager will compare the actual level of pollution P_{it} with the optimal level of pollution P^*_{it}, then their difference will be the target amount of pollution to be abated for the period $t+1$, denoted as $Abate^*_{it+1}$ in the following equation:

$$Abate^*_{it+1} = P_{it} - P^*_{it} \tag{3}$$

We also make the sluggish adjustment assumption. That is, we assume that the actual pollution abatement for the $t+1$ period, $Abate_{it+1}$, is only a fraction γ of the theoretical pollution abatement $Abate^*_{it+1}$:

$$Abate_{it+1} = \gamma(P_{it} - P^*_{it}) \tag{4}$$

It is reasonable to assume that the adjustment process is sluggish over time. One possible scenario is that many pollution abatement projects require investments in pollution abatement capital, which takes time to plan and install. Another possible explanation is that it may take time and some learning by doing to fully incorporate pollution abatement processes into the existing production technology. In either of these scenarios, the pollution will be gradually reduced over time as the abatement projects become fully operational.

The actual pollution at time $t+1$ will be expressed as the difference between the actual pollution in the last period P_{it} and the actual pollution abatement for the $t+1$ period:

$$P_{it+1} = P_{it} - Abate_{it+1} \tag{5}$$

Combining equations (4), (2), and (5), we reach the following equation:

$$P_{it+1} = \gamma(\alpha_i T_i + \beta_1 R_i) + (1-\gamma)P_{it} + \gamma\beta_2 O_{it} + \gamma\beta_3 U_{it} \tag{6}$$

Notice the first term in equation (6) can be regarded as the unobservable fixed effect. Hence, we can take the standard step to difference out the fixed effect and arrive at our main equation:

$$\Delta P_{it+1} = (1-\gamma)\Delta P_{it} + \gamma\beta_2(\Delta O_{it}) + \gamma\beta_3 \Delta U_{it} \tag{7}$$

A special case to equation (7) is when $\beta_2 = 0$. When none of the observable regulating variables such as population characteristics matter in deciding the optimal pollution, and assuming that the U_{it} term becomes part of the error term, equation (6) simplifies into the following:

$$P_{it+1} = F_i + (1 - \gamma)P_{it} + \varepsilon_{it} \tag{8}$$

where $F_i = \gamma(\alpha_i T_i + \beta_1 R_i)$ is the fixed effect and ε_{it} is the error term. And similarly, equation (7) simplifies into the following simple AR(1) model:

$$\Delta P_{it+1} = (1 - \gamma)\Delta P_{it} + \Delta\varepsilon_{it} \tag{9}$$

In our empirical analysis section, we use the above model to estimate two air pollutants: particulates (PM10) and sulfur dioxide (SO_2) for the pulp and paper industries in the United States, observed between 1985–1997. Then we make some attempt to unveil the regulatory pressure variables: the effects of population demographic characteristics on pollution.

3 Data

In our empirical study, we use two data sets: the yearly plant-level pollution data that comes from the Gray and Shadbegian (2004) study of US pulp and paper mills and the decade level population demographic characteristics data (1970–2000) from the Census. The first data set contains 306 plants from the pulp, paper, and cardboard industries (SICs 2611, 2621, and 2631) observed during the period 1985–1997. Due to the dynamic panel nature of our study, we require the plants to have at least three consecutive observations. We are left with 277 plants after this requirement. Due to the dynamic nature of

the model and taking the first difference to eliminate the fixed effects, we lose the first two years of observations. Thus, we are left with the period 1987–1997. In 1992, the Census of Manufacturing reported a total of 529 plants. Hence, we are covering about half of these plants, which tend to be larger than the average plant in the industry as the result of EPA coverage. The second data set used in our study is compiled from the 1970, 1980, 1990, and 2000 US Census of Population data for Census block groups.[2] It contains the demographic characteristics of the population within a 50-mile radius of each plant. To determine which Census block groups fall within the 50-mile radius of the plant, the distances are calculated between the plant and the centroid of each block group. Then, the values for these block groups are aggregated to determine the demographic characteristics for each plant's 50-mile radius neighborhood. For the purpose of constructing "spatially-lagged" instruments, the population demographic characteristics for the area between 50 and 100 miles from the plant (the "doughnut") are also constructed in the same fashion and included in this data set.

In our yearly plant-level pollution data set, we focus the air pollution measures on particulates (PM10) and sulfur dioxide (SO_2). These measures originally come from the Aerometric Information Retrieval System database for 1985–1990 and from the National Emissions Inventory for 1990–1997. Since there is a large variation in the reported emissions among different plants, we take the natural logarithm of the pollution levels as our pollution measures.

To study the "environmental justice" issues, we merge our plant-level yearly pollution data with the Census decade level data set. The demographic characteristics we consider represent different schemes, such as socioeconomic sta-

[2] This data has been complied in the Census-CD data sets prepared by Geolytics, Inc. and merged using the GIS.

tus, racial composition, and sensitivity of population towards pollution. To measure socioeconomic status, we use the variable (PPOOR), which is the percentage of the population below the poverty line. We also use the variable (PHSDROP), which stands for the percentage of the population who are high school drop-outs. For racial background characteristics, we use the percentage of population that is white (PWHITE) and non-white (PNONWHITE = 1−PWHITE). Children and elderly are considered to be the groups of population that are especially sensitive to the air pollution. We compute the percentage of population under six years old (PKIDS) and the percentage of total population over the age of 65 (PELDERS).

Ideally our demographic variables data should contain yearly characteristics instead of decade level data. But the reality is that this yearly data is not available at the present time. However, given that the population characteristics tend to change gradually and smoothly over the years, we can obtain approximations to the yearly level population variables using a natural cubic spline interpolation model. To complete the process of natural cubic spline interpolation, we require each plant to have the population variables for all of the four years (1970–2000). We are left with 236 plants after this requirement.

The natural cubic spline interpolation uses a cubic polynomial for approximation, as shown in the following formula:

$$Y_i(t) = a_i + b_i t + c_i t^2 + d_i t^3$$

where $Y_i(0) = y_i$ and $Y_i(1) = y_{i+1}$ for $i = 0, ..., n-1$. On top of the end condition, we require $Y_i'(1) = Y_{i+1}'(0)$ for $i = 0, ..., n-1$. The second derivatives are also set to $Y_i''(1) = Y_{i+1}''(0)$ for $i = 0, ..., n-1$. In addition to that, $Y_0''(0) = Y_n''(1) = 0$. These conditions will solve uniquely for a_i, b_i, c_i, d_i.

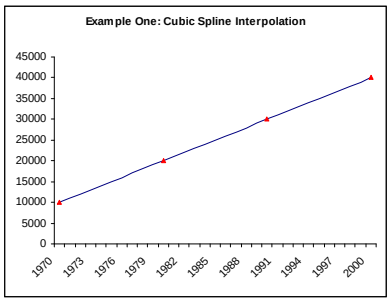

Figure 1: Cubic spline fit: straight line.

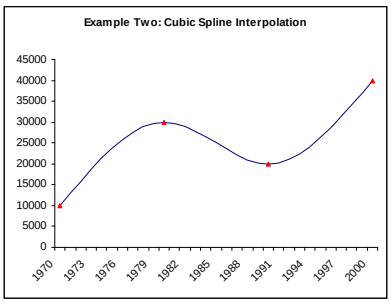

Figure 2: Cubic spline fit: curvy line.

Figures (1) and (2) show examples of the interpolation quality for four points we chose at random.

Including the demographic characteristics can create an endogeneity problem; that is, some of these groups tend to have lower income and come to live in the polluted areas due to the cheaper housing rate. To correct this problem, we use the "spatially lagged" instruments suggested by Gray and Shadbegian (2004). For each decade, we calculate each of the demographic variables for the plant neighborhood within a 50–100 mile radius of the plant. As the distance from the plant increases, the level of pollution decreases while the demographic characteristics in the general area remain similar. This will make the "spatially lagged" instruments strong.

Year	**Observations**	**PM10**	**SO_2**
1987	118	5.05 (1.96)	6.78 (1.64)
1988	133	4.89 (2.15)	6.70 (1.66)
1989	148	4.80 (2.17)	6.54 (1.91)
1990	166	4.50 (2.28)	6.34 (2.07)
1991	170	4.32 (2.28)	6.23 (2.17)
1992	207	4.18 (2.35)	5.94 (2.44)
1993	226	4.03 (2.34)	5.60 (2.76)
1994	231	3.97 (2.38)	5.45 (2.91)
1995	235	3.88 (2.41)	5.29 (3.00)
1996	233	3.76 (2.41)	5.27 (3.03)
1997	233	3.74 (2.42)	5.25 (3.03)

Notes:
(a) Both pollution measurements are in logs
(b) Mean and standard deviation in parenthesis
(c) Total number of plants is 236

Table 1: Mean and Standard Deviation for Pollution Data

Table 1 provides the descriptive statistics for each year for the log of each of the air pollutants. The means of both pollutants have been declining over the years, but there is considerable variation in the emission variables across the plants. Table 2 shows the descriptive statistics for the demographic variables in each decade.

Variable (in %)	Year	Mean and St. Dev
PPOOR	1970	11.6 (5.1)
	1980	11.3 (3.3)
	1990	12.3 (4.2)
	2000	11.5 (3.4)
PKIDS	1970	10.4 (0.8)
	1980	8.5 (1.0)
	1990	8.7 (0.6)
	2000	7.9 (0.7)
PELDERS	1970	9.5 (1.7)
	1980	10.9 (1.7)
	1990	12.8 (1.8)
	2000	12.9 (1.9)
PHSDROP	1970	46.7 (6.6)
	1980	32.7 (6.1)
	1990	24.7 (5.3)
	2000	18.6 (4.5)
PNONWHITE	1970	24.0 (31.4)
	1980	13.6 (11.0)
	1990	15.7 (12.1)
	2000	18.9 (12.9)

Notes:
(a) Mean and standard deviation are reported for each decade
(b) Based on observations for 236 plants
(c) PPOOR is the percentage of the population below poverty
(d) PKIDS is the percentage of the population under 6 years old
(e) PELDERS is the percentage of the population over the age of 65
(f) PHSDROP is the percentage of the population who are high school drop-outs
(g) PNONWHITE is the percentage of the population who are non-white

Table 2: Mean and Standard Deviation for Demographic Variables

4 Methodology

In this section we provide an overview of the econometric methodology used in our empirical analysis to study the possibility of demographic discrimination and test whether it exists. The model we are using is a panel AR(1) model with fixed effects:

$$P_{it} = \alpha_i + \rho P_{it-1} + \eta D_{it-1} + \varepsilon_{it} \tag{10}$$

where α_i represents the plant i's unobservable fixed effect, which is invariant across time, $\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$ is the unobserved error term, which could include the unobserved regulatory pressure as we have discussed in our theory section, $\rho = (1 - \gamma)$, with γ being the abatement coefficient from our theory, and P_{it} is the measured pollution variable (PM10 or SO_2) of plant i at time t.[3]

This model is very good at capturing the heterogeneity among the plants i, via the fixed effect α_i. α_i represents the plant's specific characteristics, such as the plant-specific technology for each plant. These plant-specific characteristics can not be observed or measured. Hence, they can not be controlled for in a cross-section model. The lagged AR(1) variable is used to represent the sluggish adjustment of the dependent variable, pollution.

To deal with the incidental parameter problem, we eliminate the unobserved fixed effect by taking the first difference and arrive at the equation[4]

$$\Delta P_{it} = \rho \Delta P_{it-1} + \eta \Delta D_{it-1} + \Delta \varepsilon_{it} \tag{11}$$

where $\Delta P_{it} = P_{it} - P_{it-1}$ represents the sluggish adjustment of the firm's pollution, $\rho = (1 - \gamma)$ and $\eta = \beta_2 \gamma$ according to our dynamic theoretical model. ΔD_{it-1} represents the yearly change in the demographic composition around the plant.

A nice feature of equation (11) is that it has differenced out the fixed effects, and has eliminated the need to find the control variables and estimate

[3] This equation corresponds to equation (6) in our theoretical model of pollution abatement.

[4] This corresponds to equation (7) in the theory section.

them. Therefore, although the initial equation (10) provides a nice aesthetic theoretical model, what we are really estimating here is the effect of the changes in the right hand side variables on the changes in the dependent variable.

To estimate equation (11), we use the Generalized Method of Moments (GMM) framework analogous to Arellano and Bond (1991). Our slight modification is that we use both temporally and spatially lagged variables, which must both be included in the instrumental variable matrix.

By using differencing to remove the fixed effects, we made the lagged regressor ΔP_{it} correlated with the error term in equation (11). To resolve this issue we instrument for the lagged variable ΔP_{it-1} with the optimal "temporally-lagged" instrumental variable matrix which is suggested by Arellano and Bond (1991). The instruments are all values of the levels P_{it} lagged two periods or more. However, it is worth noting that the strength of these instruments depends on the unknown parameter of interest, ρ. In particular, when the coefficient ρ is close to 1 these instruments are weak.[5]

Also, this model is suffering from the endogeneity problem in the demographic variables ΔD_{it-1}. The minorities could have moved to the polluted area near the plant due to the cheaper housing rent/price or due to the lower-wage job availability in the pulp and paper industry. To remedy this endogeneity problem we have two choices of instruments: we can either use economic instruments that come from economic theory or we can resort to "temporally lagged" instruments similar to Arellano and Bond (1991). Although the "temporally lagged" instruments are convenient and readily available, they may be weak if the time series are too persistent. To avoid this problem we chose to use economic instruments. That is, we use the "spatially-lagged"

[5] This is because when the lag coefficient is close to 1 the process becomes a random walk.

demographic variables described in the data section $\Delta\widetilde{D}_{it-1}$ to instrument for ΔD_{it-1}. Hence, the instrumental variable matrix consists of both the "temporally lagged" part for pollution and the "spatially lagged" part for demographic variables and the matrix is of the following form

$$Z_i = \begin{bmatrix} P_{i,1} & & & & & & & & & & \vdots & \Delta\widetilde{D}_{i3} \\ & P_{i,1} & P_{i,2} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \vdots & \Delta\widetilde{D}_{i4} \\ & 0 & 0 & P_{i,1} & P_{i,2} & P_{i,3} & & 0 & & 0 & \vdots & \Delta\widetilde{D}_{i5} \\ & \vdots & & & & & \ddots & & & & & \\ & 0 & 0 & 0 & 0 & 0 & \dots & P_{i,1} & \cdots & P_{i,11} & . & \Delta\widetilde{D}_{i11} \end{bmatrix}$$

We test the above model for two pollution measurements PM10 and SO_2. Our starting yearly plant level pollution dataset for the pulp and paper industry has 306 plants observed between 1985 and 1997. To construct our panel data, we require the plants to have at least three consecutive years of record. By construction we lose the first two years of data for each plant. After these requirements, we are left with 236 plants that span the years 1987–1997.

The demographic variables are in percentage terms. We use the percentage of the population that is over 65 years of age (PELDERS), the percentage of the population that is under six years old (PKIDS), the percentage of population below the poverty line (PPOOR), the percentage of the population that is non-white (PNONWHITE), and the percentage of the population that contains high school drop-outs (PHSDROP). We divide our demographic variables into different scheme groups. The first group is the pollution sensitive group. We use the demographic variables PKIDS and PELDERS, since children and the elderly are considered particularly sensitive to pollution. The second group is the economic status group. We include the demographic variable PPOOR for

this group, since whether the population below the poverty line is exposed to more pollution is an important environmental justice issue. The third group is the racial background group where we include the demographic variable PNONWHITE. This aims to address whether minorities are more exposed to pollution, which is another important environmental justice issue. The last group is the education background group for which we use PHSDROP. We are interested in whether educationally disadvantaged, high school drop-outs are more exposed to pollution.

5 Results

Table 3 reports the two-step GMM estimates with the standard errors in parentheses. This estimator tends to have smaller standard errors (see Arellano and Bond [1991]), so the confidence region is very tight. The Sargan test statistic rejects the null hypothesis of serial autocorrelation in the errors. Both Wald test and Kleibergen test, which is robust to weak instruments, indicate the joint significance of the coefficients.

For the pollution variable PM10, the point estimator for the AR(1) coefficient is $\hat{\rho} = 0.536$. For SO_2 the point estimator for the AR(1) coefficient is $\hat{\rho} = 0.417$. Both AR(1) coefficients are significantly positive. From our theory, the AR(1) coefficient has an additional economic meaning: $\rho = 1 - \gamma$, where γ is the pollution adjustment coefficient. Specifically, for PM10, the AR(1) coefficient of 0.536 implies that the pollution adjustment rate is $\gamma = 1 - 0.536 \approx 46\%$. That is, the plants tend to complete 46% of the total targeted PM10 pollution abatement (which is the difference between the actual pollution and the optimal level of pollution) over the following year. Similarly, the plants tend

to complete 58% of the targeted SO_2 pollution abatement over the following year.

Independent Variables	**PM10**		**SO_2**	
AR(1)	0.536**	(0.010)	0.417**	(0.005)
PKIDS	0.119**	(0.059)	0.193**	(0.083)
PELDERS	−0.28 **	(0.065)	−0.349**	(0.065)
PPOOR	0.127**	(0.034)	0.104**	(0.037)
PNONWHITE	0.021	(0.019)	0.034	(0.021)
PHSDROP	−0.017	(0.015)	−0.018	(0.017)
Sargan test	119.9	(65)	100.3	(65)
Wald test	99.3	(6)	39.7	(6)
K test	67.27	(6)	63.8	(6)
Number of observations	2100		2098	

Notes:
(a) Model 2 regression on all demographic variables. Time dummies are included in all equations.
(b) Pollution variables are in logs and demographic variables are in percentages.
(c) Sample Period: 1985-2000 (236 plants)
(d) Standard errors are reported in parenthesis for 2-step GMM estimates robust to heteroskedasticity.
(e) ** indicates significance at 5% level.
(f) In the case of all tests, degrees of freedom for χ^2 statistics are reported in parenthesis.
(g) The Sargan test is a two-step version of the test for serially uncorrelated errors.
(h) The Wald statistic is a test of the joint significance of the independent variables.
(i) The K statistic is the Kleibergen test for joint significance. This test is robust to weak instruments.

Table 3: Results for regression on all demographic variables

This demonstrated the relevance of our approach to the pollution regulation. It shows that for both pollution measures, PM10 and SO_2 in the pulp and paper industry, the pollution has been reducing steadily following the dynamic AR(1) process over the observed years.

Now we look at the results for each of the socioeconomic groups. For the pollution sensitive group, both of the demographic variables (PKIDS and PELDERS) are found to be significant, suggesting the presence of bias or discrimination in the regulatory pressure. A 10% increase in the percentage of children is found to be correlated with 1% higher pollution levels of PM10

and, hence, less reduction in pollution. We would expect the sign of PKIDS coefficient to be positive if the regulators lean towards reducing less pollution for the children who are considered pollution sensitive. For elders, the effect is twice as much: a neighborhood with 10% higher elderly population tends to have 2.8% lower pollution levels of PM10. This finding is against the picture of the benevolent regulators who reduce more pollution for the pollution sensitive children. However, it is not hard to find a rationale for this finding. This could be because children do not vote and their parents are less involved in the political process at their age. Young children imply relatively young parents. The relatively young parents may be too busy making a living to turn their concern for their children's health into real political pressure. The increase in the elderly population, however, leads to less pollution or more pollution reduction. This is in line with the picture that regulators reduce more pollution for the pollution sensitive elderly. Alternatively, this can also be explained by the possibility that the elderly are more active participants of the political process at their age and they potentially have the ability to impose political pressures on the pollution regulators. It is interesting to note that although the health of each population group is considered sensitive to pollution, their coefficients are of opposite sign. Given these results, our data does not support the possibility that the regulators are benevolent and act to reduce more pollution for children and the elderly who are both very sensitive to pollution. On the other hand, it does support the possibility that the regulators act in the interests of people who can actually impose political pressure on them.

For the economic status group, we find that the higher percentage of people below the poverty line in the area is correlated with higher amounts of pollution

and less pollution abatement (a 10% increase in population below poverty is correlated with a 1.2% increase in pollution). This result supports the possibility that the economically disadvantaged, who are below the poverty line, are discriminated against in their pollution exposure. However, the racial minorities (NONWHITE) coefficient is not significantand the education factor has also been found insignificant in pollution exposure.

The results for SO_2 as a pollution measurement are similar in magnitude to those with PM10 pollution. The signs and significance of each of the demographic variables are exactly the same as the ones in the PM10 analysis. Hence, we skip the discussion that should be parallel to the ones we have above for PM10. For both pollution measurements, we have found evidence of inequity for children, the elderly, and the population below the poverty line.

6 Conclusion

We have constructed a dynamic model of pollution where the amount of current emission depends on the emission in the previous year and the demographic characteristics of the population in the plant's neighborhood. To test this model, we took the data on the pulp and paper industry with pollution measurements of particulate matter of less than $10\mu m$, PM10, and sulfur dioxide, SO_2, and merged the dataset with the demographic characteristics in the plant's neighborhood as was reported in the Census. The Census decade level population data is interpolated using the natural cubic spline model to obtain yearly approximations. We have created a simple panel AR(1) model and have used both "temporally lagged" and "spatially lagged" instruments for our estimations. We have estimated our dynamic panel models using two-step

GMM procedures.

For the simple AR(1) model, without demographic characteristics, the results suggest a pollution abatement rate of 42% for PM10 and 32% for SO_2 emissions. For the second model, where we add demographic variables, we find evidence that children below the age of six and people below the poverty line are exposed to significantly higher pollution. The neighborhoods with a higher proportion of elderly population are found to be less polluted. For cautionary purposes, we do not know if the regulators actively favor or discriminate against certain population groups or if the regulators respond to political pressure. In the latter case, we may observe the favorable or discriminating treatment in pollution simply because population groups differ in their ability to impose political pressure on the environmental regulators.

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