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Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice

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Valuable comments were received from Spencer Banzhaf and other seminar participants in the "Markets for Land and Pollution: Implications for Environmental Justice" (October 2008), the Southern Economic Association (November 2008) meetings, and the "Pollution Control, Sustainability Practices, and Enforcement" session at the ASSA Meetings (2009). The opinions and conclusions expressed are those of the authors and not the Census Bureau or EPA. All papers using Census data are screened to ensure that they do not disclose confidential information.

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ABSTRACT

We examine the determinants of environmental regulatory activity (inspections and enforcement actions) for 1616 U.S. manufacturing plants in four large U.S. cities – Los Angeles, Boston, Columbus, and Houston – using data for 2000-2002. The main focus of our study is to examine whether or not regulators treat different segments of the population differently, by directing more regulatory activity at plants in rich, white neighborhoods and less in poor, minority neighborhoods, controlling for characteristics of the plant (size, age, and industry), and the plant's past environmental performance. To date, tests of "Environmental Justice" hypotheses tend to focus on whether or not polluters are disproportionately likely to locate in neighborhoods with relatively high poor/minority populations, or on whether polluters located in those neighborhoods emit disproportionately high levels of pollution. Focusing instead on the allocation of enforcement activity across neighborhoods within each city allows us to shed light on a key mechanism through which discrepancies in pollution exposure across neighborhoods could arise and persist. Our results show relatively little statistically significant evidence that regulatory activity is less intense near disadvantaged demographic groups. We do find some suggestive coefficients - plants located in minority neighborhoods face less regulatory activity - but this effect is generally insignificant, and plants located in poor neighborhoods face (insignificantly) more regulatory activity. In contrast, we do find significant effects for plant characteristics and political variables, with plants that are larger and more energy-intensive, owned by single-plant firms, and located near politically active and liberal populations, facing more regulatory activity.

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

Subject Matter Classifications: Distributional Effects, Enforcement Issues

1. INTRODUCTION

Our paper examines the allocation of environmental regulatory activity, testing a key potential explanation for "Environmental Justice" concerns.[1] In the United States environmental policymaking is carried out under a federalist system. The U. S. Environmental Protection Agency (EPA) sets national air and water quality standards for particular pollutants (e.g. $PM_{2.5}$[2]), while state regulatory agencies have the primary responsibility to implement and enforce those regulations. The power of the states to implement and enforce regulations affords them with a substantial amount of discretion (e.g. setting a plant's permitted level of air and water pollution emissions, or allocating inspections across different facilities). We might expect regulators to direct more enforcement activity at plants located in areas that receive greater benefits (or face lower costs) from pollution abatement. Regulators could also respond to political pressure, directing more activity at plants in rich, white neighborhoods and less activity at plants in poor, minority neighborhoods, which could result in poorer environmental conditions in less privileged areas, creating a potential for "Environmental Injustice". Of course, this implicitly assumes that the affected neighborhoods prefer to receive more regulatory activity; if regulatory actions result in plant closings or job losses, the community might prefer less regulatory activity.

We perform our analysis on a sample of 1616 manufacturing plants located near four large U.S. cities: Los Angeles, Boston, Columbus, and Houston. We use plant-level

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[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."

[2] $PM_{2.5}$ refers to fine particles – 2.5 micrometers in diameter and smaller – which are unhealthy to breathe and have been associated with premature mortality and other serious health effects.

information from the Census Bureau's confidential establishment-level Longitudinal Research Database (LRD). The LRD includes 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 measure the regulatory stringency being directed towards a particular plant in terms of the numbers of air pollution inspections and enforcement actions directed at that plant from 2000-2002, using data taken from EPA's Integrated Data for Enforcement Analysis database. We find evidence, as expected, that plant characteristics significantly affect the amount of regulatory activity directed at a plant. In particular, we find that bigger plants and plants with higher fuel consumption face significantly more regulatory activity, as do plants in single-plant firms (firms which own a single manufacturing facility).

We find that nearby political activity significantly affects the amount of regulatory activity directed at a plant. Plants surrounded by politically active populations (measured by voter turnout) and more liberal populations (measured by the percentage voting for the Democratic candidate for President) receive more regulatory attention. These results are broadly consistent with the results of prior research. For example, Hamilton (1995) finds that the capacity expansion decisions of commercial hazardous waste facilities are negatively correlated with political activity. Viscusi and Hamilton (1999) find that Superfund sites located in more pro-environmental areas and with greater political activity have more stringent environmental clean up targets for cancer risk, while Sigman (2001) finds EPA processes Superfund sites faster in communities with more political activity. Both of these results show that community activism is an important factor affecting EPA's bureaucratic priorities. Jenkins and Maguire (2009) find that more politically active states set higher hazardous waste taxes, providing a greater deterrent to waste disposal. However Wolverton (2009a, 2009b) finds that the location of polluting plants in two large cities in Texas is not significantly influenced by the level of community political activity.

The focus of our analysis is how the demographic characteristics of the nearby populations influence the amount of regulatory activity faced by our plants. 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 find some of the expected relationships, but relatively little statistical significance. In terms of the more sensitive groups, we find that plants with more elders nearby do face more inspections (though not more enforcement), but this effect is only significant when we exclude the other control variables from our model. Plants with more children nearby show less clear patterns, although they also tend to be more positive in models without other control variables. These findings are consistent with those of Gray and Shadbegian (2004) for a similar analysis of U.S. pulp and paper mills.

In terms of our "Environmental Justice" analysis, we also find relatively little statistical evidence that regulatory activity is less intense in plants near disadvantaged demographic groups. Plants located in minority neighborhoods, as expected, are inspected less often and face fewer enforcement actions, but both these effects are insignificant in models with a full set of controls, and plants located in poor neighborhoods tend to face (unexpectedly) more regulatory activity.[3] Some models (without a full set of control variables) found significantly fewer inspections at plants near minority populations. Most of our results are consistent with previous research by Hamilton (1995), Been and Gupta (1997), Arora and Cason (1999), Gray and Shadbegian (2004), and Wolverton (2009a, 2009b) which all find in various ways that minorities and the poor are not systematically exposed to more pollution. However, our results are inconsistent with some other existing studies that find some evidence raising possible environmental justice concerns. Sigman (2001) finds that EPA processes Superfund sites more quickly in communities with higher median income. 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. Finally, Jenkins and Maguire (2009) find (in their preferred specification) that states with larger minority populations living near waste sites set lower hazardous waste taxes, raising the likelihood of greater waste disposal, thereby raising possible environmental justice concerns in the way hazardous waste is taxed.

The remainder of the paper is organized as follows. Section 2 outlines a simple model of pollution abatement in a federalist system. In section 3 we present a description of our data and our empirical methodology. Section 4 contains our results and finally we present some concluding remarks and possible extensions in section 5.

[3] Gray and Shadbegian (2004) also found little significant evidence of diminished regulatory activity near poor and minority populations.

2. MODEL OF POLLUTION ABATEMENT REGULATION UNDER FEDERALISM

Why do profit-maximizing plants allocate resources to pollution abatement? If pollution were a pure externality, only negatively impacting people who live downwind or downstream of the emitting source, we would not expect to observe any profit-maximizing plant allocating any resources to pollution abatement. Thus, there must be some "external" pressure on the firm to provide an incentive for pollution abatement. Many sources of such external pressure exist. Some of these are market-based, such as consumer demand for products produced with "green/clean" technologies, which allows firms doing more pollution abatement to charge higher prices. The threat of civil law suits or the possibility of Coasian bargaining could provide additional incentives. If the firm's managers have a taste for 'good citizenship' (and the flexibility to spend the firm's funds on pollution abatement), that could also "internalize" the externality, from the perspective of the firm's decision-making. However, we believe that the main incentive for reducing pollution emissions in the U.S. is governmental regulatory activity, especially for the air pollutants we examine in this paper.[4] Therefore it is important to understand the determinants of the amount of regulatory pressure faced by a plant. A large part of that regulatory pressure comes from regular inspections to identify non-compliance, and from enforcement actions designed to force changes at non-compliant

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[4]The compliance-enforcement literature contains numerous studies which show the effectiveness of EPA enforcement, including Magat and Viscusi (1990), Gray and Deily (1996), LaPlance and Rilstone (1996), Nadeau (1997), Helland (1998), and Gray and Shadbegian (2005,2007).

plants, and the allocation of those inspections and enforcement actions are the focus of our analysis.

As noted above, the United States conducts environmental policymaking under a federal system, in which the US EPA sets national standards and each individual state has its own environmental regulatory agency which is responsible for implementing and enforcing regulations to meet those standards. The responsibility of the states to implement and enforce regulations affords them considerable flexibility to direct varying degrees of regulatory pressure on polluting plants, in spite of the fact that their activities are monitored by the federal EPA. In fact, 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. In addition, the vast majority of air pollution inspections and enforcement actions are performed by state, not federal, regulators. This importance of state-level decisions makes it more likely that local political pressures could influence regulatory activity (as compared to a centralized system where all the important decisions were being made in Washington D.C., far from local political influence).

Optimal regulations would maximize social welfare by setting the marginal benefit from pollution abatement equal to the marginal cost of abatement. In equation (1) below, optimal abatement values, A_i^*, differ for each plant, based on factors which impact the marginal benefits and marginal costs of abatement. The marginal benefits of pollution abatement differ across plants mainly due to the number (and characteristics) of the people who live near the plant who are being exposed to the pollution. On the other hand, the marginal costs of abatement differ across plants based mainly on their production technology, size, and age. Making the standard assumption that the marginal cost of pollution abatement increases with abatement intensity (or at least intersects the marginal benefits curve from below), plants with higher marginal benefits (or lower marginal costs) should do 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.

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

Our study focuses on the differences across plants in the marginal benefits of pollution abatement (MB_i), while also controlling for plant characteristics affecting marginal abatement costs (e.g. size, fuel use etc). We model the marginal benefit function as aggregating up the individual marginal benefits from pollution reductions 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 depend largely on the number of people in the area (measured by ρ_{xy}, the population density at a given point[5]) and the emissions that they are exposed to (E_{xy}). We measure differences in people's health susceptibility to pollution exposure by S_{xy}.[6] Finally, we allow for the possibility that the benefits accruing to different population groups are given different weights, through the use of the α_{xy} term.

[5] 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.

[6] 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}

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

Note that differences in α_{xy} across groups of people (e.g. by race or socioeconomic status) could be associated with "Environmental Justice concerns", since people with lower α_{xy} are likely to be exposed to higher pollution levels (cleaning up the pollution affecting those groups would receive a “lower benefit” in the MB=MC calculation, resulting in less cleanup). Where could these differences in α_{xy} come from? This depends in large part on how the marginal benefits are assumed to be affecting the firm’s decision about how much pollution to abate. If pollution abatement comes from the firm’s managers deciding to “do good” for the community, they may be more sympathetic to neighborhoods whose demographic composition is similar to their own. If it comes from threats of legal action or Coasian bargaining, homogenous neighborhoods with powerful community connections may get greater weight. Note that all these examples assume that the affected neighborhoods receive the benefits from pollution abatement, but not the costs (so more abatement is better for them). If abatement pressures are expected to result in plant closings or job losses, the community might in some circumstances prefer to have less pollution abatement.

The possibility that we focus on here is that state regulators are choosing their regulatory stringency (especially the frequency of inspections and enforcement actions) in order to maximize net political support for their regulatory activities (Stigler (1971), Peltzman (1976), Deily and Gray(1991)). This suggests that socio-economic groups with less political clout (e.g. poor or minorities) would be given less weight (assigned a smaller value of α_{xy}) in the agency's calculations. On the other hand, politically active people, especially those who strongly favor environmental issues, may apply extra pressure on regulators to increase the regulatory stringency applied to nearby plants, effectively giving those people a larger value of $\alpha_{xy.}$, with more regulatory activity and more pollution abatement

3. DATA AND EMPIRICAL METHODOLOGY

Our analysis uses cross-sectional data on environmental regulatory activity in 2000-2002 for 1616 manufacturing plants, located near four large cities: Los Angeles, Boston, Columbus, and Houston. We included four cities in four different states to allow us to test whether the allocation process differs between cities in higher- and lower-regulation states.[7] Those tests (results available upon request) have not shown any systematic differences in the allocation process across the four individual cities, so they are not presented here. We gathered data for all plants located within 50 miles of any of the cities from EPA databases. Plant location information (latitude and longitude) came from EPA's Facility Registry System database. The final sample of 1616 plants came from a merger of plant-level Census data and EPA data that required each plant to be present in both the Census and EPA datasets.[8]

[7] According to Hall and Kerr's (1991) 'Green Policies' index, designed to measure the stringency of state environmental regulations, Los Angeles and Boston are in higher regulation states than Columbus and Houston (scores of 0.8, 1.4, 2.0, and 2.7 respectively, where a lower score reflects stricter regulation).

[8] The scope of the sample we created for this project (i.e. analyzing only four cities) was limited by the considerable effort required to gather, merge, and clean the multiple EPA and Census datasets needed for the analysis.

Our regulatory enforcement data come from the EPA's Envirofacts and Integrated Data for Enforcement Analysis databases. These datasets allow us to differentiate between two different types of regulatory pressures faced by each plant – enforcement actions (ENFORCE) and 'inspection-type' actions (INSPECT) – directed at the plant between 2000 and 2002. Enforcement actions include notices of violation, penalties, and follow-up phone calls, while 'inspection-type' actions include onsite inspections, emissions monitoring, stack tests. Based on discussions with regulators, the number of enforcement actions is more likely to be associated with problems at the plant, while the number of inspections is more connected with the size of the plant.

Harrington (1988) illustrates that in a repeated game, a regulator could increase the expected long-run penalty for non-compliance considerably by establishing two classes of regulated plants - good and bad. The good plants are assumed to cooperate with regulators and are inspected only rarely. The bad plants are assumed to be uncooperative with regulators and face much greater inspection and enforcement activity. To control for this effect we include a lagged measure of past violations of environmental standards (VIOL_97), indicating whether the plant was out of compliance at any point in 1997[9].

We estimate four different versions of equation (3) below for the dependent variables measuring regulatory stringency. We measure stringency as the number of inspections (INSP) and enforcement actions (ENFORCE) a plant receives over the 2000-2002 period (using three years of data to provide more variation in the dependent variables). Since both INSP and ENFORCE are often zero and are otherwise relatively

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

small integers, we estimate the equations using a Poisson model (actually, we use a Negative Binomial model, to allow for the observed over-dispersion of the data, relative to the simpler Poisson model).[10, 11] Each dependent variable Y_{it} is a function of PLANT and PEOPLE characteristics, as well as STATE and COUNTY variables and CITY dummy variables:

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

where Y_{it} is one of the two dependent variables in our analysis: Air Pollution Inspections and Enforcement.

Prior to discussing the expected impacts of our neighborhood level socio-economic and demographic variables we first detail 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 Research Database (LRD). The LRD 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 LRD data, see McGuckin and Pascoe (1988)).[12]

[10] The Poisson regression model is appropriate in cases when the dependent variable is a count (e.g. number of inspections and enforcement actions). The Poisson distribution assumes that the dependent variable's mean is equal to its variance, but in many cases count data exhibit over-dispersion (a variance greater than its mean). In these cases a model that allows for over-dispersion, such as the Negative Binomial model used here, is more appropriate (and our Negative Binomial results show significant over-dispersion in our data).
[11] We also estimate each model with OLS, to test the robustness of the coefficient results.
[12] The establishment-level data in the LRD 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.

From the LRD we extract information for 2002, originally collected in the 2002 Census of Manufactures. We use the plant's total value of shipments in log form (SIZE) and capital stock in log form (CAPITAL) to measure the size of the plant. To control for fuel use, which should 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 LRD.[13] 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 identifies plants which are part of single-plant firms (firms which own no other manufacturing plants) to control for corporate structure. If single plants have less political clout then we would expect to find them receiving more attention from regulators - they might also be more apt to have paperwork violations, as compared to larger firms which could take advantage of economies of scale in providing regulatory compliance support from their corporate headquarters.

We use voting information at the county level to characterize the political climate surrounding the plant[14]. The use of voter activity to overcome externalities is discussed in Olson (1965). A positive influence on α_{xy} is expected to come from voter activity, measured using county voter turnout in the 2000 presidential election (TURNOUT). We also include DEMOCRAT, the fraction of voters in the county voting for the Democratic Presidential candidate in 2000, as an indication of voter support for more active regulatory interventions[15]. Both of these variables are expected to result in more

[13] We would like to thank John Haltiwanger for providing us with our plant's age and capital stock, which were calculated based on establishment level Census data.
[14] Unfortunately, voting data at finer levels of geographic detail (e.g. precinct-level data) cannot be used, because they are not collected in similar ways across these four states.
[15] We tried using League of Conservation Voters data on pro-environmental voting in Congress, which did get the expected positive coefficient but was consistently insignificant, perhaps

regulatory activity at a plant, since they are associated with having more politically active, liberal people living near the plant[16].

Now consider the variables which are at the heart of our analyses, those related to environmental justice concerns that plants might be treated differently based on the racial, ethnic, or socioeconomic composition of the surrounding population. In our analyses the "potentially less valued" (low α_{xy}) populations are poor and minorities. Our measure of POOR is the percentage of the nearby population living below the poverty line; our measure of MINORITY is the percentage of the nearby population which is not non-Hispanic whites. Environmental justice concerns could be raised if plants near POOR and MINORITY populations face less regulatory activity. We measure the overall population being affected by pollution from the plant (ρ_{xy}) with POPDEN, the population density around the plant, which is expected to be associated with increased regulatory activity. Possible differences in health sensitivity by age group (S_{xy} in equation 2) are represented 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). Since both groups are expected to be more sensitive to pollution, both CHILDREN and ELDERS should be positively related to regulatory activity.

We create the above mentioned socio-economic and demographic variables from detailed geographic area (Census block groups) data on population characteristics from the 2000 U.S. Census of Population, as compiled in the Census-CD datasets prepared by

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because of limited geographic variability, being measured at the Congressional district level (results available upon request).

[16] Politically active Republicans might be expected to push for less regulatory activity on ideological grounds. The political clout of Democrats might be expected to depend on the party affiliation of the state's Governor, but during our sample period only California had a Democratic governor, so we had no variation to test that hypothesis.

Geolytics, Inc. We do not know, a priori, the 'optimal' (or even most appropriate) size of a neighborhood to examine the effects of benefits and our socio-economic and demographic variables on regulatory activity. Therefore we take advantage of our ability to 'construct' neighborhoods of different sizes to see how far the benefit and political effects extend. In particular, we 'construct' four different-sized neighborhoods: one consisting of the closest block group, and three additional neighborhoods based on "circles" around the plant - all block groups that fall within R miles of the plant, where R = 1, 5 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 it happens, we did not find 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 report here the results for 1- and 10-mile circles around the plant (other results are available from the authors upon request).

We also considered alternative demographic measures, based on the heterogeneity of the population surrounding the plant, presuming that a more heterogeneous population will have a more difficult time mobilizing for political action. Researchers have considered the impact of ethnic or linguistic fragmentation as it affects economic growth in developing countries (e.g. Easterly and Levine (1997)), or the impact of racial or educational heterogeneity on community activity (e.g. Vigdor (2004) and Videras (2007)). For our analysis we constructed two homogeneity indices, each calculated as the sum of squared shares of subgroups within the population. The education homogeneity index (HOM_ED), is based on the shares of college graduates, high school graduates, and high school dropouts near the plant. The racial homogeneity index (HOM_RACE) is based on the shares of African Americans, Asians, Native Americans, Hispanics, and non-Hispanic whites near the plant (with the latter group also including "all other" racial groups).

4. RESULTS

Table 1 contains the means and standard deviations, along with variable descriptions, of all variables used in this study. In our data the average plant receives roughly twice as many air inspections as enforcement actions per year – though the inspection distribution is skewed, with more than half our plants not receiving an inspection in 2000-2002. Turning now to our key demographic variables, which allow us to test for environmental justice concerns, we see that in terms of segments of the population which may be more sensitive to pollution emissions (CHILDREN and ELDERS), less than 10% of our population is under the age of 6 and roughly 12% is over the age of 65. In terms of our variables which measure segments of the population which have less 'political clout' (POOR and MINORITY), about 14% of our population has income below the poverty line and just over 25% of our population are minorities. There is much more variation across plants for the POOR and MINORITY variables than for the CHILDREN and ELDERS variables.

In Table 2 we present the results of the basic model for air pollution regulatory activity.[17] Our basic model works quite well, explaining roughly 20% of the variation across plants in inspection and enforcement activity. The key control variables have the

[17] All the results presented below include city fixed effects – we get qualitatively similar results when we drop the fixed effects (results available from the authors).

expected sign in nearly all cases. We find that larger plants, which typically generate more pollution, face more inspections and enforcement activity. Plants which use more fuels, again expected to emit more air pollution, face significantly more regulatory activity. Plants which are owned by single-plant firms (firms which own no other manufacturing plants) also face significantly more regulatory activity. Finally, plants with past violations (VIOL_97) face greater regulatory activity, though this effect is only significant in the OLS models. The other control variables (capital intensity, labor productivity, and plant age) have less consistent and generally insignificant effects.

We add three additional variables to our basic model in Table 3 – POPDEN, TURNOUT, and DEMOCRAT. In general, the key plant-level control variables continue to have the same effect as found in the basic model in Table 2. POPDEN, our proxy for the marginal benefits from pollution abatement, has an unexpectedly negative effect on the amount of regulatory activity faced by a plant, but is only significant in the OLS model for inspections.[18] This implies that regulators are not directing additional regulatory pressure, in the form of more inspections or more enforcement actions, towards potentially high benefit plants. On the other hand, our political variables, TURNOUT and DEMOCRAT, have the expected positive signs and are generally significant. This provides evidence that regulators respond to pressure from the surrounding population, with more politically active and more liberal populations encouraging more regulatory activity.

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[18] Gray and Shadbegian (2004) find similarly odd results, using much more sophisticated measures of the marginal benefit of pollution abatement. We also tried including measures of plant density (the number of other plants in out data within a given radius of the plant), to test whether areas with many plants received fewer inspections per plant (possibly explaining the negative POPDEN results), but plant density was generally insignificant, and its inclusion in the model didn't affect the POPDEN coefficient's sign (results available on request).

In Table 4A we add demographic/socio-economic variables to our full model.[19] CHILDREN and ELDERS are two demographic groups which are expected to receive greater health benefits from pollution abatement than the rest of the population. Focusing on the results of the Negative Binomial models, we see that plants which are near more sensitive population groups (CHILDREN and ELDERS) face more inspections, as expected. However, this effect is never significant. On the other hand, ELDERS and CHILDREN show some unexpectedly negative (yet generally insignificant) effects on enforcement activity, as well as some differences between the OLS and Negative Binomial results. On the whole, we do not find convincing evidence that regulators put more pressure, in the form of inspections and enforcement activity, on plants located in areas with more sensitive populations. This is a surprise, but it may be the case that our measures of regulatory pressure (simple counts of inspection and enforcement actions) are not really capturing the amount of pressure these plants face. High-benefit plants may face other kinds of pressures (e.g. community action, permit stringency, etc.) that we cannot observe. If regulators, with limited time to perform regulatory enforcement, know that a plant is facing these other pressures, then they might not feel the need to allocate more inspections and enforcement actions to those plants.

Now we turn to the impact of POOR and MINORITY (our potentially disadvantaged populations) on regulatory activity, the focus of our "Environmental Justice" analysis. As happened with CHILDREN and ELDERS, we find little evidence that regulators treat poor or minority populations differently than other populations in their allocation of regulatory activity. MINORITY has the expected negative effect on

[19] We only provide the newly estimated coefficients in Table 4A, but in general the other variables have the same qualitative effects shown in Tables 2 and 3.

regulatory activity, but this effect is insignificant, while the POOR coefficient has an unexpectedly positive effect on regulatory activity, although this effect is also generally insignificant.

One possible concern with the results in Table 4A is that we are estimating the full model, and that some of our control variables may be capturing the mechanisms by which the demographic variables might influence regulatory activity. For example, poor and minority neighborhoods have lower voter turnout, so the significant TURNOUT effect in the model might leave little to be explained by POOR and MINORITY[20]. We tested several variations of our models, including different combinations of the demographic variables, or excluding some control variables (such as lagged violations and political activism). The remaining panels of Table 4 consider progressively simpler models. Table 4B includes our four key demographic variables and city dummies, but no other control variables. Table 4C includes only one demographic variable at a time along with city dummies. Finally, Table 4D presents simple correlations between each of the demographic variables and the regulatory activity measures. It's worth noting that dropping the other control variables results in considerably less explanatory power (lower R^2) in these analyses, as compared to those in Table 4A.

There is a tendency, most noticeable in Table 4B, for the coefficients on the demographic variables to become more consistent in sign, and occasionally become significant, when the other control variables are dropped from the model. ELDERS and CHILDREN are more consistently positive than in the full model, and are both significant in the 10-mile-circle Negative Binomial inspection model. POOR is consistently positive (but insignificant), while MINORITY remains negative and is

[20] In our dataset the correlations of POOR and MINORITY with TURNOUT are about -0.7.

significant for the Negative Binomial inspection equations. In Table 4C, where the demographic variables enter separately, the coefficients on ELDERS and CHILDREN are less consistently positive, but we now see significantly negative (negative binomial) results for POOR and MINORITY, with fewer inspections at plants in POOR and MINORITY neighborhoods. The importance of controlling for differences across cities can be seen by comparing Table 4C and Table 4D - only about half (9 of 16) of the correlations in 4D (without city controls) have the same sign as the regression coefficients in 4C (with city controls), and this discrepancy holds for all 4 of the demographic variables.

In Table 5, we consider the possibility that the homogeneity of the surrounding population might influence their ability to mobilize support for greater regulatory activity. We test homogeneity in educational attainment as well as in racial composition. We should find positive coefficients, if (as expected) more homogeneous neighborhoods are able to exert more effective pressure on regulators. We find the expected results for educational homogeneity, where we find positive effects that are usually significant, but not for racial homogeneity, where the coefficients are negative (and generally insignificant).

Given these initial results, we concentrate our attention on educational homogeneity in the remainder of Table 5 (we carried out similar analyses for racial homogeneity, without finding much of significance). We first consider a decomposition of the educational homogeneity index into its three components, the squared shares of the three educational subcategories. These components usually show positive effects on regulatory activity, consistent with the HOM_ED coefficients; the dropout share is more often negative than the others, but the differences between the components are not generally significant. We then test whether homogeneity matters differently for different populations by interacting HOM_ED with other variables: TURNOUT, POOR, and MINORITY. None of the interactions are significant, but we do find negative coefficients on POOR and MINORITY, suggesting that the advantages of homogeneity are less effective in poor or minority neighborhoods.

5. CONCLUDING REMARKS

In this paper we use a plant-level data set consisting of 1616 U.S. manufacturing plants in four large U.S. cities – Los Angeles, Boston, Columbus, and Houston – to test whether or not regulators treat different segments of the population differently when allocating regulatory activity. A key potential explanation for "Environmental Justice" concerns is that regulators might direct more regulatory activity at plants in rich, white neighborhoods and less in poor, minority neighborhoods, resulting in poorer environmental conditions in less privileged areas. We focus on differences across plants in the benefit side of the MB=MC equation, but our use of confidential Census plant-level data allows us to control for a variety of plant characteristics (size, age, productivity, capital intensity, and energy intensity) which could affect marginal abatement costs.

Our basic model for air pollution regulatory activity works quite well, explaining roughly 20% of the variation in inspection and enforcement activity, and our key control variables generally have the expected sign. One exception to this is the population density near the plant, which should increase the benefits of pollution reductions, but seems to have a negative effect on regulatory enforcement (though significant in only one model).

Examining the characteristics of the nearby population, we find that, as expected, plants in areas with more politically active (TURNOUT) and more liberal (DEMOCRAT) populations face significantly more regulatory pressure. On the demographic characteristics, the results are much weaker. We expect CHILDREN and ELDERS to be more sensitive to pollution emissions, but their coefficients are not always positive, and rarely significant.

Our measures of disadvantaged populations also show limited effects. We expect plants with more POOR and MINORITIES nearby to face less regulatory pressure. We find the expected sign for MINORITY, but these impacts are insignificant, while we find (unexpected) positive signs for POOR. Thus, we find relatively little statistical evidence that regulators are less active at plants near poor or minority populations. When other control variables are excluded from the model, the negative MINORITY effect is significant for inspections (but the POOR effect remains surprisingly positive).

We also test for the impact of population homogeneity near the plant, using measures of educational attainment and racial diversity. We find the expected impact for diversity in educational attainment (more homogeneous neighborhoods seem to have greater political clout, in terms of receiving more regulatory attention), but no impact of racial diversity on regulatory activity. Interactions of educational diversity with other demographic variables are generally insignificant.

The generally insignificant results for POOR and MINORITY do not necessarily rule out the presence of 'Environmental Justice' concerns in the allocation of regulatory activity across plants. Differences in regulatory pressure may arise through other avenues than the simple numeric count of inspections or enforcement actions. A politically well-connected population could intervene in permit renewals, organize community action against the plant, or encourage regulators to pursue qualitatively different avenues (e.g. the use of criminal penalties for violations) that we cannot observe in our data. Still, we might have expected to see some evidence of demographically-related differences in the intensity of regulatory activity if 'Environmental Justice' concerns had large effects.

We hope to extend this project in a number of directions in future work, including generating better measures of the marginal benefits of pollution cleanup at different plants (based on physical models of pollution flows), disaggregating our socio-economic and demographic variables into the eastern and western half of the circles drawn around each plant, and conducting a spatial econometric analysis of the regulatory attention paid to neighboring plants. Additional insights could be gained from a panel data analysis, relating changes in regulatory activity over time to changes in demographic patterns (this would also help address concerns about the potential endogeneity of the demographic variables, relative to spatial differences in pollution).

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TABLE 1

SUMMARY STATISTICS
(N=1616)

VARIABLE (N)	MEAN (STD DEV)	
Dependent Variables		
AIR INSP Number of air pollution inspections	0.503 (1.875)	
AIR ENFORCE Number of air pollution enforcement actions	0.267 (1.054)	
Plant-level Control Variables		
SIZE Log of total value of shipments	9.482 (1.780)	
LPROD Log of labor productivity	5.617 (1.025)	
CAPITAL Log of the capital stock	8.191 (2.474)	
FUELS Log of the cost of purchased fuels	3.908 (2.401)	
SINGLE Dummy variable =1 if this plant is a single plant firm	0.418 (0.493)	
AGE Log of the age of the plant	3.022 (0.545)	
VIOL_97 Dummy variable = 1 if the plant was out of compliance with air regulations in 1997	< 0.05	
Demographic Variables		
	1-Mile Circle	**10-Mile Circle**
POPDEN Log of population density	7.742 (1.593)	7.538 (1.165)
CHILDREN Percentage of the population under 6 years old	8.839 (2.449)	8.717 (1.271)
ELDERS Percentage of the population 65 years old and over	11.297 (4.571)	11.165 (2.532)
POOR Percentage of the population living below the poverty line	13.675 (9.587)	12.296 (5.439)

Table 1 (cont)

MINORITY 26.471 (23.021) 6.518 (18.134)
Percentage of the population who are minorities (Hispanic and/or non-white)

HOM_RACE 0.676 (0.215) 0.599 (0.209)
Homogeneity index = sum of squared shares of racial groups in population
(African Americans, Asians, Native Americans, Hispanics, and non-Hispanic whites)

HOM_ED 0.503 (0.054) 0.464 (0.045)
Homogeneity index = sum of squared shares of educational groups in population
(college graduates, high-school graduates, high-school dropouts)

Political Variables

TURNOUT 49.820 (8.460)
Percentage of the population over 18 voting in the 2000 presidential election

DEMOCRAT 54.757 (9.917)
Percentage of the population over 18 voting Democrat in the 2000 presidential election

TABLE 2
Basic Inspection and Enforcement Models

MODEL	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	ENFORCE	ENFORCE
CONSTANT	-2.537	-3.489	-1.598	-6.166
	(0.428)	(0.506)	(0.237)	(0.838)
BOSTON	0.266	0.106	0.307	1.651
	(0.167)	(0.175)	(0.092)	(0.536)
HOUSTON	1.553	1.089	1.120	3.237
	(0.193)	(0.183)	(0.107)	(0.534)
LOS ANGELES	-0.012	-1.239	0.386	2.059
	(0.174)	(0.220)	(0.096)	(0.534)
SIZE	0.099	0.139	0.044	0.127
	(0.042)	(0.053)	(0.023)	(0.079)
LPROD	0.126	-0.046	0.099	0.052
	(0.055)	(0.065)	(0.030)	(0.093)
CAPITAL	0.003	-0.025	0.012	0.020
	(0.024)	(0.027)	(0.013)	(0.041)
FUELS	0.168	0.233	0.095	0.239
	(0.024)	(0.030)	(0.013)	(0.042)
SINGLE	0.333	0.270	0.203	0.421
	(0.102)	(0.130)	(0.057)	(0.187)
AGE	0.071	0.120	-0.029	-0.204
	(0.083)	(0.107)	(0.046)	(0.138)
VIOL_97	0.960	0.227	0.638	0.335
	(0.257)	(0.216)	(0.143)	(0.335)
R^2	0.206	0.173	0.225	0.175

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.

TABLE 3
Expanded Basic Inspection and Enforcement Models

MODEL	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	ENFORCE	ENFORCE
CONSTANT	-3.596 (0.969)	-4.554 (1.130)	-2.708 (0.539)	-10.624 (1.760)
BOSTON	0.126 (0.234)	-0.029 (0.289)	0.107 (0.130)	0.809 (0.612)
HOUSTON	1.820 (0.231)	1.330 (0.233)	1.290 (0.128)	3.871 (0.588)
LOS ANGELES	0.268 (0.207)	-1.000 (0.266)	0.453 (0.115)	2.207 (0.582)
SIZE	0.102 (0.042)	0.140 (0.052)	0.045 (0.023)	0.125 (0.078)
LPROD	0.118 (0.055)	-0.061 (0.066)	0.097 (0.030)	0.040 (0.093)
CAPITAL	0.002 (0.024)	-0.024 (0.027)	0.013 (0.013)	0.024 (0.041)
FUELS	0.165 (0.024)	0.232 (0.031)	0.094 (0.014)	0.238 (0.042)
SINGLE	0.354 (0.102)	0.278 (0.129)	0.209 (0.057)	0.436 (0.188)
AGE	0.078 (0.083)	0.120 (0.107)	-0.032 (0.046)	-0.214 (0.137)
VIOL_97	0.868 (0.258)	0.148 (0.219)	0.605 (0.143)	0.330 (0.327)
TURNOUT	0.024 (0.011)	0.022 (0.013)	0.015 (0.006)	0.056 (0.021)
DEMOCRAT	0.007 (0.008)	0.006 (0.011)	0.009 (0.004)	0.035 (0.014)
POPDEN	-0.071 (0.033)	-0.040 (0.031)	-0.007 (0.018)	0.014 (0.043)
R^2	0.211	0.175	0.229	0.180

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.

TABLE 4A
Inspection and Enforcement Models with Demographics

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	1.689	1.167	2.938	1.720	0.758	0.533	1.854	4.519
	(0.639)	(0.745)	(2.100)	(2.757)	(0.356)	(1.012)	(1.169)	(3.751)
MINORITY	-0.394	-0.699	-1.875	-1.398	-0.258	-0.445	-0.424	-0.367
	(0.344)	(0.407)	(1.134)	(1.328)	(0.192)	(0.565)	(0.632)	(1.896)
ELDERS	0.957	0.855	2.858	3.206	0.505	-0.140	0.280	-11.245
	(1.188)	(1.301)	(4.151)	(4.935)	(0.661)	(1.932)	(2.312)	(7.893)
CHILDREN	-4.794	1.913	-7.569	8.405	1.429	8.040	-2.668	-4.468
	(2.166)	(2.292)	(7.618)	(8.846)	(1.206)	(3.273)	(4.243)	(13.538)
R^2	0.217	0.176	0.218	0.182	0.232	0.185	0.233	0.184

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
All models in this table contain all the variables contained in Table 3.

TABLE 4B
Inspection and Enforcement Models with Only Demographics – (Four Variables Together)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	0.847	1.037	0.399	0.570	0.399	0.651	0.456	0.872
	(0.634)	(0.829)	(1.934)	(2.581)	(0.355)	(1.108)	(1.084)	(3.574)
MINORITY	-0.768	-1.035	-1.612	-2.706	-0.367	-0.763	-0.355	-0.664
	(0.343)	(0.452)	(0.816)	(1.028)	(0.192)	(0.611)	(0.457)	(1.472)
ELDERS	0.399	0.849	7.838	11.584	0.159	0.464	3.225	9.422
	(1.245)	(1.473)	(4.141)	(5.035)	(0.698)	(2.136)	(2.322)	(7.598)
CHILDREN	-4.891	-1.009	7.647	20.597	1.254	5.968	6.624	27.734
	(2.232)	(2.443)	(7.389)	(9.780)	(1.251)	(3.366)	(4.143)	(14.431)
R^2	0.120	0.116	0.21	0.122	0.126	0.106	0.126	0.106

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
All models in this table contain city dummy variables.

TABLE 4C
Inspection and Enforcement Models with Only Demographics (One Variable per Model)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	-0.352 (0.502)	-0.313 (0.619)	-1.971 (1.136)	-3.334 (1.566)	0.089 (0.281)	0.268 (0.827)	0.018 (0.635)	0.881 (1.911)
MINORITY	-0.642 (0.278)	-0.703 (0.333)	-1.549 (0.488)	-2.620 (0.645)	-0.209 (0.156)	-0.256 (0.462)	-0.228 (0.273)	0.061 (0.816)
ELDERS	1.593 (1.146)	1.239 (1.388)	6.289 (3.038)	5.480 (3.303)	-0.061 (0.641)	-0.998 (1.971)	1.522 (1.700)	0.165 (5.081)
CHILDREN	-5.275 (2.000)	-2.262 (2.231)	-1.645 (5.813)	4.070 (6.790)	1.085 (1.120)	4.962 (2.949)	2.838 (3.249)	14.125 (9.745)

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
Each coefficient comes from a separate regression, as inspections and enforcement are regressed on one demographic variable at a time (all models also contain city dummy variables)

TABLE 4D
Inspection and Enforcement Correlations with Demographics(N=1616)

	INSP	ENFORCE
DISTANCE = 1-MILE		
ELDERS	0.010	-0.076
CHILDREN	-0.051	0.067
POOR	0.019	0.078
MINORITY	-0.025	0.067
DISTANCE = 10-MILES		
ELDERS	-0.069	-0.163
CHILDREN	0.065	0.160
POOR	0.030	0.127
MINORITY	-0.016	0.104

(as long as we only presenting demographic*enforcement correlations, I don’t think we need to present the correlations for the different minority subgroups - my discussion of these results focuses on the difference in signs between 4C and 4D, rather than the differences between the “aggregate” Minority variable and the different minority subgroups)

TABLE 5
Inspection and Enforcement Models Including Homogeneity Measures (N=1616)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
Race								
HOM_RACE	-0.414	-0.283	-1.952	-1.070	-0.135	-0.224	-1.090	-1.165
	(0.305)	(0.367)	(0.803)	(0.990)	(0.170)	(0.472)	(0.447)	(1.418)
Education								
HOM_ED	2.784	2.241	6.172	2.991	1.810	2.705	2.725	-0.637
	(0.896)	(0.959)	(1.630)	(1.748)	(0.499)	(1.387)	(0.909)	(2.433)
Education Homogeneity Decomposition								
$DROPOUT^2$	5.007	3.081	-9.978	-10.648	0.705	1.524	-5.429	-17.371
	(2.540)	(2.844)	(7.553)	(8.814)	(1.413)	(3.997)	(4.214)	(13.406)
$HSGRAD^2$	3.214	2.304	5.289	1.403	1.762	2.164	2.197	-3.904
	(0.982)	(1.053)	(1.821)	(1.982)	(0.546)	(1.566)	(1.016)	(2.961)
$COLLEGE^2$	3.889	2.354	4.016	-1.320	1.713	1.133	1.406	-9.798
	(1.385)	(1.492)	(2.749)	(3.129)	(0.770)	(2.455)	(1.534)	(5.352)
Education Interactions (separate runs)								
Hom_Ed	2.186	2.921	0.770	5.425	1.230	5.467	0.269	7.510
	(1.514)	(1.552)	(3.332)	(3.652)	(0.842)	(2.295)	(1.859)	(6.059)
Hom_Ed*	4.479	-5.257	39.210	-17.647	4.339	-19.505	17.822	-53.338
POOR	(9.136)	(9.404)	(21.098)	(23.264)	(5.080)	(12.796)	(11.774)	(36.465)
Hom_Ed	4.185	3.021	3.923	4.948	1.872	3.194	1.686	2.418
	(1.264)	(1.286)	(2.518)	(2.751)	(0.703)	(2.003)	(1.405)	(4.938)
Hom_Ed*	-5.981	-4.169	7.682	-6.996	-0.268	-2.038	3.549	-8.821
MINORITY	(3.804)	(4.518)	(6.557)	(7.592)	(2.117)	(5.971)	(3.658)	(12.451)
Hom_Ed	6.687	-1.391	2.669	-9.987	7.087	7.820	2.865	-4.542
	(4.832)	(5.317)	(6.525)	(7.289)	(2.685)	(7.998)	(3.640)	(11.668)
Hom_Ed*	-0.081	0.075	0.076	0.279	-0.109	-0.112	-0.003	0.089
TURNOUT	(0.098)	(0.109)	(0.136)	(0.152)	(0.055)	(0.173)	(0.076)	(0.259)

(Standard Errors)
All models in this table include all the variables contained in Table 4.