Abstract

This paper examines whether state governments perform systematically less environmental enforcement of facilities in communities with higher minority and low-income populations. Although this is an important claim made by environmental justice advocates, it has received little attention in the scholarly literature. Specifically, I analyze state regulatory enforcement of three U.S. pollution control laws—the Clean Air Act, the Clean Water Act, and the Resource Conservation and Recovery Act—over the period 1985–2000. To test for disparities in enforcement, I estimate a series of count models and find strong evidence across each of the three environmental laws that states perform less enforcement in poor counties, but little evidence of race-based inequities. © 2009 by the Association for Public Policy Analysis and Management.

INTRODUCTION

Environmental justice issues have been at the forefront of the environmental policy agenda for nearly two decades. Mass mobilizations of minority groups in the 1980s protesting the siting of hazardous waste and other unwanted land uses in communities such as Warren County, North Carolina, and Chester, Pennsylvania, garnered widespread attention. A nationwide study by the United Church of Christ's Commission for Racial Justice (CRJ) (1987) brought further awareness to possible environmental inequities. The CRJ study investigated the relationship between the location of hazardous waste treatment, storage, and disposal facilities (TSDFs) and poor and minority communities, and demonstrated that as the percentage of these groups increased, so too did the probability of there being a hazardous waste facility in their area.

The growing environmental justice movement led governments at all levels to respond with initiatives to address environmental inequities (real and perceived). At the federal level, the Clinton Administration made justice issues a top environmental policy priority, creating the Office of Environmental Equity (since renamed the Office of Environmental Justice) within the U.S. Environmental Protection Agency (EPA) and signing Executive Order 12898, which required all federal agencies to address any environmental inequities resulting from their policies, programs, and activities. State and local governments also responded to environmental justice concerns, advancing many initiatives aimed at remedying racial and class inequities in the distribution of environmental hazards (Lester, Allen, & Hill, 2001; Ringquist & Clark, 1999).

Scholars have conducted scores of empirical studies evaluating whether areas with larger numbers of minority and lower-income populations are disproportionately
subjected to environmental burdens. On balance, there is now good evidence to support claims of inequities both in the location of polluting facilities and in the exposure to pollution (Ringquist, 2005). Advocates of environmental justice have also claimed that there is bias in government implementation and enforcement of environmental laws. However, scholarly research examining this claim is nearly missing from the literature (Atlas, 2001; Lavelle & Coyle, 1992; Lynch, Stretesky, & Burns, 2004; and Ringquist, 1998, are exceptions).

The objective of this paper is to test whether there are race- or class-based disparities in government enforcement of environmental laws. I evaluate the pattern of state government enforcement of three federal pollution control programs—the Clean Air Act (CAA), the Clean Water Act (CWA), and the Resource Conservation and Recovery Act (RCRA)—over the period from 1985 to 2000. Specifically, I examine state regulatory enforcement behavior at the county level, using a series of count models to test whether states conduct fewer enforcement actions in counties with higher minority and low-income populations. To summarize the results, I demonstrate strong evidence that states conduct fewer regulatory enforcement actions in counties with higher levels of poverty. This finding is robust across the CAA, the CWA, and the RCRA, and the effects are significant, ranging from about 2 percent to 5 percent reduction in the amount of enforcement for each percentage increase in poverty. The results are similar for median household income in counties in the case of the CAA and the RCRA. There is little evidence, however, of racial disparities in state regulatory enforcement. Controlling for income levels, the percentage of minorities in the county generally has no independent effect on enforcement patterns.

The paper makes several additional contributions to the environmental justice literature. First, much of the current work only considers a single environmental program (Hird & Reese, 1998, is a noteworthy exception) or a single type of facility. In fact, many of the most prominent studies in the literature focus on just a small set of commercial hazardous waste TSDFs (600 or fewer) (for example, Anderton et al., 1994; Been, 1995; Been & Gupta, 1997; CRJ, 1987; Davidson & Anderton, 2000; Mohai & Saha, 2006, 2007; Oakes, Anderton, & Anderson, 1996). These facilities comprise only a small fraction of those regulated under the RCRA. Although other work has extended the analysis of environmental equity concerns to all Toxics Release Inventory (TRI) facilities (Pollock & Vittas, 1995; Ringquist, 1997), the analysis here has even a broader temporal and substantive focus. I consider state enforcement of hundreds of thousands of facilities (of which hazardous waste TSDFs and TRI facilities are a subset) under the three primary U.S. pollution control programs over the period 1985–2000. Second, the extant literature is largely cross-sectional. Most of the literature considers a single time period,1 which is problematic if there are unaccounted-for temporal changes within jurisdictions. The panel structure of the data analyzed here enables examination of cross-sectional variation as well as variation within areas over time.

The balance of the paper proceeds as follows. In the next section, I review the existing environmental justice literature and discuss the few studies that have directly considered government enforcement. I then describe the data I analyze and the empirical approach. Subsequently, I report the results of the analysis. I conclude with a discussion of areas for future research and the policy implications of my findings.

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1 There are a few notable exceptions. Been and Gupta (1997), Oakes, Anderton, and Anderson (1996), and Saha and Mohai (2005) examine the neighborhood transition hypothesis to sort out whether present disparities in facility siting are due to historical patterns of disproportionate siting or to changes in community demographics after facilities have been sited.
ENVIRONMENTAL JUSTICE LITERATURE

The scholarly literature examining race- and class-based environmental inequities has proceeded in primarily two empirical directions. First, researchers have studied whether polluting facilities are disproportionately located in minority and low-income areas. Although the context and data for these studies vary, they share a common research design. Scholars typically examine the correlation between the presence of a facility handling hazardous materials or emitting pollution and the racial and class composition of the surrounding population. The more sophisticated studies rely on multivariate regression to analyze the probability of a site being located in a high-minority or low-income area, relative to a predominantly nonminority or higher-income area. Building on the work of the CRJ (1987), numerous researchers have shown positive correlations between race, class, and the location of commercial hazardous waste facilities (for example, Been, 1995; Been & Gupta, 1997; Bullard et al., 2007; Mohai & Saha, 2006, 2007), federal Superfund sites (for example, Hamilton & Viscusi, 1999; Hird, 1993, 1994), and sources of toxics and other pollution (for example, Cutter, Holm, & Clark, 1996; Ringquist, 1997; Pollack & Vittas, 1995). The evidence is not uniform (Anderton et al., 1994; Atlas, 2002; Davidson & Anderton, 2000; Hamilton, 1995) but on balance indicates that facilities imposing or potentially imposing environmental harms are more likely to be located in minority and low-income areas.

The second direction of empirical work examines the potential linkage of pollution levels and exposure to minority and low-income groups. This is an important extension of the location studies because the location of facilities only matters to the extent to which it leads to increased environmental risks (or potential risks). Several studies have found that minority and low-income communities are exposed to higher levels of air and water pollution than are communities with fewer minorities and higher-income populations (for example, Ash & Fetter, 2004; Hird & Reese, 1998; Pastor, Morello-Frosch, & Sadd, 2006). Scholars have also examined the distribution of toxic emissions using TRI data. Here too there is growing evidence of at least modest race- and class-based inequity in the location of these releases (for example, Daniels & Friedman, 1999; Downey, 1998; Lester, Allen, & Hill, 2001; Perlin et al., 1995; Pollock & Vittas, 1995), although Holmes, Slade, and Cowart (2000) find some evidence to the contrary.

Although there is accumulating evidence of disproportionate race- and class-based environmental burdens in the areas of facility location and pollution levels, there exists very little empirical research testing for such inequities in government implementation and enforcement of environmental laws and regulations. Of the 49 studies Ringquist (2005) examined in a meta-analysis of the environmental justice literature, none considered disparities in government performance.

Yet leaders of the environmental justice movement have made explicit claims that environmental inequities are due not just to the decisions of private actors (for example, companies making siting decisions), but also to government behavior. Robert Bullard, one of the foremost voices of the movement, has suggested that “environmental racism” extends to the enactment and enforcement of environmental and land use regulations (Bullard, 1993). Writing with a colleague, Bullard later noted, “From New York to Los Angeles, grassroots community resistance has emerged in response to practices, policies, and conditions that residents have judged to be unjust, unfair, and illegal. Some of these conditions include (1) unequal enforcement of environmental, civil rights, and public health laws . . .” (Bullard & Johnson, 2000, p. 557). Collins (1993, p. 111) also suggests that environmental racism encompasses government enforcement, defining the concept as “race-based discrimination in environmental policy making; race-based differential enforcement of environmental rules and regulations. . . .”
To date, only a small number of studies have directly considered environmental justice concerns in the context of government enforcement. In each study, scholars focus on the amount of penalties levied against noncompliant facilities. Lynch, Stretesky, and Burns (2004) analyzed enforcement directed at petroleum refineries and found some evidence that they received smaller fines in response to violations when they were located in Hispanic and low-income communities. Lavelle and Coyle (1992) examined civil judicial enforcement actions and, specifically, the amount of penalties levied as part of federal district court decisions from litigation in response to violations of federal environmental laws. They studied all federal district court decisions from 1985 to 1991 involving violations of air pollution, water pollution, and hazardous waste laws, and found that, on average, fines were about $50,000 lower in high minority and poor areas around violating facilities. This finding was widely cited by environmental justice advocates and received considerable media coverage. Subsequent research by Ringquist (1998) and Atlas (2001), however, strongly rejected Lavelle and Coyle's core findings. These studies employed multivariate analysis to control for factors related to penalty amounts omitted in the Lavelle and Coyle analysis, and Ringquist analyzed a more complete set of federal district decisions. These scholars found negligible and generally statistically insignificant differences in penalty severity based on the demographic and socioeconomic composition of the area in which the violating facility was located.

As Ringquist (1998) points out, however, despite findings that federal district court outcomes are not biased against poor and minority communities, there may still be disparities at other stages of the environmental regulatory enforcement process. These disparities may include fewer inspections and less stringent responses to instances of noncompliance. Moreover, less stringent enforcement of facilities in poor and minority areas may, in part, help explain higher observed levels of pollution in these communities. This paper analyzes these earlier stages of the enforcement process.

What might explain race- and class-based inequities in environmental regulatory enforcement? Of the several explanations put forward by scholars to explain environmental inequity, two directly apply to the context of regulatory enforcement. The first explanation is intentional discrimination. Some in the environmental justice advocacy community claim that minority and low-income communities face disproportionate environmental risks due to deliberate decisions made by public actors (Bullard & Johnson, 2000). It is possible that public officials intentionally perform less enforcement of facilities in minority and low-income jurisdictions. Communities with high levels of political capacity (that is, wealth, education, group organizational skills) are more likely to overcome free rider problems and pressure government into strictly enforcing environmental laws. Even if these communities have not actively pressured government, public officials may consider the potential of community residents to respond in opposition to lax regulatory enforcement. Minorities and low-income individuals tend to have fewer of these political resources and to participate less in the political process.

Gray and Shadbegian (2004) found government performed more CWA inspections and less punitive enforcement actions at 400 pulp and paper facilities located in poor communities (the opposite in large minority communities), but their study did not focus on environmental justice issues.

Ringquist (2006) provides a good summary of the main explanations for possible race- and class-based disparities in environmental burdens.
(Rosenstone & Hansen, 1993). A few studies have demonstrated that political mobilization resources are correlated with lower pollution levels (Hird & Reese, 1998), decisions by companies about where to locate new facilities or where to expand capacity at existing facilities (Hamilton, 1993, 1995), and environmental cleanup decisions (Hamilton & Viscusi, 1999).

RESEARCH DESIGN

The empirical strategy in this paper is to examine patterns of state environmental regulatory enforcement to determine whether states perform fewer enforcement actions in areas with comparatively high minority and low-income populations. For reasons discussed below, I examine state enforcement at the level of counties. Several studies in the environmental justice literature test for race- and class-based environmental inequities at the county level, with some mixed results. A few studies examine exposure to pollution. For example, Hird and Reese (1998) demonstrate that counties with more racial and ethnic minorities face disproportionately higher levels of pollution, but find some evidence that counties with higher income also face higher aggregate pollution levels. Perlin et al. (1995) and Lester, Allen, and Hill (2001) also find that counties with more minorities confront higher levels of TRI emissions, but find inconsistent results regarding class inequities. Several studies also consider the location of waste sites and hazardous waste facilities. Hird (1993) considers the location of federal Superfund sites and finds that they tend to be located in counties with larger minority populations but also are more likely to be in counties with higher average incomes and lower poverty. Bowman and Crews-Meyer (1997) consider the location of hazardous waste TSDFs in a set of southern states, finding little evidence of race and income disparities.

One of the reasons for these mixed results may be the use of the county as the geographical scale of interest, and a county-level analysis does present some challenges for this study as well. First, counties are unequal in geographic size, which means, at times, comparing large rural areas with small urban areas. Second, there may be significant within-county heterogeneity in enforcement patterns that cannot be disentangled. Third, county-level analysis neither accounts for the exact location of environmental hazards within jurisdictions (that is, the location of facilities) nor the proximity of affected populations to these hazards.

Despite these limitations, I adopt a county-level analysis due to constraints posed by the available EPA enforcement data. The geographical data needed to precisely locate the hundreds of thousands of facilities historically regulated under the CAA, the CWA, and the RCRA considered in this study is often incomplete when available, and sometimes missing altogether. This lack of sufficient location information prevents the use of more precise distance-based methods to better link hazards to affected populations (Mohai & Saha, 2006). Nevertheless, the inability to link specific hazards to specific populations is less of a concern in this study. Unlike traditional environmental justice analyses, I am not making direct claims about the environmental risks associated with either the location of hazardous facilities or pollution levels. Rather, I am examining the pattern of government behavior across different jurisdictions to test whether state agencies enforce environmental laws less in areas with higher percentages of minorities and low-income populations.

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4 County-level information was itself difficult to compile for facilities regulated under the CWA and the RCRA because the data I compiled from the Integrated Database for Enforcement Analysis (IDEA) system did not contain county identifiers. In the case of the RCRA program, I was able to match facilities in the IDEA data set with facilities in a separate EPA database (Locational Reference Database). In the case of the CWA, I located facilities by merging the facilities in the IDEA data set with those in recently released EPA geospatial data, but this was only possible for active, major dischargers (large polluters).

5 The IDEA database from which I compiled the enforcement data contains some longitude and latitude data, but these fields are not well populated.
To test claims of race- and class-based inequities in government enforcement of environmental laws, I analyze data on state enforcement of three federal pollution control programs: the CAA, the CWA, and the RCRA. State enforcement of these programs is the appropriate level of analysis for several reasons. First, each of these programs is designed within a model of regulatory federalism and partial pre-emption, under which the EPA generally establishes national regulatory standards and defines the procedures by which these standards are to be implemented. States are then invited or required (depending on the statute) to develop regulatory programs that are at least as stringent as federal standards as a condition for being delegated the authority to implement the program. All states currently have authority to enforce the CAA, while the EPA has delegated authority to nearly all of the states to run the CWA and the RCRA programs. Second, although EPA guidance to the states attempts to mandate uniform enforcement procedures, state enforcement varies considerably due to the discretion states have to determine how they want to implement the federal programs (Sigman, 2003).

State approaches to regulatory enforcement vary, and significant work has been conducted to identify the factors that explain this variation. Several studies have found, for example, that party affiliation of governors and party control of state legislatures influences environmental regulation, with Democrats typically favoring more protective regulations than Republicans (Helland, 1998b; Wood, 1991). Interest group activity has also been shown to be associated with state regulatory behavior, although findings regarding the direction of the relationships are mixed (Hunter & Waterman, 1996; Potoski & Woods, 2002; Ringquist, 1993). Finally, state ideological orientation has been shown in some work to influence state environmental regulation (Ringquist, 1993), although Woods (2006) and Konisky (2007) found no such effect specifically in state regulatory enforcement effort. In the baseline models I estimate below, I incorporate state fixed effects to capture the effects of state institutions on enforcement patterns. Because state dummy variables only capture time-invariant phenomena, I also discuss the results of models that explicitly control for time-varying state-level factors.

Dependent Variables

The primary dependent variables I consider are the unweighted sums of actions taken by state environmental agencies to enforce the federal laws. I compiled these data from the EPA's Integrated Database for Enforcement Analysis. For each program, I sum the annual number of inspections and other compliance monitoring activities, informal punitive actions such as written letters and official notifications of violation, and formal punitive actions to move violators back into compliance such as administrative orders, consent decrees, and civil penalties. These enforcement actions are widely used measures of the general enforcement effort of federal and state governments (for example, Helland, 1998a, 1998b; Konisky, 2007; Scholz & Wei, 1986; Woods, 2006). I consider all facilities regulated under the CAA and the RCRA, whereas for the CWA I only consider major dischargers that are currently active. I present descriptive statistics for these variables and all other measures in Table 1.

The unit of analysis, therefore, is a county-year, and I analyze the time period from 1985 to 2000. The actual number of observations varies by each program for a couple of reasons. First, I only include counties in the states for which the EPA had delegated authority to implement the program. Second, in the case of the CWA

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6 As of the last year considered in this study (2000), six states had not been delegated authority to implement the NPDES program under the federal CWA: Arizona, Idaho, Maine, Massachusetts, New Hampshire, and New Mexico. Only Alaska and Iowa had not been delegated authority to implement the main program (Subtitle C) of the RCRA. I also exclude Alaska, Hawaii, and the District of Columbia from the analyses, and a small number of counties for which there were missing data.
and the RCRA, there are data available on the total number of regulated facilities, so I only consider state enforcement behavior for the counties that had a facility (that is, counties for which there was a nonzero probability of observing an enforcement action). In the case of the CAA, I consider all counties, because the EPA does not maintain a historical record of the number of active facilities falling within the jurisdiction at any given time. As explained below, I address through statistical modeling the fact that some counties may have had no state enforcement actions simply because there were no facilities.

### Measuring Race and Income

I measure the racial composition of counties in a couple of ways, using data compiled from the U.S. Census Bureau. First, I consider the percentage of the county population that is nonwhite. I then separately consider the percentage of the African American and Hispanic populations in the county to evaluate whether there are differential effects across these specific groups. The primary measures of county-level income are the percentage of the county population living below the poverty line and median household income. It is important to consider both of these variables. There may be concentrations or pockets of poverty in particular geographical sections of counties, while the remaining parts of the county have above average household incomes. An example might be a large county that has both a poor inner city and wealthy suburban areas. The hypotheses consistent with claims of race- and class-based inequities in environmental regulatory would suggest a negative relationship between percent poverty and percent minority and state
enforcement, and a positive relationship between median household income and state enforcement.

One of the challenges of studying counties is the lack of annual data. Detailed data are available for decennial years and, although the U.S. Census Bureau does compile estimates on some measures for intra-census years, the lack of annual data necessitates creation of estimates for missing years. I use linear interpolation to impute the racial and income indicators, which assumes that the changes between decennial censuses occur at equal annual increments.

**Control Variables**

I consider two sets of control variables that are frequently used in environmental justice studies. The first set of variables measures the political capacity of county residents. As noted above, there is some evidence to suggest that communities with more political capacity face fewer environmental burdens (Hamilton, 1993, 1995; Hamilton & Viscusi, 1999; Hird & Reese, 1998). I include three measures of political capacity: voter turnout, levels of education, and levels of home ownership. To measure turnout, I use the percentage of the county voting-age population that voted in the preceding presidential election. To control for varying levels of education, I include a variable measuring the percentage of the county population 25 years and older that has at least a college education. Finally, to capture levels of home ownership, I include the percentage of housing units in the county that are owner occupied. The expectations are that state environmental regulatory enforcement will be greater in counties that vote more often, have better-educated residents, and have higher levels of home ownership, because these counties are comparatively more able and more likely to overcome collective action problems and to demand regulatory enforcement.

The second set of control variables is contextual. County economies differ in important ways that will influence the level of state enforcement. Most notably, counties vary in their types of economy, from those that are primarily rural and agricultural to those that are primarily urban and manufacturing- and service-oriented. To account for these differences, I include a measure of the percentage of the county labor force employed in manufacturing positions. In addition, to account for basic differences in county demographic patterns, I include measures of population, land area, and population density. I expect there to be positive relationships between population density and regulatory enforcement in that facilities tend be located in more populated areas. Large counties, on the other hand, are more likely to be rural, which should mean less enforcement because there tend to be fewer regulated facilities in these areas.

In the analyses of the CAA, I also control for the nonattainment status of the county and for whether the county is located on a jurisdictional border. The CAA requires states to perform more stringent enforcement in counties failing to meet ambient air quality standards for criteria air pollutants (particulate matter, ground-level ozone, carbon monoxide, sulfur dioxide, nitrogen oxides, and lead), and each year the EPA designates each county as being in either attainment or nonattainment with these standards. To control for annual county nonattainment status, I include a dummy variable coded 1 if the county is in nonattainment for any one criteria air pollutant and 0 otherwise. I also control for whether a county is located

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7 Jim Snyder provided the data on the presidential vote. I compiled data on college education and home ownership from the U.S. Census Bureau.
8 I compiled the manufacturing data from the U.S. Bureau of Economic Analysis and the other data from the U.S. Census Bureau.
9 The EPA can designate a whole county or part of a county as being in nonattainment. For this analysis, I coded partial nonattainment counties as being in nonattainment.
next to another political jurisdiction (state or country) or an ocean or a Great Lake. Previous research has shown that states have incentives to perform less enforcement in areas in which they can export pollution to neighboring areas (Helland & Whitford, 2003; Konisky & Woods, 2007).

Because EPA oversight of state enforcement varies considerably, it is also necessary to include a measure of EPA monitoring activity. A common approach, which I adopt here, is to include a lagged value of the number of EPA inspections. For each program, I include a variable measuring the number of oversight inspections the EPA performed in the county in the previous year, with the expectation that more federal oversight would lead states to conduct more enforcement actions in the current year.

I also control for the size of the regulated community in each county—that is, the number (or an estimate of the number) of facilities regulated under each of the three pollution control programs. The level of enforcement effort put forth by a state in a county will certainly be related to the number of facilities that fall within its jurisdiction. I use the number of manufacturing establishments in each state as an estimate of the number of regulated facilities when considering the CAA, the number of active major facilities when considering the CWA, and the number of hazardous waste handlers when considering the RCRA.

Last, I include state fixed effects to capture any state-level, time-invariant factors that influence enforcement behavior across the 16-year time period. I also cluster the standard errors at the state level because county observations are unlikely to be independent within each state (Primo, Jacobsmeier, & Milyo, 2007). Specifically, states have different orientations toward enforcement that might influence their enforcement strategy across the counties. I also include year fixed effects to control for underlying changes in enforcement patterns at the national level.

Count Models

I estimate several count models to analyze the effects of county racial and class composition on state environmental regulatory enforcement. These models are appropriate because the enforcement data are event counts (that is, the number of inspections; the number of punitive actions) and take only discrete and nonnegative values (King, 1988; Long, 1997). In the cases of the CWA and the RCRA, I use a negative binomial regression model (NBRM). The NBRM model is preferred to the Poisson regression model (PRM) for a couple of reasons. First, it is not possible to assume independence of observations within each county. A state inspection of a facility likely leads to more/less inspections of the same facility in a given year (that is, a violating facility may receive another inspection, whereas a compliant one likely will not) as well as follow-up punitive actions when an inspection uncovers a violation. Second, each of the dependent variables indicates overdispersion, which violates the assumption of the PRM that there is equality between the conditional variance and the conditional mean.

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10 The number of facilities in a county may be endogenous with enforcement efforts because the stringency of environmental regulation may factor into industry decisions about where to locate facilities. Estimating the models without this control variable does not change the results for the variables of principal interest.

11 Clustering the standard errors does make a substantive difference. When I estimate the models described below without any clustering, some of the coefficients on the minority variables are small, negative, and statistically significant. I also estimated the models with standard errors clustered at the county level, and the results are consistent with those when clustering at the state level.

12 As a robustness check, I did estimate Poisson regression models as well. The results findings are generally consistent with those of the NBRM, with only minor differences.

13 Likelihood ratio tests of the alpha parameters also indicate overdispersion.
In the case of the CAA, I use a zero-inflated negative binomial regression (ZINB) model, which is appropriate because it accounts for the two reasons that there may be zero counts with these particular enforcement data. Dissimilar to the CWA and the RCRA, I neither have data on all CAA-regulated facilities nor do I have a good estimate of the number of facilities falling under the jurisdiction of this federal environmental statute. Therefore, I only observe government behavior at facilities at which there has been an enforcement action. As a result, counties with no enforcement actions in a year may reflect truly no state enforcement of regulated facilities, or alternatively counties that have no facilities regulated by the pollution control program (that is, there is a zero probability of enforcement). The ZINB specification explicitly models each reason we might observe no enforcement,14 and the Vuong (1989) test indicates that the model is more suitable for these data than a single equation negative binomial model that fails to account for the multiple processes for generating zeros.

RESULTS

To assess the effects of race and income on the pattern of state environmental regulatory enforcement, I estimate two models for each of the three federal environmental programs. The first models consider the income measures and the percentage of the county population that is nonwhite, whereas the second models consider the percentage of the county population that is African American and Hispanic, specifically. As the results below demonstrate, measuring the racial composition of the counties in each of these two ways does not change the principal findings. I concentrate the discussion that follows on the effects of race and class because these are most relevant for evaluating claims of environmental injustice, but I do discuss other covariates when interesting systematic relationships appear.

In Table 2, I report the coefficients from the count models. Considering first the ZINB models of state enforcement under the CAA, there is strong evidence that enforcement declines as the percentage of the county population below the poverty line increases. The relationship between median household income and state CAA enforcement is also consistent with the environmental inequity hypothesis. As the median household income of the county increases, so too does the number of enforcement actions performed by the state, which suggests that there is more enforcement of the CAA in wealthier counties. In each of the CAA models, the percentage of minority residents in the population is not related to state enforcement patterns, whether using the percentage of county population that is nonwhite or the percentage of the county population that is African American and Hispanic.

The control variables generally support the expected relationships, with the exception of the measures of political resources. Voter turnout and the percent of the county population with a college education do not affect levels of state enforcement when controlling for race, income, and other county-level factors, and the percentage of home ownership reflects an unanticipated relationship—the number of state enforcement actions declines as home ownership increases. Several of the demographic controls help explain state CAA enforcement effort. Counties with larger populations tend to have more enforcement, but counter to expectations, smaller geographical counties and more urban counties are associated with fewer actions. The nonattainment status of the county and the number of federal oversight inspections in the prior year each were positively associated with patterns of

14 The ZINB model estimates the probability of observing a specific number of state-initiated enforcement actions in a county by combining a logit and a negative binomial distribution. The ZINB model includes a logit regression model to predict the probability of there being no opportunity for the state to enforce the CAA. I estimate this model using a set of demographic variables as well as the number of manufacturing establishments, but for conciseness of presentation do not report or discuss the results.
Table 2. Count models of state enforcement actions conducted in counties.

<table>
<thead>
<tr>
<th></th>
<th>Clean Air Act (ZINB)</th>
<th>Clean Water Act (NBRM)</th>
<th>RCRA (NBRM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Poverty</td>
<td>-0.024*</td>
<td>-0.025*</td>
<td>-0.013**</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.006)</td>
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<tr>
<td>Median household income ($1000s)</td>
<td>0.032**</td>
<td>0.031**</td>
<td>0.007</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.006)</td>
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<tr>
<td>% Nonwhite</td>
<td>-0.003</td>
<td>-0.001</td>
<td>0.003</td>
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<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.003)</td>
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<tr>
<td>% Black</td>
<td>0.002</td>
<td>-0.001</td>
<td></td>
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<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
<td></td>
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<tr>
<td>% Hispanic</td>
<td>-0.002</td>
<td>-0.005†</td>
<td></td>
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<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
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<tr>
<td>% Voter turnout</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.003</td>
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<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.003)</td>
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<tr>
<td>% College educated</td>
<td>0.009</td>
<td>0.007</td>
<td>0.024†</td>
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<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>% Owner-occupied housing</td>
<td>-0.051**</td>
<td>-0.050**</td>
<td>-0.013**</td>
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<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>% Manufacturing employment</td>
<td>0.005*</td>
<td>0.005</td>
<td>0.002*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Population (1000s)</td>
<td>0.002**</td>
<td>0.002**</td>
<td>-0.000*</td>
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<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Population density</td>
<td>-0.059*</td>
<td>-0.059*</td>
<td>0.024**</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Land area</td>
<td>0.164**</td>
<td>0.162**</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Nonattainment status</td>
<td>0.505**</td>
<td>0.504**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.100)</td>
<td></td>
</tr>
<tr>
<td>Border county</td>
<td>0.117**</td>
<td>0.117*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.046)</td>
<td></td>
</tr>
<tr>
<td>EPA inspections,−1</td>
<td>0.122**</td>
<td>0.121**</td>
<td>0.033**</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>No. facilities</td>
<td>-0.000</td>
<td>-0.000</td>
<td>0.180**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Observations</td>
<td>49248</td>
<td>49248</td>
<td>25634</td>
</tr>
<tr>
<td></td>
<td>(79)</td>
<td>(80)</td>
<td>(26)</td>
</tr>
<tr>
<td>Chi-square (d.f.)</td>
<td>39173.7**</td>
<td>39166.1*</td>
<td>23882.6**</td>
</tr>
<tr>
<td></td>
<td>(79)</td>
<td>(80)</td>
<td>(26)</td>
</tr>
<tr>
<td>Vuong test</td>
<td>29.1**</td>
<td>29.1**</td>
<td></td>
</tr>
</tbody>
</table>

Note: Table reports estimates from the negative binomial part of the ZINB model only. All models include state and year fixed effects. Standard errors (in parentheses) are clustered at the state level. Significance levels: † p < 0.10, * p < 0.05, ** p < 0.01.
state enforcement. Whether the county borders another jurisdiction is positively related to state enforcement, which runs counter to the expectation that states might free ride on their neighbors by performing less enforcement in areas where air pollution is most likely to cross political boundaries.

Turning next to patterns of state enforcement under the CWA, the results are similar but not identical to the CAA program. Again, there is a strong relationship between poverty and state enforcement—controlling for other county-level phenomena, states conduct fewer enforcement actions in counties with more residents below the poverty line. Dissimilar to the CAA models, there is no statistically significant relationship between median household income and state CWA enforcement.

State enforcement of the CWA also does not appear to be strongly related to the racial composition of counties, controlling for income and other factors. When measuring minorities in terms of the percentage of the county population that is nonwhite, I do not find a statistically significant association. When considering the percentage of African Americans and Hispanics separately, I do not find an effect for the size of the African American population, but there is a small, marginally statistically significant negative relationship for the percent of the county population that is Hispanic. Across all of the models, this is the only evidence that race is related to the pattern of state enforcement at the county level, once controlling for income.

The control variables in the CWA models have similar effects to those in the CAA models reported above. The primary difference is that number of facilities regulated under the CWA is positively associated with the total number of state enforcement actions. In addition, counties with larger populations and lower population densities on average have fewer enforcement counts.

Tests of the principal environmental justice hypotheses suggest a similar pattern for state enforcement of the RCRA. Percent poverty and median household income have effects consistent with the argument that there are class-based inequities in government enforcement. States perform fewer actions in counties with higher percentages of residents living in poverty. In addition, median household income levels are positively associated with levels of enforcement; facilities in counties with higher household incomes receive more enforcement from state environmental agencies than do counties with lower household incomes. Once again, there does not appear to be a relationship between race and state enforcement of the RCRA, after controlling for income.

The results with respect to the control variables are generally consistent with the results for the CAA and the CWA. One noteworthy difference is the finding for voter turnout. Counter to expectations, higher levels of voter participation in the preceding presidential election were associated with less state enforcement of the RCRA, all else equal. Although this result was not robust across the three programs, when considered collectively with the consistently negative relationship between home ownership and enforcement, there is little evidence in these analyses to support the argument that political capacity leads counties to get more enforcement from state environmental agencies. This result conflicts with those of Hamilton (1993, 1995), Hamilton and Viscusi (1999), and Hird and Reese (1998), who all find results to the contrary. It is possible that measures of turnout, college education, and home ownership only measure potential political capacity, and it may be the case that counties with these resources have not utilized them to demand more regulatory enforcement of these programs from their state governments.

The results discussed above are robust to the inclusion of state-level control variables. In models not reported, I reestimated the count models incorporating measures of the partisan affiliation of the governor, the percent of the state legislative seats that were Democratic, state ideology (measured by the average League of Conservation Voters score for the state's delegation to the U.S. House of Representatives), and interest group strength (number of Sierra Club members and the portion of the state gross product composed of polluting industries). The core findings are
unchanged. The coefficients on the race and income variables closely correspond to those previously reported. Moreover, the state-level variables themselves were not good predictors of state regulatory enforcement effort at the county level.

What is the degree of the class-based effect on state regulatory enforcement? In Table 3, I convert the coefficients into substantively meaningful quantities. The first column in this table shows the percent change in the expected number of annual state enforcement actions in a county for each unit change in the covariate, holding all of the other variables constant at their means. The second column expresses this percentage change in terms of a standard deviation change.

The data presented in the top panel of Table 3 show that the effects of poverty on state enforcement are sizeable. For each percentage increase in county poverty, there is about a 2.3 percent decrease in the number of actions conducted by states to enforce federal clean air regulations. When considered in terms of a standard deviation shift, this equates to a 16 percent decrease in the number of actions conducted. The effects are somewhat less for the CWA, but much larger for state enforcement of the RCRA. For each percentage increase in poverty in the county, there is a 5 percent decrease in the amount of enforcement effort by the state, which amounts to a 34 percent decrease for a one standard deviation change.

The effects of median household income are also substantial. For each increase (decrease) of $1000 in median household income, there is 3.3 percent increase (decrease) in the number of state CAA. For a one standard deviation change, this amounts to an almost 32 percent difference. The magnitude of the effect is the same for the RCRA. (I present the predicted effects for the CWA, but the coefficients from the model in which they are based suggested no effect.)

Figure 1 graphically represents the effects of poverty on state enforcement by considering the relationship across the full distribution of the poverty variable (holding the rest of the variables at their means). The graph clearly shows the sharp decline in the predicted number of state enforcements as the percentage of county population living in poverty increases. Bearing in mind that the mean number of enforcement actions at the county level are about 14, 6, and 12 for the CAA, the CWA, and the RCRA, respectively, the drop in predicted enforcements for high-poverty counties compared to low-poverty counties is substantial.

The results summarized above are generally consistent across each of the three federal pollution control programs: States conduct fewer regulatory enforcement actions in poor counties, but there is little evidence of race-based disparities. To check the robustness of these findings, I also estimated the above models with a race-class interaction term because the effect of one may be conditional upon the other. The results (not reported), however, do not suggest conditional effects. When

<table>
<thead>
<tr>
<th>Program</th>
<th>Percent Change</th>
<th>Percent Change for Standard Deviation Change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percent Poverty</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clean Air Act</td>
<td>−2.3</td>
<td>−16.0</td>
</tr>
<tr>
<td>Clean Water Act</td>
<td>−1.4</td>
<td>−8.8</td>
</tr>
<tr>
<td>RCRA</td>
<td>−5.4</td>
<td>−34.0</td>
</tr>
<tr>
<td><strong>Median Household Income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clean Air Act</td>
<td>3.3</td>
<td>31.9</td>
</tr>
<tr>
<td>Clean Water Act</td>
<td>−0.7</td>
<td>−5.9</td>
</tr>
<tr>
<td>RCRA</td>
<td>3.3</td>
<td>33.1</td>
</tr>
</tbody>
</table>

*Note:* These estimates are the predicted change in county-level enforcement actions derived from the event count models reported in Table 2.
including an interaction term comprising the percent of the county population in poverty and the percent of the nonwhite population (and, separately, the percent of the county population that is African American and Hispanic), the core results are the same. The only race-class interaction term to reach statistical significance in the models is percent poverty and percent Hispanic, and the relationship only appeared in the model with state enforcement of the RCRA as the dependent variable. Moreover, the effect is small and in a direction inconsistent with race-based inequities in state regulatory enforcement.

Although the lack of support for race-based disparities is strong, there remain a couple of reasons to be cautious about these results. First, race and poverty are correlated, which may introduce multicollinearity in the models, making it difficult to tease out their independent effects. When I estimate the models omitting the income measures, the coefficients on the percent minority variables are negative, statistically significant, and of about the same magnitude as the poverty measure. Second, the county-level analysis implicitly assumes that the demographics of a county are distributed uniformly across the county. If, instead, minority populations are concentrated in particular parts of counties, and these areas coincide with facility locations, studying state regulatory enforcement patterns at the county level may mask the effects of race.

To examine this possibility, I reestimated the models with separate inspections and punitive actions dependent variables. These results are presented in Table 4, but for brevity I only include the coefficients for the variables of primary interest and when measuring the minorities variable with the size of the county’s nonwhite

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**Figure 1.** Relationship between Poverty and State Enforcement Actions Conducted in Counties.

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15 For models of punitive actions taken to enforce the CAA and the CWA, I consider a shorter time period (1990–2000) to facilitate model convergence.
Table 4. Count models of state inspections and punitive actions conducted in counties.

<table>
<thead>
<tr>
<th></th>
<th>Clean Air Act (ZINB)</th>
<th>Clean Water Act (NBRM)</th>
<th>RCRA (NBRM)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef. (SE)</td>
<td>Coef. (SE)</td>
<td>Coef. (SE)</td>
</tr>
<tr>
<td>Inspections</td>
<td>% Change</td>
<td>% Change</td>
<td>% Change</td>
</tr>
<tr>
<td>% Poverty</td>
<td>0.023* (0.011)</td>
<td>0.028* (0.011)</td>
<td>0.010** (0.002)</td>
</tr>
<tr>
<td>Median household</td>
<td>0.031** (0.010)</td>
<td>0.022* (0.013)</td>
<td>-0.003 (0.002)</td>
</tr>
<tr>
<td>income ($1000s)</td>
<td>(0.004)</td>
<td>(.006)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>% Nonwhite</td>
<td>-0.003 (0.004)</td>
<td>0.004 (.006)</td>
<td>-0.002** (0.001)</td>
</tr>
<tr>
<td>Chi–square (d.f.)</td>
<td>38821.5** (79)</td>
<td>39595.4* (74)</td>
<td>24880.2** (68)</td>
</tr>
<tr>
<td>Vuong test</td>
<td>28.0**</td>
<td>22.3**</td>
<td></td>
</tr>
</tbody>
</table>

Note: Table reports estimates from the negative binomial part of the ZINB model only. All models include the full set of controls and state and year fixed effects. Standard errors (in parentheses) are clustered at the state level. Significance levels: †p < 0.10, *p < 0.05, **p < 0.01.
population. In general, the estimates from these sets of models resemble those previously discussed. The percent of the county population in poverty remains a strong and consistent predictor of state enforcement. States conducted fewer inspections and punitive actions in counties with higher percentages of their populations living in poverty. There is also a positive relationship between median household income and the number of inspections and punitive measures taken by state environmental agencies, although again only under the CAA and the RCRA.

Finally, there is some mixed evidence regarding the effects of race. In four of the six models (and all of the models with punitive actions as the dependent variable), there is not a relationship between the percent of the nonwhite population in counties and enforcement. However, there is a small, but statistically significant, negative relationship between the size of the nonwhite population and state CWA inspections and a small but statistically significant positive relationship with state RCRA inspections. The negative coefficient in the CWA inspections model suggests a modest, race-based bias in state enforcement of the CWA, but the result for the RCRA is indicative of an opposite relationship. Considering these results collectively, there remains little systematic evidence of racial disparities in state enforcement of these pollution control laws.

DISCUSSION AND CONCLUSION

The analysis presented in this paper represents the first large-scale assessment of whether class- and race-based disparities in environmental protection extend to regulatory enforcement behavior. I find clear evidence that state enforcement behavior is strongly associated with economic class at the county level, but there does not appear to be a similar relationship between enforcement and minority groups. These findings are consistent across three of the primary U.S. pollution control programs over a 16-year period, and they conflict with much of the extant literature on environmental justice, which has demonstrated a clear relationship between race and the location of hazardous and other polluting facilities and exposure to pollution. In fact, Ringquist's (2005) summary of the environmental justice literature found that the most consistent evidence of environmental inequities was based on race, not socioeconomic status.

Although the findings in this paper are robust, they should be interpreted with care. Studying state regulatory enforcement patterns at smaller geographical scales may reveal race-based disparities. For this reason, this analysis represents just a first step in evaluating class- and race-based inequities in government enforcement behavior. Data constraints limited this study to a county-level analysis because it was not possible to precisely locate in space the hundreds of thousands of facilities historically regulated under the CAA, the CWA, and the RCRA. This limitation required use of a unit-hazard coincidence method at a comparatively large geographical scale to assess possible inequities in state regulatory enforcement. Although this is the method employed in most environmental justice studies, some have argued that it may understate or even disguise minority and income level disparities in environmental burdens because it cannot control for proximity of facilities to particular demographic groups (Mohai & Saha, 2006).

The next step in this research is to more precisely estimate the relationships between enforcement and race and class, using distance-based methods to identify the composition of the populations most proximate to regulated facilities. A series of recent empirical studies regarding the location of commercial hazardous waste handling facilities using distance-based techniques have demonstrated evidence that the effects of race and ethnicity are large, even when controlling for income and other socioeconomic attributes (Bullard et al., 2007; Mohai & Saha, 2006, 2007). This analysis will require examining state enforcement for a smaller set of facilities because it necessitates the correct geocoding of facility location. Such an analysis
will answer questions about whether the patterns found in this paper hold when moving down to smaller geographical scales. Although past research has shown that poor and minority communities often face disproportionate environmental risks, evidence that these risks stem (if even only in small part) from differential government enforcement of environmental laws and regulations adds a new dimension to the problem. Environmental injustices no longer are only a matter of private sector decision making, but also of government behavior, suggesting a different set of policy implications. For example, studies demonstrating race- or class-based inequities in the siting of hazardous waste facilities typically recommend improving the fairness of siting and permitting decisions, namely by including a wider set of actors in the decision-making process and by paying attention to the demographic composition of potentially affected communities. These are prospective policy levers that governments can use to change the way future siting and permitting decisions are made, but there is little that government can do to modify the preexisting geographical distribution of hazardous waste and other polluting facilities. The findings here, however, suggest that changes in government behavior may help remedy or at least reduce observed environmental risk disparities. Regulatory enforcement represents administrative actions that governments have the authority and capacity to modify to redress environmental inequities. Although governments cannot coerce polluting facilities to curtail their emissions in minority and low-income communities to the extent to which they are legally permissible, they can ratchet up their enforcement to address facilities that exceed emission standards and work diligently to assure high rates of compliance with environmental laws and regulations.

Because of the regulatory federalism structure that governs environmental enforcement, there are a couple of specific steps that the federal government could take to pressure states to equalize their enforcement efforts across populations. First, the federal government can condition grants and other financial assistance to state environmental agencies on their adherence to commitments of equitable enforcement across their populations. Second, the EPA can require that environmental justice concerns are directly addressed in the enforcement strategies it develops with state environmental agencies, and it can incorporate equity concerns into the Performance Partnership Agreements it negotiates with states. In conclusion, although the evidence of inequities in regulatory enforcement presented in this paper indicates that environmental justice concerns extend to government behavior, there are plausible and achievable ways for public institutions to effectively respond.

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