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Bringing the Polluters Back In: Environmental Inequality and the Organization of Chemical Production

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Abstract

Environmental justice scholars have suggested that because chemical plants and other hazardous facilities emit more pollutants where they face the least resistance, disadvantaged communities face a special health risk. In trying to determine whether race or income has the bigger impact on a neighborhood's exposure to pollution, however, scholars tend to overlook the facilities themselves and the effect of their characteristics on emissions. In particular, how do the characteristics of facilities and their surrounding communities jointly shape pollution outcomes? We propose a new line of environmental justice research that focuses on facilities and how their features combine with communities' features to create dangerous emissions. Using novel fuzzy-set analysis techniques and the EPA's newly developed Risk-Screening Environmental Indicators, we test the influence of facility and community factors on chemical plants' health-threatening emissions. Contrary to the idea that community characteristics have singular, linear effects, findings show that facility and community factors combine in a variety of ways to produce risky emissions. We speculate that as chemical firms experiment with different ways of producing goods and externalizing pollution costs, new "recipes of risk" are likely to emerge. The question, then, will no longer be whether race or income matters most, but in which of these recipes do they matter and how.

Keywords

environmental justice; health disparities; corporate pollution; Risk-Screening Environmental Indicators; fuzzy-set analysis

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Which types of chemical plants pose the greatest health threat and in which types of communities? Environmental justice scholars have long been interested in the physical dangers posed by facilities like chemical plants and the factors that make communities vulnerable to them. Much research examines the effects of community characteristics like race and income on residents' exposure to hazardous facilities and their emissions (e.g., Bryant and Mohai 1992; Ringquist 2005). However, researchers rarely study facilities themselves and the effects of *their* characteristics on emissions. In particular, no research examines how facilities' characteristics combine with those of their surrounding communities to produce health risks.

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Understanding the conjoint effects of facility and community factors on health risks is important for three reasons. First, research on the pollution effects of community characteristics is plagued by inconsistent findings. For example, most studies show that industrial pollution increases as the percentage of minorities in a neighborhood grows, but a fairly substantial number of studies find this is not true or only true in certain areas (Bryant and Mohai 1992; Ringquist 2005). Most environmental justice scholars attribute conflicting findings to the fact that studies sometimes define communities and their features differently. However, using a single set of data, a single definition of community, and a consistent methodology, Downey (2007) found that environmental inequality outcomes still vary widely across 61 major U.S. metropolitan areas. This suggests that not only are researchers' predictions about race and income having singular, linear effects on pollution wrong, but that community characteristics may interact with each other and with unmeasured characteristics of polluters to produce a variety of nonlinear effects.

Second, recent changes in environmental policy demand that more attention be paid to the intersection of community and facility factors. Since the passage of the 1986 Community Right-to-Know Act, responsibility for monitoring industrial toxins has gradually devolved from the national to the local level. At the same time, regulators have slowly abandoned end-of-pipe solutions, looking more upstream or at how industrial production is organized for alternative remedies (Ringquist 1993). Hence, there is now an urgent need to sort out the different combinations of community and facility factors associated with negative and positive emission outcomes.

Third, over the past two decades, new health science technologies have vastly expanded our understanding of toxins in the environment and their impact on humans. Regulatory regimes, however, have not actively encouraged scholars to analyze and package these data in ways that can be effectively applied to cases of environmental injustice (Frickel 2004). It appeared that this problem might be addressed in 1994 with President Clinton's signing of Executive Order #12898, the Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations, but this order was not fully implemented and was essentially ignored by his successor. With a new administration in office, there may now be an opportunity for environmental scholars to make a difference in how local environmental risks are understood and regulated.

In this article, we propose a new line of environmental justice research that focuses on facilities and how their features work together with communities' features to create more and less risky emissions. Specifically, we sketch a framework that suggests why facility and community factors likely combine to generate multiple "recipes" of emission outcomes. We also suggest how researchers can identify these recipes using novel fuzzy-set analysis (FSA) techniques (Ragin 2000). Unlike standard quantitative methods, FSA techniques can determine which of several possible combinations of factors are most relevant to an outcome. FSA can also determine whether the sets of factors associated with negative and positive outcomes fundamentally differ, which seems likely with pollution outcomes because special effort and coordination often go into minimizing emissions. Finally, we investigate how combinations of facility and community factors shape chemical plants' highly and not highly risky emissions. To do so, we use the Environmental Protection Agency's Risk-Screening Environmental Indicators (RSEI), the first publicly available data source on industrial facilities' toxic emissions and their associated health dangers.

BACKGROUND

Despite spending more money per capita on health care than any other country, the United States lags behind most industrial nations in overall health because of growing racial and class differences in mortality and morbidity (Brulle and Pellow 2006; Williams and Collins 1995). Some scholars attribute these disparities to personal habits like smoking, dieting, and exercise. However, these factors explain only a small fraction of health differences, prompting researchers to explore the role that extra-individual factors might play in creating health inequities. In particular, environmental justice scholars suggest that because pollution tends to follow the path of least resistance, poor and minority neighborhoods may be disproportionately exposed to industrial toxins that threaten health (Bullard [1990] 2000).

This claim is the subject of a burgeoning academic literature on environmental inequality.[1] An important debate within this body of work concerns whether a neighborhood's racial or income composition is the best predictor of pollution exposure (Mohai and Bryant 1992). Proponents of a racial discrimination model (e.g., Mohai and Bryant 1992) suggest that environmental harms are intentionally put in minority communities because business leaders, government officials, real estate executives, and other decision makers are racially prejudiced. In addition, restrictive housing markets allegedly force minorities to stay within or move into communities where such facilities already exist. In either case, the percent of minorities in a neighborhood is expected to be positively associated with industrial pollution. Proponents of a class model (e.g., Hamilton 1995) suggest that if minorities live nearer environmental hazards, it is because they tend to be poorer than whites. Residents with lower incomes lack the financial resources to influence siting decisions or flee from corporate polluters. Hence, any association between race and pollution should vanish once neighborhoods' income levels are accounted for. Finally, supporters of an agnostic model doubt the importance of both race and class (e.g., Anderton et al. 1994). According to these scholars, minorities and low-income residents are more exposed to pollution because they tend to live in areas that are more urban, have extensive industrial activity, and offer more affordable housing. In this view, any relationship between pollution and race or between pollution and income is likely spurious.

While these competing explanations of environmental inequality have generated important insights, empirical support has been mixed; some studies show that race has the stronger effect on pollution exposure (e.g., Szasz et al. 1993), others find that income has the bigger impact (e.g., Bowen et al. 1995), and still others show that the effects of race and income disappear when controlling for metropolitan status, manufacturing employment, and property values (e.g., Anderton et al. 1994). Some scholars try to reconcile these inconsistent findings by employing longitudinal data (e.g., Been and Gupta 1997; Oakes et al. 1996; Saha and Mohai 2005). For example, Saha and Mohai (2005) show that racial and income disparities in the siting of hazardous waste facilities did not occur until after 1970, when the Not-In-My-Backyard (NIMBY) movement, led by middle- and upper-class whites, began deflecting new facilities into minority and low-income neighborhoods.

As helpful as these longitudinal inquiries have been, they, like earlier studies of environmental inequality, tend to lose sight of this literature's larger goal: to demonstrate that health disparities are due to factors other than individual ones. That is, in treating race and income as competing predictors, researchers not only fail to consider how these factors might jointly influence pollution exposure, but they dilute the analytic significance of one extra-individual factor in stressing the importance of another. Equally important, in trying to determine if and when neighborhood race and income shape pollution outcomes, scholars

[1]See, for example, Anderton et al. 1994; Ash and Fetter 2004; Auyero and Swistun 2008; Been and Gupta 1997; Bowen et al. 1995; Brulle and Pellow 2006; Bryant and Mohai 1992; Bullard [1990] 2000; Cable, Hastings, and Mix 2002; Cable, Shriver, and Mix 2008; Downey 1998, 2007; Faber and Krieg 2000; Hamilton 1995; Hooks and Smith 2004; Mohai and Bryant 1992; Morello-Frosch and Jesdale 2006; Morello-Frosch, Pastor, and Sadd 2001; Oakes, Anderton, and Anderson 1996; Pastor, Sadd, and Hipp 2001; Pellow 2000; Pollock and Vittas 1995; Pulido 1996, 2000; Ringquist 2005; Rosner and Markovitz 2002; Saha and Mohai 2005; Sicotte and Swanson 2007; Szasz et al. 1993; Szasz and Meuser 2000.

divert attention from the fundamental question of how the production of industrial toxins is organized. Despite the fact that most pollutants are emitted at the site of production and industrial organizations are the "most intense and effective environmental destroyers of all" (Perrow 1997:66), scholars pay scant attention to the organizational characteristics of polluting facilities. Consequently, we know very little about the ways in which facilities' characteristics might combine with those of communities to create environmental risks.

We contend that scholars have not systematically examined such combinations for three basic reasons. First, they lack a conceptual framework that addresses the linkages between facilities and communities. A few scholars have sought to incorporate organizations into the analysis of environmental inequities by drawing on theories that speak of the new risks created by high-tech industries like chemical manufacturing (e.g., Beck 1986). However, because these theories focus on implications of these industries for society at large, they have less to say about the local context in which individual facilities operate. Thus, they do not provide scholars with a theoretical reason for exploring combinations of organizational and community factors.

Second, lacking a theoretical motivation to study the synergies between local facilities and neighborhoods, researchers tend to rely on methods designed to test factors' independent effects. For instance, because most quantitative research on environmental justice revolves around the question of whether race or income has the bigger impact on pollution, it favors statistical techniques like regression that assess the net effects of variables. Qualitative scholars have long been critical of such techniques, noting that they can neither capture how factors combine in complicated ways nor explain the outcomes of individual cases. They have yet to suggest, however, alternative methods that should be used to identify the most relevant combinations and their representative cases. As a result, neither qualitative nor quantitative scholars have the methodological tools to undertake this important work.

Third, research on pollution exposure has been hampered due to a lack of facility-level data on emissions and their associated health risks. When scholars study industrial pollution, they typically rely on the Environmental Protection Agency's Toxics Release Inventory (TRI), which reports the pounds of toxic chemicals released by individual manufacturing facilities. Environmental justice researchers have used the TRI to measure exposure to industrial pollution in different ways and with varying precision. From the least to the most precise, these measures include the *presence of a TRI facility*, *pound-based emissions* (total pounds of chemicals released by facilities), *hazard-based emissions* (pounds of emitted chemicals adjusted by their toxicity), and *risk-based emissions* (pounds of emitted chemicals adjusted by their toxicity, fate, pathway, and dispersion). Most environmental justice researchers use the least precise of these measures as their indicator of pollution exposure—the mere presence of TRI facilities (Saha and Mohai 2005). Several scholars, for example, examine the number of TRI plants located within Census tracts of particular cities (e.g., Szasz and Meuser 2000). By contrast, only a few scholars examine the correlates of risk-based emissions, and they all focus on outcomes at aggregated levels (e.g., Morello-Frosch and Jesdale 2006). Hence, research has yet to tease out which kinds of facilities situated in which kinds of communities pose the greatest health risk.

TOWARD AN ORGANIZATIONAL UNDERSTANDING OF ENVIRONMENTAL JUSTICE

To address the first of these limitations, we outline a framework that not only incorporates facility and community characteristics but also suggests how they might work together to produce health threatening emissions. Our framework draws on two strands of organizational literature: studies of organizational sources of inequality (Baron and Bielby

1980; Reskin, McBrier, and Kmec 1999) and research on organizational configurations (Fiss 2007; Meyer, Tsui, and Hinings 1993).

Beginning with Baron and Bielby's (1980) call to bring the firm back into the study of stratification, several sociologists have attempted to identify the organizational sources of inequality. This literature suggests that to fully understand the economic, social, or physical impact of organizations, researchers need to study the structures that differentiate organizations, such as their size, geographic scope, and legal form. Moreover, instead of assuming that these dimensions always align with one another—or ignoring them altogether, as environmental justice scholars effectively do, for example, when they tally the number of TRI plants in a community (e.g., Szasz and Meuser 2000)—this literature recommends that scholars conduct more fine-grained analyses of the effects of specific organizational structures on outcomes like pollution.

Foster (2000), for example, contends that in its later stages, capitalism averts economic crises by increasing the scale of operations, expanding to distant markets, and restructuring units as subsidiaries to gain greater access to capital funds.[2] These organizational fixes, in turn, jump start what Schnaiberg (1980) calls the "treadmill of production," which causes ecological damage through a self-reinforcing process of rising profits and consumption. This treadmill requires continuous and growing inputs of energy and material to fuel escalating demands for investment and goods. It also creates negative byproducts in the form of toxins and externalizes their costs to maintain a positive rate of return. Applying these insights, Grant and his colleagues have examined the environmental consequences of plant size (Grant, Jones, and Bergesen 2002), absentee-managed branches (Grant, Jones, and Trautner 2004), and subsidiaries (Grant and Jones 2003) and found each to be positively related to toxic emissions.

Literature on the organizational sources of inequality, however, also suggests that the structures that define establishments are not limited to internal ones like size, scope, and form. They also include external ones such as the composition of surrounding communities. That is, the local distribution of attributes like race and income is both a reflection and a determinant of an establishment's practices (Reskin et al. 1999).

Furthermore, this literature suggests that an organizational structure may not have the same effect in all instances. Because any particular structure can function as a resource or a vulnerability (Hodson and Kaufman 1982), it may have different consequences for different cases. For instance, low-income neighborhoods may be more susceptible to toxic emissions because they lack the financial resources to fend off large polluters. Or, precisely because such neighborhoods are economically depressed and therefore less desirable in the eyes of investors, they may attract smaller companies that pose less of a danger.

Another strand of literature on organizational configurations refines these arguments to suggest that establishments are best understood as constellations of interconnected structures (Fiss 2007; Meyer et al. 1993). In this view, organizations' structures are not entirely modular, and thus they should not be studied as individual independent variables. Instead, organizations are made up of different bundles of structures; scholars should therefore study how certain structural profiles are related to outcomes. Applied to the subject at hand, this suggests that factors previously found to have independent effects on emissions—internal organizational characteristics like size, absentee management, and subsidiary status, as well as external characteristics like neighborhood race and income—may also combine in complicated ways that structurally define plants and shape their environmental performance.

[2]Under the Tax Reform Act of 1986, subsidiaries also function as a liability firewall for parent firms.

A configurational perspective also rejects the notion of unifinality that says there is one optimal configuration leading to an outcome. Instead, it embraces the concept of equifinality, which states that two or more configurations can be equally effective in producing an outcome (Fiss 2007). For example, whereas scholars who attribute environmental inequities solely to racism would suggest that all facilities pollute more when located near a racial minority, a configurational perspective would suggest there may be multiple recipes of pollution and therefore the presence of a racial minority might influence the pollution behavior of some facilities but not others.

Finally, a configurational perspective asserts that the set of factors associated with a negative organizational outcome, like highly risky emissions, may not be the simple inverse of those associated with a positive outcome (Meyer et al. 1993). This logic contrasts with the symmetrical reasoning that informs correlational techniques that assume all relationships are linear in nature. It also contrasts with the reasoning informing most environmental justice research that suggests the presence or absence of a disadvantaged group will be associated with more or less pollution. According to research on organizational configurations, such an understanding is simplistic because, among other things, it often requires special effort and coordination on the part of organizations to create desirable outcomes.

Case Studies and Empirical Configurations

Although prior case study research does not focus on the intersection of facilities' internal and external characteristics and cannot answer questions about broad patterns of pollution exposure, several environmental inequality case studies comport with this configurational understanding of organizations and their consequences. Some of these studies suggest that facilities with certain mixes of *internal* characteristics may be more apt to put lives at risk. For example, in their examination of a federally operated nuclear reactor in Oak Ridge, Tennessee, Cable and colleagues (2008) document how this large and absentee-managed facility not only posed a health threat, but continued to harm workers and local residents by using its vast discretionary resources to hire experts to deny workers' and residents' claims about being poisoned.

Likewise, other studies suggest that facilities with a particular combination of *external* characteristics are more prone to threaten lives. Pollock and Vittas (1995) find that in Florida, TRI facilities tend to be located closer to low-income, African American neighborhoods than to other low-income communities; and in their study of hazardous sites and industrial facilities within Massachusetts, Faber and Krieg (2000) discover a nearly identical pattern. Downey (2000) uncovers similar results, demonstrating that low-income and working-class blacks in Detroit were less able to escape Detroit's polluted neighborhoods between 1970 and 1990 than were middle-class blacks and poor and working-class whites. Collectively, these studies suggest that a lack of financial resources, combined with restrictive housing markets, effectively confine poor African Americans to areas where dangerous plants tend to be situated.

Pastor and colleagues (2001) highlight a different combination of external factors in their study of Los Angeles County. In this study, they find that hazardous facilities are more likely to be sited in neighborhoods where there are both large African American and large Latino populations. They attribute this to the fact that mobilizing residents and creating social capital is particularly difficult in communities undergoing racial transition, or what they call ethnic churning, thus making it much harder for such communities to prevent the siting of noxious facilities in their neighborhoods. This study, and the ones described in the preceding paragraph, suggests that trying to isolate the influence of a particular racial or class factor may prevent the discovery of constellations of factors associated with pollution exposure.

Finally, other studies suggest how facilities' internal *and* external characteristics may combine to produce environmental dangers. For example, Rosner and Markovitz's (2002) study of Louisiana's infamous Chemical Corridor suggests that the tactics described by Cable and colleagues (2008) are especially likely to be used by facilities with particular organizational characteristics against racial groups that lack political clout. Specifically, they report how large and absentee-managed chemical plants routinely use expert systems to challenge African American residents' health claims.

Pulido (2000) suggests that because African Americans and Latinos perform different roles in the racialized division of labor, they may both be endangered by absentee-managed plants but for different reasons. She notes, for example, how manufacturers in Los Angeles built up that city's industrial district by locating branch plants in predominantly African American neighborhoods. Manufacturers did so not because they wished to hire African Americans, but because such neighborhoods tend to be politically weak and therefore unable to resist polluters. The same branch plants actively recruited poor, Latino immigrants to fill the hazardous, manual jobs that whites tend to avoid. Hence, unlike African Americans, poor Latinos were put at risk as a result of gradually moving into neighborhoods surrounding these plants. Such complexities are often glossed over in standard analyses that essentially ignore the characteristics of polluters and how they may affect groups differently.

Auyero and Swistun (2008) also speak to the importance of studying the intersection of organizations and their surrounding neighborhoods' socioeconomic makeup. They suggest that after U.S. petrochemical firms created branch plants in Argentina to take advantage of that country's lax environmental standards, poor Argentines gradually migrated to these branches and built shantytown communities around them. Because most shantytown residents arrived well after the branches began operating, they were often unaware of the slowly incubating contaminants that had been released. In addition, the branches were managed from afar by dominant outside actors, which made it difficult for residents to get information on the real source of their illnesses. In this case, poor Latinos' exposure was not so much a result of tactics used by corporations during the siting phase, but the chemical plant's spatially and culturally remote headquarters led to a growing sense of uncertainty.

In addition to suggesting that pollution is shaped by interconnected structures, these case studies speak to the notion of equifinality. For instance, the findings of Pastor and colleagues (2001) and Pulido (2000) suggest that even in a single area like Los Angeles, residents can be exposed to pollution under more than one set of circumstances. Moreover, additional case study research suggests that reducing dangerous emissions may require more effort than went into creating them. Saha and Mohai (2005), for example, argue that in cities like Detroit, well-to-do, white residents have become increasingly skilled at keeping hazardous facilities and poor minorities out of their neighborhoods. As a result, not only are environmental harms concentrated within disadvantaged communities, but moving those harms elsewhere poses a greater political challenge.

Propositions

The empirical patterns uncovered by these case studies suggest that polluters' community and organizational profiles are more complex than conventional quantitative research and theorizing on environmental inequality suggests. An alternative approach that focuses on the organizational and community configurations associated with pollution exposure is thus needed. To help readers appreciate how such an approach would differ from the more conventional one, we derive a set of propositions from each about the correlates and configurational recipes of facilities' life threatening emissions.

The primary goal of the conventional approach is to determine whether race, class, or some other community factor is the best predictor of pollution exposure. Applied to individual facilities, it suggests that one or more of the following will be true:

1 In communities with large populations of racial minorities (African Americans or Latinos), facilities will tend to pose a higher risk.

2 Whatever risk is associated with the presence of racial minorities can be explained by the income levels of facilities' surrounding communities.

3 Whatever risk is associated with residents' racial makeup or incomes can be explained by some other trait of facilities' surrounding communities, such as level of manufacturing activity, metropolitan status, or housing values.

4 If race, income, and other predictors affect facility emissions, they will each do so in only one way.

5 The effects of race, income, and other predictors on facility emissions are symmetrical.

By contrast, a configurational approach seeks to identify the constellation of external and internal attributes that distinguish more and less dangerous polluters. This approach is less interested in the independent effects of race and income than in how these features of communities and those of facilities jointly influence health risks. It also allows for the possibility that these factors may contribute to pollution in more than one way, and it questions the assumption of conventional research that predictors have a perfectly symmetrical relationship with positive and negative pollution outcomes. In short, a configurational approach would predict the following:

6 Communities' racial and income characteristics combine with each other and with facilities' characteristics to create multiple recipes of highly risky emissions.

7 The recipes of facilities' highly and not highly risky emissions are asymmetrical.

QUALITATIVE COMPARATIVE ANALYSIS

Whereas literature on organizational configurations and case studies of environmental inequality alert scholars to the possibility of nonlinear relationships, synergistic effects, and multiple recipes, standard methods like regression assume linearity, additive effects, and singular recipes. To be sure, regression techniques can be used to assess two-way interactions (see, e.g., work on pollution exposure by Downey [2005]). However, higher order interactions are extremely difficult to interpret within a regression format. Moreover, regression presumes that a statistically significant interaction can be generalized to all cases under investigation when, in fact, it may occur only in some cases.

To overcome this second limitation of environmental justice research, we turn to Qualitative Comparative Analysis (QCA) and its fuzzy-set variant (FSA). QCA and FSA treat cases as combinations of attributes and use Boolean algebra to derive simplified expressions of combinations associated with an outcome (Ragin 2000). For example, as Longest and Vaisey (2008) explain, given an outcome set Y and predictors A and B, QCA helps an analyst determine which combinations of A and B (i.e., AB, Ab, aB, or ab) are most likely to produce Y. In a QCA framework, the term "set" is used instead of "variable" to stress the idea that each variable has been transformed to represent an individual case's level of membership in a given condition (e.g., a facility's membership in the set of organizations with "highly risky emissions").

The combination of individual sets—for example, facilities that are large and in low-income neighborhoods—is then referred to as a "configuration." Sets are labeled with uppercase and lowercase letters. When working with crisp sets or sets that are all dichotomous indicators, uppercase letters signify 1 (fully in A) and lowercase letters signify 0 (fully out of A). When working with fuzzy sets or sets that can take on a value between 0 and 1, uppercase letters mean the level of set membership (e.g., the value of A) and lowercase letters mean 1 minus the set membership (e.g., $1 - A$). In the case of FSA, individual organizations can be more or less a member of a particular set (e.g., .33 would indicate something like "more out than in, but still somewhat in" the set, whereas .7 would signify something like "more in than out, but not entirely in" the set). Combining fuzzy sets into configurations is usually done using the minimum operator, so $AB = \min(A,B)$, or $aB = \min\{(1-A), B\}$. A case with a fuzzy score of .6 on A and .3 on B, for example, would be said to have a fuzzy score of .3 in the configuration AB.

Unlike variable based methods that are founded on the notion of unifinality and seek to estimate a single recipe for all cases under examination, QCA methods explicitly take the idea of equifinality into account, allowing different subsets of cases to produce the same outcome. Furthermore, whereas techniques like correlation and regression gauge linear relations and assume these relations are symmetric in nature, QCA methods test set relations and assume that configurations may be asymmetrical. QCA methods are thus especially well suited for determining whether configurations associated with a positive outcome differ from those associated with a negative outcome. The fuzzy-set version of QCA is particularly useful when studying outcomes like industrial emissions that cannot be neatly dichotomized as benign or dangerous.

RISK-SCREENING ENVIRONMENTAL INDICATORS

As mentioned earlier, a third limitation of environmental justice research is that scholars have not had access to data on the health threats posed by individual facilities. Risk assessment is extremely costly and time consuming, and the EPA has been unwilling to collect such data because of the storm of stakeholder objections it would face. Recently, however, the EPA developed a dataset, the Risk-Screening Environmental Indicators (RSEI), that takes into consideration all of the factors used in formal risk assessment. Specifically, it incorporates detailed data on the amounts of chemicals released by individual facilities, the toxicity of these chemicals, their environmental concentrations, and the people who are exposed to them.

The RSEI divides the United States into an array of one-kilometer square cells, with each TRI facility assigned to a cell. It then links to each facility/cell the pounds of chemicals a facility releases (from the TRI), toxicity weights for individual chemicals and chemical categories, exposure estimates based on pathway-specific reporting of releases to air and water, and the size of the cell's potentially exposed residential population.[3] Using this information, the RSEI generates scores for individual facilities that reflect the relative risk of their emissions.

To be more precise, for each type of chemical released by a plant, the RSEI multiplies the total pounds of that emitted chemical (*pound-based emission*) by the toxicity weight for the exposure route (oral or inhaled) associated with that release.[4] It then multiplies this figure

[3]With respect to air releases, the RSEI combines data on temperature and local wind patterns with facility-specific information on smokestack height, along with chemical-specific information on rates of decay, to estimate the ambient concentrations of each release in each square kilometer within a 101 km by 101 km grid (10,201 sq km) around each facility.

[4]If there is no toxicity weight for a chemical, which usually applies to only about 1 percent of the total mass of reported releases, the hazard score is set at zero.

(*hazard-based emission*) by the projected spread and fate of the released chemical (based on information about local atmospheric conditions, a chemical's molecular weight, and its rate of decay), as well as the number, sex, and age of residents in affected grid cells to derive an estimate of the risk posed by the emitted chemical (*risk-based emission*). Finally, the RSEI repeats this procedure for all other chemicals released by a facility and sums their individual risk estimates to produce a composite risk score for that facility.

To appreciate how the RSEI more accurately estimates pollution exposure, consider Table 1, which ranks the 10 dirtiest chemical plants based on their hazard- and risk-based emissions. As indicated earlier, hazard-based measures estimate the pounds of emitted chemicals adjusted by their toxicity, whereas risk-based measures estimate pounds of emitted chemicals adjusted by their toxicity, fate, pathway, and dispersion. Table 1 reveals that the four facilities with the greatest hazard-based emissions are all located in the Midwest, but none of these plants make the list for the greatest risk-based emissions. What might explain this discrepancy? Among other things, risk-based emissions take into account population density surrounding a plant. The plant with the most hazard-based emissions is located near Galena, Kansas, a rural community with a population of about 3,000 individuals. By contrast, the plant with the most risk-based emissions is located in Pasadena, Texas, which is part of the larger Houston metropolitan area and has a population of over 140,000 individuals. The RSEI thus provides a very different picture of pollution exposure than do other measures used in the past.

Despite its strengths, the RSEI also has some notable limitations. For instance, the RSEI does not cover all toxic chemicals used by industry, it does not assess dermal and food ingestion pathways, and it does not address ecological effects. In particular, the RSEI does not evaluate individual health outcomes or provide estimates of excess cases of cancer or other diseases. It is thus important to bear in mind that the type of "risk" the RSEI reports is not identical to the type discussed by public health officials who prefer to use actual counts of illness in an area. Nonetheless, the RSEI accounts for a large set of toxins regularly used by industry, considers some of the key pathways that affect health, and allows researchers to compare the potential impact of facilities' emissions on chronic health outcomes. Especially important, because it provides better estimates of pollution exposure than do previous measures, the RSEI makes claims about industrial pollution's health risks more credible to public health officials.[5]

To date, only three published studies have used RSEI data: Ash and Fetter's (2004) analysis of air pollution exposure across U.S. cities, Sicotte and Swanson's (2007) examination of Philadelphia residents' proximity to dangerous industrial facilities, and Downey's (2007) study of the 61 largest metropolitan areas in the United States.[6] These studies, however, aggregate RSEI data up to the Census block or tract levels, precluding an examination of how facility and community characteristics interact to produce health dangers.

[5]Another potential problem with the RSEI is that the TRI data used to calculate its scores are self-reported. While there might be an incentive for businesses to underreport their emissions, businesses might also overreport if they expect to be rewarded for improvements relative to a baseline emission level. There is reason to believe that the accuracy of self-reports has greatly improved since the TRI was introduced in 1987, due to routine environmental audits (Arora and Cason 1995). While businesses of a certain size might be less apt to comply with reporting requirements, our measure of facility size (number of employees) is unrelated to ignorance or violation of reporting requirements (Brehm and Hamilton 1996). Finally, we investigated whether plants that submitted late reports to the EPA had lower or higher emissions than those that submitted on time, and we found no difference between the two groups.
[6]Some scholars (e.g., Morello-Frosch et al. 2001) have studied the presence of hazardous facilities and the distribution of certain health risks within areas like Southern California, but they have not employed facility-specific data on health risks like the RSEI.

DATA, MEASURES, AND ANALYTIC STRATEGY

Data

To advance our understanding of the causes of pollution exposure, we conduct the first facility-level analysis of risk-based emissions. Specifically, we investigate the propositions mentioned earlier about facilities' highly and not highly risky emissions using fuzzy-set methods and the EPA's Risk-Screening Environmental Indicators. We focus on the health risks posed by chemical plants because they are responsible for a disproportionate share of all emitted toxins. Our dataset consists of indicators of chemical plants' risk-based emissions (from the RSEI),[7] their organizational characteristics, the makeup of their surrounding communities, and other relevant factors. We examine the combined influence of facility and community characteristics on 2,053[8] chemical plants' risk-related emissions in 2002, the most recent year for which RSEI data were available at the time this study was funded. Table 2 provides a summary of the variables used in our analyses and their data sources.

Measures

The analyses employ two dependent variables: highly risky emissions, operationalized as a facility's RSEI score, and its negation, not highly risky emissions. To test the influence of facility size, scope, and form or plants' organizational features, we use the following measures: number of employees at a facility,[9] whether a facility is a branch plant (1 = yes), and whether it is a subsidiary (1 = yes). To test the influence of communities' racial and income composition, we use measures of percent African American, percent Latino, and median household income. We focus on African Americans and Latinos because past research on environmental justice (e.g., Ringquist 1997) finds that they are significantly more vulnerable to industrial toxic emissions than are other minority groups, such as Native Americans. Each of our three indicators of community characteristics is based on information about a plant's surrounding Census tract area. Past research suggests that because of aggregation errors, it is more appropriate to measure race and class at this level than at less refined levels like zip codes (Anderton et al. 1994; Oakes et al. 1996).

Analytic Strategy

In assessing our propositions, we employ standard regression techniques as well as less conventional FSA methods. In our FSA analyses, we convert our dependent and key

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[7]Although RSEI data are originally coded into one square kilometer cells, the unit of analysis for this study is still the facility. As mentioned earlier, risk-related emissions are calculated using data on the pounds, toxicity, fate, pathway, and dispersion of chemicals emitted by a plant. The cells come into play when estimating the fate, pathway, and dispersion of emitted chemicals. For example, to determine the dispersion of chemicals or the number of individuals exposed to a facility's emissions, the RSEI tallies not only the number of people living in the grid cell where a facility is located, but also the population of any nearby cells that are downwind or downstream from the facility.

[8]We created the data file by merging information for all 3,683 chemical facilities that reported to the RSEI with Dun and Bradstreet information on 3,241 of these facilities. Dun and Bradstreet identification numbers (the variable on which we merged the files) were missing or incompatible for 974 cases, thus yielding 2,199 complete cases. The large number of cases that did not match across datasets can be partly explained by the fact that the EPA does not do quality control on this variable (EPA, personal communication). It is doubtful that there is any systematic pattern to the cases that failed to match across datasets. We conducted a t-test to determine whether the chemical plants included in our analysis have significantly different RSEI scores than those that were excluded; results indicate that they do not. In our analyses, we examine only cases with complete information on the dependent and independent variables (n = 2,053). An examination of excluded cases does not reveal that their missing values are distributed across variables in some nonrandom way, bolstering our confidence that our sample is representative.

[9]Concerns about which measure of size should be used (e.g., employees, assets, or sales) are especially important in cross-industry studies. For example, the extent to which the size of a labor force correlates with production can vary widely across industries. However, for studies like ours, which focus on a single industry, we can safely assume that the scale of operations is proportional to the number of employees (Blau and Schoenherr 1971). We experimented with an alternative measure of facility size, total square footage, and discovered that it is unrelated to emissions. We also experimented with various measures of firm size (i.e., total employees, sales, and assets) in our models. In each instance, we found that these measures have a negligible impact. We attribute this to the fact that facility size and branch plant status (another of our organizational variables) are functions of firm size and therefore likely capture most of its effect on emissions.

independent variables into fuzzy scores because several of them cannot be easily categorized as full membership (1) or nonmembership (0) in a set, which would be required if using conventional QCA techniques. For example, even with more precise data like the RSEI, it is unclear above and below what RSEI score a plant's emissions should be classified as highly or not highly risky.[10]

FSA addresses this type of problem by having researchers recode their measures continuously as degrees of membership (or in the interval between 0 and 1) based on theoretical or substantive knowledge. Key to this coding procedure is deciding which cases are the most ambiguous or should be assigned a value of .5. Once variables are calibrated, FSA can then examine not only the level of overlap between independent variables, but also the extent to which certain combinations of independent variables overlap or are a subset of the dependent variable (if X, then Y).

Although the EPA does not specify beyond what RSEI score a plant should be classified as highly risky, it does suggest employing measures of central tendency, like the mean, to screen out potentially dangerous plants and characterize their risks (U.S. Environmental Protection Agency 2003). In keeping with the EPA's recommendations, we convert our dependent variables to fuzzy scores using the following algorithm recommended by Ragin (2000) for mean-based factors:

$$\text{fuzzy score}=\exp(2 * \text{z\_ score})/(1+\exp(2 * \text{z\_ score}))$$
$$\text{where z\_ score}=(\text{raw\_ score} - \text{mean})/(\text{standard deviation})$$

According to this formula, cases with scores closer to 0 are more out of a set, whereas cases with scores closer to 1 are more in a set. In calibrating our indicators of facility and community characteristics, we use the same formula if no theory- or knowledge-based information exists about their membership properties. Where such information does exist, we use the calibration procedure built into FSA that asks researchers to specify what values constitute strong membership (.95), ambiguous membership (.5), and weak membership (.05). For example, in keeping with several environmental and employment laws that use size to determine which plants must be most closely regulated (see Grant et al. 2002), we designate plants with more than 1,000 employees as full members of the set of large plants (.95), plants with 500 employees as ambiguous members (.5), and those with fewer than 15 employees as weak (.05). Consistent with research on organizations and racial tokens that suggests minorities are more often discriminated against once they are greater than 15 percent of a population (Emerson, Yancey, and Chai 2001), we code our measures of percent African American and percent Hispanic as full members (.95) of the "majority" set when a group comprises 99 percent or more of a community's population, ambiguous (.5) when it comprises 15 percent, and weak (.05) when it comprises 1 percent or less. In keeping with studies that define low-income residents as having salaries under $25,000 (about the 25th percentile), we code Census tracts with median household incomes below $10,000 as full members (.95) of the set of low-income neighborhoods, tracts with $25,000 as ambiguous members (.5), and those with more than $100,000 as weak members (.05).[11] Table 2 shows how our dependent and key independent variables are calibrated.

Table A1 in the Appendix reports the truth table used in our fuzzy-set analyses. In addition to showing all observed configurations of our key independent variables, it reports the number of cases with greater than .5 membership in each configuration. The table also

[10]RSEI scores for chemical plants range from 0 to 919,064, with a mean of 2,401 and a standard deviation of 27,591.

[11]In analyses not reported here, we explored the possibility that median household income and our emission measures may have a curvilinear relationship, but we did not find any evidence of such a relationship.

shows the consistency of each configuration, or the degree to which membership in that configuration is a subset of membership in the outcome. Consistency scores for Y (highly risky emissions) and ~Y (not highly risky emissions) are listed.

To eliminate logically irrelevant configurations, FSA requires researchers to specify a set of criteria for excluding and coding configurations. In our analyses, we drop configurations that contain fewer than 10 cases. We then code configurations as positive (1) if they have consistency scores of 95 percent or higher (we arrived at this threshold figure based on an examination of gaps in the upper range of consistency, see Ragin [2000]).[12] Finally, we use FSA to specify the minimum number of configurations needed to logically cover all positive (1) configurations in the data.

Consistent with past research, we expect facilities that are large, are branches, or are subsidiaries to be a subset of plants with highly risky emissions. We also expect that facilities located in communities with large African American or large Latino populations, or whose residents have low incomes, will tend to belong to the same subset. Conversely, we expect facilities that lack these characteristics to be a subset of plants with not highly risky emissions. The FSA software that we employ (Ragin fsQCA 2.0) handles these predictions automatically in its counterfactual procedure where it asks the researcher if a factor's presence or absence is expected to be related to an outcome. At the same time, FSA allows for the possibility that factors might still have an effect opposite of that predicted, in keeping with our earlier argument that organizational structures may act as resources or vulnerabilities. FSA's chief drawback is that it is constrained to a limited number of variables because with the addition of each new variable, the possible number of configurations grows exponentially. We feel this disadvantage is more than offset by FSA's ability to sort out the most relevant configurations from superfluous and redundant ones.

FINDINGS

Conventional Analysis

In Table 3, we assess three of the propositions suggested by conventional research on environmental inequality using the standard OLS techniques typically employed in this literature. Specifically, to determine whether facilities' highly risky emissions (operationalized here as facilities' RSEI scores) are a function of neighborhoods' racial composition (first proposition), residents' class standing (second proposition), or some other community property (third proposition), we add to a basic regression equation containing only percent African American and percent Latino (Equation 1); measures of median household income (Equation 2); and percent manufacturing, metropolitan status, and property value (Equation 3).

We see that percent African American and percent Latino are positively related to highly risky emissions in Equation 1, but that neighborhood income (Equation 2) has a negligible impact on risky emissions. In Equation 3, manufacturing activity is positively and significantly associated with highly risky emissions, but metropolitan status and property value are not. Most important, neither these three community factors nor neighborhood income do much to explain the influence of percent African American or percent Latino. In general, these results not only support the first proposition—racial dynamics shape the distribution of environmental harms—but they comport with most prior studies that find race matters more than class in shaping the distribution of environmental harms (see

[12]Using this procedure, we arrived at the same threshold (95 percent) for not highly risky emissions.

Ringquist 2005). Equation 3 appears to capture what has become the classic model of environmental inequality research.

However, as Equation 4 reveals, this classic model ignores how facilities' characteristics such as size and being a branch plant, which are positively and significantly associated with the dependent variable, contribute to environmental risks. In addition, this model, which is designed to isolate effects of race and class, fails to take into account the numerous ways these factors might intersect with facility characteristics to produce risks. It also makes no allowance for the possibility that racial, class, and organizational factors may influence emissions in more than one way. As a comparison of Equations 4 and 5 shows, this model effectively forces factors to have perfectly symmetrical relationships with negative and positive outcomes. In short, the parsimonious logic that informs the classic model hinders development of a more nuanced understanding of pollution exposure.

Fuzzy-Set Analyses

Table 4 reports an FSA analysis of chemical facilities' highly risky emissions (operationalized here as facilities' "fuzzified" RSEI scores). In keeping with Proposition 6, but contradicting Proposition 4, Table 4 reveals that residential and organizational factors combine in complicated ways to produce multiple (four) recipes of highly risky emissions. When interpreting FSA results, it is important to keep in mind that no single attribute within a recipe can be interpreted outside the context of the other attributes. This is because, unlike regression techniques that abstract variables from the cases in which they exist, FSA treats individual cases as combinations of attributes. This means that chemical facilities defined by the first recipe are located in communities that have large African American populations (AF-AMER) *and* low incomes (LOWINC). Facilities defined by the second recipe are located in communities that have large African American populations (AF-AMER) *and* large Latino populations (LATINO). Facilities defined by the third recipe are situated in communities that have large African American populations (AF-AMER) *and* are large plants (SIZE) *and* are branches (BRANCH). Finally, facilities defined by the fourth recipe are situated in communities that have large Latino populations (LATINO) *and* low incomes (LOWINC) *and* are branches (BRANCH). That a factor like large African American population is present in three of the four configurations indicates not only that it shapes highly risky emissions in three distinct ways, but also that it is not always associated with highly risky emissions. Compare these results with those in Table 3 that suggest the presence of African Americans has one and only one kind of impact and that African American presence is always positively associated with highly risky emissions.

All of the recipes in Table 4 contain at least one racial ingredient, and income is an ingredient in two of the recipes. In addition to contradicting the null income result in Table 3, these findings contradict Proposition 2, that the association between race and pollution is a mere aberration that can be explained by income. These findings also contradict Proposition 1, in the sense that race's influence is contingent on the presence of other community and organizational factors. Later, we will examine whether the configurations in Table 4 are still related to highly risky emissions when controlling for manufacturing activity, metropolitan status, property values, and other potentially confounding factors.

While it may not be immediately clear why the particular recipes in Table 4 are related to highly risky emissions, the fact that they resemble patterns uncovered in case study research suggests what mechanisms might be at work (see Table 5). For example, the fact that the first recipe resembles the findings of Pollock and Vittas (1995), Krieg (1995), and Downey (2000) that low-income African Americans have an especially hard time avoiding polluters would suggest that *spatial containment* may explain why this recipe is associated with risky emissions. Likewise, the second recipe comports with Pastor and colleagues' (2001) findings on residential turnover, suggesting that *ethnic churning* creates situations in which businesses can more easily externalize their pollution. The third recipe mirrors the results of Cable and colleagues (2008), and especially Rosner and Markovitz (2002), that *power imbalances* in the form of large, absentee-managed branches put African American neighborhoods at risk regardless of neighborhood income levels. Finally, the fourth recipe is reminiscent of the scenario described by Pulido (2000) and Auyero and Swistun (2008), suggesting that poor Latino migrants may be exposed to toxins (see also Skolnick 1995) in part because facilities' distant headquarters engender *ambiguous information* about who is ultimately to blame for environmental harms.

In Table 6, we conduct another fuzzy-set analysis to determine which combinations of facility and community factors lead plants to have not highly risky emissions. There are four recipes associated with this outcome, as was the case with highly risky emissions in Table 4. The recipes identified here, however, are not the mirror opposite of those reported in Table 4. This supports Proposition 7, that the recipes associated with negative and positive emission outcomes are asymmetrical, and contradicts Proposition 5, drawn from conventional environmental inequality research, that the effects of race, income, and other predictors on facility emissions are symmetrical.

Whereas only two of the four recipes identified in Table 4 are unique combinations of facility and community factors, this is true of all the recipes in Table 6. In addition, being a large facility (SIZE) is an essential ingredient in only one of the recipes for highly risky emissions, while being a small facility (size) is essential in every recipe for not highly risky emissions. Furthermore, subsidiary status does not define any of the recipes of highly risky emissions, but it is a defining ingredient in three of the four recipes for not highly risky emissions. Specifically, in three of these recipes it is the absence of subsidiary facilities that is important.

Perhaps the most striking manifestation of asymmetry is the fact that low-income neighborhoods (LOWINC) are associated with *both* highly and not highly risky emissions (see recipes 1 and 4 in Table 4 and recipes 1, 2, and 3 in Table 6). In addition to underscoring our earlier point that organizational and community structures can function as both resources and vulnerabilities, these and other examples of asymmetry speak to the inadequacy of (1) conventional environmental inequality theory and (2) regression techniques, like those employed in Table 3, that effectively force factors to have singular, linear effects. The findings also suggest that the reason why past environmental justice studies have produced inconsistent results is that effects of residential factors *are* inconsistent and often depend on other community and organizational factors. Finally, results suggest that conventional OLS findings, such as those reported in Table 3, can lead researchers to erroneously conclude that factors such as median household income are not associated with pollution outcomes when, in fact, they are in a subset of cases.

DISCUSSION

How might FSA findings, like the ones presented here, advance basic and applied research on environmental inequality? With respect to basic research, quantitative scholars have focused almost entirely on the kinds of communities in which polluters are situated, ignoring the organizational characteristics of polluters themselves. In addition, quantitative scholars favor linear regression techniques that are poorly suited for studying higher-order interactions between facility and community characteristics. As we demonstrated, FSA overcomes both of these problems by providing researchers with the tools needed to assess complex combinations of community and facility factors. FSA can also be used as a heuristic tool to identify relevant configurations that can then be tested in a regression format to see whether they have effects net of other potentially relevant factors (Hodson and Roscigno 2004; Roscigno and Hodson 2004). Table 7 illustrates how this can be done, using a random effects regression model[13] to assess the independent effects of the configurations identified by FSA on highly risky emissions.

Instead of using a series of interaction terms to represent these configurations, which would be highly cumbersome for specifying third and fourth level interactions, we use these configurations' fuzzy-set scores to determine whether their membership in our solution terms is statistically significant above their "main effects" and various controls.[14] Results indicate that, in each instance, the combinations of facility and community characteristics identified by FSA significantly shape highly risky emissions after accounting for their main effects, the extent of manufacturing activity in a facility's surrounding tract, whether a facility is located in a metropolitan area, the value of local housing, the specific sub-industry to which a facility belongs, and the pounds of chemicals a facility processes.[15] Without FSA, it would have been virtually impossible to know in advance which of the many possible interactions between our facility and community measures (2^K or 64 in total) warranted testing.

This article also contributes to basic research by demonstrating one potentially effective approach for selecting polluters for qualitative case study research. Qualitative scholars have long argued that to understand the mechanisms that produce environmental inequities, one must study the histories of individual polluters. However, like quantitative scholars, they have struggled to identify which polluters with which features merit special attention. Qualitative scholars can begin to address this shortcoming by thinking of FSA solutions as typologies of cases.

Suppose, for example, that qualitative scholars want to better understand facilities that pose an especially great health threat. Rather than examining convenient or theoretically interesting facilities, as is the common practice, scholars could select individual cases that Table 4 indicates are empirically associated with highly risky emissions and then investigate how these facilities' defining community and organizational characteristics are related to each other over time. This would generate new theory that could be tested in subsequent research. For instance, by studying individual facilities that have all of the ingredients of the third recipe in Table 4, researchers could determine whether these absentee-managed branches were originally located in communities with many African Americans or whether African Americans gradually moved into neighborhoods hosting such branches. In general, by first determining the organizational and community profiles of facilities that currently pose the greatest danger, qualitative scholars could more systematically study and theorize the historical processes that give rise to particular forms of environmental inequality (see Pellow 2000).

In terms of applied or policy oriented research, one of the reasons regulators created the RSEI was to determine which plants should be most closely monitored. While targeting plants with high RSEI scores is an important step toward reducing dangerous emissions, this strategy ignores the attributes that make facilities dangerous in the first place, some of which

[13]We use a random effects regression model available in Stata that can specify plants belonging to the same firm and having a shared error; it also accounts for the fact that each firm does not have the same number of plants.

[14]One potentially relevant factor is the physical age of a plant. Unfortunately, Dun and Bradstreet do not collect plants' physical ages, nor are the data available through any other secondary source. We attempted to gather this information ourselves via phone and mail, but we were able to obtain reliable data for only 60 percent of the plants in our sample. Moreover, we found that for this restricted sample, age is not associated with risk-based emissions.

[15]Regression results are basically the same when using uncalibrated versions of our dependent variables.

may be more easily altered than others. If regulators are to tailor policies to fit local circumstances, they must take into account these differences.

According to QCA practitioners (Schneider and Wagemann 2006), remote conditions are usually less amenable to change because they are, by definition, temporally or spatially removed from the outcome being explained. On the other hand, immediate conditions are normally more amenable because, theoretically, they have closer connections to the outcome of interest. When deciding how to reduce a particular facility's life-threatening emissions, regulators would thus be wise to focus on the immediate elements that FSA suggests must be in place for facilities of that type to pose a risk. Consider, for example, facilities defined by the fourth recipe for highly risky emissions. It is probably legally and logistically impossible for regulators to make amends for industrial contamination by physically removing poor Latino residents from a plant's surrounding neighborhood. Regulators may be able, however, to create incentives for absentee-managed plants to better communicate their risks to Spanish-speaking populations or to hire more administrators from the local Latino community who would have a greater stake in reducing emissions.

Finally, note that under existing laws, a claim of environmental racism can be discredited if there is evidence that some other factor, like income, also influences the distribution of an environmental harm (Cable et al. 2002). Moreover, U.S. courts will not hear any arguments against income- or class-related discrimination. Yet, as our analyses demonstrate, the impact of race on pollution is not always in addition to that of class. In some instances, race shapes pollution outcomes in concert with class. Hence, if courts are unwilling to grant plaintiffs' lawyers the same freedom as defense lawyers to use arguments about the relative influence of race, perhaps results like ours can persuade them to allow arguments about race's synergistic impact.

CONCLUSIONS

In this article, we sought to advance our understanding of the joint influences of organizational and community factors on health-threatening emissions. Toward that end, we proposed a new framework that suggests why these factors may work together to shape facilities' environmental performance. We also conducted the first empirical analysis of the physical dangers posed by individual facilities' emissions using novel FSA techniques and the EPA's newly developed Risk-Screening Environmental Indicators. Contrary to environmental justice scholars' suggestion that community characteristics have uniform, independent effects on emissions, we find that facility and community factors combine in complex ways to produce highly and not highly risky emissions. Discovery of these multiple and asymmetrical recipes of risk helps explain why results of past environmental justice research are so inconsistent. Future research and policymaking on environmental justice should devote more attention to how facilities organize the production of chemicals differently in different communities.

If this line of inquiry is to develop, scholars must investigate other actors and outcomes than the ones studied here. For example, researchers could examine organizational entities like the military and the health threat it poses to disadvantaged groups like Native Americans (see Hooks and Smith 2004). Researchers should also investigate the specific health dangers faced by children and the elderly. Although these groups are particularly vulnerable to toxins, scholars have not systematically examined which group is most vulnerable to which types of polluters and in which types of communities. In addition, our findings for the chemical industry raise important questions for comparative industry analysis. For instance, scholars will want to examine which combinations of factors are associated with environmental risks for food processing, auto, mining, and other industrial facilities. It would also be interesting to explore how environmental risks are jointly produced by multiple plants of the same industry or a mix of different industries. Finally, scholars will need to employ longitudinal data to investigate issues of causality that we have only begun to address with our cross-sectional data. For example, one could use FSA methods to determine at what point in time particular configurations of community and organizational factors first become associated with risky emissions and the stability of those associations (see also Isaac and Griffin 1989). It could be, as Saha and Mohai's (2005) study suggests, that these patterns all began to crystallize in the 1970s when the Not-In-My-Backyard (NIMBY) movement gained momentum, or perhaps different formations of environmental inequality congealed at different times.

Our study also builds bridges with research on public health. Despite their mutual interest in explaining health inequities, research on environmental justice and public health has developed along separate tracks. The former focuses on groups' proximity to hazardous facilities, whereas the latter concentrates more on actual health outcomes. By employing more exact estimates of the health risks posed by facilities and demonstrating that estimated risks are conditioned by how individual facilities are organized (internally and externally), our study narrows the gap between these bodies of research and makes environmental justice scholars' claims about the structural causes of health inequities more credible.

In addition, our study advances the broader literature on neighborhood effects (Sampson, Morenoff, and Gannon-Rowley 2002). This literature suggests that neighborhood conditions shape important physical, social, psychological, educational, and labor market outcomes and that individuals living in economically or racially disadvantaged communities may be more vulnerable to harm than those living in other communities. Researchers often attribute these differences to a shortage of voluntary organizations in poor minority neighborhoods that would enable residents to reduce violence, crime, and other harmful behavior by building trust and developing problem solving capacities. Yet, because studies of neighborhood effects rely on regression techniques that treat neighborhoods' demographic traits and organizations as distinct variables, they have not determined exactly how and in which instances the characteristics of individuals, neighborhoods, and organizations jointly influence harmful outcomes. Literature on neighborhood effects also pays surprisingly little attention to organizational structures of a commercial nature that can harm residents, undermine their capacity to mobilize, and transform places into commodities. Our study thus makes two important contributions to the neighborhood effects literature. First, we suggest how neighborhood effects scholars can use FSA to investigate the conjoint effects of community and organizational factors on life-threatening outcomes. Second, we suggest that commercial as well as civic organizations may help explain the influence community features have on such outcomes.

Finally, our results recast the perennial debate among environmental justice researchers over race versus class. They suggest that instead of conceiving of these factors as competing predictors and extracting them from their organizational context, scholars need to determine how race, class, and polluters' internal attributes (e.g., their size, geographic scope, and legal form) coalesce to produce risky exposures. Indeed, we expect that as the current economic crisis continues and chemical companies are forced to experiment with novel ways of producing goods and externalizing pollution costs, new and more complex recipes of risk will emerge. The question, then, will no longer be whether race or class matters most, but in which of these recipes do they matter and how.

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Appendix

Biographies

Don Grant is Professor of Sociology at the University of Arizona. His main fields of interest are stratification, work, the environment, and culture. In addition to his ongoing research on the social and environmental determinants of health related disparities, he is currently investigating caring labor, workers' emotional well-being, and the cultural meanings of suffering.

Mary Nell Trautner is Assistant Professor of Sociology at the University at Buffalo, SUNY. Her research and teaching interests are in the areas of law and society, gender, organizations, and labor. Her current work focuses on legal decision making, public policy, and access to justice, specifically how tort reform impacts the trajectory of personal injury cases. Some of her work examines how lawyers decide which cases to accept and which to decline, and she is currently developing a project that analyzes why only some injured patients decide to seek legal representation against doctors and hospitals.

Liam Downey is Associate Professor of Sociology at the University of Colorado at Boulder. His primary research interests revolve around race and class inequality in the environmental, political, and economic realms. He is currently studying environmental inequality in metropolitan America, the impact that visible environmental hazards have on residential mobility into and out of environmentally hazardous neighborhoods, and the role that economic and political inequality play in creating environmental degradation.

Lisa Thiebaud is a doctoral student in the Department of Sociology at the University of Arizona. Her work focuses on welfare and poverty at the state level in the United States. She has recently started her dissertation work, in which she plans to combine quantitative data with longitudinal case studies to explore state welfare benefit generosity.

Table 1

10 Dirtiest Chemical Plants

Plant Name	City	State
10 Dirtiest Plants (Hazard-Based Emissions)		
Jayhawk Fine Chemicals Corp.	Galena	KS
Pharmacia and Upjohn Co.	Kalamazoo	MI
Pfizer Inc. Parke-Davis Div.	Holland	MI
Onyx Environmental Services	West Carrollton	OH
Celanese Ltd. Clear Lake	Pasadena	TX
Lenzing Fibers Corp.	Lowland	TN
BP Chemicals Green Lake	Port Lavaca	TX
Equistar Chemicals Victoria	Victoria	TX
Firestone Polymers	Sulphur	LA
Lyondell Chemical Co. Bayport	Pasadena	TX
10 Dirtiest Plants (Risk-Based Emissions)		
Air Prods. L.P.	Pasadena	TX
CIBA Speciality Chemical Corp.	Suffolk	VA
Exxon Mobil	Baton Rouge	LA
DDE Louisville	Louisville	KY
Lenmar	Baltimore	MD
DuPont	Old Hickory	TN
Sensient Colors	Gibraltar	PA
Albemarle Corp.	Orangeburg	SC
Linde Gas	La Porte	TX
Dak Americas L.L.C.	Moncks Corner	SC

Table 2

Variable Summaries and Calibrations

Variable	Data Source	Calibration (Fuzzified Score)
Dependent Variables		
Highly Risky Emissions	RSEI	exp(2*z_score)/(1+ exp(2*z_score))
Not Highly Risky Emissions	RSEI	Negation of above
Key Independent Variables		
African American	U.S. Census	1% = .05, 15% = .5, 99% = .95
Latino	U.S. Census	1% = .05, 15% = .5, 99% = .95
Household Income	U.S. Census	10000 = .05, 25000 = .5, 100000 = .95
Facility Size	Dun and Bradstreet	15 = .05, 500 = .5, 1000 = .95
Branch Plant	Dun and Bradstreet	No = 0, Yes = 1.0
Subsidiary	Dun and Bradstreet	No = 0, Yes = 1.0
Controls		
Percent Manufacturing	U.S. Census	
Metropolitan Area	U.S. Census	
Median Property Value	U.S. Census	
Sub-industry Dummies	TRI	
Chemicals On-Site	TRI	

Table 3

Regression Analysis of Highly and Not Highly Risky Emissions

	Highly Risky Emissions				Not Highly Risky Emissions
	(1)	(2)	(3)	(4)	(5)
% African American	58.347* (26.350)	55.652* (29.375)	59.821* (30.353)	59.060* (31.036)	−59.060* (31.036)
% Latino	103.582** (33.750)	102.209** (34.318)	84.765* (41.152)	131.261** (38.403)	−131.261** (38.403)
Median Household Income		−.010 (.044)	.020 (.060)	.033 (.065)	−.033 (.065)
% Manufacturing			198.683* (112.627)	290.067** (115.712)	−290.067** (115.712)
Metropolitan Area (1 = yes)			1366.048 (1403.682)	1288.062 (1829.026)	−1288.062 (1829.026)
Property Value			−.017 (.014)	−.014 (.015)	.014 (.015)
Facility Size				1.685* (1.003)	−1.685* (1.003)
Branch Plant				3206.049* (1462.837)	−3206.049* (1462.837)
Subsidiary				1247.190 (1761.026)	−1247.190 (1761.026)
Constant	399.032	869.685	−3607.327	−7369.662	7369.662
R^2	.031	.033	.054	.076	.076
N	2,053	2,053	2,053	2,053	2,053

* $p < .05$;

** $p < .01$ (one-tailed test).

Table 4

FSA Reduced Configurations for Highly Risky Emissions

Optimal Solution	Coverage	Consistency
AF-AMER*LOWINC	.331	.953
AF-AMER*LATINO	.191	.953
AF-AMER*SIZE*BRANCH	.181	.936
LATINO*LOWINC*BRANCH	.138	.976
Solution Coverage: .431		
Solution Consistency: .925		

Note: AF-AMER = African American population; BRANCH = branch plant; LATINO = Latino population; LOWINC = low income; SIZE = facility size; and SUBSID = subsidiary. Consistency is a measure of *how often* the solution is a subset of the outcome or the degree to which cases sharing a particular combination of conditions agree in displaying the outcome in question. Coverage measures *how much* of the outcome is explained by the solution or the empirical relevance of a particular combination of conditions.

Table 5

FSA Recipes of Highly Risky Emissions and their Possible Mechanisms

Recipe	Relevant Studies	Possible Mechanism
AF-AMER*LOWINC	Downey (2000); Faber and Krieg (2000); Pollock and Vittas (1995)	Spatial Containment
AF-AMER*LATINO	Pastor et al. (2001)	Ethnic Churning
AF-AMER*SIZE*BRANCH	Cable et al. (2008); Rosner and Markovitz (2002)	Power Imbalances
LATINO*LOWINC*BRANCH	Auyero and Swistun (2008); Pulido (2000)	Ambiguous Information

Note: AF-AMER = African American population; BRANCH = branch plant; LATINO = Latino population; LOWINC = low income; SIZE = facility size; and SUBSID = subsidiary.

Table 6

FSA Reduced Configurations for Not Highly Risky Emissions

Optimal Solution	Coverage	Consistency
latino*LOWINC*size*branch	.682	.959
af-amer*LOWINC*size*subsid	.643	.648
latino*LOWINC*size*subsid	.701	.955
af-amer*lowinc*size*subsid	.415	.966
Solution Coverage: .401		
Solution Consistency: .959		

Note: AF-AMER = African American population; BRANCH = branch plant; LATINO = Latino population; LOWINC = low income; SIZE = facility size; and SUBSID = subsidiary.

NIH-PA Author Manuscript

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Table 7

Random Effects Regression Analysis of the Influence of Configurations on Highly Risky Emissions

	(1)	(2)	(3)	(4)
AF-AMER* LOWINC	.039* (.020)			
AF-AMER* LATINO		.037* (.021)		
AF-AMER* SIZE* BRANCH			.087** (.026)	
LATINO* LOWINC* BRANCH				.029** (.011)
Percent Manufacturing	.001 (.000)	.001* (.000)	.001* (.000)	.001 (.000)
Metropolitan Area (1 = yes)	.007 (.008)	.008 (.009)	.008 (.008)	.007 (.009)
Median Property Value	−.005 (.006)	−.005 (.006)	−.002 (.004)	−.004 (.005)
Industrial Inorganic Chemicals	.012* (.007)	.013* (.007)	.009* (.005)	.013* (.007)
Plastics	.014* (.007)	.015* (.008)	.011* (.006)	.015* (.008)
Drugs	−.007 (.009)	−.007 (.009)	−.008 (.010)	−.007 (.010)
Soaps and Detergents	−.002 (.002)	−.001 (.001)	−.003 (.004)	−.001 (.001)
Paints	−.005 (.006)	−.004 (.006)	−.003 (.008)	−.004 (.007)
Industrial Organic Chemicals	.001 (.002)	.002 (.002)	.003 (.004)	.002 (.003)
Agricultural Chemicals	−.005 (.005)	−.002 (.004)	−.003 (.006)	−.003 (.004)
Chemicals On-Site	.004** (.000)	.004** (.000)	.004** (.000)	.004** (.000)
Constant	.464***	.474***	.461***	.471***
R^2	.113	.109	.136	.119
N	2,053	2,053	2,053	2,053

Note: The configurations are entered in “raw” form (i.e., min(x1,x2, … xn). Models also include the main effects of these configurations’ conditions, which are entered in “set” form (i.e., ranging from 0 to 1). For presentational purposes, the main effects are not reported here.

* $p < .05$;

** $p < .01$ (one-tailed test).

Table A1

Truth Table for Configurations

Af-Amer	Latino	LowInc	Size	Branch	Subsid	N	Y Consistency	~Y Consistency
0	0	0	0	1	0	325	.710171	.752027
0	0	0	0	0	0	299	.662514	.714974
0	0	0	0	0	1	167	.697773	.736123
1	0	0	0	1	0	124	.867775	.886337
1	0	0	0	0	0	85	.88085	.922046
0	1	0	0	0	0	72	.868146	.90446
0	0	0	1	1	0	71	.869953	.841407
0	1	0	0	1	0	66	.905846	.924691
1	0	0	0	0	1	57	.875211	.903312
0	0	0	1	0	1	34	.839639	.853379
0	1	0	0	0	1	31	.905483	.922045
1	0	0	1	1	0	30	.954815	.919431
1	0	1	0	1	0	29	.965315	.964989
1	1	0	0	0	0	22	.956973	.975628
0	0	0	1	0	0	19	.900506	.918071
1	0	1	0	0	0	19	.963609	.962241
1	1	0	0	1	0	18	.975465	.984544
1	0	1	0	0	1	16	.95183	.964221
0	1	1	0	1	0	15	.97853	.973294
0	1	1	0	0	0	12	.975031	.985686
1	0	0	1	0	1	9	.956603	.955111
0	1	0	1	0	1	8	.955446	.959552
1	1	0	0	0	1	7	.979892	.985657
0	1	0	1	0	0	6	.962171	.964583
0	1	0	1	1	0	6	.980037	.964594
1	0	0	1	0	0	6	.975242	.977131
1	1	1	0	0	0	6	.982763	.987906
1	0	1	1	0	1	5	.984258	.967653
1	0	1	1	1	0	5	.993707	.963194

Af-Amer	Latino	LowInc	Size	Branch	Subsid	N	Y Consistency	~Y Consistency
1	1	0	1	1	0	5	.993381	.989235
1	1	1	0	1	0	5	.995787	.990705
0	0	1	0	0	1	3	.993543	.988773
0	1	1	0	0	1	3	.983215	.985771
1	1	1	0	0	1	3	.990827	.993652
0	0	1	0	1	0	2	.997366	.991938
0	0	1	1	0	1	2	.994382	.99576
1	1	1	1	0	1	2	.989036	.991367
0	0	1	0	0	0	1	.995087	.994007
0	0	1	1	0	0	1	.998946	1
0	0	1	1	1	0	1	.998358	.983077
0	1	1	1	0	1	1	.993158	.992712
1	0	1	1	0	0	1	.995748	.998072
1	1	0	1	0	0	1	.99848	1
1	1	0	1	0	1	1	.998064	.996938
1	1	1	1	0	0	1	.998793	1
1	1	1	1	1	0	1	.999381	.995674