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# Regulatory Enforcement, Riskscapes, and Environmental Justice

AQ11 **David Konisky and Christopher Reenock**

*Does environmental regulation vary over poor and minority communities? An uneven governmental response may follow from regulators' varying incentives to negotiate enforcement challenges. We argue that regulators confront two in particular. Regulators can pursue political enforcement, responding to mobilized interests, regardless of environmental risk, or they can pursue instrumental enforcement, responding to at-risk communities, regardless of political mobilization. To examine these competing strategies, we use an original dataset from the EPA's Risk-Screening Environmental Indicators model to develop a geographic "riskscape" combined with census tract community data and facility-level enforcement data. We find that state regulatory agencies pursue a mixture of political and instrumental enforcement, but that these tactics are applied unevenly across traditional environmental justice communities. Specifically, state agencies devote more attention to facilities in communities with relatively higher risk, but less attention in the area of punishment for violations for facilities located in Hispanic communities. Importantly, this lack of attention to Hispanic communities is not mediated by the relative level of risks that they face, but it is to a significant extent in communities in which environmental justice advocacy organizations operate.* AQ2

**KEY WORDS:** environmental justice, risk, regulation, policy implementation



## Introduction

Scholars have devoted significant effort to identify and quantify the degree to which poor and minority communities in the United States experience disproportionate environmental burdens. This "environmental justice" literature has become increasingly sophisticated, both theoretically and empirically, and there has accumulated considerable evidence of race- and class-based environmental burdens in facility location and exposure to pollution (Konisky, 2015; Mohai & Saha, 2015; Ringquist, 2005; Szasz & Meuser, 1997).

Much less attention has been given to the question of whether there are similar disparities in the enforcement of environmental laws. This is an important question to examine for several reasons. First, from the vantage of policy implementation, disparities in regulatory outcomes raise questions about the nature of administrative




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decision making, and the factors and incentives that lead regulatory officers to pursue less vigorous enforcement in some communities. Second, from an environmental protection standpoint, enforcement disparities may partially explain observed patterns of inequitable pollution levels. For example, less stringent enforcement of facilities located in low-income or minority communities may contribute to higher levels of pollution if these facilities more frequently violate their emissions standards. In addition, firms may be more inclined to located polluting facilities in jurisdictions governed by agencies with reputations for lax enforcement. The presence of regulatory disparities is also important from a normative perspective. When government fails to fairly implement public policy, it violates core equal protection principles. Such violations can threaten to undermine trust and confidence in government institutions themselves.

To date, evidence on the presence of regulatory enforcement disparities is mixed. Some research shows race- or class-disparities in regulatory actions such as compliance inspections and administrative sanctions for violations, while other studies find few such disparities (Dion, Lanoie, & Laplante, 1998; Gray & Shadbegian, 2012; Konisky, 2009a; Konisky & Reenock, 2013; Scholz & Wang, 2006). Although the findings are inconclusive, studies in the literature share the same basic research design. Researchers estimate regression models to isolate the independent effect of the racial, ethnic, and/or income composition of an area hosting a regulated entity (e.g., a power plant regulated by the Clean Air Act [CAA]) on various regulatory actions of federal and/or state agencies. Negative correlations are taken as evidence of disparities—that is, that facilities located in places with more minority and/or low-income populations are less often the targets of government enforcement efforts.

These models do not reveal causal mechanisms, but they establish a pattern suggestive of enforcement disparities. Researchers in this literature, however, typically do not make distinctions among minority and lower-income communities, and failure to do so may account, at least in part, for the varied findings. Specifically, some of these communities are more over-burdened from pollution risks than others, either due to hosting more polluting facilities, because the facilities in their area are especially significant sources of pollution, or as the result of overall ambient environmental conditions. As such, statistical correlations between enforcement and demographic measures may disguise the importance of environmental risk.

Ignoring environmental risk is also problematic theoretically. Government agencies responsible for enforcement may pursue different strategies in deciding how to allocate their effort. One strategy is to pursue *political enforcement*, which may very well be responsive—positively or negatively—to the characteristics of the communities hosting regulated facilities. Alternatively, agencies may opt for a risk-based or *instrumental enforcement* approach in which they instead allocate their resources based on the risks that communities experience. That is, agencies might simply dedicate more time and effort to facilities located in areas where the marginal benefit of enforcement action is largest. Given that environmental risk and community demographics are not perfectly correlated, failure to account for risk may result in an incomplete understanding of the nature of regulatory enforcement disparities.

In this paper, we aim to disentangle the relationships between community characteristics, environmental risk, and enforcement, using an original dataset that combines fine-grained geographic data on environmental risk with census data on community demographics and facility-level data on regulatory enforcement. Specifically, we use information from the EPA's Risk-Screening Environmental Indicators (RSEI) model to develop a geographic "riskscape" (Abel, 2008; Abel & White, 2011; Ash & Robert Fetter, 2004; Morello-Frosch, Pastor, & Sadd, 2001) for the entire United States, which we then merge with demographic measures of the percentage of the neighborhood population that is African-American, Hispanic, and below the poverty line for approximately 6,500 active, major air polluters regulated under the CAA between 2009 and 2011. We then estimate regression models to evaluate the pattern of state government enforcement effort at polluting facilities in minority and low-income areas (the bulk of CAA enforcement is done by state agencies, rather than the EPA). Controlling for other economic and political contextual factors, the analysis tests whether enforcement disparities are exacerbated or mitigated by underlying levels of community risk.

To summarize our central results, we find that state regulatory patterns are characterized by both instrumental and political responsiveness. State regulatory agencies dedicate greater regulatory attention to facilities located in areas characterized by relatively higher risk and in this respect their response is instrumental. Yet, we also find that enforcement decisions are associated with demographic factors, and specifically with respect to facilities located in communities with large Hispanic populations. Not only are CAA regulated facilities in Hispanic communities less likely to receive detection attention, they are also less likely to be punished for violations. Importantly, this lack of attention to Hispanic communities is not mediated by the relative level of risks that they face, but it is to a significant extent in communities in which environmental justice advocacy organizations operate. When advocacy organizations are present, firms located in relative more risky Hispanic communities receive more regulatory attention.



The balance of the paper proceeds as follows. In the next section, we review the existing literature on disparities in regulatory enforcement, and explain why interpretation of existing evidence on regulatory disparities is hampered by the failure to account for geographic variation in environmental risk. We then describe our approach, including the new data we bring to the questions at hand. Subsequently, we describe our modeling strategy and results, and the conclude with the implications of our analysis for the environmental justice literature and for policy.

AQ3

## What Accounts for Regulatory Enforcement Disparities?

The lion's share of empirical research on environmental justice investigates the extent to which poor and minority communities disproportionately reside in places with unwanted land uses and higher than average levels of pollution. The decision on where to site a solid or hazardous waste disposal facility, a major source of air or water pollution, or another potential source of environmental risk requires the involvement of regulatory agencies, since firms must first obtain permits to develop such land uses. In this way, government officials have at least an indirect role in any observed class- or race-based disparities in facility siting, and scholars have long argued that government permitting often fails to seriously consider impacts on vulnerable populations (Gauna, 2015; Lazarus & Tai, 1999; National Academy of Public Administration, 2001).

The government's role in shaping the geographic pattern of environmental (dis)-amenities, however, entails far more than issuing permits. Decisions regarding pollution standards can have significant implications for patterns of pollution, and the EPA, for example, historically has not considered the distributional implications of its standards (Noonan, 2015). Government agencies also have the responsibility to assure compliance with the pollution limits mandated by permits. And, even if these limits are established in such a way that they do consider potential disproportionate impacts on poor and minority communities, emissions sources may violate these limits in face of lax enforcement. Research has demonstrated that robust enforcement is an important factor in firms' compliance decisions (Gray & Shinshack, 2011), and the EPA and most state agencies have traditionally relied on deterrence strategies to implement major pollution control programs (Rechtschaffen & Markell, 2003).

Given the importance of enforcement, it is perhaps not surprising that scholars have begun to evaluate the degree to which there are class- and/or race-disparities in government enforcement efforts. Of most relevance for this study is the literature that addresses whether the EPA and/or state agencies perform fewer enforcement actions when the regulated source of pollution is located in a community with a large proportion of poor and minority residents.[1] Existing research has come to mixed findings on this question. Several studies have found that inspections of facilities regulated under the Clean Water Act (CWA) are less likely when the facilities are located in an area with a high percentage of poor (Konisky, 2009a; Konisky & Schario, 2010) or low-income populations (Earnhart, 2004b; Helland, 1998; Scholz & Wang, 2006). Other work shows a similar pattern for CAA facilities (Konisky & Reenock, 2013). Moreover, facilities in areas with large poor populations tend to be associated with fewer punitive enforcement measures under the CAA, the CWA, and the Resource Conservation and Recovery Act (Gray & Shadbegian, 2004; Konisky & Schario, 2010), although there are exceptions (Dion et al., 1998). With respect to race and ethnicity, results are similarly mixed, with some showing a negative association between the percentage of African-American and Hispanic residents in an area and the likelihood of an inspection, and others finding little such evidence (Konisky, 2009a; Konisky & Schario, 2010; Liang, 2015; Opp, 2010; Scholz & Wang, 2006; Spina, 2015). This pattern extends to punitive actions taken by agencies in response to firms' violations. One study found that CAA facilities located in high-percent minority areas were less likely to experience administrative orders compared to facilities in low-percent minority areas (Mennis, 2005), while other work has found that CWA facilities tend to be associated with more punitive actions when located in areas with more minorities (Gray & Shadbegian, 2012; Konisky & Schario, 2010).

These inconclusive results may be explained by any number of reasons, including differences in the programs and time periods studied and differences in data measurement and statistical modeling strategies. Moreover, even where the evidence does point to disparities, studies do not provide (nor do they claim to) direct evidence that regulatory officials are explicitly discriminating against poor and minority communities. Scholars in fact have put forward alternative explanations, most notably that these communities tend to have and exert fewer political resources, which results in less ability to secure attention from regulatory officials (Gray & Shadbegian, 2012). For this reason, demographics can serve as a reasonable indicator of potential political mobilization. And, there is evidence that minority communities, when actually mobilized, such as through the presence of environmental justice advocacy organizations, receive more regulatory attention (Konisky & Reenock, 2013).

Interpreting the results of existing studies is also hampered by researchers' assumption that less enforcement activity in poor and minority communities is a good indicator of regulatory disparities. However, regulatory officials may look to factors beyond community demographics when allocating limited enforcement resources. Specifically, they may pursue a more instrumental approach that emphasizes risk mitigation—that is, strategically devoting resources to situations where the benefits of government intervention are potentially the largest. To the extent that pursuing environmental justice goals conflicts with risk mitigation goals, studies may not be providing a complete picture of the nature of regulatory enforcement disparities.

The failure of past work to consider environmental risk potentially creates two inter-related problems, one theoretical and one inferential. From a theoretical standpoint, regulatory officials often have to be attentive to the demands of multiple political principals (Dixit, 1997; Miller, 2005; Waterman & Meier, 1998) and complicated task environments (Bohte & Meier, 2002; Scholz & Wei, 1986) which can create cross-cutting incentives to prioritize different dimensions when delivering policy implementation. Resource constraints, human and financial, further constrain options.

In the present context, regulatory officials may pursue a *political enforcement* strategy that incorporates environmental justice goals. The EPA, for example, has long had policies in place that ostensibly instruct the agency to target enforcement actions to poor and minority communities (Konisky & Reenock, 2015), and many states have similar initiatives (Abel, Salazar, & Robert, 2015; Bonorris, 2010; Kim & Verweij, 2016; Ringquist & Clark, 2002).[2] These types of policies may be particularly important given evidence that environmental institutions tend to, at least historically, not have much staff diversity (Adams & Moreno, 1988; Riccucci, 2009; Snow, 1992; Taylor, 1989). From a representative bureaucracy perspective (Krislov, 2012; Meier, 1975; Sowa & Selden, 2003), this might generate or exacerbate uneven policy delivery. To the extent to which agencies responsible for enforcement are not themselves representative of poor and minority communities, it is possible that they are less attentive to diversity goals and the ideals set forth in environmental justice policy (Soni, 2000), and perhaps less inclined to carry out enforcement activities in these communities. That is, policy norms or goals imposed from the top-down, may not be fully realized which is consistent with the well-understood set of principal-agent problems that often plague administrative agencies.

Political pressures, however, may emerge not just from the top-down, but also from the bottom-up (Daley & Layton, 2004). In this way, political influences may come directly from the communities hosting regulated sources of pollution. Communities with more political resources may be more successful in pressuring government agencies to be vigilant in their enforcement of regulated sources of pollution in their areas. Alternatively, because poor and minority communities tend to have fewer political resources, overcoming collective action problems is more difficult, and they may be less effective in pressuring officials to pursue strong enforcement (Konisky & Reenock, 2013). The importance of political capacity is not limited to enforcement, of course, and scholars have demonstrated is relationship with environmental decision making in other areas of policy such as waste management decisions (Hamilton, 1995) and the remediation of contaminated sites (Hamilton & Viscusi, 1999).

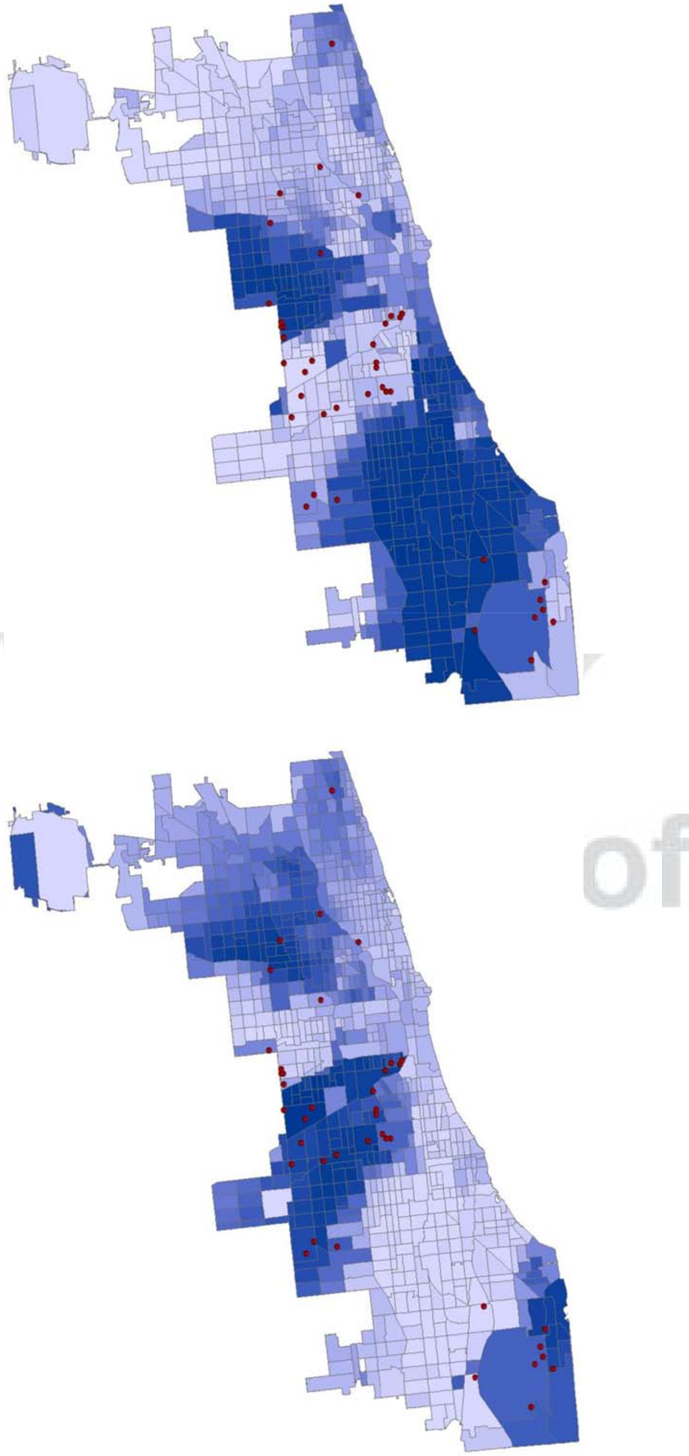
The most relevant point to emphasize here is that regulatory officials may weigh multiple factors when deciding how to allocate their limited enforcement resources. In addition to being responsive to political demands—top-down or bottom-up—officials may also pursue a more *instrumental enforcement* strategy that targets their limited resources to communities experiencing the higher environmental risks. And, of course, these strategies are not mutually exclusive.

It is also important to note that another perspective might point to intentional discrimination as an explanation for lower enforcement efforts in poor and minority communities. Environmental justice scholars, for example, have often asserted these types of bias as central reasons for uneven and unfair enforcement of environmental protection and public health laws (Bryant, 1995; Bullard, 1993; Bullard & Johnson, 2000; Collin, 1993). We argue that intentional discrimination is increasingly difficult to maintain in the presence of either greater environmental hazards or political mobilization. However, when the incentives to pursue instrumental or political enforcement are low, we cannot rule out the possibility of intentional discrimination.



The related inferential problem stems from an implicit assumption made in existing studies that poor and minority communities always experience environmental risks. Although there is ample evidence to support a conclusion that this is true, on average, it is unlikely the case for all such communities. And, if regulatory officials are pursuing an instrumental approach focused on risk, simply looking at patterns of enforcement actions across community demographics may not provide either a clear picture of disparities or a good indicator of policy effectiveness.

To illustrate the nature of this inferential problem, consider the maps of the City
F1 of Chicago presented in Figure 1. The left map shows the percentage of the population in each census tract that is African-American, while the right map shows the same for Hispanics (darker shades of blue indicate higher percentages). The red dots are the location of major sources of air pollution (described more below). There are a couple of clear patterns in these maps that are worth highlighting. First, African-Americans and Hispanics live in their highest proportions in different parts of Chicago, and for each group, there are large proportions in multiple areas of the city. Whereas the census tracts with the highest percentages of African-Americans are south and immediately west of downtown Chicago, those with the highest percentages of Hispanics are northwest and southwest of downtown and then again in the



COLOR

**Figure 1.** Demographics for City of Chicago at the Census Tract Level for Both Percent African-American (Top Panel) and Percent Hispanic (Bottom Panel). Major Stationary Air Sources Appear as Red Dots.

area near the border with the State of Indiana. A second item to note is that major sources of air pollution are located in the census tracts with both large percentages of African-Americans and Hispanics, but in higher numbers in Hispanic tracts.

In a typical study of government enforcement disparities, a researcher would analyze these data to estimate the correlation between enforcement actions and these demographics. A negative correlation would be taken as evidence that officials direct less effort to facilities located in places with higher proportions of minorities (or similarly, low-income populations). Such an approach, however, cannot differentiate the varying levels of environmental risk confronting communities. Simply hosting a significant source of pollution is insufficient for this purpose because facilities present different risks depending on the amount and nature of their pollution, and the fact that the risks experienced by any given community likely are caused by other sources of pollution as well. Moreover, while past research shows that low-income and minority communities on average experience higher environmental risks, the actual nature of the risks may vary tremendously from one community to the next.

Our analysis resolves this problem by introducing separate data on environmental risk. To show the utility of incorporating risk data, consider the additional maps
F2 of Chicago displayed in Figure 2. These versions show the same census tract and facility location information as before, but we have also added census tract-level information on environmental risk. These environmental risk data, derived from the EPA's RSEI model as we explain below, are relative risks scores, such that higher values indicate an area experiencing higher levels of risk for air pollution. The smallest size triangle represents the value of half the median, the next size the median, the third size one standard deviation above the median, and largest size two standard deviations above the median.

There are a couple of important items to take away from these maps. First, looking at the two maps together, the census tracts with highest levels of risk in the City of Chicago are those with the highest percentages of African-Americans and Hispanics. Second, there is considerable variation in the risks levels of census tracts with similar percentages of these minority groups. For example, census tracts with large percentages of African-Americans in the southern part of the city generally reside in areas with less environmental risk (often half the median) than census tracts with similar compositions of African-Americans in the western part of the city. This fact underscores the importance of considering *both* demographic information and risk information in studies of enforcement disparities; considering just the former, as has become the standard in the literature, may lead to an incomplete understanding of the nature of enforcement patterns, and incorrect interpretation of the factors that might be motivating regulatory officials in their decisions about which facilities to target. It is to this task of unpacking the relationships among demographics, environmental risk, and enforcement patterns that we now turn.

## Research Design

To examine regulatory enforcement patterns in poor and minority communities, we begin with a standard approach that examines associations between government

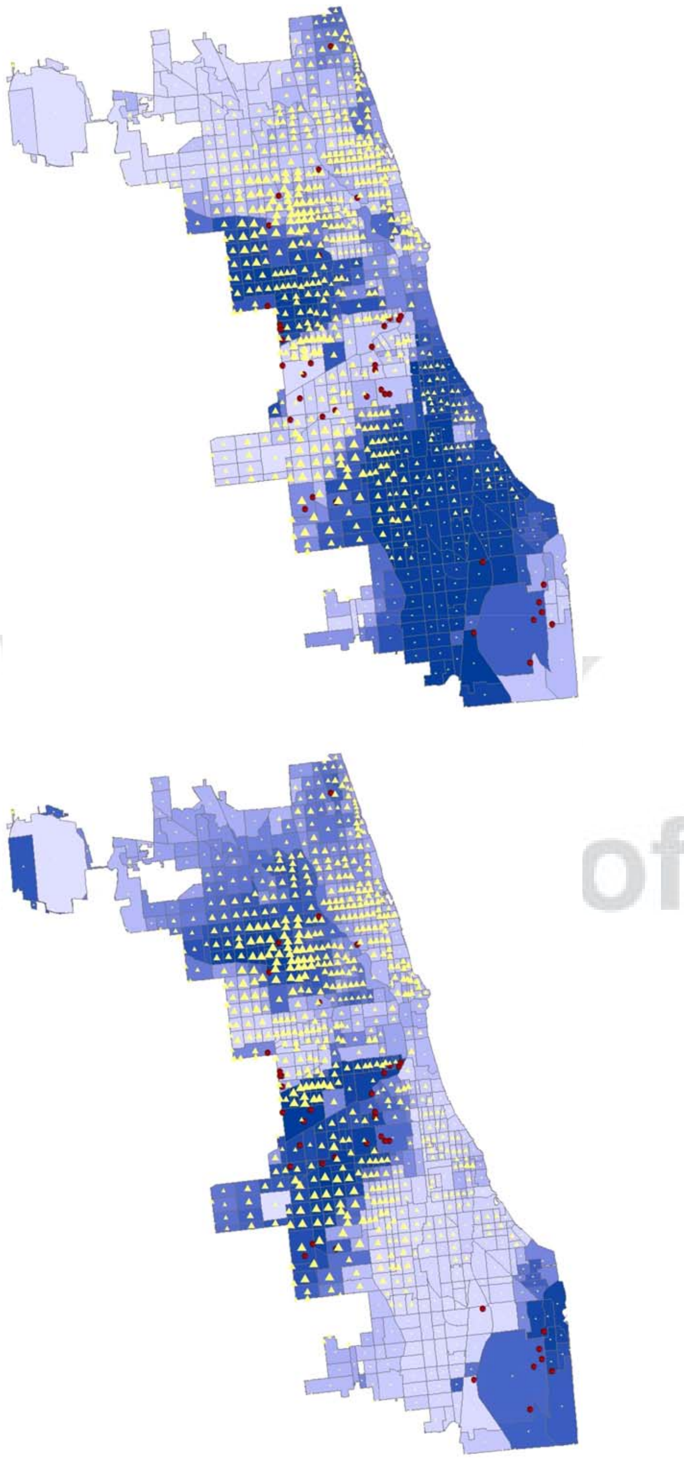


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Figure 2. Demographics for City of Chicago at the Census Tract Level for Both Percent African-American (Top Panel) and Percent Hispanic (Bottom Panel). Major Stationary Air Sources Appear as Red Dots. Relative Risk Scores Displayed as Scaled Triangles.

enforcement actions and community characteristics. We use this analysis as a baseline from which we can better understand the value of introducing a measure of environmental risk. To accomplish these tasks, we require facility compliance data, demographic data, and environmental risk data at a high level of geographic resolution. In this section, we first discuss the data we analyze in the study, and then our estimation strategy.

## *Data*

The policy domain for our analysis is the federal CAA. Enacted in 1970, the CAA tasks EPA with implementing the various features of the statute, which include regulating the emissions of criteria and toxic pollutants from stationary and mobile sources. Similar to other federal pollution control statutes, the CAA relies on a model of cooperative federalism for implementation. While the EPA is primarily responsible for setting national air pollution standards (e.g., national ambient air quality standards, technology standards for new sources of pollution), states are largely responsible for the day-to-day implementation of the program through their federally improved State Implementation Plans. Among the duties that states carry out include permitting and enforcement (states can also set their own emissions standards, as long as they exceed those of the EPA). For this reason, we focus our empirical attention on the enforcement activities of state government agencies, who collectively carry out upwards of 90 percent of all enforcement of the CAA (Environmental Council of the States, 2006).

The set of CAA-regulated facilities we study are "major" air sources, which are large emitters of pollutants covered by the CAA. Major sources are required to obtain a Title V operating permit, and typically include sources that either have the potential to emit 100 tons per year or more of any criteria air pollutant or to emit hazardous air pollutants above certain thresholds as determined by EPA guidance. Major sources include large fossil fuel power plants, factories, hospitals, incinerators, among other types of facilities. For reasons explained below, we focus on the three-year period from 2009 to 2011 in our analysis. During this period, there were about 13,400 active, major air sources in operation in the United States, and we study 6,500 of them which report also report toxic air emissions as part of the Toxics Release Inventory (TRI). We focus on this subset of facilities because the environmental risk date we examine (described below) measures risk from these specific emissions.[3]

*Enforcement Measures.* The dependent variables we analyze are state-led CAA enforcement actions. Historical enforcement data are available from the EPA as part of their Enforcement and Compliance History Online (ECHO) data sets, from which we created two separate measures: state inspections and state punitive actions. For each major air source, we sum the total number of state-led inspections and state-led punitive actions directed toward it over the 2009–11 period. Inspections are the principal means by which state governments determine the compliance status of regulated facilities and usually (although not always) they include emissions tests as well as assessments of the pollution control technologies in place at the facility to address emissions. Punitive actions include measures taken to bring noncompliant firms back into compliance, and include both informal actions such as notifications of violation and formal actions such as administrative orders, consent decrees, and civil penalties. These measures reflect the amount of regulatory enforcement effort directed to individual air sources. As such, they provide a reasonable measure of the relative effort being put forth by agency officers to implement the CAA.[4] In our sample, the mean number of inspections and punitive actions directed at major air sources was 16.7 (standard deviation = 23.0) and 0.86 (standard deviation = 2.77), respectively. (Descriptive statistics for all data are reported in Table S1 in the Supporting Information Appendix.) AQ10

*Neighborhood Demographics.* Empirical studies in the environmental justice literature typically consider several demographic measures to potential capture class- and race-based disparities, and we do the same here. Specifically, to characterize vulnerable communities we use three variables: percent African-American, percent Hispanic, and percent poverty. Using data from the Census Bureau's 2010 decennial census, we used an areal apportionment method (Konisky & Reenock, 2015; Konisky & Schario, 2010; Mohai & Saha, 2006, 2007, 2015) to create "neighborhood-level" measures of the demographic characteristics around each of the 6,500 air sources in our sample.[5] We first locate each source in geographical space using latitude and longitude information from the EPA Facility Registry System. Then using Geographic Information Systems (GIS) software, we construct a 1-mile circular "buffer" around each facility, and then intersect this buffer area with a geospatial map of U.S. census tracts. The resulting intersections are then used as weights for each demographic attribute, where the weight is the proportion of each census unit contained within facility's 1-mile circular buffer. Then, using these weights, we compute a weighted average to measure the percentage of African-Americans, Hispanics, and people living below the federal poverty line that reside within 1-mile of the facility.[6] The mean percentage of African-Americans, Hispanics, and individuals in poverty in our sample is 14.0 percent (standard deviation = 19.6), 11.9 percent (standard deviation = 17.1), and 16.0 percent (standard deviation = 9.50), respectively. In sensitivity analysis, we also show that results are substantively the same when using alternative buffer distances of 2 miles and 3 miles.

*Neighborhood Risk.* Our measure of neighborhood-level risk begins with fine-grained geographical data used by the EPA in its RSEI model. Although these data have previously been used in the environmental justice literature (Ash & Robert Fetter, 2004; Bouwes, Hassur, & Shapiro, 2001; Sicotte & Swanson, 2007; Williams, 2010), this study is the first to exploit the data to investigate enforcement disparities. The RSEI model is a publicly-available screening tool developed by the EPA to assess the impact of chemical releases into the environment. The model begins with data from the TRI, which is comprised of self-reported releases of designated hazardous pollutants to the air, water, and land by facilities covered by the program.[7] Because TRI data only include the level of releases, they do not reveal much information about environmental risk—that is, without knowing the toxicity of the chemicals released and the pattern of dispersion, one cannot infer anything meaningful about who is exposed and the degree of risk experienced.

The RSEI model begins with TRI releases, and then integrates information on the toxicity of the chemicals released, their fate and transport through the environment, the route and extent to which there is human exposure, and finally the number of people that are affected. The model then generates numerical values—unit-less, relative risk scores—that can be analyzed and compared at a variety of different levels, such as facilities, geographic regions, and industrial sectors (Environmental Protection Agency, 2015b).[8] To compute these risk scores, the RSEI model uses a geographic grid system for the United States composed of 810 m by 810 m cells, for each of which it estimates ambient concentrations of TRI pollutants. Then, adjusting for the toxicity of the chemical releases and making some standard assumptions about human exposure, the model generates a risk score for each 810 m by 810 m cell. The score then for a facility is produced by aggregating the scores for these individual grids for each facility, for up to 50 km from the facility which the EPA has determined is necessary to fully capture the impacts of TRI pollutants (Environmental Protection Agency, 2015b).

There are a couple of important points about these data to note. First, the facilities used by the RSEI model to create the relative risk scores include facilities that are not in our sample of major air sources (i.e., some TRI facilities are not major air sources). This does not create a problem for our analysis, however. The idea here is that state agencies make decisions about which facilities to target with enforcement based on the level of risk experienced by the community, regardless of the proportion of the risk that is directly attributable to the facility in question. This is consistent with the approach recently employed at the federal level by the EPA in its enforcement targeting decisions (Environmental Protection Agency, 2015a). Second, RSEI generates relative risk scores, so they are only meaningful in comparison to themselves. Importantly, it should not be assumed that geographic areas with low scores experience no environmental risks from air pollution.[9]

In this analysis, we use the data computed for each individual 810 m by 810 m cell. These micro data, provided to us by the EPA, offer an opportunity to measure neighborhood level risk at a very small level of geography. Ash and Robert Fetter (2004) do this for block groups in their analysis of exposure to pollution hazards among low income and minority neighborhoods. We do something similar here, with two distinctions. First, we use the areal apportionment method described above to create a neighborhood-level measure of environmental risk. Specifically, we first aggregate the risk score data to the census tract level, and then weight the scores using the proportion of the overall of the tract boundaries with the 1-mile circular buffer we create around each facility. In essence, we create a "riskscape" for the entire country, and then use it to construct the specific risk experienced by the neighborhood around each major source of air pollution. These data are then consistent with how we measure neighborhood demographics. Second, we use the risk data to test our hypotheses about the factors affecting state enforcement priorities. That is, we examine whether risk, both on its own and in combination with demographic attributes, are associated with regulatory enforcement actions. In our statistical analysis, we use the logged value of the risk score because of the extreme right skewed distribution of the risk scores. The mean relative risk score in our sample is 0.33 (standard deviation = 0.63) and ranges between 0 and 4.71.

### *Estimation Strategy*

To examine the relationships between community demographics and environmental risk, and their associations with state regulatory enforcement actions, we estimate a series of regression models. Specifically, because our dependent variables are counts (i.e., the number of inspections, and separately the number of punitive actions directed at major air sources), we estimate negative binomial regression models[10] of the following basic form:

$$E_i = \beta\ \mathrm{EJ}_i + \gamma\ \mathrm{Risk}_i + \delta\ \mathrm{EJ}_i * \mathrm{Risk}_i + \eta\ \mathrm{Controls}_i + \theta\ S_j + \epsilon_{it} \tag{1}$$

where $i$ indexes facilities, $j$ indexes states, $E$ is a measure of state enforcement actions, EJ is a vector of environmental justice community indicators (percent poor, percent African-American, and percent Hispanic), *Risk* is the measure of environmental risk, *Controls* is a vector of control variables discussed below, $S$ is a fixed effect for states, and $\epsilon$ is an error term which we allow to be serially correlated across states. The inclusion of state fixed effects controls for unobservable factors within states that do not vary temporally, and allows us to identify relationships based on within state variation. Although we have three years of data, we elected to pool the data across years because the relevant variation for us to exploit is cross-sectional. In addition, we are not able to estimate panel models with a facility fixed effect to capture unobserved facility-level characteristics, because the key independent variables of interest do not vary by facility over time.

Endogeneity presents a challenge for any empirical investigation, including our estimation strategy. In particular, we must address three possible sources of endogeneity: omitted variable bias, sample selection, and reverse causality. To minimize the threat of endogeneity due to omitted variable bias and sample selection, we rely upon a strategy of statistical regression adjustment. We include a large suite of control variables to control for not only current conditions in the immediate environment of the facility but also changes in these conditions over the preceding 10 years. The logic underlying our choice of controls is to cover any possible factors that may incentivize firm location choice, demographic migration patterns, and firm compliance decisions. This suite of control variables includes factors that may contribute to non-random distribution in risk and demographic characteristics, and their correlation to environmental enforcement.

Specifically, we include a host of additional variables measured at the neighborhood level using the same procedure as described above to generate our measures of community demographic attributes. These variables include total population (per 1,000 people), the percentage of the population with at least a high school education, the percentage of the population with a college degree, median household income, and median home value.

In addition, we control for possible heterogeneity across firms. We include controls for different types of major air polluters, by creating a series of dummy variables for facilities in the electric utility, manufacturing, mining, and oil and gas sectors. Our models also include a measure of air pollution severity in the area in which the facility is located. Specifically, using information from the EPA Green Book, we include a variable that measures the number of years (from 2009 to 2011) the county in which the facility is located was in nonattainment with the national standard for at least one criteria air pollutant regulated by the EPA.[11] In terms of economic conditions, we use the average county-level unemployment rate from 2009 to 2011 derived from Bureau of Labor Statistics data. We also include a dummy variable coded one for facilities that were determined to be in noncompliance with the CAA, and zero otherwise, and a measure of the EPA enforcement actions taken during the 2009–11 period.[12] These measures control for consistent findings in the literature that regulatory behavior tends to coincide with both determinations of noncompliance as well as the oversight enforcement carried out by the EPA.

Our models also include several measures to address the possibility that our treatment (i.e., demographics or environmental risk) is not randomly selected. A bias in sample selection may emerge in our data for the following three reasons. First, lax state regulatory enforcement in an geographic area may result in poorer ambient environmental conditions, which in turn might reduce property values and rents and induce migration of low-income and minority populations to these areas.[13] Second, lax enforcement might encourage an influx of polluting firms to an area, creating additional environmental risks to local communities. And, third, lax enforcement might encourage low performing firms to move to an area, which too may lead to higher environmental risk in some areas. These are challenging issues to address with only three years of data, especially when the siting of the facilities in our sample often occurred many decades ago.[14] To address these concerns with available data, we include several additional control variables in our model: changes in each of the demographic measures from 2000, changes in the number of manufacturing establishments with at least 20 employees from 2000 to 2008 (the year immediately prior to our sample), and historical inspection rates measured at both the state and facility level to account for past enforcement activity. Collectively, these additional variables can help to rule out these alternative explanations for any observed correlations we detect between community demographics, environmental risk, and state enforcement effort.

Finally, to minimize the threat of endogeneity due to reverse causation, we face a trade-off. The EPA only provided us with three years of the finely detailed risk data necessary for our investigation. The uniqueness of these data and their limited availability restricts the suite of solutions that we can pursue to address endogeneity. The uniqueness of these data inhibits us from finding an instrument for our risk scores. (If a reasonable instrument was available at such a fine level of detail, we would not have needed to seek out the RSEI micro data in the first place.) Moreover, the limited temporal domain prohibits us from a standard differences-in-differences design to assess changes in enforcement patterns among facilities that have experiences shifts in risk and/or demographics relative to those that have not. Last, we have not been able to identify any discontinuities in our data that would allow us to exploit a regression discontinuity design. As such, we are left with theory. Many of the associations that we report below are drawn from conditional expectations that we test using statistical interactions. Any account of reverse causation therefore, would need to account for the associations that we observe conditional on other constituent terms in our interaction models. Although we believe that such an alternate story is challenging to produce, given our inability to strongly identify our statistical model, we do not report the associations in the statistical models as "causal effects." Rather we report them as associations in our data that offer *a priori* evidence of a causal effect. This is completely in keeping with our goal of determining whether government enforcement patterns are associated with varying levels of risk and/or demographics, and thereby consistent with political enforcement, instrumental enforcement, or a mixture of these approaches.

## Results

We begin by estimating a traditional model on our relevant regulatory outputs. To facilitate interpretation, all variables measuring risk, percent poverty, percent African-American, and percent Hispanic are standardized. As a result, all effects are relative to moving away from the mean of these variables. In the interest of space, we only comment on the relationships of central interest to the study.



In the first set of models, we consider whether different communities, based on demographics, attract differential enforcement attention from state regulatory officials. Table 1 shows the full results, and we display the coefficients for the key variables in Figure 3 below. The darker plots refer to the model absent any control for risk, while the lighter plots report the coefficients for the models controlling for risk (discussed below). *Without controlling for risk*, we see that of the six coefficients estimated on various demographic indicators, state regulators only appear to be less aggressive against facilities located within Hispanic communities on punitive actions. Facilities in poor communities and African-American are no more likely to receive greater (or lesser) attention from state regulators.[15]

What are we to make of these results? This of course depends upon one's perspective. The absence of differential regulatory treatment across many of our community indicator variables might suggest administrative blindness to the plight of poor and minority communities. If these communities are exposed to higher risk and government is ignoring them, then questions about policy equity and fairness loom large. Alternatively, the absence of differential treatment across these communities may indicate regulators' efforts to target facilities based upon which communities are experiencing greater risk, regardless of community demographics. The critical point here is that, absent controlling for risk, the interpretation of a null finding is difficult to untangle.

Figure 3 also displays the key results when controlling for relative risk (the lighter shaded plots). Including risk in the models has several benefits. First, we see that our estimates are largely unchanged across the two models. We continue to see that regulators do not treat firms differentially in poor and African-American

**Table 1.** Parameter Estimates for State Enforcement (1-Mile Buffer)

| | Inspections Model 1 (Base) | Model 2 (w/Risk) | Model 3 (Conditional) | Punitive Actions Model 4 (Base) | Model 5 (w/Risk) | Model6 (Conditional) |
|---|---|---|---|---|---|---|
| ln(risk score) | | 0.0368* | 0.0473* | | 0.0967 | 0.1133** |
| | | (0.0187) | (0.0200) | | (0.0499) | (0.0401) |
| Percent poverty | 0.0402 | 0.0387 | 0.0274 | 0.1429 | 0.1331 | 0.0735 |
| | (0.0336) | (0.0339) | (0.0329) | (0.0934) | (0.0975) | (0.0865) |
| Percent African-American | −0.0049 | −0.0093 | −0.0102 | 0.0044 | −0.0051 | 0.0074 |
| | (0.0314) | (0.0311) | (0.0299) | (0.0563) | (0.0552) | (0.0541) |
| Percent Hispanic | −0.0298 | −0.0368 | −0.0201 | −0.2418** | −0.2552** | −0.2062** |
| | (0.0262) | (0.0264) | (0.0301) | (0.0433) | (0.0442) | (0.0498) |
| ln(risk)*percent poverty | | | 0.0179 | | | 0.1039* |
| | | | (0.0281) | | | (0.0446) |
| ln(risk)*African-American | | | −0.0108 | | | −0.0900* |
| | | | (0.0260) | | | (0.0392) |
| ln(risk)*percent Hispanic | | | −0.0257** | | | −0.0911** |
| | | | (0.0080) | | | (0.0182) |
| Utility facility | 0.4715** | 0.4771** | 0.4772** | −0.0920 | −0.0799 | −0.0991 |
| | (0.0707) | (0.0713) | (0.0693) | (0.1709) | (0.1694) | (0.1646) |
| Manufacturing facility | 0.1498** | 0.1470** | 0.1464** | 0.2606 | 0.2489 | 0.2434 |
| | (0.0495) | (0.0505) | (0.0494) | (0.1440) | (0.1417) | (0.1441) |
| Mining facility | 0.1754 | 0.1823 | 0.1845 | 0.2511 | 0.2658 | 0.3022 |
| | (0.2289) | (0.2296) | (0.2262) | (0.3728) | (0.3671) | (0.3575) |
| Oil and gas facility | 1.2126* | 1.2284* | 1.2032* | 0.1351 | 0.1555 | 0.0349 |
| | (0.5748) | (0.5699) | (0.5718) | (0.4546) | (0.4261) | (0.4379) |
| Population (thousands) | −0.0235* | −0.0220* | −0.0216* | −0.0205 | −0.0171 | −0.0172 |
| | (0.0094) | (0.0095) | (0.0096) | (0.0208) | (0.0200) | (0.0191) |
| Percent highshool education | 0.0032 | 0.0034 | 0.0031 | −0.0034 | −0.0027 | −0.0051 |
| | (0.0020) | (0.0021) | (0.0019) | (0.0049) | (0.0052) | (0.0048) |
| Percent college education | −0.0060** | −0.0063** | −0.0065** | −0.0045 | −0.0053 | −0.0056 |
| | (0.0021) | (0.0021) | (0.0019) | (0.0051) | (0.0052) | (0.0050) |
| Median income ($thousands) | 0.0027 | 0.0031 | 0.0027 | 0.0059 | 0.0067 | 0.0047 |
| | (0.0023) | (0.0022) | (0.0023) | (0.0063) | (0.0062) | (0.0060) |
| Median home value ($thousands) | −0.0004 | −0.0005 | −0.0004 | −0.0004 | −0.0005 | −0.0002 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0007) | (0.0007) | (0.0008) |
| Δ Percent African-American | −0.0021 | −0.0024 | −0.0027 | −0.0019 | −0.0034 | −0.0041 |
| | (0.0027) | (0.0027) | (0.0027) | (0.0077) | (0.0077) | (0.0076) |

**Table 1.** *cont.*

| | Inspections | | | Punitive Actions | | |
|---|---|---|---|---|---|---|
| | Model 1 (Base) | Model 2 (w/Risk) | Model 3 (Conditional) | Model 4 (Base) | Model 5 (w/Risk) | Model6 (Conditional) |
| Δ Percent Hispanic | −0.0022 | −0.0022 | −0.0031 | 0.0172** | 0.0175** | 0.0145** |
| | (0.0029) | (0.0029) | (0.0032) | (0.0047) | (0.0056) | (0.0042) |
| Δ Percent poverty | −0.0045 | −0.0046 | −0.0038 | −0.0082 | −0.0083 | −0.0048 |
| | (0.0044) | (0.0044) | (0.0044) | (0.0084) | (0.0086) | (0.0082) |
| Δ Median income ($thousands) | 0.0027 | 0.0024 | 0.0028 | 0.0003 | 0.0000 | 0.0021 |
| | (0.0022) | (0.0022) | (0.0023) | (0.0044) | (0.0045) | (0.0040) |
| Δ Median home value ($thousands) | −0.0003 | −0.0002 | −0.0003 | 0.0002 | 0.0001 | 0.0001 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0012) | (0.0012) | (0.0013) |
| Δ Manufacturing establishments (2000–08) | 0.0017 | 0.0020 | 0.0017 | 0.0047* | 0.0056* | 0.0047 |
| | (0.0016) | (0.0017) | (0.0014) | (0.0021) | (0.0023) | (0.0025) |
| County # years non-attainment | 0.0417* | 0.0357 | 0.0350* | 0.1053** | 0.0899* | 0.0912* |
| | (0.0183) | (0.0192) | (0.0177) | (0.0392) | (0.0433) | (0.0401) |
| Average county unemployment (2009–11) | 0.0020 | 0.0037 | 0.0037 | 0.0493 | 0.0549* | 0.0531* |
| | (0.0115) | (0.0119) | (0.0113) | (0.0279) | (0.0272) | (0.0247) |
| Average state inspection rate (1999–2008) | −7.7364** | −7.7839** | −7.7760** | 24.3169** | 24.2269** | 24.3745** |
| | (0.4834) | (0.4969) | (0.4444) | (1.1608) | (1.2181) | (1.1368) |
| Average facility inspection rate (1999–2008) | 0.7356** | 0.7400** | 0.7423** | 0.3662 | 0.3840* | 0.3692 |
| | (0.1210) | (0.1202) | (0.1190) | (0.1981) | (0.1940) | (0.1983) |
| Non-compliance (2009–11) | 0.3250** | 0.3237** | 0.3249** | 0.8953** | 0.8950** | 0.8891** |
| | (0.0443) | (0.0442) | (0.0448) | (0.0824) | (0.0832) | (0.0832) |
| # EPA inspections (2009–11) | 0.0351** | 0.0345** | 0.0341** | | | |
| | (0.0116) | (0.0115) | (0.0114) | | | |
| # EPA punitive actions | | | | 0.3051** | 0.2870** | 0.2744** |
| | | | | (0.0794) | (0.0724) | (0.0707) |
| Constant | 6.5389** | 6.5409** | 6.5673** | −18.1842** | −18.2249** | −18.0528** |
| | (0.3247) | (0.3166) | (0.3005) | (1.0156) | (0.9997) | (0.9179) |
| Alpha | 0.3802** | 0.3793** | 0.3781** | 2.3661** | 2.3505** | 2.3113** |
| | (0.0508) | (0.0507) | (0.0503) | (0.2853) | (0.2837) | (0.2784) |
| Log-likelihood | −22926.72 | −22919.97 | −22911.51 | −6866.05 | −6860.42 | −6847.81 |
| AIC | 45901.45 | 45889.95 | 45879.03 | 13792.10 | 13774.84 | 13753.63 |
| BIC | 46064.17 | 46059.45 | 46068.87 | 13995.50 | 13957.91 | 13950.25 |
| *N* | 6504 | 6504 | 6504 | 6504 | 6504 | 6504 |
| State FE | YES | YES | YES | YES | YES | YES |

*Note*: Standard errors in parentheses. State dummy variables not shown. Statistical tests are two-tailed. Statistical significance: $^{**}p < 0.01$, $^{*}p < 0.05$.

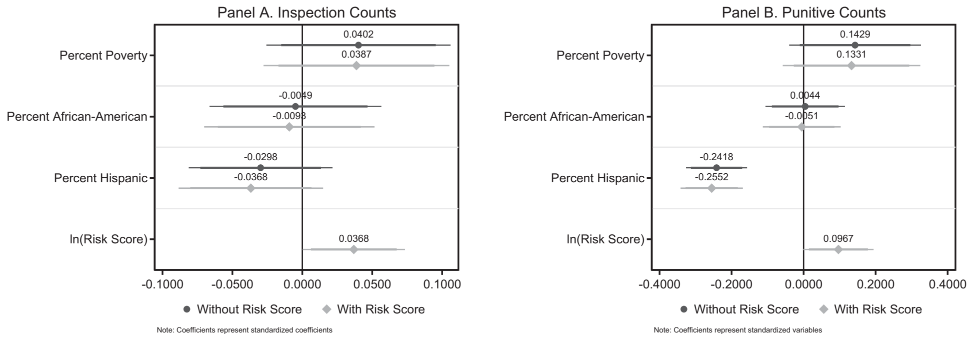


**Figure 3.** Coefficient Plots of Key EJ Variables for Additive Models. Panels Represent Estimates Derived for Different Regulatory Outputs: Inspections (Left), Punitive Actions (Right).

communities. Controlling for risk, however, does alter our interpretation of how regulators treat facilities in Hispanic communities. With risk in our model, we can no longer interpret the negative finding for Hispanic communities as perhaps being driven by Hispanics living in less risk prone areas. This is not the case. Second, we see that for regulatory outputs, state regulators are more aggressive against facilities that are located in communities exposed to more risk—government is being proactive against facilities where risk is higher. Facilities in communities with higher risks are inspected at a higher rate, and, while not significant at the two-tailed level ($p < 0.053$), there is suggestive evidence that punitive actions track positively with risk as well. This pattern is consistent with an instrumental approach to enforcement.

Perhaps the greatest advantage to controlling for risk is that it allows us to make some progress on interpreting what a null finding means substantively for environmental justice communities. We can, with greater confidence, conclude that government is not necessarily ignoring facilities in poor and African-American communities. Rather, given the variance in risk within these communities, regulators appear to be targeting facilities based upon a community's risk profile rather than its demographics profile. Of course, this is not the case with facilities in Hispanic neighborhoods. *Even controlling for risk*, regulators are less likely to detect and punish noncompliance against firms in Hispanic communities.

Collectively, thus, regulators are engaging in a combination of political and instrumental enforcement. Across poor and minority communities, regulators are dedicating enforcement resources to areas that experience higher levels of environmental risk. However, the differential effort across these communities also suggests that they are engaged in political enforcement; a purely instrumental, risk-based approach would mean that there is no additional correlation with demographic indicators, which is the not case for facilities located in Hispanic communities.

We are, however, also interested in whether communities experiencing varying levels of relative risk attract different attention from state regulators. To examine this possibility, we estimate the effect of our demographic indicators conditional on the community's relative risk score. The full results of this analysis are shown in Models 3 and 6 of Table 1. Our results suggest that while communities with higher levels of

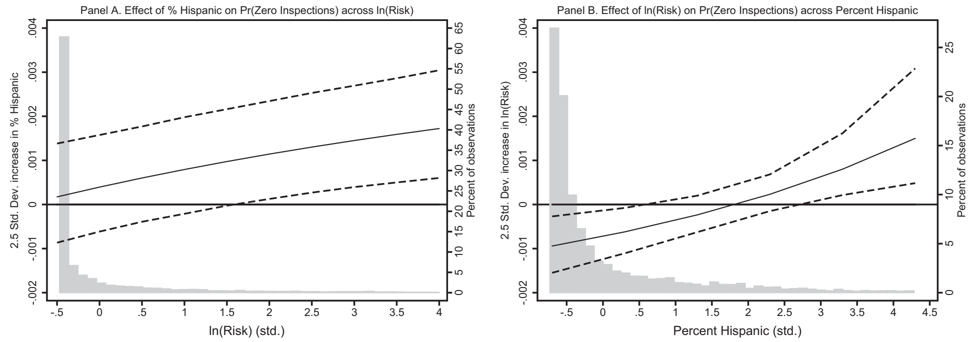


**Figure 4.** Marginal Effect of Percent Hispanic on Inspections Over ln(Relative Risk) (Left Panel). Marginal Effect of ln(Relative Risk) on Inspections Over Percent Hispanic (Right Panel). 95% Confidence Interval Shown Between Dashed Lines.

relative risk attract greater attention from state regulators, on average, this attention is uneven across communities. With respect to inspections, at average levels of community demographics, regulators exert greater detection effort against facilities in higher risk areas. However, they are no more likely to inspect facilities in poor or African American communities even if they are experiencing higher risk. This pattern changes for firms in Hispanic communities. Regulators treat facilities in Hispanic communities differently as their relative risk increases. Specifically, as relative risks increase in Hispanic communities, regulators inspect facilities less frequently.

With respect to punitive actions, facilities located in poor communities are more likely to receive attention from state regulators as risk increases. Facilities in African-American communities are less likely to receive attention, at higher levels of relative risk. Last, enforcement officers are less likely to punish facilities in Hispanic communities with average risk profiles. Similar to facilities in African-American communities, this regulatory leniency is greater for facilities in Hispanic communities with *higher* risk profiles. The average facility in a Hispanic community with relatively high risk scores can expect to receive fewer inspections, as well as fewer punitive actions for violations.

To better display this relationship, below we present marginal effect plots of key variables on the predicted probability of either an inspection or punitive action output. Given that our dependent variable is a count, we must identify a particular outcome value, a given number of inspections or punitive actions, that is substantively interesting and linked to our theoretical expectations. We elected to examine the marginal effects of risk and demographics on the predicted probability of zero inspections and zero punitive actions. A central claim in the literature is that poor and minority communities receive less regulatory attention relative to other communities. Focusing on how risk and demographics affect the likelihood of regulatory officers taking no actions seemed particularly appropriate, despite any potential awkward prose implications for our discussion.

F4 The left panel of Figure 4 plots the marginal effect of a two and a half standard deviation increase from the mean in the percent Hispanic on the probability of zero inspections against a facility. This increase is equivalent to moving from the average percent Hispanic community, around 13 percent, to a majority Hispanic community around 50 percent. This effect is plotted across the range of relative risk scores. The right panel of Figure 4 plots the marginal effects of a two and a half standard deviation increase from the mean in the relative risk scores on the probability of zero inspections against a facility. This effect is plotted across the range of percent Hispanics. The probability of zero inspections is a fairly rare event in our data; the unconditioned probability of zero inspections in our data is 0.013. Based on our model, the conditional predicted probability of observing zero inspections, with all variables set to their mean or mode, is 0.003. This will be the base probability against which we compare our substantive findings on inspections.

The left panel of the figure suggests that over the range of relative risks, regulators are no less likely to inspect facilities within Hispanic neighborhoods when relative risk levels are low. However, for relatively higher risk levels, regulators are increasingly less likely to inspect facilities in more Hispanic neighborhoods. At average risk (ln(Risk) = 0 on the *x*-axis), regulators inspect facilities in more Hispanic neighborhoods similarly to non-Hispanic neighborhoods. However, at higher levels of relative risk, say two standard deviations above the mean, facilities in Hispanic neighborhoods experience a higher (0.001) probability of not being inspected. This effect may appear substantively small, but recall that the conditional probability of zero inspections is 0.003. Therefore, a marginal increase of 0.001 over this base probability represents a 33 percent increase over the base. The size of this effect is on par with the marginal probability of a facility being an electric utility or 28 percent larger the median home value of the area within with a facility is located.

The right panel of the figure suggests that over the range of percent Hispanics, regulators are more likely to inspect facilities within risky neighborhoods when there are very few Hispanics in the community. However, in more Hispanic neighborhoods, regulators are not motivated to inspect facilities despite higher relatively higher risk levels. Moreover, this relationship changes direction at sufficiently Hispanic communities. At the average of percent Hispanics in a community (percent Hispanic = 0 on the *x*-axis), regulators are less likely to conduct no inspections against a facility in a relatively riskier community. The marginal effect between these communities is an approximate decrease of 0.00075 in the probability of having zero inspections or a 25 percent decrease over the base. The estimated effect of risk on not inspecting facilities is null as Hispanic communities increase, until the very highest concentrations of Hispanics. In these predominantly Hispanic communities increased risk is associated with an increase in facilities not being inspected.

Next, we consider the marginal effects for Hispanic communities on punitive actions. These results are plotted in Figure 5 below. The panels are organized similarly to Figure 4 above, but the outcome is now the probability of zero punitive actions rather than zero inspections. The probability of zero punitive actions is not a rare event in our data. The unconditioned probability of zero punitive actions in our data is 0.70. Based on our model, the conditional predicted probability of observing zero punitive actions, with all variables set to their mean or mode, is 0.62. This will be the base probability against which we compare our substantive findings on actions.

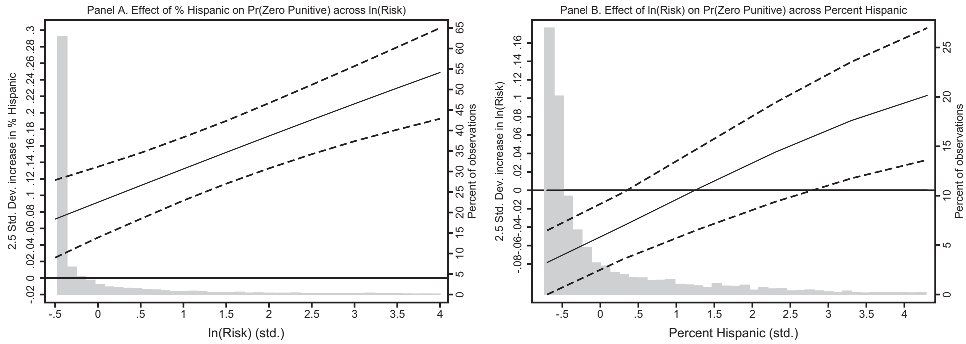


**Figure 5.** Marginal Effect of Percent Hispanic on Punitive Actions Over ln(Relative Risk) (Left Panel). Marginal Effect of ln(Relative Risk) on Punitive Actions Over Percent Hispanic (Right Panel). 95% Confidence Interval Shown Between Dashed Lines.

The left panel of the figure suggests that over the range of relative risks, regulators are no less likely to punish facilities within Hispanic neighborhoods when relative risk levels are low. However, for relatively higher risk levels, regulators are increasingly less likely to punish facilities in more Hispanic neighborhoods. At average risk or ln(Risk) = 0, regulators are more likely to take zero actions against facilities in Hispanic communities with a marginally lower probability of 0.09, about 14 percent lower than the base conditional probability. However, at higher levels of relative risk, say two standard deviations above the mean, facilities in Hispanic neighborhoods experience a marginally higher (0.17) probability of not being punished, about 27 percent higher probability of not being punished than the base.

The right panel of the figure suggests that over the range of percent Hispanics, regulators are more likely to punish facilities (less likely to produce no punitive actions) within risky neighborhoods when there are very few Hispanics in the community. However, in more Hispanic neighborhoods, regulators are not motivated to punish facilities despite higher relatively higher risk levels. At average percent Hispanics in a community (scaled percent Hispanic = 0, or around 13 percent Hispanic), regulators are more likely to punish facilities in relatively riskier communities. The marginal effect is a decrease of approximately 0.06 in the probability of an average facility having zero punitive actions. Substantively this represents an approximate 10 percent decrease in the probability of zero actions from the base. The estimated effect of risk on not taking punitive actions against facilities is null as Hispanic communities increase, until the very highest concentrations of Hispanics. Again, we see that in predominantly Hispanic communities increased risk is associated with an increase in facilities not being punished.

## Do Environmental Justice Institutions Help?

The issue of environmental justice reached the mainstream policy agenda in early- to mid-1990s, and since then, institutions have developed to address uneven exposure to environmental hazards. Communities have responded to environmental justice concerns by mobilizing and forming environmental justice interest groups, with a goal of reducing inequities in environmental citing and policing. Konisky and Reenock (2013) demonstrate that the presence of such grass roots community groups reduces state regulators' propensity to ignore noncompliance among firms and creates incentives for firms to enhance their compliance record.

As a final analysis, we consider whether environmental justice institutions, such as community interest groups, attenuate the enforcement patterns that we observe between community demographics and risk profiles.[16] We use data on environmental justice group mobilization data similar to those from Konisky and Reenock (2013). Specifically, we counted up the number of environmental justice organizations operating at the 3-digit zip code level, using data from a directory published by the Environmental Justice Resource Center (2000), when then created a weighted average of the number of groups, where the weights are the geographic intersections of 3-digit zip codes and the 1-mile buffer around each facility. While, these data are the best available data to assess mobilization, it is important to note that the status of groups may have changed in the time period between their original collection and when our data begin. The mean weighted average of groups ranged from 0 to 12 with a mean of 0.56 and a standard deviation of 1.32. About 30 percent of the facilities in our data have an EJ group fall within their 1-mile buffer.

To examine the possibility that community mobilization, as captured by the presence of environmental justice organizations, may attenuate uneven treatment of risk-exposed minorities, we re-estimate our models interacting our risk and community demographic variables with measures of EJ groups. Table 2 reports the results of these models. Models 1 and 3 display the results for the total number of EJ groups while Models 2 and 4 display a dichotomous measure of EJ group presence (coded one if there is a group, and zero otherwise). In each model, we continue to find a negative coefficient on the interaction between risk and the percentage of Hispanics as in Table 1. The difference here is that this coefficient now represents the conditioning effect of risk (or percent Hispanic) on the relationship between percent Hispanic (or risk) and the regulatory outputs, *when there are no EJ groups present*. The magnitude of these coefficients are similar to those estimated in Table 1.

To examine the effect of community mobilization, we can compare this two-way interaction with the three-way interaction between risk, demographics, and our EJ groups measures. If groups are successful in their policy goals, then we would expect the three-way interaction to be either null (i.e., Hispanic communities receive no different regulatory attention as relative risk increases) or positive (i.e., Hispanic communities receive more regulatory attention as relative risk increases). The results suggest that EJ groups encourage regulators to pay more attention to Hispanic communities at greater risk. In each of the models estimated, the coefficient estimated on the three-way interaction between EJ groups, Hispanics and risk is positive and statistically significant ($p < 0.05$). This suggests that in the presence of community EJ groups, the negative correlation between risk, demographics, and regulatory outputs is positive rather than negative—government pays more attention compared to similar communities without such groups. Compared to the models estimated in Table 1, the relationship between the presence of an EJ group (Models 2 and 4) reduces the marginal effect of risk (over Hispanic communities) on regulatory inspections by

**Table 2.** Parameter Estimates for EJ Groups and State Enforcement (1-Mile Buffer)

| | Inspections | | Punitive Actions | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| ln(risk score) | 0.0485* | 0.0438 | 0.1430** | 0.1316* |
| | (0.0204) | (0.0226) | (0.0468) | (0.0519) |
| Percent poverty | 0.0025 | 0.0005 | 0.0333 | 0.0058 |
| | (0.0331) | (0.0360) | (0.0994) | (0.1003) |
| Percent African-American | −0.0039 | −0.0152 | 0.0251 | 0.0313 |
| | (0.0308) | (0.0314) | (0.0633) | (0.0788) |
| Percent Hispanic | −0.0129 | −0.0000 | −0.2180** | −0.1781** |
| | (0.0225) | (0.0259) | (0.0658) | (0.0671) |
| ln(risk)*percent poverty | 0.0276 | 0.0219 | 0.0980 | 0.0930 |
| | (0.0284) | (0.0288) | (0.0541) | (0.0588) |
| ln(risk)*African-American | −0.0048 | −0.0146 | −0.1009* | −0.1250 |
| | (0.0292) | (0.0336) | (0.0504) | (0.0816) |
| ln(risk)*percent Hispanic | −0.0367** | −0.0505** | −0.1008** | −0.1409** |
| | (0.0090) | (0.0150) | (0.0202) | (0.0329) |
| # EJ groups | 0.0174 | | 0.0375 | |
| | (0.0137) | | (0.0346) | |
| # EJ groups*ln(risk score) | 0.0026 | | −0.0863** | |
| | (0.0095) | | (0.0334) | |
| # EJ groups*percent poverty | 0.0303** | | 0.0381 | |
| | (0.0086) | | (0.0236) | |
| # EJ groups*percent African American | −0.0144 | | −0.0289 | |
| | (0.0087) | | (0.0239) | |
| # EJ groups*percent Hispanic | −0.0180 | | −0.0019 | |
| | (0.0108) | | (0.0288) | |
| # EJ groups*ln(risk score)*percent poverty | −0.0139* | | 0.0068 | |
| | (0.0068) | | (0.0268) | |
| # EJ groups*ln(risk score)*percent African American | −0.0024 | | 0.0261 | |
| | (0.0072) | | (0.0206) | |
| # EJ groups*ln(risk score)*percent Hispanic | 0.0081* | | 0.0225* | |
| | (0.0040) | | (0.0113) | |
| EJ group | | 0.0475 | | 0.0711 |
| | | (0.0286) | | (0.0751) |
| EJ group*ln(risk score) | | 0.0184 | | −0.0853 |
| | | (0.0375) | | (0.0796) |
| EJ group*percent poverty | | 0.0650* | | 0.1575* |
| | | (0.0291) | | (0.0638) |
| EJ group*percent African American | | −0.0191 | | −0.1005 |
| | | (0.0366) | | (0.0939) |
| EJ group*percent Hispanic | | −0.0634* | | −0.0939 |
| | | (0.0251) | | (0.0949) |
| EJ group*ln(risk score)*percent poverty | | −0.0172 | | 0.0011 |
| | | (0.0346) | | (0.0706) |
| EJ group*ln(risk score)*percent African American | | 0.0044 | | 0.0747 |
| | | (0.0314) | | (0.0923) |
| EJ group*ln(Risk score)*percent Hispanic | | 0.0386* | | 0.0947** |
| | | (0.0169) | | (0.0314) |
| Controls suppressed | — | — | — | — |
| State FE | YES | YES | YES | YES |

*Note*: Standard errors in parentheses. State dummy variables not shown. Statistical tests are two-tailed. Statistical significance: $^{**}p < 0.01$, $^{*}p < 0.05$.



roughly 54 percent and on punitive actions by roughly 50 percent. This relationship if rather strong. Put another way, the only evidence that we have of regulators being more likely to ignore facilities in relatively more risky, Hispanic communities is when those communities have no EJ groups.

## Discussion

State environmental regulators are sensitive to both political and instrumental incentives. As a result, regulatory inattentiveness does not necessarily suggest bias against poor and minority communities, but it may. Under certain conditions, regulatory inattentiveness may be instrumental. When facilities are located in relatively lower risk environments, regulators dedicate scarce resources toward other facilities regardless of income or race. Of course not all regulatory inattentiveness is instrumental. Under other conditions, inattentiveness may have a political basis. Our analysis shows that, when facilities are located in both relatively higher risk/Hispanic communities, regulators dedicate their scarce resources toward other facilities.

Of course evidence of uneven enforcement remains in our models even after accounting for environmental risk and political mobilization. What then is behind this residual uneven enforcement? It may be that our measures of risk and mobilization are not sufficiently precise to completely capture regulatory officers' incentives. Or, it may be evidence of intentional discrimination. Without accurate measures of regulatory officers' latent intentions to discriminate, we simply cannot determine this.

The immediate question we face is what to make of the discrepancy between traditional EJ communities? Facilities in poor communities appear to receive no different attention, while facilities in Hispanic communities and African American communities (for punitive actions only) receive less attention on regulatory outputs. It is important to note that this pattern of conflicting results is not uncommon, and several studies have shown specifically that Hispanic communities tend to experience disproportionate impacts, for example, with respect to proximity to waste sites and exposure to air pollution (Baden & Coursey, 2002; Bell & Ebisu, 2012; Crowder & Downey, 2010). In this study, we cannot directly explain why we observe differences in regulatory enforcement across traditional environmental justice communities. One possibility relates to ideas from arguments about representative bureaucracy. Relative to even African-Americans, Hispanics hold fewer positions in government agencies—at least in the federal workforce (Riccucci, 2009)—and this could translate into differences in the allocation of enforcement effort. Of course, without data to test this possibility, this is only speculation, but an area that merits future inquiry.

An alternative explanation that we think is especially plausible regards the positive legacy of the environmental justice movement. As we enter the fourth decade of this movement in the United States, it is plausible that the differential treatment we observe in these data are perhaps counterintuitively related to the movement's achievements. African-American communities, particularly those with high numbers of low-income residents, were the core of the movement's early organization. It may well be the case that 30 years on, the communities central to the movement's beginnings have begun to reap the benefits of their advocacy.

To date, the Hispanic community has not been mobilized at similar levels on environmental justice issues. For example, according to a directory of environmental justice organizations (the same source of information we used to generate a measure of environmental justice groups), there are nearly 3 times as many organizations that primarily serve African-Americans compared to Hispanics (Environmental Justice Resource Center, 2000). The comparatively less mobilization of Hispanics may be due to a variety of reasons. First, Hispanic communities often have more recent immigrants that face additional obstacles in overcoming collective actions problems, ranging from basic language hurdles to familiarity with the policy process and government institutions. Second, and this reason is not independent of the first, members of the Hispanic community may have higher levels of distrust with state and federal institutions. The policy consequence of this distrust may be a lower level of perceived political mobilization and a resulting lower level of regulatory attention. Our investigation of this possibility accords with prior work suggesting that community mobilization may mitigate regulatory inattention (Konisky & Reenock, 2013). In communities with an EJ interest group presence, regulatory inattention to African American and Hispanic communities was either no different from or greater than other communities having no interest group mobilization.

We believe, on the whole, our results offer a cautionary note on the use of economic and racial data as proxies for environmental risk. Our use of risk data allowed us to accurately characterize risk, independent of economic or racial community characteristics. As a result, we were able to differentiate between instrumental and political motivations behind regulatory inattentiveness. Without the environmental risk data that we applied in the current analysis, we may have been tempted to conclude that the lack of regulatory attention to a given community was clear evidence of bias or that regulatory attention necessarily implied greater environmental risk. Our findings suggest that the U.S. riskscape is more complicated than either of these relatively simplistic assessments of regulatory (in)attention.

From a policy standpoint, our analysis also suggests that there may be a need to reconfigure current enforcement strategies. In developing its comprehensive new environmental justice initiative, *Plan EJ 2014*, the EPA has clearly directed attention to the merits of political enforcement. And, the EPA has already begun to incorporate demographic considerations into its own enforcement priorities (Environmental Protection Agency, 2015a). Yet, our analysis shows that such an approach, if performed without close attention to varying risk levels experienced by traditional environmental justice communities, may not be particularly effective if the objective is to efficiently use limited enforcement resources in communities most vulnerable to environmental burdens. The agency has developed information tools such as its EJSCREEN model, however, that, should enable the agency to target its enforcement efforts in poor and minority communities at most risk. Of course, given that the lion's share of enforcement of the CAA and other federal pollution control programs occurs at the state level, the EPA needs to insist that the state agencies given authority to implement these programs adopt a similar strategy. Our analysis here suggests that this is not being done currently, much to the detriment of minority communities. These types of disparities are not inevitable, and can be addressed by willing and attentive state agencies interested in delivering policy in a fair and equitable manner.

## Notes

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1. There is a separate literature that has investigated outcomes from federal district court decisions to determine whether monetary penalties issued as part of cases are on average lower when the noncompliant facility is located in a poor and/or minority community. The most definitive study in this literature finds no such disparities (Ringquist, 1998).
2. There is little evidence that enforcement disparities have diminished as the result of federal and state policy interventions (Konisky, 2009b; Konisky & Reenock, 2015).
3. Our sample includes major air sources that were active and operational in each month of the three years of our study. Any facility that was inactive during this period, was excluded from the analysis.
4. It is important to note that a punitive action taken against a facility is a sanction against a facility for a violation of an emissions limit, and may not relate closely to the cumulative risk in the area in which a facility is located.
5. Most studies in the environmental justice literature use census units such as counties, tracts or block groups, or zip codes to develop demographic measures of for communities "hosting" a facility. However, there are two-well known problems with this approach. First, demographic characteristics may not be uniformly distributed among the population of the geographic unit, a particular problem when counties are used. This assumption is also the case with the areal apportionment method, but is less problematic if census tracts or block groups are used as the building blocks. Second, the relevant population may extend to adjacent geographies, especially when a facility is located on the border.
6. In a small number of cases, the demographic data from the census was missing for some census tracts; in these cases, we imputed a value based on the average of the other intersected units.
7. The TRI was put in place as part of the 1986 Emergency Planning and Community Right to Know Act. The law requires facilities in specified sectors (e.g., manufacturing, mining) to report their releases of toxic substances if they exceed a specific threshold. The program has been modified several times over the years to expand the chemicals included and to extend the reporting requirements to additional facilities.
8. More details on the RSEI model are available from the EPA at http://www2.epa.gov/rsei, and in additional technical guidance (Environmental Protection Agency, 2015b).
9. The numerical values computed from the RSEI model, for example, do not account for exposure to criteria air pollution (e.g., particulate matter, ozone, etc.) or to pollutants generated from mobiles sources. Moreover, the RSEI data only capture one type of risk, those from toxic emissions, and thus do not account for any cumulative burdens that communities may experience.
10. We estimate negative binomial models instead of Poisson models because of overdispersion in each of our dependent variables.
11. To the degree that the nonattainment status of an area is related to regulatory enforcement behavior, including this control may also pick up some of the "instrumental" enforcement motive of regulatory officers. However, the geographic level of nonattainment determinations is broad, whereas the RSEI data provide an opportunity for a finer level of resolution.
12. An instrumental enforcement strategy may also respond to facility noncompliance, since violations of CAA obligations may generate risk for a community that is not fully captured by the TRI-based measure. Controlling for noncompliance captures some of this, but imperfectly, since facilities can be determined to be in noncompliance for other reason as well.
13. This is consistent with the "minority move-in" argument that is often discussed in the environmental justice literature in the context of facility siting decisions. For a recent discussion, see Mohai and Saha (2015).
14. The EPA does not track the siting date of the facilities it regulates, and doing so independently for the more than 13,000 facilities in our sample would incredibly burdensome.

15. These findings, which are reported in the Supporting Information Appendix S2, are robust to our usage of 2- and 3-mile buffers around each facility.

16. We also considered centralized top-down institutions, such as whether states have adopted formal environmental justice policies with an eye toward increasing awareness of environmental justice issues. We used available information from the latest edition of a report on state environmental justice policy put together by the University of California Hastings College of Law, in association with the American Bar Association (Bonorris, 2010) to code whether a state had either legislation or an administrative policy that was designed, at least in part, to incorporate environmental justice considerations into their policy implementation. Sixteen states had such a policy in place as of 2010 (Alabama, Arkansas, California, Connecticut, Illinois, Indiana, Massachusetts, Maryland, Minnesota, New Hampshire, New Jersey, New Mexico, New York, Oregon, Pennsylvania, and West Virginia). In the end, we felt that such a coarse measure did not validly reflect differences across state policies and elected to not pursue this analysis.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web-site.

**Table S1**: Descriptive Statistics

**Table S2**: Parameter Estimates for State Enforcement (2-Mile and 3-Mile buffer)

**Table S3**: Parameter Estimates for EJ Groups and State Enforcement (1-Mile Buffer)

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