# Assessing Evidence of Environmental Inequities: A Meta-Analysis

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***Abstract***

*Over the past decade activists, academics, and policymakers have devoted a great deal of attention to "environmental equity," or the notion that sources of potential environmental risk may be concentrated among racial and ethnic minorities and the poor. Despite these efforts, the existence and extent of environmental inequities is still the subject of intense scholarly debate. This manuscript reports the results from a meta-analysis of 49 environmental equity studies. The analysis demonstrates that while there is ubiquitous evidence of environmental inequities based upon race, existing research does not support the contention that similar inequities exist with respect to economic class. © 2005 by the Association for Public Policy Analysis and Management*

## INTRODUCTION

Over the past decade activists, academics, and policymakers have devoted a great deal of attention to "environmental equity," or the notion that sources of potential environmental risk may be concentrated among racial and ethnic minorities and the poor. While many researchers have concluded that these potential risks were located disproportionately in poor and minority areas, a substantial number of studies by other researchers rebut these claims. The resulting uncertainty regarding the existence of environmental inequities is of obvious scholarly importance. Inequity is a constant theme across the social sciences, and disagreements like those noted above prevent our being able to draw conclusions regarding the existence, extent, and sources of inequity. Uncertainty regarding the existence of environmental inequities has important consequences outside of the academy as well. A large and vocal "environmental justice movement" has risen around the notion that environmental burdens are distributed unfairly. Advocates within this movement have lobbied successfully for public policies to redress environmental inequities (Ringquist, 2003). However, the legitimacy of the grievances advanced by the environmental justice movement, the power of its claims on the political process, and the justification for continued policy change to address perceived environmental inequities all hinge on resolving the current uncertainty regarding the existence of environmental inequities.

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The tools of meta-analysis are particularly well-suited for extracting generalizable conclusions from contradictory studies. Developed to study the overall effects of psychological treatments and educational reforms, meta-analysis treats original quantitative studies as individual pieces of data. The meta-analyst extracts an "effect size" from each study weights the effect size by its associated uncertainty, and then aggregates the results across all studies on a particular topic. The statistical precision and sophistication of meta-analysis have improved dramatically since the introduction of the tool in the 1970s, and one can routinely find discussions of new meta-analysis tools in the statistical literature (for example, Duval & Tweedie, 2000; Goutis, Casella, & Wells, 1996; Li & Begg, 1994).

Despite these methodological advances, scholars in the core social science disciplines have been slow to adopt the technique. One explanation for this reluctance may be unfamiliarity, since the technique is most commonly used within the experimental traditions of psychology, education, and medicine. A second explanation is that meta-analysis traditionally has had difficulty aggregating the results of the multivariate quasi-experimental models typically used in the social sciences. Nevertheless, over the past several years, meta-analytic studies have begun to appear in leading journals in economics (Card & Krueger, 1995; Kremers, Nijkamp, & Rietveld, 2002; Smith & Huang, 1995), political science (Church, 1993; Gerber, Green, & Nickerson, 2001; Lau et al., 1999), and sociology (Crain & Mahard, 1983; Stanley & Jarrell, 1998; Wagner & Gooding, 1987). In addition, meta-analysis is increasingly being used by policymakers when making regulatory decisions (Berlin & Colditz, 1999).

This manuscript employs the tools of meta-analysis to draw conclusions about the inequitable distribution of sources of potential environmental risk with respect to race and class, and to test several hypotheses regarding why conclusions about the existence of environmental inequities vary across studies. While the manuscript does not attempt to determine whether there is a causal relationship among race, class, and the distribution of sources of potential environmental risk, the meta-analysis can help determine whether such inequities exist currently.

## THE CONTENTIOUS ENVIRONMENT OF ENVIRONMENTAL EQUITY

### Environmental Equity and Public Policy

The overwhelming majority of environmental equity research examines the relationship between the current distribution of sources of potential environmental risk and current demographic conditions. This research seeks to document the existence and extent of current environmental inequities, if they exist. Early research in this vein helped mobilize, and later research helped sustain, environmental justice advocates who lobbied successfully for policy changes to address these inequities. At the federal level, the most obvious response to advocates' concerns was the creation of the Office of Environmental Justice (OEJ) within the Environmental Protection Agency (EPA). OEJ actively works with community groups to identify and remedy perceived instances of environmental injustice and supports local environmental justice community groups with grant money. Policy changes motivated by perceived environmental inequities go far beyond the creation of OEJ, however. Members of the policy community inside and outside of government have sought to reorient the core environmental management tasks of standard setting, permitting, and enforcement and turn them in to tools for combating environmental inequities (Hammer, 1996; Lazarus & Tai, 1999; Ringquist, 2004). Nor has policy activity in this area been limited to the federal level. Nearly all states have reorganized their environmental protection bureaucracies to address environmental justice issues, and state legislatures continue to adopt legislation in this vein (Bonorris 2004; Ringquist & Clark, 1999). The scope of the policy response to perceived environmental inequities might be seen as remarkable, given the uncertainty as to whether current environmental inequities actually exist on a large scale.

Given their focus on current environmental inequities, neither the original studies nor the meta-analysis can tell us much about the *causes* of environmental inequities, if they exist. A small number of studies do explicitly attempt to evaluate this causal relationship by analyzing the demographic characteristics of communities at the time various noxious facilities were originally sited (for example, Been, 1997), but results from these few causal models are not included in the meta-analysis because the models ask a different question. Consequently, the meta-analysis can only establish *whether* environmental inequities currently exist, *where* these inequities exist (with respect to race or class), and give some indication of the *magnitude* of these inequities. In effect, the meta-analysis will tell us if the actions of federal and state governments aimed at addressing environmental inequities are justified in some elemental sense. By not investigating the causes of environmental inequities, however, the analysis cannot determine whether these actions are likely to be effective.

### Inconsistent Conclusions in the Study of Environmental Equity

*Contradictory Conclusions from Individual Analyses*. The first study to systematically examine environmental equity on a national scale was completed by the United Church of Christ's Commission on Racial Justice (CRJ) in 1987. The CRJ gathered data on the location of commercial hazardous waste handlers and created a statistical model to predict the location of these facilities. This model showed that as the percentage of poor and minority residents of a neighborhood increased, the likelihood that the neighborhood contained a hazardous waste site increased as well, even when controlling for region, urbanization, and land value (CRJ, 1987). An update to the CRJ report found that these same relationships existed in the 1990s (Goldman & Fitton, 1994). More recent research has also found that poor and minority neighborhoods are more likely to contain commercial hazardous waste facilities (Been, 1995, 1997), though other researchers have found no inequities in the distribution of these facilities (Anderton et al., 1994a; Hamilton, 1995).

Indeterminacy regarding potential environmental inequities is not limited to commercial hazardous waste facilities. For example, Ringquist (1998) finds that hazardous waste handlers of any sort are more likely to be located in areas with large numbers of poor and minority residents, while Davidson and Anderton (2000) find no relationship among race, class, and the location of these facilities. Similarly contradictory findings exist with respect to facilities that produce and release toxic chemicals. Burke (1994), Daniels and Friedman (1999), Perlin, Setzer, Creason, and Sexton (1995), Pollock and Vittas (1995), Ringquist (1997), and Sadd, Pastor, Boer, Snyder (1999) find that these chemicals are concentrated in poor and minority areas, but Bowen et al. (1995) and Holmes, Slade, and Cowart (2000) find no such relationship, while Kriesel (1996) finds that this relationship varies between states. One observes similarly contradictory findings across a broad range of sources of potential environmental risk (see Ringquist, 2003, for a review).

*Contradictory Conclusions from Literature Reviews*. Disagreements between individual studies might be inevitable in a topic receiving as much scholarly attention as environmental equity. At the very least, such disagreements would be benign if, despite them, one could draw generalizable conclusions about the existence and extent of environmental inequities. Indeed, such disagreements would even be healthy if a systematic investigation into the causes of the disagreements led to improved analysis in this area. Sadly, neither of these situations currently exists. Reviews of the environmental equity literature have themselves reached varying conclusions. Paul Mohai and Bunyan Bryant (1992) examined 21 separate environmental equity studies and found that 94 percent demonstrated racial inequities in the distribution of environmental risk and 80 percent pointed out inequalities based on wealth. Similarly, Benjamin Goldman (1993) surveyed 64 relevant empirical studies, 63 of which found significant environmental disparities by income or race. On the other hand, reviews of the relevant literature by the General Accounting Office (1995) and William Bowen (2001) found no systematic evidence of environmental inequities, and Foreman (1998, p. 27) concludes that "even a reasonably generous reading of the foundational empirical research alleging environment inequity . . . must leave room for profound skepticism regarding the reported results."

## Why Different Studies Find Different Results: Four Hypotheses

A close reading of the literature suggests four possible explanations for why studies disagree about the existence of environmental inequities. While this list is not exhaustive, it encompasses most of the reasons for disagreement identified by authors in this area.

*Source of Potential Environmental Risk.* The source of potential environmental risks may affect conclusions regarding inequities in the distribution of these risks in at least three ways. First, some risks may be distributed inequitably, while others are not. Thus, conclusions regarding the existence of environmental inequities may vary depending upon the particular risk vector examined. We should not be surprised if studies employing different dependent variables produce different results. Second, noxious facilities differ dramatically in their degree of potential risk and in the degree to which this risk is offset by associated benefits. In short, not all sources of pollution fit the definition of locally undesirable land use, or "LULU," equally well. Finally, the term *potential* environmental risk is used here because while most environmental equity research examines the location of noxious facilities, simply living next to these facilities may not affect one's exposure to actual risk. What matters from a risk perspective is not the existence of these facilities, but exposure to the pollution they may release. Thus, while noxious facilities may be located in areas with large numbers of poor and minority residents, this does not mean that there are inequities with respect to risks posed by actual levels of pollution.

*Levels of Aggregation, or the Definition of "Community."* Environmental equity research generally examines whether poor and/or minority communities are more likely to contain potential environmental risks, and defines "community" using a particular geographic area. Scholars have tested environmental equity hypotheses using states (Lester, Allen, & Hill, 2001), cities (Lester, Allen, & Hill, 2001), counties (Hird & Reese, 1998), postal ZIP codes (CRJ, 1987), census tracts (Been, 1995), census block groups (Pollock & Vittas, 1995), and various units defined using Geographic Information System (GIS) software (Morello-Frosch, Pastor, & Sadd, 2001). The unit of analysis may have important consequences for the conclusions generated by environmental equity research, largely due to the possibility of aggregation bias when using larger units. A number of scholars have claimed that evidence for or against environmental inequities is affected by aggregation bias. For example, Anderton et al. (1994a) argue that the positive association between race, class, and the location of commercial TSDFs at the ZIP code level are artifacts of just this type of aggregation bias. Similarly, both Bowen et al. (1995) and Taquino, Parisi, and Gill (2002) show that conclusions regarding environmental inequities may depend upon the unit of aggregation used in the analyses.

There is no clearly superior definition of "community" for all environmental equity analyses; one must match the definition of community to the actual geographic area affected by the noxious facility or pollutant. Still, investigating the effect of aggregation bias on environmental equity research is valuable for at least two reasons. First, if the results of this research are plagued by aggregation bias, as some claim, evidence of environmental inequity ought to vary by level of analysis. We can use the tools of meta-analysis to test claims of overall aggregation bias in environmental equity research. Second, if evidence for and against environmental inequities does vary by level of aggregation, this poses significant challenges for advocates who would have government act to redress these inequities.

*Defining Comparison Groups*. Environmental equity researchers must be concerned about systematic differences between areas with and without potential sources of risk that are independent of the factors of interest (for example, race and class). Most researchers in this area address these differences using control variables, comparing all areas with sources of potential environmental risk to all areas without these sources. A few researchers, however, employ a strategy that limits membership in the comparison group in some way. For example, Anderton et al. (1994a) select for analysis only those metropolitan statistical areas (MSAs) containing at least one commercial hazardous waste facility, excluding all non-MSA areas and all MSAs without these facilities. The comparison group in this study, then, is census tracts without such facilities in a limited number of MSA. This restriction on comparison groups is justified on the grounds that any MSA without a hazardous waste facility cannot be considered a legitimate alternative location for existing facilities. An additional tract restriction is justified on the grounds that only contiguous tracts are likely alternative sites for existing facilities.

Critics of restricting comparison groups in this manner claim that it is relatively easy to model those characteristics that make an area an unlikely host for a hazardous waste facility, so exercising artificial domain restrictions when defining comparison groups does little more than reduce the power of statistical tests by reducing sample sizes. Moreover, such domain restrictions can have far more pernicious effects. In effect, these studies generate their samples by selecting on the dependent variable. If, as environmental justice advocates claim, there is a strong positive relationship between race or class and environmental risk, selecting for analysis only those areas containing sources of these risks will produce two effects. First, to the extent that race or class predict risk, selecting a sample based on the presence of sources of these risks guarantees that the sample itself embodies part of this relationship, which in turn biases the race and class coefficients in such analyses to lie near zero. Second, selection on the dependent variable will substantially reduce the variation in the independent variable of interest (for example, percent minority population), which in turn increases the standard error of the coefficient estimate for this variable. Together these effects predispose samples selected in this fashion toward finding no relationship among race, class, and environmental risk. Indeed, Been (1997) demonstrates that the null results of Anderton et al. (1994a) are a function of this artificial domain restrictions on comparison groups.

*Study Quality: Controlling for Alternative Explanations.* There are different perspectives on how one demonstrates the existence of environmental inequity. One perspective simply requires a bivariate relationship between race or class, and potential environmental risk to conclude that inequities exist. This perspective recognizes that there are significant racial disparities in income, educational attainment, residential location, and political power. Since these factors shape private and public institutions, the aggregate impact of institutional decisions can often be discriminatory or reflect institutional discrimination. To the extent that these economic and political factors covary with race, it makes little sense to discuss the influence of these forces in isolation from race (Omi & Winant, 1994). A more restrictive and conventional view states that inequities exist only if the racial and class characteristics of communities display a significant relationship with the distribution of potential environmental risks independent of other factors related to race and class. Clearly, the results from statistical models of environmental equity may vary with the independent variables included in the analysis. According to the conventional view adopted here, higher quality studies are defined as those that control for alternative explanations for the distribution of potential environmental risk. One can conclude that environmental hazards are disproportionately located in poor and minority communities only after other explanations for the location of hazards have been controlled for or ruled out.

## RESEARCH DESIGN AND DATA GATHERING

### Designing Research Questions

*Crafting Research Questions.* The first step in the meta-analysis was to identify initial research questions encapsulating the most important points of contention regarding environmental justice. As noted above, environmental justice advocates and their critics offer a wide range of perceived sources and expressions of inequities in environmental protection. The core questions for most environmental justice researchers, however, have centered on the extent to which various sources of risk are concentrated with respect to race and class. In environmental justice research, race is invariably measured using the percentage of Black, Latino, or non-White residents in a particular community. Economic class is measured two ways: using median household income in a community, or using the percentage of community residents with incomes below the poverty line. Thus, environmental inequities exist when the concentration of environmental risk vectors is associated with the race, income, or poverty status of community residents. The research questions, then, focus on whether noxious facilities and pollution levels are inequitably distributed with respect to race, income, and poverty.

*Key Moderating Variables.* After identifying research questions, we must identify those factors that might be expected to affect the relationships among race, class, and potential environmental risks reflected in these questions. I took as my starting point the most common sources of disagreement in the literature regarding the existence of environmental inequities and used these disagreements to identify four classes of moderating variables to be included in the study.

The first class of moderating variable is the source of potential environmental risk, or the type of outcome variable. Sources of potential environmental risks examined by environmental justice researchers run the gamut from the location of hazardous waste incinerators to the location of industrial hog farms to the concentration of criteria air pollutants. I initially sought to investigate eight sources of potential risk: commercial hazardous waste TSDFs; all hazardous waste TSDFs; Superfund sites; incinerators; sources of toxic pollutants identified by the Toxics Release Inventory (TRI); factories receiving environmental permits; pollution levels; and other potential risk sources. After examining the literature, it became clear that there were too few studies examining some of these sources to support a meta-analysis. Consequently, I aggregated effects across three general types of potential environmental risk: noxious facilities, Superfund sites, and levels of pollution.

The second class of moderating variables identifies study characteristics that might affect the degree of racial or class inequity associated with potential sources of environmental risk. Perhaps the biggest source of contention regarding the existence of environmental inequities is the level of aggregation used when investigating this question (see Anderton, 1994a; Been, 1997; Bowen et al., 1995). The initial categorization scheme employed eight levels of aggregation; census block groups; census tracts; ZIP codes; cities/MSAs; counties; states; GIS areal units; and other. After consulting the literature, these eight categories were collapsed to four: states, cities and counties; ZIP codes; census tracts and block groups; and GIS units.

The third class of moderating variables identifies the type of control group employed in the studies. Specifically, these variables distinguish studies that compare areas with potential sources of environmental risk to all areas without these sources from studies that compare areas with potential sources of environmental risk to some limited subgroup of areas without these sources. I refer to these latter studies as employing limited nonhost comparison groups.

The final class of moderating variables includes indicators of study quality. Measuring study quality is difficult, largely due to the inherently subjective nature of most indicators of quality (Wortman, 1994). Consequently, I decided to use two limited but relatively objective indicators of quality; the extent to which the study includes adequate statistical controls, and whether the study was published in a peer-reviewed outlet. Many factors predicting the location of LULUs vary with race and income. Higher-quality studies, then, are those that control for these other factors. The most important of these potential confounding factors—and therefore included in the meta-analyses that follow—are population density, property values, and the existence of a manufacturing infrastructure (see Anderton et al., 1994a).

*The Final Research Framework.* Through the process outlined above, I constructed the following list of final research questions, conditioned by the key moderating variables:

1. Are potential environmental risks inequitably distributed with respect to the race of area residents?
   a. Do racial inequities vary by the type of potential environmental risk?
   b. Do racial inequities vary by the unit of aggregation or definition of community?
   c. Do racial inequities vary by the type of comparison group employed?
   d. Do racial inequities vary by study quality?
2. Are potential environmental risks inequitably distributed with respect to the economic class of area residents?
   a. Do class inequities vary by the type of potential environmental risk?
   b. Do class inequities vary by the unit of aggregation or definition of community?
   c. Do class inequities vary by the type of comparison group employed?
   d. Do class inequities vary by study quality?

As should be clear from the above discussion, aggregating statistical results across studies does not simply allow us to draw a single conclusion regarding the presence or absence of environmental inequities. Meta-analysis allows us to investigate whether evidence of environmental inequities varies systematically across type of potential risk, level of aggregation, type of comparison group, and quality of study. There are adequate data to answer these questions, and the answers will provide a reasonably good summary of extant knowledge regarding the existence of environmental inequities in the United States.

## The Data Gathering Process

In gathering data, I identified six types of publications that might contain studies for inclusion in the meta-analysis: peer-reviewed articles; nonpeer-reviewed articles; books and book chapters; government documents; private reports issued by interest groups or think tanks; Ph.D. dissertations and Master's theses. Four search strategies were employed to obtain studies of each type. First, a research team conducted a series of computer searches of traditional databases of books, articles, dissertations, and theses, and government documents, using the keywords "environmental equity," "environmental justice," and "environmental racism." Second, the team compiled a list of interest groups and think tanks with an interest in environmental justice or environmental policy and searched the websites of these organizations for environmental equity reports. Third, the Office of Environmental Justice at the U.S. Environmental Protection Agency, and all state environmental justice commissions listed by Ringquist and Clarke (1999), were contacted and asked to provide copies of or links to government reports in this area. Finally, we employed the "ancestry" method whereby we identified potentially relevant studies in the reference section of studies obtained through traditional means.

The literature search produced literally thousands of "hits." To impose structure on this chaotic situation, the team employed three successively more restrictive criteria to identify the small subset of studies that were suitable for the meta-analysis. First, we identified a set of what we called "potentially relevant studies" from the thousands of items produced by our keyword searches. Potentially relevant studies were identified solely through their bibliographic references. We took a catholic approach to what constituted a potentially relevant study, excluding only publications from popular outlets (for example, newspapers and news magazines), publications that obviously made it into the search results because they contained the keywords but in a nonsensical order, book reviews, and publications that did not focus on our research questions. All remaining studies were placed in the category of potentially relevant. We identified 297 potentially relevant studies and assigned each a unique study ID number that it would keep through all subsequent coding and analysis.

We examined each potentially relevant study in more detail by obtaining the study abstract or a study summary. The goal of this examination was to separate "relevant" studies from the much larger class of potentially relevant studies. Potentially relevant studies were excluded from the class of relevant studies if they were (a) nonanalytic (that is, descriptive), (b) nonquantitative, (c) non-U.S., or (d) examined a dependent variable other than those in our research questions. Relevant studies, then, were those that were analytic in nature, used statistical techniques to test hypotheses, and focused on racial or class inequities in the distribution of noxious facilities, Superfund sites, or pollution levels in the United States. Eighty-eight relevant studies met all of these criteria. To make sure that all members of the research team were using the same criteria to identify relevant studies, we took a random sample of 60 potentially relevant studies and had each member of the research team code each study. The measure of intercoder reliability was .85.

Next, we obtained the full text of each relevant study in order to determine if the study was "acceptable" for the meta-analysis. Relevant studies could be deemed unacceptable if (a) a mistake was made in concluding that the study was relevant or (b) the study was relevant but contained insufficient statistical detail in the reporting of results to be included in the meta-analysis. A surprisingly large number of highly regarded and frequently cited studies failed on this last criterion, including studies by Anderton et al., (1994b), Bullard (1990), McCaull (1976), the U.S. GAO (1983 and 1995), and Zimmerman (1993). We found a total of 49 acceptable studies through this method. These 49 studies are listed in the Appendix. Finally, from each acceptable study we extracted the data necessary to calculate effect sizes and coded values for each moderating variable. I calculated a total of 1,141 effect sizes from the 49 acceptable studies. Effects within each study were assigned a unique identification number, so that each effect could be identified through a combination of the study ID and effect ID numbers.

### Turning Studies into Data

To conduct the meta-analysis, results from all studies must be transformed into a common metric, the effect size. Effect sizes can be calculated from mean differences or from correlation coefficients. Because nearly all of the acceptable studies described above employ multivariate models, the analyses that follow make use of the most common correlation-based effect size measures: Fisher's $Z_r$ (see Rosenthal, 1994). Calculating Fisher's $Z_r$ requires the t-scores and p-values from the individual parameters associated with the race and class variables in the original studies. Where possible, I calculated exact t-scores and p-values from the information provided in the study (for example, parameter estimates, standard errors, and degrees of freedom). Several studies reported neither a t-statistic nor the information necessary to calculate this statistic, instead simply identifying whether a particular coefficient was statistically significant. For these studies, I assigned a p-value equal to the reported alpha level for significant coefficients, and equal to 0.5 for non-significant coefficients. This approach only allows calculation of a lower bound for correlation between race or class and sources of environmental risk, which will attenuate the associated effect size. Finally, two studies reported effects through the use of group means. I conducted difference of means tests for these studies and derived an exact p-value for the calculated t-statistic. When calculating p-values and t-scores, the sign of the original coefficient was discarded. For the meta-analysis, the sign of the effect was determined by whether the coefficient was consistent with evidence of environmental inequities. Coefficients reflecting environmental inequities were coded as positive, and vice versa.

## UNIVARIATE ANALYSES: AVERAGE EFFECT SIZES

### Calculating Average Effect Sizes

Testing whether existing research supports the existence of environmental inequities on some broader scale requires calculating an average effect size for all acceptable studies. Calculating average effect sizes requires several steps. First, estimates from individual studies must be transformed into a standardized mean effect, which in the present case is accomplished using $Z_r$. Second, in many cases a single study will produce multiple effect sizes. Among the acceptable studies used here, Hird and Reese (1998) report 117 different estimates of environmental equity effects, while Allen (2001) reports only one. To prevent a single study from having undue influence on the results of the meta-analysis, a single average effect is calculated for each study generating more than one effect. Finally, average effects for each study are aggregated across studies into an overall average effect.

How one goes about averaging effect sizes across studies depends upon the researchers' perspective on what individual study effect sizes represent, and on relevant statistical criteria. Because almost all effects in environmental equity analysis come from multivariate analyses, I employ a random effects model. Random effects models assume that cross-study variation in effect sizes is the product of random sampling error and a nonrandom component stemming from unspecified sources of variation in the population parameter itself (for example, model specifications in individual studies; see Hunter and Schmidt, 1990; Shadish and Haddock, 1994). Q-tests support the use of the random effects approach to estimating average effect sizes. In addition to average effects across studies, I calculate 95 percent confidence intervals for these average effect sizes.

While calculating confidence intervals will allow us to determine whether average effect sizes are significantly different from zero, in most cases the absolute magnitude of these effects is more interesting than whether they are statistically significant. We can assess the magnitude of effects sizes using two methods. First, it is worth noting that $Z_r$ is simply a peculiar log transformation of r, where r is a correlation coefficient (Fisher, 1928). Thus, average effect sizes themselves are good approximations of correlation coefficients. Second, Cohen (1988) has given the following rules of thumb for evaluating correlation based effect sizes: $r < 0.10$ is a small effect, $r = 0.25$ is a moderate effect, and $r > 0.40$ is a large effect.

## Average Equity Effects and Race

Table 1 reports average effect sizes for environmental inequities based upon race. Fifteen average effect sizes are calculated, one overall effect and separate effects for each of the moderating factors discussed above. Averaging results across all acceptable studies, I find significant evidence for environmental inequities based upon race; the average effect size is 0.072 (statistically significant at $p < 0.01$). Using standard criteria, the average effect size for race may be as low as 0.044 or as large as 0.099. This overall average effect size, however, masks some limited inter-study variation in racial effects.

First, the significant relationship between race and environmental risk is not specific to any particular type of risk. Both noxious facilities and pollutants are more highly concentrated in communities with large percentages of racial and ethnic minorities. While average effect size associated with Superfund sites is higher than that for either noxious facilities or pollution levels, there is substantially more uncertainty surrounding this estimate so that the average race effect from these studies is not statistically significant at 0.10 (though it is statistically significant at 0.12). Second, conclusions supporting the existence of race-based environmental inequities are not the product of aggregation bias. Average effect sizes are significantly larger than zero regardless of the unit of analysis employed in the acceptable studies. Moreover, while the magnitude of average effects does vary by level of aggregation, these differences are hardly as systematic as critics emphasizing potential aggregation biases predict. If aggregation bias were a significant problem

**Table 1.** Average effect size and confidence interval for race, by moderating factor.

| Moderating Factor | Average Effect Size | 95 Percent Confidence Interval | Number of Studies |
|---|---|---|---|
| Overall | | | |
| Racial inequity | 0.072*** | 0.043 – 0.099 | 48 |
| Type of risk | | | |
| Noxious facilities | 0.044*** | 0.021 – 0.068 | 27 |
| Superfund sites | 0.055 | –0.029 – 0.139 | 6 |
| Pollution levels | 0.050*** | 0.017 – 0.083 | 16 |
| Level of aggregation | | | |
| State/county/city | 0.078*** | 0.024 – 0.132 | 16 |
| ZIP code | 0.074*** | 0.015 – 0.134 | 10 |
| Census boundary | 0.041*** | 0.019 – 0.064 | 25 |
| GIS unit | 0.246* | –0.029 – 0.522 | 4 |
| Comparison group | | | |
| All nonhost areas | 0.072*** | 0.043 – 0.100 | 41 |
| Limited nonhost areas | 0.043 | –0.027 – 0.113 | 11 |
| Study quality | | | |
| Density | 0.052*** | 0.030 – 0.074 | 28 |
| Land value | 0.025*** | 0.014 – 0.036 | 23 |
| Manufacturing | 0.029*** | 0.017 – 0.040 | 22 |
| All three controls | 0.032*** | 0.018 – 0.045 | 13 |
| Peer reviewed | 0.078*** | 0.041 – 0.116 | 36 |

Note: * $p < .10$, ** $p < .05$, *** $p < .01$, 2-tailed test.

in environmental equity studies, all other things equal, the average magnitude of estimated inequity effects should increase monotonically with the size of the unit of aggregation. On the contrary, average effect sizes from studies employing states, cities, or counties; ZIP codes; and census tracts are not statistically different from one another (analysis not shown). Moreover, the largest estimated effects come from studies employing GIS areal units, which are almost always smaller than census tracts. Third, the method used to construct comparison groups has an important effect on the conclusions one draws regarding race-based environmental inequities. Studies that compare communities containing sources of environmental risk with all communities that do not contain these risks produce a statistically significant average effect size. When studies limit their comparison groups by selecting on the dependent variable, we find no evidence of race-based environmental inequities. Finally, evidence of race-based environmental inequities is not limited to lower quality studies; significant racial inequities exist regardless of how one defines study quality.

We can draw at least three conclusions from the analysis in Table 1. First, race-based environmental inequities exist, and this conclusion is unaffected by the type of risk examined, the level of aggregation employed, or the type of control variables used in the analysis. Second, the only studies that do not demonstrate the existence of race-based inequities in the distribution of potential environmental risks are those employing the questionable practice of selecting on the dependent variable when constructing comparison groups. Third, while race-based environmental inequities exist, the average magnitude of these inequities is small, ranging from 0.025 to 0.078 (the outlying effect of 0.246 from studies employing GIS defined communities is an obvious exception to this conclusion). One perspective on these conclusions might be that race-based environmental inequities are statistically significant but substantively not very important. This perspective should be tempered, however, by two caveats. First, given the limited statistical reporting in many original studies, many of the individual effect sizes represent lower bounds on the relationship between race and environmental risk. Thus, the average effect sizes should be seen as lower bounds as well. Second, these are average effects; effect sizes may be substantially larger (or smaller) in particular studies and communities.

### Average Inequity Effects and Income

In environmental equity studies, economic class is most commonly measured using household income. The third and fourth columns of Table 2 report the average effect size and 95 percent confidence interval for this measure. The 34 studies employing income-based measures of economic class show clear evidence of class-based environmental inequities. The average effect size is 0.059 (significant at $p < 0.01$), and this effect may be as small as 0.019 or as large as 0.100. Unlike the situation with race-based environmental inequities, however, this average income-based inequity measure masks important inter-study variation in the relationship between class and the sources of environmental risk.

Controlling for key moderating variables, the average effect sizes show a mixed picture of the extent of environmental inequities. Four of these conditional average effects show a negative relationship between the average income level in communities and the existence of environmental risks in these communities (that is, positive evidence of environmental inequities). In particular, studies examining noxious facilities, studies employing census tracts or block groups, studies employing all nonhost areas as control groups, and peer-reviewed studies show that potential sources of environmental risk are concentrated in lower-income areas. On the other hand, higher-quality studies (as defined by the use of appropriate control variables) show an *inverse* relationship between the income of area residents and the concentration of environmental risk vectors. Moreover, even the statistically significant average effect sizes are quite small, ranging from 0.043 to 0.082. Overall, then, there is only weak evidence of significant income-based environmental inequities.

### Average Inequity Effects and Poverty

The first two columns of Table 2 report the average effect size for poverty-based class effects and the 95 percent confidence interval for these effects. From the 20 studies using poverty rates to operationalize economic class, we find no evidence that sources of potential environmental risk are concentrated in lower-class areas. Indeed, the average effect size of –0.024 (significant at $p < 0.01$) illustrates the general conclusion that poverty rates are *inversely* related to sources of potential environmental risk; that is, these risks are less likely to be located in areas of extreme poverty. This average effect may be as small as –0.006 or as large as –0.042. The results from calculating average effect sizes conditioned by the moderating variables are less consistent for poverty than they are for race, but these results reinforce the conclusions from the overall effect size for poverty. The meta-analysis finds an inverse relationship between poverty rates and environmental risk in stud-

**Table 2.** Average effect size and confidence interval for economic class, by moderating factor.

| Moderating Factor | Poverty Effect[a] Size (N) | 95 Percent Confidence Interval | Income Effect[a] Size (N) | 95 Percent Confidence Interval |
|---|---|---|---|---|
| Overall | | | | |
| Economic inequity | –0.024*** (20) | –0.042 – –0.006 | 0.059*** (34) | 0.019 – 0.100 |
| Type of risk | | | | |
| Noxious facilities | –0.027** (12) | –0.051 – –0.004 | 0.043* (22) | –0.002 – 0.088 |
| Superfund sites | –0.024 (4) | –0.080 – 0.032 | 0.014 (4) | –0.055 – 0.084 |
| Pollution levels | –0.042 (5) | –0.103 – 0.019 | 0.024 (13) | –0.032 – 0.080 |
| Level of aggregation | | | | |
| State/county/city | –0.098*** (5) | –0.138 – –0.058 | 0.007 (12) | –0.063 – 0.076 |
| ZIP code | –0.010 (4) | –0.041 – 0.021 | 0.070 (10) | –0.020 – 0.159 |
| Census boundary | 0.010 (10) | –0.021 – 0.041 | 0.082** (16) | 0.011 – 0.153 |
| GIS unit | 0.172 (2) | –2.277 – 2.621 | na (1) | na |
| Comparison group | | | | |
| All nonhost | –0.017 (16) | –0.041 – 0.007 | 0.065*** (32) | 0.021 – 0.109 |
| Limited nonhost | –0.036 (5) | –0.078 – 0.006 | 0.025a (4) | –0.023 – 0.075 |
| Study quality | | | | |
| Density | –0.030** (11) | –0.053 – –0.007 | –0.006 (19) | –0.032 – 0.020 |
| Land value | –0.016*** (13) | –0.028 – –0.004 | –0.020*** (11) | –0.036 – –0.004 |
| Manufacturing | –0.022*** (13) | –0.037 – –0.007 | –0.034*** (11) | –0.052 – –0.015 |
| All three factors | –0.021** (8) | –0.040 – –0.002 | –0.025** (6) | –0.046 – –0.003 |
| Peer reviewed | –0.031*** (16) | –0.049 – –0.012 | 0.062** (23) | 0.005 – 0.118 |

Note: * $p < .10$, ** $p < .05$, *** $p < .01$, 2-tailed test. [a]Effect size calculated using fixed effects model.

ies examining noxious facilities, in studies at the state/city/county level, and in all high-quality studies. Clearly, the evidence shows no general pattern of environmental inequities existing in poverty-stricken areas.

## MULTIVARIATE ANALYSES: META-ANALYTIC REGRESSION

### Meta-Analytic Regression Analysis

The average effect size analyses presented above are analogous to a series of weighted one-sample difference of means tests. A more powerful method for understanding cross-study differences in estimated effects would evaluate the potential causes of these differences in a multivariate framework. Meta-analytic regression analysis (MAR) was designed for this purpose. In a traditional MAR, the dependent variable is the average effect size from each study and the independent variables are study characteristics such as the measurement of the dependent variable or personal characteristics of the author (for example, gender). Coefficients from MAR are unbiased, but parameter standard errors must be corrected using the procedure outlined by Hedges (1994).

Three obstacles stand in the way of the broad use of MAR in the social sciences. The first obstacle stems from the fact that related studies in the social sciences inevitably estimate different models, usually by employing different sets of control variables. The foundation of MAR is that the effect size from each study represents one estimate of a common global effect size that all studies attempt to measure. Studies do not report identical estimates of this global effect due to sampling error. This assumption is untenable when the estimated effect sizes come from studies employing different multivariate models, since the parameters these studies estimate are unique to the model specification employed in each study. Effect sizes from different multivariate studies, therefore, are not estimates of a single global effect size.

The second and third obstacles stem from the fact that MAR was developed with the expectation that observations would be single effects from individual studies. For studies producing multiple effects (for example, studies reporting the results from multiple experiments or models), this requires averaging effects within studies. Intra-study averaging, however, may eliminate meaningful variations in effects. In the present case, imagine a study that examines both the presence of noxious facilities in a census tract and the amount of pollution released by those facilities. Furthermore, imagine that the study employs a model for each dependent variable that does not include controls for population density and land values, and a second model that does contain these controls. Since the effect sizes calculated from these models reflect meaningful variation with respect to study characteristics, calculating a single average effect size makes no sense in this example. One might handle this situation by calculating a series of intra-study average effects conditional upon study characteristics, but this strategy would prove unworkable beyond a few study characteristics. In short, MARs that employ multiple effect sizes from each study are far more useful to social scientists, but this procedure produces the remaining complications for the MAR analysis. The second obstacle facing the MARs is that a few studies that produce many effects may dominate the analysis, calling into question the generalizability of the results. The final obstacle is that multiple effect sizes calculated from the same study will almost certainly be correlated, violating the independence of observations assumption that underlies all of regression analysis, including MAR.

I address the first obstacle in the following manner. Following standard practice, I reconceive of the MAR as being based on the notion that single studies provide estimates of a global parameter that is *conditional upon the control variables present in the multivariate models.* The presence or absence of the various control variables is then entered as a set of independent variables in the MAR. Including specific model characteristics as predictor variables in MAR accounts for much, but not all, of the nonsampling error differences in effect sizes across multivariate studies. Such differences will also be produced by unobservable factors that vary across studies. Moreover, this type of variation will be particularly likely when analyzing social science questions like those at issue in environmental justice. This second source of variation in effect sizes across studies is controlled for using random effects MAR models. In a random effects model, effects sizes are adjusted using both a standard fixed-effects inverse variance weight and a random effects weight that accounts for unobservable sources of heterogeneity in effects sizes. I calculate the random effects component of this weight using the method of moments procedure recommended by Raudenbush (1994).

I address the second complication by estimating three regression models for each dependent variable that employ a second set of weights; that is, I use traditional weighted least squares to analyze the random effects effect sizes described above. Results in the first column of Tables 3–5 come from models where all observations (that is, all random effects effect sizes) are weighted equally. Results in the second column of Tables 3–5 come from models where each observation is weighted by the inverse of the number of effect sizes produced by the study. This has the effect of weighting each study equally in the random effects MAR. An argument could be made, however, that more comprehensive studies (that is, those that estimate more models and therefore generate more effects) ought to receive more weight in the MAR. Reflecting this position, the third column of Tables 3–5 come from models where each observation is weighted by the inverse of the square root of the number of effects produced by the study. Finally, I address the third complication by calculating Huber-White robust standard errors that control for the fact that observations (that is, effect sizes) are not random, but are clustered within studies.

## Regression Inequity Effects and Race

I begin the discussion of the MAR results by noting the peculiar importance of the intercept in these models. In most regression analyses, the intercept has little sub-

**Table 3.** Meta-analytic regression results predicting the size of estimated racial inequity effects.

| Moderating Factor | Effect Sizes Equally Weighted | Studies Equally Weighted | Studies Unequally Weighted |
|---|---|---|---|
| Baseline inequity | | | |
| Constant | 0.0979*** | 0.1996*** | 0.1342*** |
| Type of risk | | | |
| Superfund sites | –0.0107 | –0.0151 | –0.0049 |
| Pollution levels | –0.0132 | –0.0487* | –0.0300** |
| Level of aggregation | | | |
| ZIP code | –0.0067 | –0.0422 | –0.0083 |
| Census boundary | –0.0298* | –0.0735** | –0.0471* |
| GIS unit | 0.0433 | 0.1319 | 0.0800 |
| Comparison group | | | |
| Limited nonhost areas | –0.0431** | –0.1127* | –0.0488* |
| Study quality | | | |
| Density | –0.0012 | –0.0154 | –0.0134 |
| Land value | –0.0356** | –0.0496 | –0.0342* |
| Manufacturing | –0.0194 | –0.0219 | –0.0066 |
| Peer reviewed | 0.0408** | 0.0146 | 0.0251 |
| Study scope | | | |
| National level | –0.0471*** | –0.0731* | –0.0634*** |
| $R^2$ | 0.30 | 0.68 | 0.45 |
| Sample size | 680 | 680 | 680 |

Note: Figures are coefficients from weighted random effects MARs. Significance levels calculated using clustered robust standard errors adjusted via Hedges (1994).
* $p < .10$; ** $p < .05$; *** $p < .01$, one-tailed tests.

stantive meaning. In the MAR models, however, the intercept is interpreted as a baseline measure of environmental inequity from studies where all moderating variables take on a value of zero. In Table 3, this baseline is an estimate of racial inequities from nonpeer-reviewed sub-national studies of noxious facility locations, conducted at the state, city, or county level, that employ all nonhost areas as comparison groups and do not include control variables for population density, property values, or manufacturing infrastructure. These baseline estimates range from roughly 0.10 in the model where all observations are weighted equally to roughly 0.20 in the model where all studies are weighted equally. In all cases these estimates are statistically significant, and they are of small to moderate magnitude according to the rules of thumb established by Cohen (1988).

A central question for MAR analysis is whether this estimated baseline inequity effect changes appreciably under different study conditions. Table 3 shows that two study characteristics affect these effect size estimates regardless of the weighting scheme applied to the observations. First, estimates of race-based environmental inequities are significantly smaller in studies using data from the entire United States, compared with those using data from particular regions, states, or localities. Second, estimates of race-based environmental inequities are significantly smaller in studies that identify comparison groups by selecting on the dependent variable. In addition, the effect of the level of aggregation on estimated inequities is uneven. Inequities from studies using ZIP codes are not appreciably different from those employing states, cities, or counties. While racial inequities are significantly smaller in studies using census tracts or block groups, the estimate of racial inequities is actually larger in studies aggregating data according to GIS areal units, though these estimates are not statistically significant. The evidence is similarly mixed regarding the effect that types of environmental risk have on estimates of racial inequities. There appears to be solid evidence that pollution levels are distributed less inequitably than are noxious facilities, but the same is not true for Superfund sites. Finally, the measures of study quality have surprisingly little effect on the estimated magnitude of race-based environmental inequities—controlling for land values appears to attenuate estimates of these inequities, but controlling for population density and manufacturing infrastructure does not, and there is little evidence of publication bias in these results.

### Regression Inequity Effects and Income

The results from the income MAR models are broadly similar to those from the race-based models. First, the intercepts show positive baseline levels of income-based environmental inequities, but these estimates are from 10 to 25 percent smaller than the comparable race-based inequities, and this effect is only statistically significant in the model where all observations are weighted equally. Second, studies that examine the entire country produce smaller estimates of income-based environmental inequities than do studies that look at a particular region, state, or locality. Also, studies that identify comparison groups by selecting on the dependent variable produce smaller estimates of income-based inequities. Moreover, the negative effects of both study score and comparison group construction are large enough to offset the baseline levels of income-based environmental inequities. Also, similar to the race-based models, measures of study quality have little effect on estimates of income-based environmental inequities. On the other hand, there are some notable differences between the results in Table 4 and those in Table 3. For example, neither the level of aggregation employed by studies nor the type of risk

**Table 4.** Meta-analytic regression results predicting the size of estimated income inequity effects.

| Moderating Factor | Effect Sizes Equally Weighted | Studies Equally Weighted | Studies Unequally Weighted |
|---|---|---|---|
| Baseline inequity | | | |
| Constant | 0.0774* | 0.1872 | 0.1076 |
| Type of risk | | | |
| Superfund sites | –0.0616 | –0.1223 | –0.0797 |
| Pollution levels | –0.0723** | 0.0336 | –0.0400 |
| Level of aggregation | | | |
| ZIP code | 0.0041 | 0.0291 | 0.0403 |
| Census boundary | 0.0945 | 0.0506 | 0.0600 |
| GIS unit | 0.0559 | 0.0797 | 0.0557 |
| Comparison group | | | |
| Limited nonhost areas | –0.1504* | –0.1794 | –0.1554* |
| Study quality | | | |
| Density | –0.1100* | –0.0801 | –0.0787 |
| Land value | –0.0591* | 0.0283 | –0.0453 |
| Manufacturing | –0.1184 | –0.0420 | –0.0921 |
| Peer reviewed | 0.1271 | –0.0075 | 0.0707 |
| Study scope | | | |
| National level | –0.0238 | –0.1733** | –0.0866* |
| $R^2$ | 0.07 | 0.41 | 0.11 |
| Sample size | 298 | 298 | 298 |

Note: Figures are coefficients from weighted random effects MARs. Significance levels calculated using clustered robust standard errors and adjusted via Hedges (1994).
* $p < .10$; ** $p < .05$; *** $p < .01$, one-tailed tests.

examined in studies has a consistent effect on estimates of income-based environmental inequities. Furthermore, it is worth noting that the goodness of fit measures for the income-based models are significantly smaller than those for the race-based models, suggesting that other unmeasured factors might help explain cross-study differences in income-based environmental inequities.

### Regression Inequity Effects and Poverty

The results from the poverty-based MAR models are substantially different from either the race- or income-based models. To begin with, the baseline estimate of poverty-based environmental inequities is markedly unstable; this estimate is negative and significant in the model where observations are weighted equally (suggesting noxious facilities are *less* likely to be located in communities with high poverty levels), positive and significant in the model where studies are weighted equally (suggesting that noxious facilities are more likely to be located in communities with high poverty levels), and insignificant in the model where studies are weighted unequally

**Table 5.** Meta-analytic regression results predicting the size of estimated poverty inequity effects.

| Moderating Factor | Effect Sizes Equally Weighted | Studies Equally Weighted | Studies Unequally Weighted |
|---|---|---|---|
| Baseline inequity | | | |
| Constant | –0.0511** | 0.1152** | 0.0227 |
| Type of risk | | | |
| Superfund sites | 0.0085 | –0.0074 | 0.0130 |
| Pollution levels | 0.0009 | –0.1068** | –0.0003 |
| Level of aggregation | | | |
| ZIP code | 0.0616*** | –0.0257 | 0.0296 |
| Census boundary | 0.1117*** | 0.1961*** | 0.1680*** |
| GIS unit | 0.0471 | 0.2535** | 0.1684* |
| Comparison group | | | |
| Limited nonhost areas | –0.0392** | –0.2963*** | –0.1250*** |
| Study quality | | | |
| Density | –0.0152 | –0.1772*** | –0.0811*** |
| Land value | 0.0012 | 0.0393 | 0.0290 |
| Manufacturing | 0.0165 | 0.0690 | 0.0706* |
| Peer reviewed | –0.0402* | –0.1133** | –0.1176*** |
| Study scope | | | |
| National level | –0.0103 | –0.0633* | –0.0149 |
| $R^2$ | 0.49 | 0.64 | 0.41 |
| Sample size | 163 | 163 | 163 |

Note: Figures are coefficients from weighted random effects MARs. Significance levels calculated using clustered robust standard errors and adjusted via Hedges (1994).
* $p < .10$; ** $p < .05$; *** $p < .01$, one-tailed tests.

(suggesting that there is no relationship between poverty levels and the location of noxious facilities). The one constant here is that all estimated baseline inequity effects are substantively small. The effects of the level of aggregation on estimates of poverty-based environmental inequities are much more consistent, but wholly unexpected. The results in Table 5 suggest that poverty-based inequities are larger in studies that employ census tracts and GIS units, and perhaps even in studies employing ZIP codes, when compared with studies aggregating data at the state, county, or municipal level. Even the measures of study quality produce unexpected results that are inconsistent with the race- and income-based models. While poverty-based environmental inequities are smaller in studies that control for population density, these estimated inequities are also consistently and significantly smaller in peer-reviewed studies. Indeed, the only area in which the results from the poverty-based models is consistent with those from the race and income models is in the construction of comparison groups; studies generating their comparison groups by selecting on the dependent variable generate smaller poverty-based inequity effects than do studies that use all nonhost communities as comparison groups.

## CONCLUDING REMARKS

Significant disagreements exist regarding the presence of race- and class-based environmental inequities in the United States. The meta-analyses completed here seek to resolve some of these disagreements using an increasingly sophisticated and demanding set of analytic tools. These tools generated generally consistent results regarding the existence of environmental inequities. With respect to race, the average effect size analysis and meta-analytic regressions all show that environmental inequities based on these characteristics are ubiquitous. Some scholars have protested that race-based inequities are limited in scope, produced by misspecified models, or are the artifacts of aggregation bias. While the magnitude of race-based environmental inequities does vary with respect to these factors (though not always in the ways envisioned by critics), the results of the meta-analysis show that protests claiming that these factors can explain away such inequities are empirically unsustainable. On the other hand, the evidence supporting the existence of class-based environmental inequities is substantially weaker. While the average effect size analysis and one of the MAR models show that sources of potential environmental risk are concentrated in low-income communities, this conclusion is not consistent across types of risk, levels of aggregation, study quality, or regression model weighting schemes. In short, while some environmental risks in some places may be concentrated in low-income areas, this result is not generalizable across areas and risk vectors. Moreover, the most consistent evidence regarding class-based environmental inequities suggests that potential sources of environmental risk are less likely to be located in areas of hardcore poverty. Protests to the contrary by environmental justice advocates are, in general, empirically unsustainable. Finally, only discussing the existence of environmental inequities does not make full use of meta-analytic results. Indeed, meta-analysis may be used most profitably to estimate the magnitude of effects, not their existence. By most yardsticks, the magnitudes of class- and race-based environmental inequities are quite modest. Whether we interpret the average effect sizes and MAR parameter estimates as correlation coefficients or employ Cohen's rules of thumb, the estimated effects for race- and class-based environmental inequities cluster in the "small" range.

Some environmental justice advocates have offered perceived inequities as a justification for fundamentally reshaping the goals and characteristics of environmental decisionmaking in government (Lazarus & Tai, 1999; Ringquist, 2004). The results reported above suggest that the claims placed by environmental justice advocates on the political system have some merit in that race and income based environmental inequities are real as well as perceived. On the other hand, the relatively modest magnitude of these inequity effects suggests that remedying inequities probably should not be the primary goal when reinventing environmental regulation. Rather, promoting environmental equity, while important, ought to be viewed as one among a series of competing goals that would include enhancing the efficiency, effectiveness, innovativeness, and responsiveness of environmental regulation.

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