NATIONAL CENTER FOR
ENVIRONMENTAL ECONOMICS

Environmental Justice: Do Poor and Minority Populations Face More Hazards?

Wayne B. Gray, Ronald J. Shadbegian, and Ann Wolverton

Working Paper Series

Working Paper # 10-10
September, 2010

U.S. Environmental Protection Agency
National Center for Environmental Economics
1200 Pennsylvania Avenue, NW (MC 1809)
Washington, DC 20460
http://www.epa.gov/economics

Environmental Justice: Do Poor and Minority Populations Face More Hazards?

Wayne B. Gray, Ronald J. Shadbegian, and Ann Wolverton

NCEE Working Paper Series
Working Paper # 10-10
September, 2010

Environmental Justice: Do Poor and Minority Populations Face More Hazards?

Wayne B. Gray[a], Ronald J. Shadbegian[b], and Ann Wolverton[c]

Abstract

In this paper, we examine the large and expanding area of Environmental Justice (EJ). The research in this area has developed from examining relatively simple comparisons of current demographic characteristics near environmental nuisances to performing multiple regression analysis and considering demographics at the time of siting. One area that has received considerably less attention is the identification of potential mechanisms that could be driving observed EJ correlations. We extend the current literature by examining one possible mechanism: the intensity of regulatory enforcement activity. If regulators pay less attention to the environmental performance of plants located near poor and minority areas, those plants might feel less pressure to pursue pollution abatement projects, increasing environmental hazards in those areas. We perform our analysis on a sample of manufacturing plants located near four large U.S. cities: Los Angeles, Boston, Columbus, and Houston. Our analysis of regulatory activity found little evidence that demographic variables have a significant impact on the allocation of regulatory activity. In particular, regulatory activity does not seem to be less intense in plants located near particular demographic groups. It is true that plants located in minority neighborhoods are inspected less often and face fewer enforcement actions, but these effects are nearly always small and insignificant, and plants located in lower-income areas seem to face (surprisingly) more regulatory activity. In a separate analysis, we also find very little evidence that demographic variables significantly influence pollution emissions. . In summary, the results presented here do not show much evidence to support EJ concerns about either regulatory activity or pollution emissions, at least within the set of plants, pollutants, and time periods covered in our analysis.

Keywords: Environmental Justice, regulatory activity, enforcement, political, poor, minority

Subject Matter Classifications: Air Pollution, Distributional Effects, Enforcement Issues

JEL Classifications: D21, Q52, Q56

a. Clark University and NBER, wgray@clarku.edu
b. National Center for Environmental Economics, U.S. Environmental Protection Agency, shadbegian.ron@epa.gov.
c. National Center for Environmental Economics, U.S. Environmental Protection Agency, wolverton.ann@epa.gov.

We would like to thank Kaushik Ghosh for excellent research assistance. The research in this paper was conducted while the authors were Special Sworn Status researchers at the Boston Research Data Center. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau or U.S. Environmental Protection Agency. This paper has been screened to ensure that no confidential data are revealed.

INTRODUCTION

During the 1980s the concept of "Environmental Justice" (EJ) gained prominence in the United States with the publication of studies by the General Accounting Office (1983) and the United Church of Christ (1987), suggesting that predominantly minority and low-income communities were being exposed to disproportionately higher levels of environmental hazards.[1] Since that time the literature has evolved from examining simple correlations between community characteristics and exposure to environmental harm to relatively sophisticated analyses that seek to control for other factors that may affect exposure to environmental hazards. The range of environmental hazards being considered has also expanded. Finally, the possibility of reverse causation has been explored, with the presence of environmental hazards leading to a possible influx of lower-income residents. We provide some discussion of the development of the EJ literature in the early parts of this chapter.

One area that has received less attention is the identification of potential mechanisms that could be driving observed EJ correlations. We extend the current literature by examining one possible mechanism for observed correlations between the demographic characteristics of the community and higher levels of pollution: regulatory enforcement activity. Regulators have some degree of discretion in the way they set permitted pollution levels, inspect plants for potential violations, and/or enforce regulations across facilities. Economic theory suggests that it would be rational for a social planner to direct more of its resources towards enforcing regulations where the potential benefits of abatement are greater (or alternatively, where the costs are lower). However, it is possible that regulators are also susceptible to political pressure. In this case, regulators would direct greater resources towards more politically active communities since they may complain, sue, or make life difficult for the regulator absent action. In other words, the costs of ignoring neighborhood sentiments are arguably greater in some places than they are in others. The level of political and community activism is, in turn, often correlated with socioeconomic factors such as race and poverty, which could lead to potential environmental inequities across neighborhoods.

We perform our regulatory activity analysis on a sample of manufacturing plants located near four large U.S. cities: Los Angeles, Boston, Columbus, and Houston. Our dataset combines EPA data on facility-level enforcement and emissions, Census of Manufacturers data on characteristics including facility age and size, county-level voting data, and 1970-2000 Census of Population data on local community characteristics. We examine two sets of demographic variables: one representing groups expected to have relatively high sensitivity to air pollution (children and elders), and the other representing disadvantaged groups (poor and minorities). We do find significant effects of many plant characteristics on regulatory activity, with larger, fuel-intensive plants and plants in single-plant firms facing greater activity. Plants with past violations and plants in

---

[1] According to the Office of Environmental Justice at EPA, environmental justice exists when "no group of people, including racial, ethnic, or socioeconomic group, … bear[s] a disproportionate share of the negative environmental consequences resulting from industrial, municipal, and commercial operations."

counties with higher voter turnout also face greater activity. These results are consistent with prior research, and are consistent with our expectations.

In contrast, the demographic measures, including the EJ variables, tend to have insignificant and unexpected effects. In particular, we find little evidence that regulatory activity is less intense in plants located near disadvantaged demographic groups. However, plants located in minority neighborhoods, as expected, are inspected less often and face fewer enforcement actions, but these effects are nearly always insignificant, and plants located in lower-income areas seem to face (surprisingly) more regulatory activity. Thus we find little or no evidence for an EJ effect on the regulatory activity related to air pollution, as directed towards these plants.

We also conducted a more traditional EJ analysis, examining air pollution emissions and toxic releases from these plants, to see whether we observe higher emissions from plants located near disadvantaged groups. As part of this analysis we attempt to control for endogeneity between facility emissions behavior and household location decisions by examining community characteristics prior to the emissions decision. Given the possibility for strong correlation between emissions today and emissions in prior periods, we examine whether selecting community characteristics further back in time affects the results. In general, we failed to find much evidence that emissions are correlated with community socioeconomic factors. While this offers no support for EJ effects it is important to note that our regressions also did not find many significant effects for the plant characteristics or political variables.

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature. Section 3 outlines a simple model of how decisions by regulators and firms might be affected by neighborhood characteristics. In section 4 we present a description of our data and our empirical methodology. Section 5 contains our results and finally we present some concluding remarks and possible extensions in section 6.

1. LITERATURE REVIEW

This paper draws from two distinct literatures. The first is what we term the Environmental Justice literature. Traditionally, researchers in this area have largely focused on examining waste facility or landfill locations and determining whether they are positively correlated with community characteristics such as percent minority or poor. As the literature has expanded, researchers have looked more broadly at other types of plants and a broader set of environmental indicators including emissions and enforcement measures. Empirical techniques have also grown more sophisticated, for instance considering the effect of endogeneity between plant location and/or emission decisions and household decisions on where to live on regression results. Since part of this paper focuses on how regulatory activity relates to community characteristics, we also draw on the lessons learned from the enforcement and compliance literature. This literature typically seeks to explain how the allocation of regulatory activity and the particular characteristics of a plant affect compliance with existing environmental regulations. Only rarely does this literature consider whether community characteristics have any direct bearing on either the way in which the regulatory entity enforces regulation or how plants comply with them. We briefly discuss the few papers that tie these two literatures together.

The question of whether poor or minority communities face disproportionate impacts from emissions – also referred to as “Environmental Justice” concerns - first came into the national spotlight in 1982. A protest of a landfill siting in North Carolina that year caught both the media and governments’ attention and resulted in a number of studies related to the issue. The GAO (1983) published a study of four hazardous waste landfills, pointing out that these sites are surrounded by predominantly poor and minority communities. Likewise, the United Church of Christ (1987) studied the connection between where waste facilities are sited and the socioeconomic characteristics of their neighboring communities and found evidence of a disproportionate location pattern. These studies, and many that followed, paint a mixed picture with regard to the correlation between waste facility location and poor and minority communities. For instance, Zimmerman (1993) finds evidence that more minorities live in neighborhoods with inactive hazardous waste sites, but that the poor do not. Likewise, Boer et al. (1997) find that hazardous waste sites are positively correlated with race but that the relationship is more complicated with regard to income. Sadd et al (1999) and Baden et al. (2007) find that whether race and ethnicity are correlated with waste site location depends on factors such as geographic scale and the way in which the surrounding community is defined, though Sadd et al. (1999) find that income remains significant across specifications.[2]

While the location of a polluting plant or site obviously has an impact on the surrounding community, what is arguably of greater concern to residents living in the vicinity of a polluting plant is the hazard associated with such emissions. This may manifest itself through the plant’s emissions behavior as well as how well existing regulations are complied with or enforced by regulators. Hamilton (1995) is one of the first empirical papers in the economic literature to implicitly examine the role of community characteristics in decisions of how much to emit. He does this by examining the capacity expansion decisions of hazardous waste treatment, disposal, and storage facilities (TSDFs). He finds that race is not a significant determinant of site expansion but that income is positively related to site expansion. Furthermore Hamilton finds that voter turnout is negatively related to site expansion. Gray and Shadbegian (2004) examine inspection and enforcement actions and levels of air and water emissions at pulp and paper mills and find that communities with more minorities appear to emit less pollution, though poorer neighborhoods face greater levels of pollution.

Several other studies find evidence of significant positive correlation between race or poverty and emissions. For instance, Rinquist (1997) finds that both race and income are significant determinants of the level of TRI emissions in a neighborhood, but they are not the most important variables. Kriesel et al. (1996) also find that race is significant and positively related to TRI emissions, though this result is not robust to the addition of other socioeconomic characteristics such as education and property values. Percent in

---

[2] See Shadbegian and Wolverton (2010) for a more detailed survey of these and other plant location studies.

poverty is positively related to emissions in all specifications.[3] Brooks and Sethi (1997) examine the relationship between the level of TRI air pollution and community characteristics, weighting by the relative toxicity of each pollutant. They find that race is significant and positively related to air emissions. All other socioeconomic variables - such as income, education, property values, and voter participation - are also significant. Shadbegian, Gray, and Morgan (2007) compare the overall net health benefits that were achieved under Title IV of the 1990 Clean Air Act Amendments to test whether there were unforeseen consequences of the regulatory change in terms of adverse impacts on particular socio-economic groups, but they find very few Environmental Justice concerns.[4] Finally, Jenkins, Maguire, and Morgan (2004) find that communities with relatively more minorities receive lower 'host' fees for the siting of landfills, while richer communities receive higher 'host' fees.

Most of these studies do not take a very sophisticated approach to mapping emissions across geographic space to more accurately identify potentially affected communities, instead relying on Census based definitions or concentric circles to define neighborhoods and assuming all households within a given area are exposed to the same amount of pollution. Nor do these studies account for potential spatial correlation across neighborhoods. Both are areas that would benefit from future research.

To date, there have been only a few studies that examine the relationship between regulatory activity and the characteristics of the surrounding community. Shadbegian and Gray (2004, 2009) find little evidence that plants located in poor and minority areas face less regulatory stringency. On the other hand, Earnhart (2004) finds that per capita income is positively correlated with the likelihood of an inspection at municipal wastewater treatment facilities in Kansas. Two other studies examine different types of regulatory activity and find important connections with community characteristics. Viscusi and Hamilton (1999) conclude that Superfund sites situated in areas that are more pro-environment and more politically active also have more stringent environmental clean up targets for reducing cancer risk. Sigman (2001) looks at the speed with which EPA processes contaminated Superfund sites, and finds that the sites appear on its National Priority List for cleanup more quickly if the site is located in a community with more political activity and higher median income.[5]

ENDOGENEITY

[3] Pargal and Wheeler (1996) also examine how water pollution varies with community characteristics in Indonesia.
[4] Shadbegian, Gray and Morgan (2007) also examine the spatial distribution of Title IV net benefits across regions.
[5] It is also worth noting several related papers that look at how regulatory stringency varies with distance to the border of a neighboring state or country. Traub and Sigman (2007) find that pro-environment states are also those with the most stringent state regulations for water quality and hazardous waste. Sigman (2005) finds that plants located near jurisdictional borders face less regulatory oversight than other plants in the state. Helland and Whitford (2003) and Gray and Shadbegian (2004) find that plants near state borders emit more pollution.

A common criticism of papers that examine the relationship between neighborhood composition and emissions or enforcement activity is that they do not adequately control for endogeneity. In other words, just as plants may take neighborhood characteristics into account when deciding on how much to pollute, households may take pollution levels into account when deciding where to live. We would expect households to prefer living in relatively less polluted communities, all else equal. This should result in lower property values and lower rental prices in more polluted areas, which may make those areas relatively more attractive to income-constrained households, depending on their "willingness to pay" for environmental quality. Thus we could observe a positive correlation between poverty and environmental risk which would appear to support EJ concerns, but which reflects the opposite direction of causation – the poor "moving towards" higher-pollution (and low-rent) neighborhoods.

Studies that are concerned about endogeneity between plant location and household location decisions often use socioeconomic characteristics that correspond to the time at which the facility siting decision was made in their regressions. These studies find mixed results with regard to the sign and significance of race and poverty variables. Been (1994) finds that one dataset shows evidence of disproportionate siting in minority communities at the time of siting, while a second dataset demonstrates that the correlation between location and percent minority developed after siting. Similarly, Been and Gupta (1997) find that, while waste disposal sites were correlated with race and income variables in 1990, this relationship did not hold for percent poor or percent African-American at the time of siting (though it continues to be significant for percent Hispanic). On the other hand, Pastor et al. (2001) find evidence that hazardous waste sites in Los Angeles are positively correlated with race and ethnicity of the neighboring community at the time that the location decision is made. Baden and Coursey (2002) find that Superfund sites in Chicago are positively correlated with poverty in the 1960s but that this relationship dissipates by the 1990s, while they find little evidence of such a correlation with race in either time period. Wolverton (2009) finds that race and ethnicity are not related to the location decisions of Texas manufacturing plants that report to the Toxic Release Inventory, while poverty appears to have the opposite sign from what is expected; it is negatively related to plant location.

Finally, several studies examine how the socioeconomic characteristics of a neighborhood change after a polluting facility is located there. For instance, Lambert and Boerner (1995) find that housing values grew less rapidly in locations where there was at least one waste site, and percent minority increased more rapidly in these locations than it did in other neighborhoods. Hersh (1995) finds evidence that both white and rich households tended to leave neighborhoods after the siting of a dirty plant, while minorities tended to move into these more polluted areas. However, Cameron and Crawford (2003) find little evidence that minorities move into neighborhoods with Superfund sites, though they do find that single-parent households tend to move closer to these sites due to lower housing prices.

In the case of plant emissions behavior, using socioeconomic characteristics that are measured prior to the measurement of emissions may not be sufficient to control for endogeneity. If a facility has been in place for many years, and has an established pattern of emissions behavior from which it rarely deviates, then the neighborhood could have already adjusted to the emissions level many years before it is being measured in the data. Since there are likely to have been prior changes on the part of both the facility and the community in response to each others' actions, both actual and expected, any observed relationship between community characteristics and pollution emissions may in fact be *ad hoc*. It is therefore important to establish a context within which the relationship between emissions and neighborhood composition can be meaningfully evaluated. This issue can also arise for plant location decisions if the siting process takes many years, so that households have time to move before the final siting date. In one example of this type of research, Arora and Cason (1999) attempt to control for endogeneity by matching TRI air emissions to community demographic characteristics that are measured several years prior to the date when emissions are measured.. They find that race has a significant positive effect on TRI emissions in non-urban areas of the south, but not elsewhere in the country.

In this paper, we also attempt to control for potential endogeneity between both the regulators' decisions of how much to inspect facilities and enforce existing regulation as well as plants' decisions of how much to emit and households decisions of where to live. Using establishment-level Census data, we can distinguish between newly opened facilities, whose location decisions should depend on current values of community characteristics, and older facilities, whose location decisions should depend on community characteristics when the facility opened. We explore whether relationships between facility emissions and community characteristics are affected by better accounting for the timing of facility siting. An area open for future research is to take a more structural approach to modeling the interaction between household decisions of where to live and decisions by firms and regulators.

2. A MODEL OF REGULATORY ACTIVITY AND EMISSIONS

Why do profit-maximizing plants re-allocate their scarce resources away from production to pollution abatement? Assuming pollution is a pure externality that only negatively affects people who live downwind or downstream of the polluter, we would not expect to observe any profit-maximizing plant abating any pollution. Thus, firms must be facing some "external" pressure to internalize the externality, thereby providing an incentive for them to abate pollution. Numerous sources of such external pressure exist. For example, consumers may be willing to pay more for products produced with "green/clean" technologies, which allows firms doing more pollution abatement to enjoy increased demand for their products or charge higher prices. On the other hand, the threat of civil law suits or the possibility of Coasian bargaining to recoup damages done by emissions could provide additional incentives to abate pollution. Furthermore, if it is important for the firm's management to be a 'good corporate citizen' (and if it has the flexibility to spend the firm's funds on pollution abatement), then that could also motivate the firm to "internalize" the externality. However, we believe that the principal incentive for abating emissions in the U.S. is governmental regulatory activity, particularly for the air pollutants we examine in this paper. Therefore it is important to understand what determines the amount of regulatory pressure faced by a plant. A significant part of that regulatory pressure comes from regular inspections to detect non-compliance, and from enforcement actions intended to bring non-compliant plants into compliance. The allocation of these inspections and enforcement actions is the focus of our analysis.

In the United States, environmental policymaking occurs via a system of environmental federalism. At the federal level, the U.S. Environmental Protection Agency (EPA) promulgates national regulations and, for the most part, each individual state is responsible for implementing and enforcing those regulations. The responsibility of the states to implement and enforce regulations provides them significant flexibility to allocate varying degrees of regulatory pressure on polluting plants, even though their activities are monitored by the EPA. More specifically regarding air pollution, state regulators have the responsibility and authority to write the State Implementation Plans, which identify permitted air emissions at individual facilities, in order to meet ambient air quality requirements. Furthermore, the overwhelming majority of air pollution inspections and enforcement actions are executed by state, not federal, regulators. The major role state-level decision-makers play in carrying out environmental policy makes it more likely that local political pressures could influence regulatory activity (relative to a centralized system).

Optimal regulations would maximize social welfare by setting environmental standards so that the marginal benefit from pollution abatement equals the marginal cost of abatement. In equation (1) below, optimal abatement values, A_i^*, will be different for each plant due to factors that influence the marginal benefits and marginal costs of abatement. The marginal benefits of pollution abatement vary across plants primarily due to the number (and characteristics) of the people who live near the plant and therefore are exposed to its emissions. On the other hand, the marginal costs of abatement vary across plants largely due to their production technology, size, and age. If we make the standard assumption that marginal abatement costs increase with abatement intensity (or at least intersects the marginal benefits curve from below), plants with higher marginal benefits (or lower marginal costs) should perform more abatement. If A* is the optimal abatement level, we have $d A_i^* / dPLANT_i < 0$ for PLANT characteristics that increase marginal costs, and $d A_i^* / dPEOPLE_i > 0$ for PEOPLE characteristics that increase marginal benefits.

(1) $MC(PLANT_i, A_i^*) = MB(PEOPLE_i, A_i^*)$

The focus of our study is on how the differences in the marginal benefits of pollution abatement (MB_i) across plants affects regulatory activity, but we also control for plant characteristics affecting marginal abatement costs (e.g. size, fuel use etc). We model the marginal benefit function by aggregating individual marginal benefits from pollution abatement for all people living around a plant, as shown in equation (2) below. The locations of the people are indexed by x and y. The marginal benefits MB_i from pollution abatement at a given plant are largely a function of the number of people in the area (measured by ρ_{xy}, the population density at a given point)[6] and the level of emissions to which they are exposed (E_{xy}). We measure differences in how sensitive people's health outcomes are to pollution exposure by S_{xy}.[7] Finally, we allow for the possibility that the benefits accruing to different population subgroups are given different weights, through the use of the α_{xy} term.

$$(2)\quad MB_i = \iint_{xy} \alpha_{xy} S_{xy} E_{xy} \rho_{xy}\, dx\, dy$$

Where could these differences in α_{xy} come from? This depends critically on how the marginal benefits from abatement are assumed to motivate the decisions made by firms and regulators. Suppose that decisions about pollution abatement are driven by the desire (on the part of regulators or the firm's managers) to "do good" for the community, as measured in terms of the community's willingness to pay for the pollution reduction. In this case, we might see more abatement in neighborhoods where residents have demonstrated that they value environmental quality highly. If instead pollution abatement decisions are driven by threats of legal action or Coasian bargaining, then better connected or more powerful neighborhoods should receive more abatement. It is important to note that the above discussion assumes that the affected neighborhoods receive the benefits from pollution abatement, but not the costs (so that more abatement is unambiguously better for them) - if pollution abatement pressures are expected to cause plant closings or job losses, some communities might prefer to receive less pollution abatement.

Note that variation in α_{xy} across different subgroups (e.g. by race or socioeconomic status) could be connected with "Environmental Justice" concerns. People with lower α_{xy} receive less weight in the calculation of marginal benefits, so regulators are likely to direct less regulatory activity towards polluters on their behalf. Since regulatory activity provides a major incentive to reduce pollution, communities of people with low α_{xy} are likely to be exposed to higher pollution levels (technically, abating pollution affecting those groups would receive a "lower benefit" in the MB=MC calculation, resulting in less abatement if the marginal cost curve cuts the marginal benefit curve from below).

In this paper we focus on the possibility that state regulators choose levels of regulatory stringency (especially the frequency of inspections and enforcement actions) to maximize net political support for their regulatory activities (see Stigler (1971), Peltzman (1976), and Deily and Gray(1991)). If state regulators behave in this manner then this suggests that socio-economic groups with less political clout (e.g. poor or minorities) would be

[6] Our only direct measure of the overall benefits from pollution abatement at a particular plant is population density. This implicitly assumes equal exposures Exy for everyone included in equation 2, although we do test different-sized neighborhoods around the plants, which could allow for some diminution of impact with distance.

[7] Our interpretation focuses on health benefits from pollution abatement, but if people differ in the utility they assign to pollution reductions, those differences could also translate into different values of S_{xy}

given less weight (assigned a smaller value of α_{xy}) in the agency's regulatory calculus. In addition to socio-economic variables, measures of political activity and/or pro-environmental support within a neighborhood, may apply additional pressure on regulators to raise the regulatory stringency for nearby plants, effectively giving those neighborhoods a larger weight in the agency's regulatory decision-making. On the other hand, a regulator who values equity highly might choose to provide more regulatory activity and more pollution abatement in more vulnerable neighborhoods, as a way of offsetting the other disadvantages that those neighborhoods face.

In our empirical work, we also test for a relationship between pollution emissions and neighborhood characteristics. The above discussion has primarily focused on a connection between the decision by regulators to allocate their inspection and enforcement activity across plants and the characteristics of the nearby population, with the possible outcome that plants located near poor and minority populations receive less regulatory activity. A similar argument could be made regarding the pollution emissions from those plants, linked at least in part to the regulatory activity they face. A major incentive for plants to reduce their pollution is the existence of regulators with the power to detect and punish regulatory violations. Plants that face greater regulatory attention (more inspections to detect violations and/or more enforcement actions to punish violations) will tend to emit less pollution. Thus EJ concerns, if they arise, would appear with opposite signs: less regulatory activity and more emissions near poor and minority populations.

DATA AND EMPIRICAL METHODOLOGY

We begin by assembling data for all manufacturing plants located within 50 miles of four major cities – Los Angeles, Boston, Columbus, and Houston - from various EPA databases. Plant location information (latitude and longitude) come from EPA's Facility Registry System database. We then combine these EPA data with confidential establishment-level Census data taken from the Longitudinal Business Database (LBD). The LBD contains annual information on individual manufacturing plants, including total value of shipments, labor productivity, capital stock, fuels, and age of the plant; we use data for 2002, originally collected in the 2002 Census of Manufactures. We required plants to have both EPA and Census data, which results in a final sample of 1616 plants for our analysis of regulatory activity; the sample sizes for our analysis of emissions vary by data source, with 926 plants having air emissions data and 569 plants having data on toxic releases.

We measure the level of regulatory activity as the number of air pollution inspections and enforcement actions directed towards a particular plant from 2000-2002. These data are taken from EPA's Integrated Data for Enforcement Analysis (IDEA) database. We distinguish between two kinds of regulatory pressure faced by a plant – enforcement actions (ENFORCE) and 'inspection-type' actions (INSPECT). ENFORCE includes notices of violation, penalties, and follow-up phone calls, while INSPECT includes onsite inspections, emissions monitoring, and stack tests. Based on discussions with regulators, we expect the number of enforcement actions to be associated more closely with problems at the plant, while the number of inspections is more likely to be related to the size of the plant and the overall monitoring intensity level for that regulatory agency.

In the majority of economic models of government regulation, a regulatory agency promulgates standards with which regulated firms are required to comply. Compliance is generally achieved by having inspectors visit plants to discover violations and to impose penalties on violators. Becker (1968) established that if both the probability of being caught and the penalty for violations are high (relative to the costs of compliance), then we expect profit-maximizing firms to optimally choose to comply with regulations. However, for numerous regulatory agencies, the actual number of inspections performed is small relative to their regulated population and penalties are infrequently imposed. Becker's model seems to imply that there is a limited incentive for firm's to comply with regulations - yet most firms still seem to comply.

On the theoretical side, this conundrum of 'excessive' compliance has led to several strands of literature. The non-economics literature has stressed the significance of social norms and a corporate culture that encourages compliance. Researchers in this literature have conducted interviews to identify how and to what extent corporate decisions are affected by pressures from both regulatory agencies and the general public. In the economics literature, Harrington (1988) demonstrated that in a repeated game a regulator can raise the expected long-run penalty for non-compliance considerably by establishing two categories of regulated plants - cooperative and non-cooperative. The cooperative plants are assumed to comply with regulations and are rarely inspected. The non-cooperative plants are assumed to resist regulation and therefore face much greater regulatory activity.[8] To control for this "Harrington" effect we include a lagged measure of past violations of environmental regulations (VIOL_97), indicating if the plant was out of compliance at any point in 1997.[9] In our data we find that such violations are relatively rare, as expected.

We also conduct an analysis of the emissions from these plants, using two distinct EPA datasets. From the 2002 National Emissions Inventory, we collect annual emissions (in tons per year) in 2002 of four air pollutants: nitrogen oxide (NOx), particulates (PM_{10}), sulfur dioxide (SO_2), and volatile organic compounds (VOC), all expressed in log form. To make it easier to compare analyses across air pollutants, we limit the sample to plants which report emissions for all four pollutants. From the 2002 Toxic Release Inventory we collect the annual releases in 2002 of all chemicals reported by each plant (in pounds per year), expressed in log form (TRI). To allow for different toxicity across these chemicals, we calculate an alternative measure (TRI-TOX) consisting of the plant's TRI releases multiplied by each chemical's inhalation toxicity score, as used in the EPA's

---

[8] A number of studies examine the effectiveness of EPA enforcement in increasing compliance with air emission regulations. For instance, Gray and Deily (1996) find increases in compliance at steel mills; Nadeau (1997) finds reductions in the length of spells of non-compliance at pulp and paper mills, and Gray and Shadbegian (2005) find increases in compliance at pulp and paper mills. Henderson (1996) finds a significant impact of county non-attainment status on peak ambient concentrations of air pollutants.

[9] It would be interesting to know if these violations are related to paperwork violations or actual emissions violations, but unfortunately this information is not included in the air pollution compliance data used here.

Risk-Screening Environmental Indicators (RSEI) model, with the weighted sum expressed in log form. The emissions models are similar to the regulatory activity models discussed above, except that they omit the "lagged violations" variable.

We estimate equation (3) below for several dependent variables. For regulatory activity, our dependent variables, INSPECT and ENFORCE, are often zero and are otherwise relatively small integers, leading us to use a Negative Binomial model to allow for the observed over-dispersion of the data.[10,] We also estimate each model with OLS, to test the robustness of the coefficient results. On the emissions side, we have 6 dependent variables, corresponding to the different pollutant measures. Each dependent variable Y_{it} is modeled as a function of PLANT and PEOPLE characteristics, as well as COUNTY (political) variables and CITY dummy variables:

$$(3) \quad Y_{it} = F(PLANT_{it}, PEOPLE_{it}, COUNTY_{it}, CITY_{i})$$

where Y_{it} is one of the eight dependent variables in our analysis: INSPECT, ENFORCE, NOx, PM_{10}, SO_2, VOC, TRI, and TRI-TOX.

Prior to discussing the expected effects of our neighborhood level socio-economic and demographic variables we first discuss the plant-, state-, and county-level control variables included in each model. Our plant level control variables include plant size, capital stock, fuel use, productivity, plant age, and corporate structure from the Census Bureau's confidential plant-level Longitudinal Business Database (LBD). The LBD includes annual information on individual manufacturing plants, including total value of shipments, labor productivity, capital stock, fuels, and age of the plant. These data are collected in the Census of Manufactures and Annual Survey of Manufacturers (for a more detailed description of the LBD data, see McGuckin and Pascoe (1988)).[11] From the LBD we extract information for 2002, originally collected in the 2002 Census of Manufactures. We use both the plant's total value of shipments (SIZE) and capital stock (CAPITAL) in log form to measure the size of the plant. To control for fuel use, expected to be positively correlated with air emissions, we use the log of the cost of purchased fuels. Our control for plant age (AGE) is based on the first year the plant appears in the LBD. We control for the plant's efficiency using labor productivity (LPROD) measured as real output per employee. Finally, we include a dummy variable (SINGLE), which indicates a single-plant firm (i.e., a firm which owns no other manufacturing plants), to control for corporate structure. If single plants have less political power then we would expect them to receive more regulatory scrutiny – it is

[10] The Poisson regression model is appropriate when the dependent variable is count data (e.g. number of inspections and enforcement actions). The Poisson model (distribution) assumes that the dependent variable's mean is equal to its variance, but in many cases the variance is greater than the mean with count data (e.g. over-dispersion). In these cases a model, such as the Negative Binomial model used here, that allows for over-dispersion is more appropriate (and our Negative Binomial results show significant over-dispersion in our data).
[11] The establishment-level data in the LBD are collected and protected under Title 13 of the U.S. Code. Restricted access to these data can be arranged through the U.S. Census Bureau's Center for Economic Studies (CES). See http://www.ces.census.gov/ for details.

possible that they might also be more likely to have paperwork violations, relative to larger firms which could benefit from regulatory compliance support from their corporate headquarters. On the other hand, EPA and many state regulatory agencies provide compliance assistance targeted towards smaller firms, and some regulations have specific exemptions for small businesses, which could offset the disadvantages of being a smaller firm.

We use voting information at the county level, taken from data compiled and published by the U.S. Census Bureau, to describe the political climate of the area near the plant.[12, 13] Olson (1965) describes the ability of voter activity to overcome negative externalities. A positive influence on α_{xy} is expected to come via greater voter activity, measured using county voter turnout in the 2000 presidential election (TURNOUT). We also include DEMOCRAT, the percentage of voters in the county voting for the Democratic Presidential candidate in 2000, as an indication of voter support for more active regulatory interventions. We expect both of these variables to increase regulatory activity at a plant, since they are associated with having more politically active people living near the plant. They should also decrease emissions from the plant.[14]

We also include a set of variables to measure the marginal benefit of abatement associated with a given plant. As argued above, the marginal benefits MB_i from pollution abatement at a given plant largely depends on the number of people in the area, the emissions that they are exposed to, and their health susceptibility to pollution exposure. The overall population being affected by emissions from the plant (ρ_{xy}) is measured by POPDEN, the population density around the plant, with higher POPDEN leading to greater MB. Potential differences in health sensitivity by age group (S_{xy} in equation 2) are measured by CHILDREN (the percentage of the nearby population under the age of 6) and ELDERS (the percentage of the nearby population over the age of 65). Both groups are more sensitive to air pollutants, so we expect higher values of both CHILDREN and ELDERS to result in higher MB. In our empirical results, we would expect to see positive coefficients on these three variables in the regulatory activity analysis, and negative coefficients in the emissions analysis.

Finally, we turn to the variables that are most closely related to Environmental Justice concerns related to the racial, ethnic, or socioeconomic composition of the population living near the plant. In our analyses the "potentially less valued" (low α_{xy}) populations are poor and minorities. We measure POOR as the percentage of the nearby population living below the poverty line; MINORITY is measured as the percentage of the nearby population which is not non-Hispanic whites. If plants near POOR and MINORITY populations face less regulatory activity and/or are exposed to more emissions, this would raise potential Environmental Justice concerns.

---

[12] The original source of these data is CQ Press, 2001, *America Votes 1999-2000*, Washington, DC.

[13] We would like to use voting data at finer levels of geographic detail (e.g. precinct-level data) however we cannot do so because they are not collected at similar levels of detail across these four states.

[14] Republicans who are more politically active could be expected to push for less regulatory activity on ideological grounds. On the other hand, the political clout of Democrats could be expected to depend on the party affiliation of the state's Governor. During our sample period only California had a Democratic governor, so we could not test that hypothesis.

We generate the above mentioned socio-economic and demographic variables from detailed geographic data (at the Census block group level) measuring population characteristics from the 1970-2000 U.S. Censuses of Population, as compiled in the Census-CD datasets prepared by Geolytics, Inc. We do not know, *a priori*, the 'optimal' (or even most suitable) size of a neighborhood to study the effects of benefits and our socio-economic and demographic variables on regulatory activity. Therefore we take advantage of our ability to 'create' neighborhoods of different sizes to test how far the benefit and political effects extend. In particular, we 'create' two different-sized neighborhoods consisting of all block groups that fall within R miles of the plant, where R = 1 and 10. Distances are calculated between each plant and the centroid of each block group to determine which block groups fall within R mile(s) of the plant, and the block group values for each population characteristic are aggregated to get the overall value for each plant. As might be expected, we find somewhat similar, but not always perfectly consistent results across different neighborhood sizes (some demographic variables had stronger effects when measured in smaller neighborhoods; others were stronger when measured in larger neighborhoods).

We mentioned earlier the distinction between current-year and siting-year measures of neighborhood characteristics in EJ analyses. Our measures of regulatory activity come from 2000-20002, while our measures of emissions come from 2002, so our current-year neighborhood measures are taken from the 2000 Census. To calculate the siting-year measures, we identified the first year of data for the plant in the LBD. Those plants in the LBD before 1976 were assigned to the 1970 Census data, while plants that first appeared in the LRD in 1977-1986, 1987-1996, 1997-2002 were assigned, respectively, to the 1980, 1990, 2000 Census data. Our earliest demographic data is from 1970, and roughly half of our plants are assigned the 1970 Census for their siting-year. Only a very small fraction are assigned the 2000 Census for their siting-year, so the siting-year and current-year values are usually from different years, but the siting-year and current-year values are still fairly highly correlated.

3. RESULTS

The summary statistics for our dataset are shown in Table 1. In terms of regulatory activity, the average plant receives about twice as many inspections as it does enforcement actions, although both types of activity are relatively rare (fewer than half of our plants are inspected during the 2000-2002 period, while some plants receive multiple inspections; the distribution of enforcement actions is even more skewed). This is primarily due to our sample data being drawn from all manufacturing plants, rather than being focused on large polluters. This can also be seen in our measures of air pollution emissions and toxic releases, both of which are relatively small. Of our plant characteristics, expenditures on fuels show considerable variation across plants. Nearly half of our plants come from single-plant firms, while about two-thirds were in operation before 1978. For the demographic variables, we see some increases in the percentages of poor and minority populations as we move from the siting-year to the year 2000, along with a shifting of the population towards older age groups. We also see greater variability for the 1-mile-circle variables than we do for the 10-mile-circles. Because our data come from relatively densely populated areas near cities, we focus most of our attention on the 1-mile results, but we also present the 10-mile results as a sensitivity check.

Table 2 presents the results of a basic model for regulatory activity, depending only on our measures of plant characteristics along with dummy controls for city and industry. We show the results for four regressions: two regressions examine how often a plant is inspected, while two regressions examine the enforcement actions taken against a plant. In each case, we run a basic ordinary least squares (OLS) and a negative binomial (NB) regression. For the most part, the coefficients are significant, with signs consistent with our expectations. Larger plants and plants with greater fuel expenditures (likely to be associated with higher air pollution emissions) receive greater regulatory attention. Labor productivity and capital intensity are not generally significant, although plants with higher labor productivity seem to receive somewhat less attention. Plants with past violations also receive greater attention (though this effect is only significant for the OLS models). The results for older plants are mixed, with a suggestion of more inspections but fewer enforcement actions, possibly connected to grandfathering. Plants in single-unit firms face significantly more regulatory activity, perhaps due to having lower political clout with regulators. The basic model explains about 19-27 percent of the overall variation in regulatory activity.

Tables 3 and 4 expand the basic model by adding the demographic variables that are at the heart of the EJ analysis, along with measures of political activity. The tables differ in terms of the timing of the demographic variables – Table 4 includes current demographic measures from the year 2000, while Table 3 includes demographic measures from the time that the plant was sited (as noted earlier, our earliest demographic data is from 1970, so older plants are assigned 1970 values – very few plants are assigned 2000 as their siting-year). We might expect the current demographics to be more relevant, since the regulator is making decisions about regulatory allocation currently, but siting-year demographics could affect the size and location of plants at the time of their initial construction, which could affect current emissions and thus the incentives for regulatory attention.

First, note that the control variables from our basic model are essentially unaffected by the expansion of the model, either in terms of coefficient magnitude or significance. The political measures, voter turnout and percent voting Democratic, have the expected positive signs. Higher voter turnout is associated with significantly more inspections and more enforcement actions, while voting Democratic is only significant for enforcement actions.

On the other hand, the demographic measures are insignificant for the most part, and often have unexpected signs. Based on the benefits from pollution abatement discussed earlier, we would expect positive signs for population density, as well as the fraction of the population under 6 and over 65, while concerns about EJ suggest the possibility of finding negative coefficients on the fraction that is poor and minority. The siting-year coefficients on the under 6 and over 65 variables are both surprisingly negative (though insignificant), while the year-2000 coefficients tend to be positive, though not always significant. The EJ variables are more consistent across the two tables, with higher minority populations receiving less attention, while poorer populations receive (surprisingly) more attention, although these effects are also only occasionally significant. The expanded model with both plant and community socioeconomic and demographic characteristics explains roughly the same degree of variation when compared to the basic model, about 19-27 percent of the overall variation in regulatory activity.

Table 5 provides an alternative version of the full model, defining the demographic variables in terms of 10-mile circles around the plant, rather than 1-mile circles. The results for both the siting-year and the year-2000 demographic measures are broadly similar to those in Tables 3 and 4. Again, we do not see the expected positive coefficients on the measures of children and elderly in the population, although now the age-related demographic variables remain negative in the year-2000 results (where they had been positive in Table 4), and population density is more consistently (surprisingly) negative. The EJ variables show the same results as before, with plants in high-minority areas facing less regulatory activity, while plants in high-poverty areas face more activity. Given that inspections and enforcement activities are relatively rare events, it is perhaps not surprising to see they have little relation to average community characteristics (e.g. are not significant), which may be a poor reflection of interim sorting behavior on the part of households.

Now consider the magnitudes of these impacts, by examining the impact of a one standard deviation increase in each of the explanatory variables, using the results from Table 4, model M9 as illustrative. Plant characteristics, such as size and fuel usage, are the most consistently significant, and they also have a relatively large impact: increasing log size by one standard deviation (1.8) is predicted to increase inspections by 0.25, while increasing log fuel usage by one standard deviation (2.4) is predicted to increase inspections by 0.34. Increasing voter turnout has an impact similar in magnitude (0.31), while the impact of percent Democrat is considerably smaller (except for model M12, where enforcement actions are predicted to increase by 0.32). The demographic variables show considerably smaller impacts, less than 0.1 in most cases, although the surprisingly positive effect of POOR in model M9 is 0.15.

We now turn to measures of the pollution emissions from each plant, considering both 4 major air pollutants and 2 measures of toxic releases, starting with a basic model in Table 6. Overall, the plant characteristics show less significance, as compared to the models of regulatory activity examined earlier. Fuel usage continues to have large positive effects that are consistently significant, but it is the only variable that does so. Plant size is nearly always positive, but is usually insignificant. Productivity and capital intensity are generally insignificant, and vary in sign across pollutants. For two important pollutants (PM_{10} and SO_2), older plants have significantly higher emissions, but the effect of age on other pollutants is negative and insignificant. The overall explanatory power of the models is relatively high, ranging from 32 to 70 percent, due to the significance of the city and industry dummies. The model does a much better job of explaining variation in NOx, PM_{10}, and VOC emissions than it does for SO_2 and TRI emissions.

Expanding the model, as shown in Tables 7 and 8, has little impact on the plant-level coefficients, either in terms of magnitude or significance. We would generally expect to see opposite signs for the political and demographic variables here, as compared to the earlier models of regulatory activity: negative for population density, children and elders, positive for poor and minority. Population density is consistently negative, and often significant, but children and elders often have positive signs, and are also sometimes significant (the only exception being negative coefficients in the TRI models using year-2000 measures). The political variables show little impact – never significant, with smaller coefficients than in the earlier models. Finally, the EJ variables show little consistent effect, with few significant coefficients and different signs across different pollutants. There is some tendency for the EJ coefficients in the year-2000 model to be more often positive than in the siting-year model, which is consistent with the expectation of sorting based on neighborhood quality, as described earlier. Still, the coefficients are not often significant, and the patterns are not always consistent across pollutants, so these results should be considered suggestive.

Table 9 presents results for demographic variables defined in terms of 10-mile circles. The siting-year age variables have the expected negative sign for the measures of air pollution emissions, unlike the corresponding 1-mile variables in Table 7 (though they are not statistically significant). Population density also has the expected negative sign, and is often significant. For the EJ variables, we see the expected positive coefficients more often than in Table 7. Turning to the year-2000 results, the age-related variables (surprisingly) shift towards being more positive, while the EJ variables are a bit more negative. This does not correspond to the results we saw for 1-mile circles in Table 8, where the EJ coefficients became more positive as we shifted to the current year.

4. CONCLUSION

In this paper, we examine the large and expanding topic of Environmental Justice. The research in this area has developed from relatively simple comparisons of current demographic characteristics near environmental nuisances to multiple regressions and consideration of demographics at the time of siting. The evidence for EJ concerns in the literature is mixed: there is a large body of studies that find correlations between population characteristics and environmental risks. Many studies that include the use of siting-year demographics find that this reduces the magnitude and significance of any EJ effects, although other studies continue to find significant effects. The types of pollutants being considered has also expanded, beginning with hazardous waste sites but being applied to more broadly distributed air and water pollutants, as in this study.

In this paper, we add to the literature by exploring the relationship between regulatory activity and community characteristics, a relatively under-studied area in the literature. We also examine plant emissions behavior. These regressions focus on all manufacturing facilities near four large U.S. cities. We also separately considered the effect of matching plant and regulatory behavior to siting-year or current (year-2000) demographics in an attempt to control for the possible effects of endogeneity.

In the analysis of regulatory activity, we found significant connections between plant characteristics and activity, with larger plants and heavy fuel-using plants facing more activity. In addition, we found plants in areas with high voter turnout also faced more regulatory activity. However, we did not find significant evidence that demographic variables have a large impact on the allocation of regulatory activity: plants in areas with large minority populations did have somewhat fewer actions, but these effects were small and generally insignificant; plants in high poverty areas seem to face (surprisingly) more enforcement actions, sometimes significantly more. Our other demographic variables (population density and fractions of those under 6 and over 65) also tended to be insignificant, and often had unexpected signs. On the whole, these results provide little evidence for EJ concerns in the allocation of regulatory activity among these plants. Expanding the range of the demographic variables from 1-mile-circles to 10-mile-circles did not have much effect on the results. In general, the variation we are able to explain in the regressions is almost entirely due to plant characteristics.

The analysis of pollution emissions found fewer significant effects among the factors in the basic model. Plants with greater fuel usage did emit significantly more air emissions (and also had higher toxic releases), but that was the only variable with significant effects on all pollutants. Larger plants also tended to have more emissions, but not always significantly more; older plants had higher emissions of particulates and sulfur dioxide, but lower emissions of other pollutants. Population density did have the expected negative sign (and occasional significance), but the political variables did not show significant effects on any pollutant. The demographic variables did not show much significance, and often had unexpected signs. For example, the poor and minority variables, measured in the siting year, were associated with lower emissions more often than not. However, these signs did shift when we used year-2000 measures, which provides some (weak) evidence in support of the "moving to a nuisance" interpretation of EJ results in other studies, with a suggestion that plants with higher emissions levels may see shifts in their nearby demographic composition towards a higher poor and minority population. The results using 10-mile-circles were not very different, although they did not show a consistent pattern between the siting-year and year-2000 results.

The results presented here do not show much evidence to support EJ concerns, at least within the set of plants and pollutants covered in our analysis for the time period studied. The analysis of regulatory activity showed a number of significant impacts from plant characteristics and political activity with the expected signs, but the demographic variables were generally insignificant, had smaller effects than the other variables in the model, and often had unexpected signs. Thus it does not appear that regulatory activity is disproportionately focused on plants in majority, high-income communities. Our analysis of air pollution emissions and toxic releases also fails to find strong EJ effects: the signs on the EJ coefficients vary across different pollutants and across different EJ measures, and the EJ coefficients are usually insignificant. The emission models as a whole show fewer significant coefficients than the regulatory activity models. This may reflect our sample, including all plants from the manufacturing sector near four large cities: the variability in demographic characteristics may be less than would be found in a nationwide sample, while the production processes at our plants are more heterogeneous than earlier studies which examined plants from a single industry.

Despite the considerable body of existing literature addressing EJ issues, there still remain important areas for future research. As noted earlier, EJ studies have tended to focus on outcomes rather than the processes that determine those outcomes. Our results here do not provide much evidence for EJ differences in enforcement activity, but it would be useful to examine the activities of regulatory agencies in other contexts (e.g. Sigman (2001) finds a faster processing of Superfund sites located in higher-income areas). One challenge is that regulatory activity can be difficult to quantify: inspections and other enforcement actions are recorded for air pollution and water pollution, but the intensity of those inspections may differ in ways we do not measure. Other potential mechanisms for EJ impacts include neighborhood environmental activism and differences in managerial attention, but those may be more difficult to measure.

There is a broader issue related to the choice of pollutants being analyzed. The early history of EJ concerns was focused on hazardous waste sites, and on local communities that faced a number of environmental hazards as well as other disadvantages. The regulatory process surrounding those sites tends to be individually designed, and deals with very locally focused hazards. In contrast, air pollution emissions can affect people hundreds of miles away, and these emissions are covered by federal regulations and incorporated into State Implementation Plans. This may reduce the flexibility of regulators to respond to differences in population characteristics near the regulated plants.

In a more narrowly focused sense, the analysis presented here could also be extended, to bring together the analysis of emissions and regulatory activity, perhaps in a Seemingly Unrelated Regression (SUR)-like analysis. This could help us identify whether surprisingly high/low emissions at a plant result in surprisingly high/low regulatory activity at the plant – providing additional information about heterogeneity across plants not already captured by the violation measures. The models of pollution emissions might also benefit from controls for differences in production processes and pollution abatement opportunities, beyond those already captured with the two-digit SIC industry dummies.

REFERENCES

Arora, S., T. Cason, “Do community characteristics influence environmental outcomes? Evidence from the Toxic Release Inventory,” Southern Economic Journal 65: 691-716 (1999).

Baden, B., D. Noonan, and R. Turaga (2007). "Scales of Justice: Is There A Geographic Bias in Environmental Equity Analysis?" Journal of Environmental Planning and Management 50: 163–185.

Baden, B., and Coursey, D. (2002). "The Locality of Waste Sites Within the City of Chicago: A Demographic, Social, and Economic Analysis." Resource and Energy Economics 24: 53-93.

Becker, Gary (1968) "Crime and Punishment: An Economic Approach," Journal of Political Economy 76: 169–217.

Been, V. (1994). "Locally Undesirable Land Uses in Minority Neighborhoods: Disproportionate Siting or Market Dynamics?" The Yale Law Journal 103: 1383 - 1421.

Been, V., and F. Gupta (1997) "Coming to a Nuisance or Going to a Barrios? A Longitudinal Analysis of Environmental Justice Claims," Ecology Law Quarterly 24: 1-56.

Boer, T., M. Pastor, J. Sadd, and L. Snyder (1997). "Is There Environmental Racism? The Demographics of Hazardous Waste in Los Angeles County?" Social Science Quarterly 78: 4: 793 - 809.

Brooks, N., and R. Sethi (1997). "The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics." Journal of Environmental Economics and Management 32: 233 - 250.

Cameron, T., and G. Crawford (2003). "Superfund Taint and Neighborhood Change: Ethnicity, Age Distributions, and Household Structure." University of Oregon Working Paper no. 39.

Deily, M., and W. Gray (1991). Enforcement of pollution regulations in a declining industry, Journal of Environmental Economics and Management 21: 260-274.

Earnhart, D. (2004). "The Effects of Community Characteristics on Polluter Compliance Levels." Land Economics 80: 408-432.

Gray, W., and M. Deily (1996). "Compliance and Enforcement: Air Pollution Regulation in the U.S. Steel Industry," Journal of Environmental Economics and Management 31: 96-111.

Gray, W., and R. Shadbegian (2004). "Optimal Pollution Abatement – Whose Benefits Matter and How Much," Journal of Environmental Economics and Management 47: 510-534.

Gray, W., and R. Shadbegian (2005). "When and Why do Plants Comply? Paper Mills in the 1980s," Law and Policy 27: 238-261.

Hamilton, J. (1995). “Testing for Environmental Racism: Prejudice, Profits, Political Power?,” Journal of Policy Analysis and Management 14: 107-132.

Harrington, W. (1988).“Enforcement Leverage when Penalties are Restricted,” Journal of Public Economics 37: 29-53.

Helland, E., and A. Whitford (2003). “Pollution Incidence and Political Jurisdiction: Evidence from the TRI” Journal of Environmental Economics and Management 46: 403-424.

Henderson, V. (1996). “Effects of Air Quality Regulation.” American Economic Review 86: 789-813.

Hersh, R. (1995). "Race and Industrial Hazards: A Historical Geography of the Pittsburgh Region, 1900-1990." Resources for the Future Discussion Paper 95-18.

Jenkins, R., K. Maguire, and C. Morgan (2004), “Host Community Compensation and Municipal Solid Waste Landfills,” Land Economics 80: 513-528.

Kriesel, W., T. Centner, and A. Keeler (1996). “Neighborhood Exposure to Toxic Releases: Are There Racial Inequalities?” Growth and Change 27: 479 – 499.

Lambert, T., and C. Boerner (1995). Environmental Inequity: Economic Causes, Economic Solutions. Policy Study 125. Center for the Study of American Business.

McGuckin, R., and G. Pascoe (1998). “The Longitudinal Research Database: Status and Research Possibilities,” Survey of Current Business.

Nadeau, L. (1998). “EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance,” Journal of Environmental Economics and Management 34: 54-78.

Olson, M. (1965). The Logic of Collective Action. Harvard University Press, Cambridge, MA.

Pargal, S. and D. Wheeler (1996). “Informal Regulation of Industrial Pollution in Developing Countries: Evidence from Indonesia.” Journal of Political Economy 104: 1314-1327.

Pastor, M., Sadd, J., and J. Hipp, J. (2001). “Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice.” Journal of Urban Affairs 23: 1-21.

Peltzman, S. (1976).“Toward a More General Theory of Regulation” Journal of Law and Economics 19: 211-240.

Rinquist, E. (1997). “Equity and the Distribution of Environmental Risk: The Case of TRI Facilities.” Social Science Quarterly 78: 811 ‐ 829.

Sadd, J., M. Pastor, T. Boer, and L. Snyder (1999). “’Every Breath You Take…’ The Demographics of Toxic Air Releases in Southern California.” Economic Development Quarterly 13: 107 ‐ 123.

Shadbegian, R., and W. Gray. (2009) “Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice” U. S. E.P.A. National Center for Environmental Economics Working Paper no. 2009-02.

Shadbegian, R., W. Gray, and C. Morgan (2007). “Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis” in Acid in the Environment: Lessons Learned and Future Prospects (eds., Gerald Visgilio and Diana Whitelaw), Springer Science+Media, Inc.

Shadbegian, R. and A. Wolverton (2010). “Location Decisions of U.S. Polluting Plants: Theory, Empirical Evidence, and Consequences,” International Review of Environmental and Resource Economics 4: 1-49

Sigman, H. (2001). “The Pace of Progress at Superfund Sites: Policy Goals and Interest Group Influence,” Journal of Law and Economics 44: 315-344.

Sigman, H. (2005). “Transboundary Spillovers and Decentralization of Environmental Policies” Journal of Environmental Economics and Management, 50: 82-101.

Stigler, G. (1971). “The Theory of Economic Regulation” Bell Journal of Economics and Management Science 2: 3-21.

Traub, L., and H. Sigman (2007). “Voluntary Decentralization in Environmental Policy: Cooperative Federalism" as a Strategic Interaction” National Bureau of Economic Research Working Paper No. 13238

United Church of Christ (UCC) (1987). Toxic Waste and Race in the United States. UCC: Commission for Racial Justice.

United States General Accounting Office (GAO) (1983). Siting of Hazardous Waste Landfills and Their Correlation with Racial and Economic Status of Surrounding Communities. Washington, DC.

Viscusi, W., and J. Hamilton (1999). “Are Risk Regulators Rational? Evidence from Hazardous Waste Cleanup Decisions,” American Economic Review 89: 1010-1027.

Wolverton, A. (2009), “Effects of Socio-Economic and Input-Related Factors on Polluting Plants’ Location Decisions,” The B.E. Journal of Economic Analysis & Policy 9, 1 (Advances), Article 14.

Zimmerman, R. (1993). "Social Equity and Environmental Risk." Risk Analysis 13: 649 - 666.

Table 1
Summary Statistics
(N=1616 unless otherwise noted)

Variable	Mean	(s.d.)	Description/Source
EPA Integrated Data for Enforcement Analysis (IDEA) and Envirofacts			
Inspect	0.503	(1.875)	Total air pollution inspections, 2000-2002
Enforce	0.267	(1.054)	Total air pollution enforcement actions, 2000-2002
Viol97	0.028	(0.165)	Dummy, plant had air pollution violation during 1997
Air Pollution Emissions - EPA 2002 National Emissions Inventory (N=926)			
NOx	1.141	(1.569)	Nitrogen oxides (log of tons emitted per year)
PM10	0.641	(1.123)	PM10 (log of tons emitted per year)
SO2	0.577	(1.381)	Sulfur dioxide (log of tons emitted per year)
VOC	1.717	(1.497)	Volatile organic compounds (log of tons emitted per year)
Toxic Releases - EPA 2002 Toxic Release Inventory (N=569)			
TRI	6.323	(4.526)	Total releases (log of pounds released)
TRI-TOX	9.178	(6.306)	Toxicity-adjusted releases (log of pounds released * toxicity)
Plant-Level Data - Census Longitudinal Business Database (2002 Census of Manufactures)			
LTVS	9.482	(1.797)	Log(total value of real shipments in 2002)
LP	5.617	(1.025)	Log(real output per worker hour in 2002)
LCAP	8.191	(2.474)	Log(real book value of capital stock in 2002)
LCF	3.908	(2.400)	Log(real expenditure on fuels in 2002)
SU	0.418	(0.493)	Dummy, single-unit firm in 2002
PRE1978	0.649	(0.477)	Dummy, plant existed in LBD before 1978
County-level Voting Data - 2000 Presidential election			
Dem	54.76	(9.92)	Percent voting for Democratic Presidential candidate
Turnout	49.82	(8.46)	Percent of population aged 18 or over who voted

Table 1 (cont)
Summary Statistics
(N=1616 unless otherwise noted)

Variable	Mean	(s.d.)	Description/Source
Census Demographics – 1 mile circle, plant-siting year (1970-2000 Census)			
Poor1	0.107	(0.074)	Fraction of population below poverty line
Nw1	0.113	(0.180)	Fraction of population minority (not non-Hispanic white)
Kids1	0.104	(0.026)	Fraction of population under 6 years old
Eld1	0.094	(0.042)	Fraction of population 65 years old and over
Lpden1	7.186	(2.322)	Log(population density)
Census Demographics – 1 mile circle, 2000 Census of Population			
Poor1_2000	0.137	(0.096)	Fraction of population below poverty line
Nw1_2000	0.265	(0.230)	Fraction of population minority (not non-Hispanic white)
Kids1_2000	0.088	(0.024)	Fraction of population under 6 years old
Eld1_2000	0.113	(0.046)	Fraction of population 65 years old and over
Lpden1_2000	7.770	(1.448)	Log(population density)
Census Demographics – 10 mile circle, plant-siting year (1970-2000 Census)			
Poor10	0.099	(0.038)	Fraction of population below poverty line
Nw10	0.119	(0.132)	Fraction of population minority (not non-Hispanic white)
Kids10	0.099	(0.015)	Fraction of population under 6 years old
Eld10	0.098	(0.027)	Fraction of population 65 years old and over
Lpden10	7.175	(1.641)	Log(population density)
Census Demographics – 10 mile circle, 2000 Census of Population			
Poor10_2000	0.123	(0.054)	Fraction of population below poverty line
Nw10_2000	0.265	(0.181)	Fraction of population minority (not non-Hispanic white)
Kids10_2000	0.087	(0.013)	Fraction of population under 6 years old
Eld10_2000	0.112	(0.025)	Fraction of population 65 years old and over
Lpden10_2000	7.538	(1.165)	Log(population density)

Table 2
Determinants of Regulatory Activity
Basic Model - Plant characteristics only
(N=1616; std. err.)

MODEL	OLS	N.B.	OLS	N.B.
Dep. Var.	INSPECT	INSPECT	ENFORCE	ENFORCE
	M1	M2	M3	M4
LTVS	0.136***	0.176***	0.077***	0.175**
	(0.045)	(0.057)	(0.025)	(0.084)
LP	-0.000	-0.154**	0.007	-0.079
	(0.064)	(0.078)	(0.035)	(0.112)
LCAP	0.013	-0.009	0.015	0.019
	(0.023)	(0.025)	(0.013)	(0.038)
LCF	0.148***	0.200***	0.077***	0.192***
	(0.026)	(0.033)	(0.015)	(0.046)
SU	0.351***	0.281**	0.215***	0.419**
	(0.104)	(0.131)	(0.057)	(0.193)
PRE1978	0.176**	0.106	0.011	-0.283*
	(0.090)	(0.108)	(0.049)	(0.151)
VIOL97	0.844***	0.146	0.568***	0.320
	(0.255)	(0.213)	(0.141)	(0.325)
Constant	-2.269***	-2.938***	-1.442***	-7.000***
	(0.586)	(0.550)	(0.323)	(1.097)
lnalpha		-0.482***		0.252
		(0.178)		(0.199)
R-squared	0.236	0.186	0.264 .	0.190

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies

Table 3
Determinants of Regulatory Activity
Full Model – Plant-Siting-Year Demographics
(N=1616; std. err.)

MODEL	OLS	N.B.	OLS	N.B.
Dep. Var.	INSPECT	INSPECT	ENFORCE	ENFORCE
	M5	M6	M7	M8
LTVS	0.138***	0.180***	0.080***	0.186**
	(0.045)	(0.056)	(0.025)	(0.084)
LP	-0.002	-0.160**	0.006	-0.094
	(0.064)	(0.078)	(0.035)	(0.113)
LCAP	0.015	-0.013	0.015	0.017
	(0.023)	(0.025)	(0.013)	(0.038)
LCF	0.145***	0.191***	0.075***	0.184***
	(0.027)	(0.034)	(0.015)	(0.047)
SU	0.376***	0.300**	0.225***	0.459**
	(0.104)	(0.131)	(0.057)	(0.194)
PRE1978	0.205**	0.065	0.004	-0.398**
	(0.100)	(0.119)	(0.055)	(0.168)
VIOL97	0.783***	0.130	0.543***	0.298
	(0.257)	(0.215)	(0.142)	(0.318)
eld1	-0.631	-0.500	-0.468	-2.611
	(1.477)	(1.741)	(0.816)	(2.452)
kids1	-3.166	-1.316	-1.245	-1.229
	(2.056)	(2.447)	(1.135)	(3.304)
poor1	0.977	0.753	0.343	1.201
	(0.853)	(1.024)	(0.471)	(1.304)
nw1	-0.351	-1.028**	-0.287	-0.882
	(0.342)	(0.483)	(0.189)	(0.566)
lpden1	-0.017	0.004	0.009	0.034
	(0.022)	(0.021)	(0.012)	(0.034)
dem	0.003	0.003	0.007*	0.034**
	(0.008)	(0.011)	(0.004)	(0.014)
turnout	0.027**	0.023*	0.014**	0.057***
	(0.012)	(0.013)	(0.006)	(0.021)
lnalpha		-0.532***		0.199
		(0.185)		(0.205)
R-squared	0.241	.189	0.268	.197

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies

Table 4
Determinants of Regulatory Activity
Full Model – Year 2000 Demographics
(N=1616; std. err.)

MODEL	OLS	N.B.	OLS	N.B.
Dep. Var.	INSPECT	INSPECT	ENFORCE	ENFORCE
	M9	M10	M11	M12
LTVS	0.141***	0.176***	0.081***	0.185**
	(0.045)	(0.056)	(0.025)	(0.084)
LP	-0.003	-0.155**	0.008	-0.076
	(0.064)	(0.078)	(0.035)	(0.113)
LCAP	0.013	-0.008	0.015	0.021
	(0.023)	(0.025)	(0.013)	(0.038)
LCF	0.142***	0.195***	0.074***	0.184***
	(0.026)	(0.034)	(0.015)	(0.046)
SU	0.387***	0.296**	0.224***	0.432**
	(0.104)	(0.131)	(0.057)	(0.194)
PRE1978	0.176*	0.110	0.005	-0.281*
	(0.090)	(0.110)	(0.050)	(0.154)
VIOL97	0.753***	0.079	0.537***	0.272
	(0.256)	(0.218)	(0.142)	(0.322)
eld1_2000	0.400	0.534	0.187	-0.545
	(1.182)	(1.291)	(0.655)	(1.942)
kids1_2000	-5.840***	1.579	0.713	7.029**
	(2.160)	(2.288)	(1.197)	(3.350)
poor1_2000	1.540**	0.800	0.717**	0.414
	(0.637)	(0.751)	(0.353)	(1.032)
nw1_2000	-0.305	-0.565	-0.233	-0.587
	(0.343)	(0.402)	(0.190)	(0.573)
lpden1_2000	-0.062*	-0.032	-0.011	-0.012
	(0.036)	(0.035)	(0.020)	(0.047)
dem	0.003	0.006	0.007*	0.038***
	(0.008)	(0.012)	(0.004)	(0.015)
turnout	0.031***	0.024*	0.016**	0.058***
	(0.012)	(0.013)	(0.006)	(0.021)
lnalpha		-0.518***		0.193
		(0.184)		(0.204)
R-squared	0.247	0.188	0.268	0.199

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies

Table 5
Determinants of Regulatory Activity
Full Model – 10-mile Demographics
(N=1616; std. err.)

MODEL	OLS	N.B.	OLS	N.B.
Dep. Var.	INSPECT	INSPECT	ENFORCE	ENFORCE
	M13	M14	M15	M16
eld10	-1.654	-2.407	-2.697	-9.380
	(3.388)	(4.341)	(1.874)	(5.814)
kids10	-8.333*	-7.511	-4.854*	-13.202
	(4.531)	(5.503)	(2.507)	(8.144)
poor10	0.852	1.581	2.364*	7.112*
	(2.396)	(2.838)	(1.326)	(3.645)
nw10	-1.144	-1.929**	-0.391	-1.125
	(0.752)	(0.955)	(0.416)	(1.257)
lpden10	-0.060	-0.072*	-0.029	-0.037
	(0.038)	(0.042)	(0.021)	(0.077)
R-squared	0.245	0.192	0.269	0.198

MODEL	OLS	N.B.	OLS	N.B.
Dep. Var.	INSPECT	INSPECT	ENFORCE	ENFORCE
	M17	M18	M19	M20
eld10_2000	1.043	2.696	-1.025	-14.725*
	(4.132)	(4.909)	(2.289)	(7.974)
kids10_2000	-9.855	7.444	-3.983	-7.750
	(7.592)	(8.825)	(4.207)	(13.710)
poor10_2000	2.667	1.566	1.678	5.678
	(2.090)	(2.750)	(1.158)	(3.820)
nw10_2000	-1.774	-1.408	-0.389	-1.244
	(1.136)	(1.334)	(0.629)	(1.954)
lpden10_2000	-0.083	-0.151*	-0.062	-0.159
	(0.080)	(0.088)	(0.044)	(0.124)
R-squared	0.247	0.193	0.269	0.199

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies, along with the full set of control variables from earlier models.

Table 6
Determinants of Emissions
Basic Model - Plant characteristics only
(std. err.)

Dep. Var.	NOx M21	PM10 M22	SO2 M23	VOC M24	TRI M25	TRI-TOX M26
LTVS	0.020	0.051*	0.025	0.215***	0.142	-0.021
	(0.032)	(0.028)	(0.041)	(0.040)	(0.184)	(0.272)
LP	0.085*	-0.012	-0.024	-0.080	0.294	0.177
	(0.046)	(0.040)	(0.058)	(0.057)	(0.263)	(0.388)
LCAP	0.024	0.003	0.030	-0.009	0.063	0.226*
	(0.016)	(0.014)	(0.021)	(0.020)	(0.088)	(0.131)
LCF	0.303***	0.142***	0.158***	0.087***	0.349***	0.472***
	(0.020)	(0.017)	(0.025)	(0.025)	(0.095)	(0.140)
SU	-0.007	0.013	-0.059	0.001	0.241	-0.138
	(0.075)	(0.064)	(0.095)	(0.092)	(0.428)	(0.632)
PRE1978	-0.006	0.109**	0.266***	-0.081	-0.122	-0.302
	(0.064)	(0.055)	(0.081)	(0.078)	(0.343)	(0.506)
R-squared	0.696	0.561	0.368	0.495	0.390	0.315
N	926	926	926	926	569	569

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies

Table 7
Determinants of Emissions
Full Model – Plant-Siting-Year Demographics
(std. err.)

Dep. Var.	NOx	PM10	SO2	VOC	TRI	TRI-TOX
	M27	M28	M29	M30	M31	M32
LTVS	0.022	0.054*	0.027	0.213***	0.138	0.004
	(0.032)	(0.028)	(0.041)	(0.040)	(0.185)	(0.274)
LP	0.085*	-0.008	-0.019	-0.077	0.318	0.190
	(0.046)	(0.040)	(0.059)	(0.057)	(0.263)	(0.390)
LCAP	0.021	0.001	0.030	-0.010	0.067	0.233*
	(0.016)	(0.014)	(0.021)	(0.020)	(0.089)	(0.132)
LCF	0.298***	0.137***	0.157***	0.084***	0.309***	0.431***
	(0.020)	(0.017)	(0.026)	(0.025)	(0.097)	(0.144)
SU	-0.014	0.007	-0.063	0.000	0.222	-0.122
	(0.075)	(0.064)	(0.095)	(0.092)	(0.430)	(0.639)
PRE1978	-0.046	0.080	0.289***	-0.136	-0.344	-0.333
	(0.072)	(0.062)	(0.092)	(0.089)	(0.377)	(0.559)
eld1	1.735*	2.252**	1.580	1.176	13.955**	15.025*
	(1.038)	(0.891)	(1.322)	(1.279)	(5.664)	(8.413)
kids1	2.536*	2.281*	0.735	2.282	16.130**	7.788
	(1.498)	(1.286)	(1.908)	(1.846)	(7.785)	(11.564)
poor1	0.529	0.433	0.766	-1.350*	-2.764	-2.391
	(0.627)	(0.538)	(0.798)	(0.772)	(3.193)	(4.742)
nw1	-0.290	-0.261	0.123	-0.125	-1.631	-0.763
	(0.294)	(0.252)	(0.375)	(0.362)	(1.329)	(1.974)
dem	0.001	0.006	0.005	0.005	-0.005	-0.024
	(0.006)	(0.005)	(0.008)	(0.007)	(0.030)	(0.044)
turnout	0.000	0.010	0.009	0.005	0.028	-0.004
	(0.008)	(0.007)	(0.010)	(0.010)	(0.046)	(0.069)
lpden1	-0.048***	-0.032**	-0.032	-0.017	-0.094	-0.168
	(0.016)	(0.014)	(0.021)	(0.020)	(0.070)	(0.104)
R-squared	0.700	0.568	0.372	0.500	0.406	0.325
N	926	926	926	926	569	569

* $p<0.10$, ** $p<0.05$, *** $p<0.01$
All models include city dummies and 2-digit SIC industry dummies

Table 8
Determinants of Emissions
Full Model – Year 2000 Demographics
(std. err.)

Dep. Var.	NOx	PM10	SO2	VOC	TRI	TRI-TOX
	M33	M34	M35	M36	M37	M38
LTVS	0.021	0.053*	0.032	0.215***	0.151	-0.044
	(0.032)	(0.028)	(0.041)	(0.040)	(0.186)	(0.274)
LP	0.092**	-0.006	-0.013	-0.078	0.285	0.151
	(0.046)	(0.040)	(0.058)	(0.057)	(0.264)	(0.391)
LCAP	0.020	0.001	0.025	-0.011	0.070	0.226*
	(0.016)	(0.014)	(0.021)	(0.020)	(0.090)	(0.132)
LCF	0.302***	0.142***	0.157***	0.090***	0.337***	0.476***
	(0.020)	(0.017)	(0.025)	(0.025)	(0.096)	(0.142)
SU	-0.011	0.014	-0.056	0.008	0.330	-0.141
	(0.074)	(0.064)	(0.094)	(0.092)	(0.433)	(0.640)
PRE1978	0.016	0.115**	0.276***	-0.073	-0.107	-0.262
	(0.064)	(0.055)	(0.081)	(0.079)	(0.345)	(0.510)
eld1_2000	1.535*	1.328*	2.658**	2.597**	-0.811	-1.010
	(0.859)	(0.741)	(1.090)	(1.059)	(4.307)	(6.362)
kids1_2000	3.766**	1.993	4.696**	1.030	-6.542	-7.298
	(1.601)	(1.380)	(2.031)	(1.972)	(7.622)	(11.257)
poor1_2000	0.420	0.470	1.351**	-1.223**	2.055	-0.495
	(0.483)	(0.416)	(0.613)	(0.595)	(2.395)	(3.538)
nw1_2000	0.268	0.302	0.074	0.437	-1.295	1.785
	(0.282)	(0.243)	(0.358)	(0.348)	(1.295)	(1.913)
dem	-0.003	0.001	0.004	0.001	-0.017	-0.046
	(0.006)	(0.005)	(0.007)	(0.007)	(0.030)	(0.044)
turnout	-0.005	0.006	0.006	0.001	0.025	-0.016
	(0.008)	(0.007)	(0.010)	(0.010)	(0.047)	(0.069)
lpden1_2000	-0.096***	-0.057**	-0.069**	-0.024	-0.092	-0.269
	(0.026)	(0.022)	(0.033)	(0.032)	(0.114)	(0.168)
R-squared	0.702	0.567	0.380	0.503	0.397	0.322
N	926	926	926	926	569	569

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies

Table 9
Determinants of Emissions
Full Model – 10-mile Demographics
(std. err.)

Dep. Var.	NOx	PM10	SO2	VOC	TRI	TRI-TOX
	M39	M40	M41	M42	M43	M44
eld10	-0.529	-0.065	1.913	-3.057	5.124	13.625
	(2.492)	(2.140)	(3.164)	(3.092)	(12.930)	(19.128)
kids10	-1.181	-1.394	-2.411	-2.012	15.700	0.985
	(3.045)	(2.614)	(3.865)	(3.777)	(18.482)	(27.339)
poor10	2.103	2.193	1.171	-1.236	11.677	10.308
	(1.687)	(1.448)	(2.141)	(2.092)	(8.608)	(12.734)
nw10	0.514	0.429	1.310*	-0.017	-4.500*	-2.244
	(0.586)	(0.503)	(0.744)	(0.727)	(2.678)	(3.961)
lpden10	-0.133***	-0.107***	-0.146***	-0.010	-0.258*	-0.426*
	(0.032)	(0.028)	(0.041)	(0.040)	(0.123)	(0.182)
R-squared	0.703	0.573	0.382	0.498	0.405	0.329
N	926	926	926	926	569	569

Dep. Var.	NOx	PM10	SO2	VOC	TRI	TRI-TOX
	M45	M46	M47	M48	M49	M50
eld10_2000	4.674	2.709	9.083*	-0.594	-5.789	6.776
	(3.057)	(2.641)	(3.874)	(3.801)	(15.419)	(22.858)
kids10_2000	1.974	0.157	1.039	-0.851	-5.527	14.047
	(5.180)	(4.475)	(6.564)	(6.441)	(29.257)	(43.372)
poor10_2000	-0.177	-0.989	2.692	-2.565	9.127	7.381
	(1.573)	(1.359)	(1.993)	(1.956)	(8.319)	(12.332)
nw10_2000	1.649*	1.988**	0.820	-0.065	-2.214	-0.903
	(0.860)	(0.743)	(1.090)	(1.070)	(4.065)	(6.027)
lpden10_2000	-0.258***	-0.195***	-0.217**	0.029	-0.503*	-0.544
	(0.057)	(0.049)	(0.072)	(0.070)	(0.270)	(0.401)
R-squared	0.705	0.570	0.388	0.499	0.402	0.323 N
	926	926	926	926	569	569

* p<0.10, ** p<0.05, *** p<0.01
All models include city dummies and 2-digit SIC industry dummies, along with the full set of control variables from earlier models.