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Measuring Corporate Environmental Justice Performance

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ABSTRACT

Measures of corporate environmental justice performance can be a valuable tool in efforts to promote corporate social responsibility and to document systematic patterns of environmental injustice. This paper develops such a measure based on the extent to which toxic air emissions from industrial facilities disproportionately impact racial and ethnic minorities and those on low incomes. Applying the measure to 100 major corporate air polluters in the United States, we find wide variation in the extent of disproportional exposures. In 54 cases, minorities, who represent 31.8% of the US population, bear excess burden; in 15 of these cases, the minority share exceeds half of the total human health impacts from the firm's industrial air pollution. In 66 cases, poor people, who represent 12.8% of the US population, bear excess burden. Copyright © 2010 John Wiley & Sons, Ltd and ERP Environment.

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Introduction

This paper analyzes corporate environmental justice (EJ) performance, measured in terms of the human health impacts of airborne emissions of toxic chemicals from industrial facilities. Prior studies of corporate environmental performance have focused primarily on total emissions of pollutants, remediation efforts, or aggregate environmental damage. Prior studies of EJ have examined the extent to which hazards disproportionately impact specific groups, such as racial minorities. This paper is the first effort to combine these by constructing a measure of corporate EJ performance.

Aslaksen and Synnestvedt (2003) discuss the prospects for deepening the links between economic performance, environmental performance, and broader social performance. The literature on broader social performance focuses on child labor, bonded labor, and other intolerable working conditions, but it does not, as a rule, include EJ.

The difference between studies of corporate environmental performance and of EJ is, in part, methodological: in corporate environmental performance the unit of analysis is the source of pollution, the firm or an individual

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facility; in EJ the unit of analysis is the receptor, the community or households on the receiving end. The two strands of research also differ in their audiences and aims. The main audiences for research on corporate environmental performance are socially responsible managers, investors, and consumers, with the main aim being to improve firm behavior. The main audience for EJ research is the impacted communities and responsible government officials, the main aim being to protect communities from disproportionate hazards.

Research on corporate environmental performance has documented the beneficial effect of *mandated* environmental reporting, in particular, pollutant release and transfer registers, on both governance processes around industrial sites and the ultimate environmental performance of firms (Sullivan and Gouldson, 2007).

This paper presents a measure of corporate EJ performance, bridging the gap between research on corporate environmental performance and that on EJ. Our measure is based on data that link pollution exposures to pollution sources. The audiences for this work include both corporate social responsibility (CSR) advocates who want information about this important dimension of environmental performance and EJ advocates who want documentation on systematic patterns in corporate behavior. The paper is organized as follows.

First, we describe the datasets and methodology for matching the exposure data and Census data. Our environmental data come from a source-and-receptor model of air-toxics release and exposure from the US Environmental Protection Agency (EPA). We merge the EPA data with socioeconomic data from the US Bureau of the Census to analyze exposure disparities by race, ethnicity, and income. This facility-level information is aggregated to obtain firm-level measures using a dataset on corporate ownership of industrial facilities developed at the Political Economy Research Institute of the University of Massachusetts, Amherst.

Then we present the measure of corporate EJ performance, and report the results of applying it to 100 large corporations operating throughout the United States. The corporations are those listed in the latest edition of the Political Economy Research Institute's *Toxic 100 Air Polluters* which uses the same data sources to rank firms on the basis of total human health hazards resulting from air toxics emissions at their facilities.

Next we present within-class rankings for firms in two industrial sectors that rank high in toxic air emissions: oil refining; and plastics and synthetic materials. Community-based EJ activists generally have focused on impacts from specific facilities, such as the Solutia (former Monsanto) plant in Anniston, Alabama, but whether the exposure patterns at individual facilities can be generalized to overall corporate behavior is seldom evident.[1] Academic EJ researchers generally have focused on the aggregate pollution loads imposed on people of color and low-income communities, but whatever the overall extent of disproportionate impacts, there is no reason to assume that disparities are constant across firms (Ash and Fetter, 2004; Pastor *et al.*, 2006; Mohai and Saha, 2007). We show that the extent to which firms in the same industrial sector impose disparate pollution burdens on different groups can and does vary substantially.

We then examine the relationship between corporate EJ performance and total human health risk for the Toxic 100 to assess whether a measure of EJ performance adds value to a more conventional measure of corporate environmental performance. Finally, we conclude by discussing potential uses of these data in research on the determinants and effects of corporate EJ performance and in efforts to improve corporate performance.

Data and Methods

The underlying data for the corporate EJ measure come from three sources: the EPA's Risk-Screening Environmental Indicators (RSEI); the 2000 US Census of Population and Housing; and the Political Economy Research Institute's corporation-facility identification dataset. This section describes these data sources and how we combine them in order to construct a measure of corporate EJ performance.

RSEI

First, we describe two sets of data emerging from the EPA's RSEI: the aggregated version which is contained in the EPA's RSEI public-release data; and the disaggregated RSEI Geographic Microdata (RSEI-GM) which currently

[1] On the Anniston case, see US Senate Committee on Appropriations (2002) and Bryan (2003).

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are not available to the public at large. Our measure relies on the latter, but it is useful first to describe the public-release data. Full documentation of the RSEI model is available from Office of Pollution Prevention and Toxics (2004).

RSEI Public-Release Data

Estimates of exposure to airborne toxics emitted by industrial facilities across the United States are generated by the RSEI project of EPA. The RSEI project starts with information on annual releases of more than 600 chemicals from more than 20,000 facilities, reported in the Toxics Release Inventory (TRI) (US EPA, 2009b), the US pollutant release and transfer register.[2] RSEI then incorporates data on the relative toxicity of these chemicals, their fate and transport (taking into account chemical breakdown rates, stack heights, exit-gas velocities, prevailing wind currents, etc.) and the resulting exposures. For each air release (that is, each facility-chemical pair), RSEI estimates exposures in each km^2 of a 101 km x 101 km grid centered on the facility. The EPA publicly releases facility-level measures of the resulting human health hazards, aggregated over the 10,201 1-km^2 cells within the grid and across chemicals. These 'RSEI scores' are used by federal and state environmental officials to prioritize enforcement actions.

The TRI was created at the direction of the Congress under the Emergency Planning and Community Right-to-Know Act passed in 1986 after the Bhopal chemical plant disaster. The Act requires industrial facilities to submit annual data to EPA on deliberate and accidental releases of roughly 600 toxic chemicals into air, surface water, and the ground. TRI data are available on an annual basis starting in 1987. In 2005, more than 20,000 TRI-reporting facilities released a total of 1.5 billion pounds of toxic chemicals into the air, and additional toxics were released from offsite incinerators. The TRI is widely used in both corporate environmental performance and EJ literature: the corporate performance studies typically use TRI data on the total mass (pounds) of emissions, while EJ studies typically analyze the geographical distribution of TRI-reporting facilities in relation to the demographics of the communities in which they are located.

The TRI data are the jewel in the crown of the environmental 'right-to-know' movement in the United States. Valuable as they are, the TRI data have important limitations. Some of these stem from the nature of the data: the releases are annual totals, estimated, self-reported, and limited to listed chemicals from qualifying facilities and processes. One of the most significant limitations is that the TRI simply reports pounds of chemical releases, often generating press stories that identify local 'top polluters' on this basis. Such reporting does not account for variations in the toxicity of different chemicals, some of which, pound-for-pound, are as much as ten million times more toxic than others. Nor does it take into account the fate and transport of these chemicals in the environment, or the number of people impacted. Finally, because the TRI reports facility-by-facility data, the cumulative impact on communities that are affected by multiple facilities is not evident.[3]

The RSEI project was launched by the EPA in the mid-1990s to address several of these limitations. The EPA Office of Pollution Prevention and Toxics processes the TRI data on the quantity of each chemical released by each facility to create the RSEI. To assess the human health risks posed by each release, the EPA combines this with information on: (1) toxicity, or how dangerous the chemical is in terms of chronic human health effects; (2) fate and transport, or how the chemical spreads from the point of release to the surrounding area; and (3) population exposure, or how many people live in the affected areas and are exposed to inhalation of different concentrations of the chemical.

Each air release begins at a stack, leaking valve, open canister, or other source within the facility, or at the stack of an offsite incineration facility to which it ships wastes. The Industrial Source Complex-Long Term (ISCLT3)

[2] Sullivan and Gouldson (2007) provide more detail on the content and impact of the TRI, including both the strengths of the TRI, such as the inclusion of both stack and fugitive air releases and many chemicals and chemical groups, and the caveats of pollutant release and transfer registers, such as reliance on engineering estimates rather than measured releases, short sampling periods, and the absence of connection between release data and regulation (permits, violations, enforcements, and remedies).

[3] The TRI data capture the largest point-source air pollution emissions in the United States, but they do not capture emissions from mobile sources, such as trucks, automobiles, ships, and aircraft. The TRI also excludes facilities that are not required to report by virtue of small size or belonging to non-listed industrial sectors. Potentially significant air polluters not covered for these reasons include gas stations, dry cleaners, and auto-body shops.

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model, a Gaussian-plume fate-and-transport model, is used to map how the chemical spreads from the point of release in the surrounding geography.[4] EPA combines data on temperature and local wind patterns with facility-specific information on smokestack height and the exit velocity of released gases, together with chemical-specific information on molecular weight and rates of deposition and decay, to estimate the ambient concentrations of each release in each grid cell.

By multiplying the mass (pounds) of each chemical by a toxicity weight, EPA compares the toxicological significance of releases of different chemicals. The EPA's toxicity-weighting system is based on peer-reviewed databases from several sources: the EPA's Integrated Risk Information System (IRIS); the EPA's Office of Pesticide Programs Reference Dose Tracking Reports; the US Department of Health and Human Services Agency for Toxic Substances and Disease Registry; the California Environmental Protection Agency Office of Environmental Health Hazard and Assessment; and the EPA's Health Effects Assessment Tables. For some chemicals listed in the TRI, no consensus has been reached on the appropriate toxicity weight; these chemicals are currently excluded from the fully-modeled RSEI score. In recent years, the excluded chemicals have represented about 1% of the total mass of reported toxic air releases nationwide.

Although all TRI chemicals are toxic, their hazards to humans vary widely. For carcinogens, the EPA's toxicity-weighting system uses inhalation-based dose-response estimates of the excess lifetime cancer risk per unit of concentration. The toxicity-weighted concentration is proportional to an individual's excess risk of cancer from that concentration. For non-carcinogens, the toxicity-weighting system uses the 'Reference Concentration', which is the highest level of exposure concentration with no adverse health impact, and expresses toxicity-weighted exposures as multiples of this (e.g., 'six times the highest safe concentration').

Equivalence between the non-carcinogenic and carcinogenic scales has been set by the EPA Science Advisory Board at a Reference Concentration being equivalent to a carcinogenic risk of 250 excess cancer cases per million persons. At the extreme ends of the resulting toxicity scale for the chemicals on the TRI list, one pound of friable asbestos is equivalent, in terms of inhalation toxicity, to 27 million pounds of chlorodifluoromethane (HCFC-22). The RSEI toxicity model is additive across chemicals, without cross-chemical interactions, and the implicit dose-response function is linear, without threshold or other nonlinear effects.

The RSEI project overlays the grid of toxicity-weighted air pollution concentrations upon a population grid drawn from block-level data from the US Census. The calculation of aggregate human health risk is based on population exposure to given toxicity-weighted concentrations. In addition to the number of people in each 1-km^2 grid cell, the RSEI's population weights take into account the age and sex composition of the population, because exposure varies by the volume of air inhaled per unit of body weight. This variation is captured in a distinct inhalation exposure factor (IEF) by age and sex groupings.[5] The RSEI score thus represents the aggregate human health risk borne by the population, based on the number of people and the extent of exposure.

The RSEI score for a given release (facility-chemical) affecting a given grid cell is:

$$\text{RSEI Score}_{fcg} = \sum_{a}\sum_{s} \text{Population}_{asg} \times \text{IEF}_{as} \times \text{Toxicity}_{c} \times \text{Concentration}_{fcg} \tag{1}$$

where Population_{asg} is the population of sex s in age category a in cell g; IEF_{as} is the inhalation factor for persons of sex s in age category a; Toxicity_c is the toxicity weight for chemical c; and $\text{Concentration}_{fcg}$ is the estimated concentration at cell g for chemical c released by facility f.

[4] Geographic buffers based on plume modeling provide a more accurate picture of exposure to industrial air releases than do simple circular or distance-weighted buffers (Chakraborty and Armstrong, 1997; Saha and Mohai, 2005).

[5] The population-exposure values reflect the cubic meters of air inhaled by a person (roughly 20 cubic meters per 70 kg of body mass) per day. Inhalation exposure factors are used to convert toxicity-weighted air concentrations into human exposures, according to the following formula: 0.341 x (count of males, aged 0 to 17) + 0.209 x (males, 18 to 44) + 0.194 x (males, 45 to 64) + 0.174 x (males, 65 and Up) + 0.310 x (females, aged 0 to 17) + 0.186 x (females, 18 to 44) + 0.165 x (females, 45 to 64) + 0.153 x (females, 65 and Up). The factors are intended to reflect biological differences in inhalation uptake by age and sex, although some analysts have criticized them for false precision (Morello-Frosch, Pers. Comm. 2007). The inhalation exposure factors could, in principle, alter environmental justice results because age and sex composition vary by racial and ethnic group. Groups that are disproportionately young register higher exposure; groups that are disproportionately female register lower exposure. In practice, age-sex structures are sufficiently similar that results do not differ appreciably. Furthermore, the effects of age composition and sex composition apply in opposite directions for both African Americans and for poor persons; both groups are disproportionately young and female (US Bureau of the Census, 2008). Person-weighted, as opposed to IEF-weighted, results are available from the authors on request.

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The release-cell score, measuring the impact of a given release on a given cell, represents the total human health risk in that location. In the case of carcinogens, this score is directly proportional to the number of excess statistical cancer cases. The EPA's main objective in creating the RSEI was to assist federal and state agencies in setting priorities for environmental protection. To this end, the release-cell scores are aggregated (across chemicals and cells) on a facility-by-facility basis:

$$\text{RSEI Score}_f = \sum_c \sum_g \text{RSEI Score}_{fcg} \tag{2}$$

The RSEI methodology described above has been subjected to extensive internal and external reviews, including a peer review by external risk-assessment experts, three peer reviews by the EPA's Science Advisory Board, peer reviews by the States, and submission for public comment.[6]

The facility-wise RSEI scores are made available to government agencies and the public in the RSEI public-release data, available for free from EPA. The public-release data include information on the contribution of each chemical to the facility's RSEI score, but they do not include disaggregated information on the geographic cells impacted by the toxic releases.

The RSEI Geographic Microdata (RSEI-GM)

Because EPA developed the RSEI data for the purpose of prioritizing facilities (i.e., sources for enforcement and clean-up), the public-release data are not designed for examining differences among communities (i.e., receptors) in terms of their exposure to industrial toxic releases. The corporate EJ measure requires use of the disaggregated RSEI-GM data, which provide 1-km^2 cell-by-cell estimates of exposure to airborne toxics identified by source facility and chemical. The disaggregated data are not available to the public, owing to their daunting size and complexity. EPA has, however, made the geographic microdata available to the research community.

At an earlier stage, EPA provided partially disaggregated RSEI data on total estimated health hazards from air toxics for each of the roughly two million impacted 1-km^2 grid cells. These data were not fully disaggregated; instead they were summed over all releases, i.e., aggregated on a cell-by-cell basis across facilities (sources) and chemicals. The aggregate RSEI score for cell g is

$$\text{RSEI Score}_g = \sum_f \sum_c \text{RSEI Score}_{fcg} \tag{3}$$

where f indexes facility and c indexes chemical. Although these earlier data provided no distinction among sources, the total human health risk was measured at fine geographic resolution. By merging this receptor-based measure of aggregate hazards with Census data, two published EJ studies (Bouwes *et al.*, 2003; Ash and Fetter, 2004) have analyzed hazards in relation to race, ethnicity, and income using these data for the years 1997 and 1998, respectively. Both studies found statistically significant evidence of disproportionate impacts, by race and ethnicity (controlling for income) and by income (controlling for race and ethnicity).

To develop corporation-specific measures of EJ performance, we use the fully disaggregated geographic microdata, which identify impacts by source facility and receptor cell (RSEI Score$_{fg}$). The RSEI-GM data provide this information. Unlike most other data used in the investigation of environmental inequalities, the RSEI-GM data offer:

1. National scope and coverage of a wide range of industries, chemicals, and facilities. The RSEI-GM data include almost all (99% by weight) of the air releases reported to the TRI. The TRI is the most comprehensive list of industrial toxic releases in the United States, in 2005 covering 494 chemicals and chemical groups released by 23,438 facilities in manufacturing, metal mining, electrical power generation, waste storage and processing, and chemical storage, as well as Federal facilities. The criteria for inclusion in TRI reporting include industrial sector and the quantity of toxic chemicals processed at the facility.

[6] For details, see Office of Pollution Prevention and Toxics (2004).

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2. Fate, transport, and exposure modeling at precise geographic resolution. The fate-and-transport model permits the unbiased measurement of exposure at receptor sites resulting from point-source air releases, with a high degree of geographic specificity. The focus on exposure at the receptor site outflanks the 'How near is near?' debate in the EJ literature as to what distance best fits the notion of 'closeness' to a point source (Boyce, 2007).
3. Identification of the source facility for each pollutant release. The data on ambient concentrations of toxics at receptor sites are disaggregated by source facility and chemical. Unlike the EPA's Ambient Air Monitoring Program (US EPA, 2009a) and other pollution-exposure data based on ambient measures of aggregate levels of pollutants at the receptor site, the RSEI-GM makes it possible to track exposure to its source. The simultaneous identification of source and exposure is perhaps the most important and distinctive strength of the RSEI-GM.
4. Toxicity weighting, expressing the human health risk of emissions per quantity released. The EPA's toxicity-weighting system permits comparison of toxic releases from disparate industrial processes.
5. Construction by well-documented methods that have undergone extensive peer review. The EPA's RSEI data are among the most rigorously reviewed environmental datasets in the nation, and they carry the imprimatur of the Federal regulatory authorities.
6. Almost 20 years of annual data. Longitudinal RSEI-GM data make it possible to advance debates over causality and policy in the EJ literature that revolve around matters of timing: which came first, the people or the pollution? In this paper, we simply provide a cross-sectional analysis of corporate EJ performance to identify patterns for further exploration and explanation. In future analysis, however, longitudinal data provide an important tool for untangling the interplay of the three variables that decompose the corporate environmental impact on different communities: (1) siting, or the location of new polluting facilities in existing communities; (2) move-in, or the decision of households to locate in relation to polluting facilities; and (3) performance, or the ways that industrial processes, output, and pollution control are managed across facilities.

In summary, the RSEI-GM database offers a remarkable tool for the analysis of EJ issues in the United States. Its fine geographic resolution exceeds that of other national exposure databases, such as the National Air Toxics Assessment (NATA). By measuring exposure, it circumvents the how-near-is-near problem that has plagued EJ studies based simply on proximity to point sources. Disaggregation by source and chemical permits the identification of problematic industrial sectors and processes. The linkage of release and exposure (i.e., source and receptor) provided by the RSEI-GM is unparalleled by any other national dataset. The longitudinal character of these data enables time-series and panel analyses that can shed light on trends as well as levels of exposure, and on the dynamic interplay between demographic and environmental change.

The RSEI-GM data thus extend the range and complexity of EJ research questions that can be feasibly addressed. In this paper, we show how the data can be used to measure corporate EJ performance.

Census of Population and Housing: The Spatial Join

The 2000 US Census of Population and Housing provides the social, economic, and demographic data for construction of our measure. Census blocks, defined by roads and other geographic features, are the smallest geographic unit of data published by the Census. The data provided at this level include counts of the race, sex, and age of residents. With the help of local committees, the Census Bureau defines Census block groups, which typically contain roughly 30 blocks that correspond to neighborhoods, a method that ensures a degree of socioeconomic homogeneity. Block groups contain 600 to 3,000 people.[7] The block group is the smallest geographic unit for which the Census Bureau publicly releases socioeconomic data, including counts of the number of people in poverty.

The Census and RSEI-GM data are well-matched in terms of geographic precision, but they are not in the same geographic format. The RSEI-GM model divides the United States, including Puerto Rico, into 1-km^2 cells, of which seven million are within the 101 km x 101 km catchment of at least one industrial facility and almost three million have positive toxics exposure. Census blocks and block groups have irregular boundaries, and they can be

[7] As blocks fully partition block groups, block groups fully partition Census tracts, the next level of aggregation, which on average contain 4,000 residents.

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larger or smaller than 1 km². Working with the EPA, its contractor, and a consortium of academic researchers, we constructed a crosswalk by which Census geography is spatially joined with the 1-km² grid-cell data.[8] The spatial join was effected by a complete intersection of Census blocks with 1-km² cells. Each 1-km² cell is associated with the share of each of the Census blocks that it intersects.[9] The join of cells to blocks is extended to census block groups as well.

In this way we can count, by age category and sex, the number of poor people, blacks, Latinos, Asian-Americans, American Indians, and non-Hispanic whites in each of the 1-km² cells:

$$\text{Population}_{rasg} = \sum_{b} \alpha_{gb} \times \text{Population}_{rasb} \tag{4}$$

where Population_{rasg} is the estimated population of race or ethnicity r, age a, and sex s in cell g; Population_{rasb} is the population of race r, age a, and sex s in Census block b, and α_{gb} is the percentage of Census block b that lies in grid cell g. The year 2000 Population_{rasb} of Census block b is extracted from the Summary File 1 data from the Census. The crosswalk term, α_{gb}, is used by the EPA to incorporate population densities in the RSEI project. (See Appendix 1: Diagram for Spatial Join for an illustration of the join.)

Using this method, we obtained age-sex-race/ethnicity population counts for each grid cell g. Our race/ethnicity population counts, segmented by age-group and sex, were derived at the 1-km² grid-cell level from the block-grid spatial merge, using exactly the same method that the EPA's RSEI model uses in its total population counts. We then compute:

$$\text{RSEI Score}_{rfcg} = \sum_{a} \sum_{s} \text{Population}_{rasg} \times \text{IEF}_{as} \times \text{Toxicity}_{c} \times \text{Concentration}_{fcg} \tag{5}$$

where RSEI Score_{rfcg} is the score from releases of chemical c by facility f for people of race or ethnicity r in cell g. Summing over the 10,201 cells around each facility, the score expresses the aggregate health risk to minority group r from exposure to a given release:

$$\text{RSEI Score}_{rfc} = \sum_{g} \text{RSEI Score}_{rfcg} \tag{6}$$

For the impact from all of the releases from a single facility,

$$\text{RSEI Score}_{rf} = \sum_{c} \sum_{g} \text{RSEI Score}_{rfcg} \tag{7}$$

The Census does not report income data at the block level, but only at the block-group level and higher aggregations (in Census Summary File 3). For this reason, the poverty specific population counts are derived from a spatial merge of block-group data with the grid cells.[10] We tested whether applying this broader block-group aggregation to the racial/ethnic population data caused results to vary much from those obtained from the spatial merge at the finer block level, and found that there is little difference in the results.

Corporation-Facility Matching

To develop corporate performance measures, one more step is required: matching individual facilities to their corporate parents. The Corporate Toxics Information Project, which we direct, has developed a dataset for this

[8] In addition to the authors, other members of the RSEI-GM research consortium are based at the University of Michigan, the University of Southern California, the University of California, Berkeley, and Occidental College.
[9] Each Census block is also associated with the share of each of the one or more 1-km² cells that it intersects, but the 1-km² cell is the fundamental unit of observation in this analysis.
[10] The Census poverty data are reported by age-group but not by sex, and the age-groups are less disaggregated than those at the block level used by the RSEI model: where RSEI distinguishes 18 to 44 and 45 to 64, the Census block-group data on the poor report 18 to 64 as a single category. Hence we averaged the age-specific exposure factors for males and females; for example, (0.341 + 0.310) / 2 = 0.326 for persons aged 0 to 17. For the combined age group, we computed a span-weighted average: (27/47 x (0.209 + 0.186)/2 + 20/47 x (0.194 + 0.165))/2) = 0.190 for persons aged 18 to 64.

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purpose. This parent-facility matching requires continuous updating to track mergers and acquisitions, transfers of facilities to new owners, and the entry of new facilities into the TRI and RSEI databases. Extracting information on company ownership of facilities from the TRI reports, Dun & Bradstreet's Million Dollar Database, Mergent Online, http://www.hoovers.com, company websites, printed reports, and telephone calls, the Corporate Toxics Information Project matches facilities to their parent companies.

As with additivity across chemicals in the RSEI model, we assume additivity across facilities in generating corporate scores as the sum of scores of the component facilities. By aggregating the RSEI scores of the facilities owned by individual parent companies, the Corporate Toxics Information Project produces *The Toxic 100*, a ranking of the largest corporations operating in the United States on the basis of the total human health risk from air toxics emissions from their facilities, as measured by the RSEI data. The most recent edition of the Toxic 100 (available at http://www.peri.umass.edu/toxic100/) identifies the top polluters among the companies that appeared in the year 2007 on the Fortune 500, Fortune Global 500, and S&P 500 lists of the country's largest corporations, and on the Forbes Global 2000 list of the largest 500 US-based and 500 foreign-based corporations, using RSEI data (version 2.1.5) that refer to the year 2005.[11] *The Toxic 100* therefore reports 2005 air pollution from industrial facilities in the United States, based on the latest available (2007) data on ownership structure.

A Measure of Corporate EJ Performance

In this section we present our measure of corporate EJ performance for the 100 large firms that appear in the latest edition of the *Toxic 100 Air Polluters*. The measure indicates the extent to which the human health impacts from releases of toxic air pollutants at industrial facilities owned by the corporation are borne by specific subgroups of the US population. Two corporate EJ performance indicators are reported here: the first measures impacts on racial and ethnic minorities, and the second measures impacts on people with incomes below the national poverty line.

Measuring Group Shares of Human Health Risk

To measure human health risk for a given corporation, we aggregate the race/ethnicity- specific and poverty-specific scores for the facilities it owns.

$$\text{RSEI Score}_{rF} = \sum_{f \in F} \text{RSEI Score}_{rf} \tag{8}$$

where r indexes racial/ethnic or poverty categories, and f indexes facilities owned by firm F.

Our corporate EJ measure is the percentage share of these groups in the total human health risks generated by air toxics releases from the firm's facilities. To obtain this, we divide this score by the total RSEI score for the firm, as reported in the *Toxic 100*:

$$\text{CEJP}_{rF} \equiv \text{RSEI Score}_{rF}/\text{RSEI Score}_{F} \tag{9}$$

Corporate EJ performance is a purely distributional measure, in that it does not distinguish between a disproportionate share of a small total human health impact and a disproportionate share of a large total impact. Later we examine the relationship between the corporate EJ measure and total pollution impacts.

To assess whether the share of impacts accruing to specific population groups is 'disproportionate', we must choose an appropriate counterfactual to define a 'proportionate' impact. The most straightforward benchmark for

[11] We have adjusted the RSEI data for 2005 for reporting changes to the Release Year 2005 TRI data that occurred after the TRI 2005 Public Data Release.

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this purpose is the share of the group in the national population. In the 2000 Census, racial and ethnic minorities[12] constituted 31.8% of the US population, and people living below the official poverty line were 12.9%.

Alternative benchmarks for assessing disproportionality include the share of the group in the population of the specific regions (e.g., states or metropolitan areas) in which the firm's facilities are located, or their share in the firm's labor force. A region-specific benchmark would be consistent with the view that the facility siting decisions of firms are often 'within-region' choices, constrained by the desire to locate within a certain part of the country for ease of access to input or output markets (Pastor *et al.*, 2001). An employment-based benchmark would provide a rough gauge of the balance between 'costs' and 'benefits' to specific groups, sometimes invoked in discussions of the supposed 'jobs-versus-environment' tradeoff. Both alternatives would apply different benchmarks to different firms, complicating the task of inter-firm comparisons.

Our corporate EJ measure can be compared to these and other benchmarks. In the tables presented here, we report national population shares as the most straightforward standard for comparison.[13] The basic comparison is between the share of the EJ group in the population and its share of the burden from toxic exposure.

It is also of interest to see how a specific firm compares with other firms. For this purpose, our tables also show group shares of human health hazards aggregated over all firms and facilities in the RSEI-GM database and aggregated over the universe of the large firms represented in the *Toxic 100*. For all firms, the share of minorities and the poor in 2005 were 34.8% and 15.3%, respectively (above their respective national population shares of 31.8% and 12.9%). The shares for the *Toxic 100* firms were slightly lower than for all firms, but still above the shares of these groups in the national population.

Inter-firm comparisons can also be made within specific industrial sectors. Aslaksen and Synnestvedt (2003), among others, identify the importance of 'best-in-class' approaches to relative and absolute investment screens. To illustrate the possibilities of the new corporate EJ performance measure, we report within-class corporate EJ measures for firms in the plastics and oil refining sectors below.

Results

Table 1 reports the corporate EJ performance *minority* measure for the top ten firms ranked on this basis from the firms in the Toxic 100. In all ten cases, more than half of the human health impacts resulting from the firm's air toxics releases are borne by minority groups. Two of these firms – ExxonMobil and Arcelor Mittal – also rank in the top ten of *The Toxic 100* itself; in other words, they rank very high in total pollution burden as well as the share of the burden borne by minorities. In both cases, the main subgroup contributing to the large impact on minorities is blacks. In the case of ExxonMobil, the black share of total human health impacts is 55.5% –the highest share of any firm in the Toxic 100.

Looking at the bottom three lines in Table 1, we can compare group shares of health hazards for all firms in the Toxic 100 and the entire RSEI-GM database to their shares in the US population. Again, the disproportionate burden borne by blacks is evident: their share of the total pollution burden (18.1%) is more than 50% greater than their share of the national population (11.8%). Although the US EJ literature began with analysis of disproportionate exposure of African Americans, or in some cases aggregated all nonwhites into a single category, recent entries including Ash and Fetter (2004), Anderton *et al.* (1994a, 1994b), Been (1994), and Pastor *et al.* (2001) have emphasized the importance of disaggregating minorities into more specific sub-categories. In the case of Hispanics, Asian-Pacific Islanders, and American Indians, their shares of the total pollution burden are somewhat below their shares of the national population. This is consistent with the finding of Ash and Fetter (2004) that within metropolitan statistical areas (MSAs), Hispanics tend to live in significantly more polluted neighborhoods than

[12] We classify as minority all persons reporting either Hispanic for ethnicity or a response other than white for race. The breakout columns for blacks, Asians and Pacific Islanders, American Indians refer to persons reporting exactly one race and non-Hispanic ethnicity. The breakout column for Hispanics may refer to people of any race. Because of the multiracial and other categories, the breakout columns do not sum to the total for minorities (US Bureau of the Census, 2001).

[13] The use of population shares as a benchmark means, of course, that it is possible for facilities or firms to have disproportionately high impacts on whites and the non-poor, as well as on minorities and the poor. We focus on the latter because these groups bear the greatest overall impacts and are the subject of EJ concern.

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	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share
National Oilwell Varco	78.0	22.3	53.0	2.0	0.7
ExxonMobil	69.1	55.5	10.4	2.2	0.3
General Dynamics	69.0	11.1	49.1	6.7	1.0
Hess	66.5	15.6	47.6	4.9	0.3
Freeport-McMoran Copper & Gold	62.1	2.9	57.1	0.5	1.6
Arcelor Mittal	61.6	46.6	12.5	1.3	0.3
Valero Energy	59.9	38.7	18.3	1.8	0.5
Akzo Nobel	58.6	44.4	10.4	2.4	0.3
Public Service Enterprise Group (PSEG)	57.0	18.2	26.8	10.1	0.4
Northrop Grumman	56.6	49.8	3.3	1.8	0.4
Toxic 100 Firms	34.2	19.8	10.5	2.1	0.5
All Firms	34.8	18.1	12.6	2.2	0.6
US Population	31.8	11.8	13.7	3.7	0.7

Table 1. Corporate Environmental Justice Performance: Minorities

	Poor Share
National Oilwell Varco	26.5
Hess	26.4
ExxonMobil	25.4
Akzo Nobel	25.2
Arcelor Mittal	24.9
Northrop Grumman	22.6
Archer Daniels Midland (ADM)	22.5
Rowan Cos.	21.6
Nucor	21.2
General Dynamics	20.9
Toxic 100 Firms	15.2
All Firms	15.3
US Population	12.9

Table 2. Corporate Environmental Justice Performance: People in Poverty

non-Hispanic whites, but that this effect is moderated in national-level data by the fact that Hispanics tend to live in MSAs that have less industrial toxic air pollution than the national average. By contrast, Ash and Fetter (2004) found that blacks not only live 'on the wrong side of the environmental tracks' at the MSA level, but also are concentrated in MSAs with above-average industrial air toxics pollution.

Table 2 reports the corporate EJ performance *poverty* measure, again for the top ten firms ranked on this basis from the Toxic 100. Not surprisingly, there is considerable overlap with Table 1: seven firms place in both lists. In the cases of the top two firms – National Oilwell Varco and Hess – the share of human health impacts borne by people living below the poverty line is more than double their share in the national population. Three firms that rank in the top ten by the corporate EJ poverty measure – ExxonMobil, Arcelor Mittal, and Archer Daniels Midland – also rank in the top ten of the *Toxic 100 Air Polluters* itself.

Appendix 1 presents these measures for all of the firms in the Toxic 100 universe, together with their Toxic 100 rank, number of TRI-reporting facilities, number of releases (i.e., chemical-facility combinations), and total human health hazard (RSEI) score. The firms with the highest shares for Hispanics, Asian/Pacific Islanders, and American

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Indians are, respectively, Freeport-McMoran Copper & Gold, Avery Dennison, and Northeast Utilities; in each case, the share of these subgroups in the firm's human health impacts is more than three times their share in the national population.

Environmental justice performance at the facility level

A firm's corporate EJ performance score reflects firmwide patterns of facility EJ performance, weighted by the extent to which its 'dirtiest' facilities (i.e., the facilities with the highest total RSEI scores) are located in places where the EJ shares are higher (or lower) than average.

To illustrate this point, we examine facility-level measures of EJ performance for ExxonMobil, the corporation with the highest share of total impacts borne by blacks. Table 3 presents data for the firm's top five facilities, ranked by RSEI scores, and for a composite of the fifty other ExxonMobil facilities that contribute to the firm's score. The top five facilities account for more than 90% of the corporate score, and their EJ performance will effectively determine the EJ performance of the entire company. It is evident that the top two facilities, both of which are in Baton Rouge, Louisiana, drive the result for blacks. It is also noteworthy that the next two facilities, refineries in Baytown, Texas, and Torrance, California, both have exceptionally large shares of Hispanics and, in the case of Torrance, Asian/Pacific-Islanders.

Within-class Rankings

This section investigates whether inter-firm differences in EJ performance persist within specific industrial sectors, taking as examples two particularly 'dirty' sectors, the manufacture of plastics (and other synthetic materials) and oil refining. Because firms often are diversified – owning facilities in a number of different industrial sectors – we restrict the comparison to facilities in the sectors of interest. The TRI and RSEI data include SIC (Standard Industrial Classification) codes for each reporting facility; we use these to select the relevant set of facilities for each firm.[14]

Tables 4 and 5 report the corporate EJ scores for firms in the oil and plastics/synthetics sectors, respectively. To conserve space, we report scores only for firms whose total human health hazard from air emissions from facilities in the relevant sector surpass a threshold level.[15]

	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share	Poor Share
Baton Rouge Refinery (LA)	62,269	78.0	75.3	1.1	1.0	0.1	31.1
Baton Rouge Chemical (LA)	24,748	73.1	70.0	1.2	1.1	0.1	29.1
Baytown Refinery (TX)	18,405	54.6	15.0	35.8	2.6	0.5	15.3
Torrance Refinery (CA)	6,710	69.9	10.8	40.9	15.5	0.7	15.1
Joliet Refinery (IL)	6,277	33.7	16.5	13.0	2.9	0.2	7.8
50 Additional Facilities	10,347	50.8	23.2	23.4	2.6	0.8	17.3
55 Total Facilities	128,758	69.1	55.5	10.4	2.2	0.3	25.4

Table 3. Minority and Poverty Shares of Airborne Human Health Risk: Exxon-Mobil Facilities

[14] Oil-refining facilities correspond to three-digit SIC code 291; plastics and synthetic materials manufacturing facilities correspond to four-digit SIC codes 2820-2824. Some facilities engage in production activities in multiple industrial sectors, for which they can report up to six SIC codes. We select all facilities that report production in the relevant codes. Starting with the TRI 2006 Public Data Release, SIC codes have been replaced by NAICS codes.
[15] As a cut-off, we use a combined RSEI score of 5,000 for the relevant facilities.

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	Facilities	Releases	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share	Poor Share
Pasadena Refining System Inc.	1	36	25,291	73.6	12.6	57.7	2.4	0.6	25.1
Hess	2	110	12,564	67.4	14.6	49.8	4.9	0.3	26.9
Chevron	7	432	5,584	66.2	17.4	31.9	13.3	0.6	18.9
ExxonMobil	8	564	115,370	65.5	51.9	10.2	2.4	0.3	24.6
Valero Energy	17	1,031	83,416	59.8	38.6	18.3	1.8	0.5	19.7
BP	6	386	48,841	56.2	16.4	32.6	5.8	0.6	16.3
Citgo Petroleum Corp.	7	314	29,364	47.8	28.5	15.7	2.3	0.4	19.4
Suncor Energy	1	35	20,378	45.3	6.9	33.6	2.5	1.3	12.9
Royal Dutch Shell	6	291	11,430	43.5	8.8	25.5	6.0	1.0	12.2
Motiva Enterprises L.L.C.	5	173	14,707	42.2	35.6	4.1	1.4	0.3	16.8
Sinclair Oil Corp.	3	171	12,459	35.3	18.2	6.8	1.1	5.3	20.3
ConocoPhillips	17	790	90,478	34.8	19.6	10.6	2.3	0.9	15.4
Sunoco	5	176	24,896	34.0	22.9	5.8	3.8	0.3	16.3
Marathon Oil	7	364	11,277	33.8	16.3	13.6	1.9	0.6	14.3
Tesoro	6	315	24,640	24.5	2.6	11.6	5.9	1.8	10.0
All Oil Refining	163	6,836	555,298	51.3	27.9	18.8	2.9	0.7	19.0
All Firms	102,636	16,470	14,576,982	34.8	18.1	12.6	2.2	0.6	15.3
US Population	–	–	–	31.8	11.8	13.7	3.7	0.7	12.9

Table 4. Minority and Poverty Shares of Airborne Human Health Risk: Oil Refining

The firms are ranked within-class on the basis of the share of human health impacts borne by minority groups.[16] In the case of the oil industry, the greatest minority-share rankings go to Pasadena Refining, ExxonMobil, Chevron, and Hess: minorities account for more than 65% of the impacts from their oil-refining facilities. Tesoro, Marathon Oil, and Sunoco achieve least minority-share rankings, with minorities accounting for less than 35% of the impacts, although Tesoro is the only ranked firm whose minority share of health impacts is below the minority share in the US population at large (31.8%).

In the case of the plastics and synthetic materials sector, Neville Chemical Co., Eastman Chemical, and General Electric achieve least minority-share rankings, with minorities accounting for no more than 10% of the impacts. The worst-in-class rankings in this sector go to BP, ExxonMobil, and Resinall Corporation, with minorities accounting for more than 60% of the impacts.

Total Human Health Impact and Corporate EJ Performance

The relationship between corporate environmental performance, here measured in terms of total human health impact from air toxics emissions at facilities owned by the firm, and corporate EJ performance is of interest for three reasons.

First, if the correlation between these two dimensions of performance were extremely high – i.e., the biggest polluters also had the biggest shares of minorities and the poor in the resulting health impacts – then the calculation of a separate corporate EJ performance measure might not be worth the effort: overall corporate environmental performance would tell us all we need to know.

[16] Rankings based on the share borne by people with incomes below the poverty line (reported in the last column of the tables) yield similar results.

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	Facilities	Releases	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share	Poor Share
BP	2	203	14,864	77.0	15.0	44.3	15.4	0.8	20.6
ExxonMobil	9	289	26,770	71.7	66.3	3.4	1.2	0.2	28.3
Resinall Corp.	2	21	14,150	62.5	60.2	1.2	0.3	0.4	32.3
Goodyear	2	30	6,185	58.6	20.7	33.7	3.3	0.4	18.5
Royal Dutch Shell	1	63	8,824	48.2	10.3	34.2	2.7	0.5	13.0
Georgia Gulf Corp.	3	135	11,138	45.7	41.7	1.8	1.3	0.3	22.5
Dow Chemical	23	1,181	62,806	43.4	17.1	23.9	1.3	0.4	15.0
Apollo Mgt. (Hexion Specialty Chem.)	23	370	62,766	40.3	14.8	22.1	2.1	0.5	13.2
Hercules Inc.	5	32	7,366	40.2	21.5	15.3	1.7	0.5	20.8
Witco Corp.	2	62	6,553	38.8	34.5	2.3	1.1	0.2	16.9
Westlake Olefins Corp.	4	42	6,352	38.3	34.1	2.0	1.2	0.2	16.5
E.I. du Pont de Nemours	25	732	222,229	37.1	31.6	2.8	1.0	0.3	17.9
Michelin Group	1	17	5,436	35.5	31.5	1.5	0.7	0.2	17.0
Stepan Co.	1	25	12,345	35.1	18.2	12.8	2.8	0.2	8.2
BASF	13	140	22,579	31.3	22.8	4.7	1.4	0.4	13.0
Solutia Inc.	5	72	6,336	29.0	20.5	5.6	0.9	0.9	15.2
Invista S. A. R. L.	7	106	17,580	26.5	20.1	3.8	0.6	0.5	13.7
Rohm and Haas	14	323	7,955	25.1	17.1	2.7	3.6	0.3	21.3
U. S. Polymers Accurez LLC	1	10	8,397	24.8	17.6	3.0	1.6	0.4	18.3
Innovene USA LLC	3	69	5,404	24.1	19.1	1.9	0.6	0.2	16.7
Lubrizol Corp.	8	147	10,211	21.1	14.7	2.7	1.7	0.3	12.7
Mitsubishi Chemical	2	20	6,906	20.8	12.5	4.3	2.6	0.2	10.6
Lanxess	3	43	10,549	17.4	11.7	2.8	1.5	0.2	9.9
Zeon Chemicals LP	2	23	14,759	17.0	11.5	2.1	1.6	0.2	8.7
Cytec Industries Inc.	7	108	10,957	12.3	6.0	3.2	1.1	0.5	14.1
High Voltage Engineering Corp.	1	4	6,555	11.2	3.0	5.5	1.9	0.2	6.2
General Electric	8	225	12,541	10.0	5.6	2.0	1.0	0.2	11.5
Eastman Chemical	4	252	98,292	9.9	6.4	1.7	0.6	0.2	15.1
Neville Chemical Co.	1	22	28,498	7.6	4.9	0.6	1.2	0.1	6.6
All Plastics	543	8,898	847,404	34.1	22.6	8.3	1.6	0.3	16.0
All Firms	102,636	16,470	14,576,982	34.8	18.1	12.6	2.2	0.6	15.3
US Population	–	–	–	31.8	11.8	13.7	3.7	0.7	12.9

Table 5. Minority and Poverty Shares of Airborne Human Health Risk: Plastics and Synthetic Materials

Second, there are plausible *a priori* reasons to expect that the correlation between the two will be positive, albeit imperfect. The reason is that where inequalities of power and wealth between polluters and the 'pollutees' who bear environmental costs are larger, one outcome is likely to be a larger overall magnitude of pollution. Wealth inequalities can yield this result under the standard assumptions of benefit-cost analysis, in which the value of an adverse health impact is measured in terms of a person's willingness to pay to avoid it. To put matters bluntly, in this calculus the health and lives of the poor are worth less than those of the rich. Where the society's decisions about environmental policies are shaped by political influence, in addition to benefit-cost calculations, power inequalities can further contribute to this outcome. For example, Boyce (2002) has suggested that environmental policies are governed by a 'power-weighted social decision rule', in which what matters are not only the monetary

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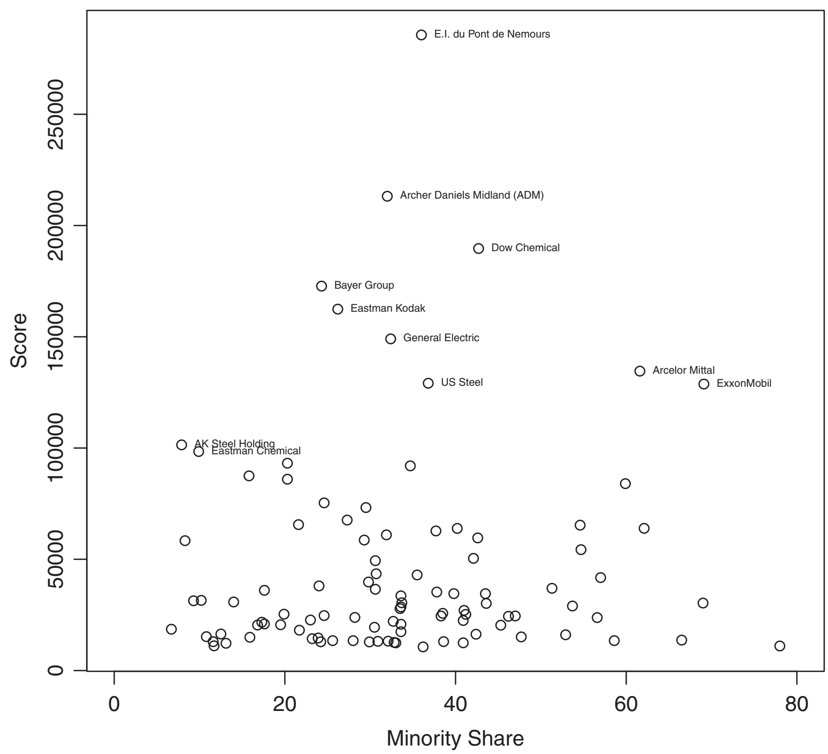

Figure 1. Total Human Health Impact and CEJP for Minorities: Toxic 100
Source: Toxic 100 Corporate RSEI Score and Appendix 1.

values of costs and benefits but also the power of the parties to whom these accrue. The relationship between corporate environmental performance and corporate EJ performance can provide one test of this hypothesis.

A final reason why this relationship is worth examining is that if, instead of a positive correlation, the two were inversely related – such that disproportionate impacts were concentrated among relatively minor polluters – then this might mitigate, to some degree, findings of environmental injustice.

To examine this relationship, we plotted total RSEI scores against our corporate EJ measures for the firms appearing in the *Toxic 100*. The results are shown in Figures 1 and 2 for the corporate EJ minority and poverty measures, respectively.

In both cases, the plots show a weak positive relationship, consistent with the expectation that the overall magnitude of pollution will be correlated with the distribution of the resulting burdens, but not so strongly correlated as to obviate the need for measures of the latter. The relationship between overall corporate environmental performance and corporate EJ performance is an obvious direction for future research.

Conclusions

The measure of corporate EJ performance presented in this paper provides meaningful new information on an important dimension of corporate behavior. For ethical reasons, it is of interest to know not only how much pollution is released by a firm's industrial facilities, but also how the resulting human health impacts are distributed across racial, ethnic, and income groups. The corporate EJ performance measure provides this information.

Apart from ethical concerns, there may be good legal and financial reasons for corporations and investors to pay attention to this dimension of firm performance. EJ, defined in terms of both race/ethnicity and income class,

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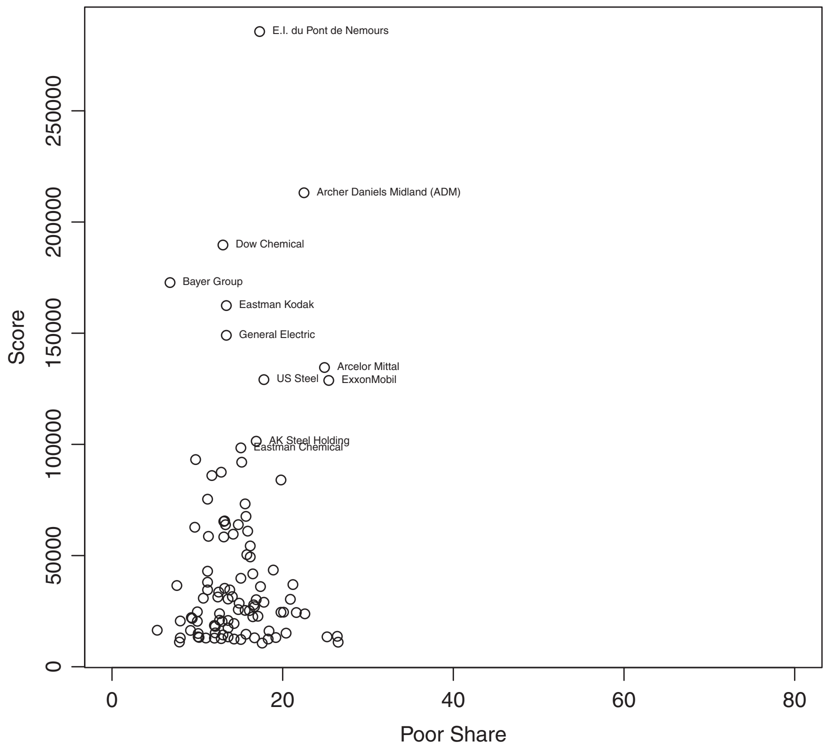

Figure 2. Total Human Health Impact and CEJP for Poverty: Toxic 100
Source: Toxic 100 Corporate RSEI score and Appendix 1.

became an explicit objective in federal government policy making in 1994, when President Clinton signed Executive Order 12898 directing each government agency to take steps to identify and rectify 'disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income populations'. In the case of minorities, moreover, systematically disproportionate burdens could prove to be grounds for legal challenges under the US Civil Rights Act.[17] Public and private responses could translate environmental injustice into legal or social liabilities that affect the firm's bottom line. Aslaksen and Synnestvedt (2003) investigate the possibilities for this type of translation further.

Regular measurement of corporate EJ performance can provide stakeholders – investors, managers, regulators, consumers, and residents of affected communities – with a report card for assessing levels and changes in performance. Furthermore, because the fate-and-dispersion model can be used to estimate concentrations from hypothetical releases, it can be used to predict the environmental and EJ impacts of planned expansions or decreases in air toxics emissions.

The method developed here meets the challenge posed by Sullivan and Gouldson (2007) to expand the informational breadth of pollutant release and transfer registers and to place emissions into the broader context of local conditions. This low-cost method uses existing, mandatory, and standardized data to improve the level of information about CSR.

The corporate EJ performance measure is scalable, and as we have demonstrated, it can be used to compare both firms and facilities within firms. It can be readily extended to industrial sectors, specific chemicals, or other classifications of industrial point-source pollution.

[17] For discussion of this and other bases of legal challenges to environmental disparities, see Yang (2002) and Rechtschaffen *et al*. (2009).

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We believe that the joint measurement of total impact and disparate impacts provides the most robust picture of corporate environmental performance. Although correlated, neither measure adequately conveys information about the other. Both dimensions are relevant, and both should – and can – be incorporated into the assessment of CSR.

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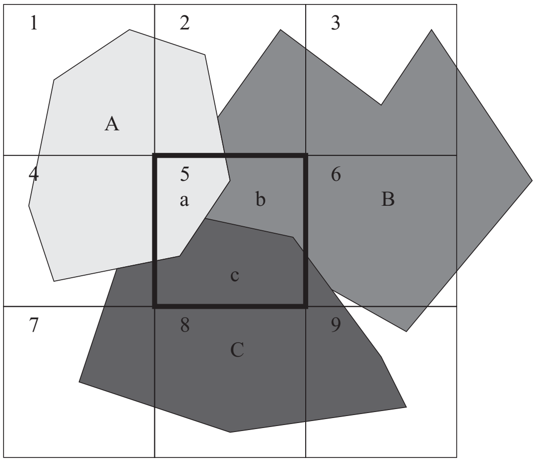
Appendix 1: Diagram for Spatial Join

The diagram illustrates how Census blocks are apportioned to RSEI grid cells in Equation (4). The Census blocks are represented by the irregular polygons A, B, and C. The grid cells are represented by the squares 1,2, … ,9.



We give as an example the apportioning Census block populations to grid cell 5. Let $a \subset A$, $b \subset B$, $c \subset C$ be the area of Census blocks A, B, and C that intersects grid cell 5. Thus, $\alpha_{5A} = a/A$ is the percentage of Census block A that lies in grid cell 5. (These α are available from US EPA.) We assume that population is evenly distributed within each block and, hence, that $\alpha_{5A} = a/A$ of the population of Census block A lives in grid cell 5.

The population of grid cell 5 is constructed as

$$\text{Population}_5 = \alpha_{5A} \times \text{Population}_A + \alpha_{5B} \times \text{Population}_B + \alpha_{5C} \times \text{Population}_C$$

which is equivalent to Equation (4). We use an identical procedure for sub-populations by age, sex, and race.

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	Toxic 100 Rank	Facilities	Releases	RSEI Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share	Poor Share
E.I. du Pont de Nemours	1	58	1,277	285,661	36.0	29.9	3.4	1.0	0.4	17.3
Archer Daniels Midland (ADM)	2	34	211	213,159	32.0	25.9	2.7	1.1	0.2	22.5
Dow Chemical	3	41	1,415	189,673	42.7	15.0	23.6	2.8	0.4	13.0
Bayer Group	4	16	289	172,773	24.3	3.2	18.5	1.4	0.4	6.8
Eastman Kodak	5	6	142	162,430	26.2	14.2	8.2	2.0	0.3	13.4
General Electric	6	130	828	149,061	32.4	11.7	16.1	2.7	0.5	13.4
Arcelor Mittal	7	24	304	134,573	61.6	46.6	12.5	1.3	0.3	24.9
US Steel	8	12	281	129,123	36.8	29.3	4.6	0.9	0.4	17.8
ExxonMobil	9	55	1,452	128,758	69.1	55.5	10.4	2.2	0.3	25.4
AK Steel Holding	10	9	124	101,428	7.9	5.0	0.9	0.7	0.2	16.9
Eastman Chemical	11	5	284	98,432	9.9	6.4	1.7	0.6	0.2	15.1
Duke Energy	12	22	410	93,174	20.3	14.7	2.9	1.5	0.3	9.8
ConocoPhillips	13	45	1,269	91,993	34.7	19.6	10.4	2.5	0.9	15.2
Precision Castparts	14	29	195	87,500	15.8	5.0	5.3	2.7	0.6	12.8
Alcoa	15	61	574	85,983	20.3	11.1	5.2	1.5	1.2	11.7
Valero Energy	16	36	1,442	83,993	59.9	38.7	18.3	1.8	0.5	19.8
Ford Motor	17	35	444	75,360	24.6	15.4	5.1	2.0	0.3	11.2
General Motors	18	45	662	73,248	29.5	17.9	7.3	1.7	0.4	15.6
Goodyear	19	27	211	67,632	27.3	19.1	4.3	1.6	0.4	15.7
E.ON	20	10	194	65,579	21.6	17.1	1.8	1.1	0.2	13.2
Matsushita Electric Indl	21	4	18	65,346	54.6	48.1	3.6	1.4	0.3	13.1
Freeport-McMoran Copper & Gold	22	18	168	63,911	62.1	2.9	57.1	0.5	1.6	14.8
Apollo Mgt. (Hexion Specialty Chemicals)	23	35	423	63,880	40.2	14.9	21.9	2.1	0.6	13.3
Avery Dennison	24	13	102	62,740	37.7	8.3	14.4	12.7	0.2	9.7
BASF	25	45	603	60,984	31.9	24.5	4.3	1.1	0.3	15.9
Owens Corning	26	37	143	59,609	42.6	14.2	22.0	4.4	0.5	14.2
Dominion Resources	27	19	196	58,642	29.3	21.4	3.5	2.2	0.3	11.3
Allegheny Technologies	28	29	168	58,375	8.3	5.2	1.2	0.6	0.2	13.1
BP	29	58	1,271	54,336	54.7	16.9	30.9	5.4	0.7	16.2
Honeywell International	30	57	411	50,417	42.1	30.3	8.8	1.9	0.3	15.8
International Paper	31	52	608	49,385	30.6	25.5	2.6	1.0	0.4	16.2
Ashland	32	67	646	43,492	30.7	20.6	5.9	1.6	0.3	18.9
Constellation Energy	33	14	108	42,972	35.5	21.5	10.2	2.1	0.3	11.2
Public Service Enterprise Group (PSEG)	34	9	97	41,773	57.0	18.2	26.8	10.1	0.4	16.5
AES	35	14	191	39,789	29.8	14.0	13.9	1.2	0.3	15.1
Progress Energy	36	14	234	38,027	24.0	12.3	7.7	2.1	0.6	11.2
Nucor	37	29	317	36,963	51.3	46.9	2.6	0.7	0.3	21.2
United Technologies	38	42	150	36,526	30.6	21.7	5.7	2.0	0.3	7.6
Timken	39	15	79	36,047	17.6	12.9	1.1	0.5	0.4	17.4
Berkshire Hathaway	40	62	419	35,285	37.8	24.3	10.1	1.5	0.7	13.2
SPX	41	12	49	34,559	39.8	19.6	14.6	3.2	0.5	11.2
Royal Dutch Shell	42	19	609	34,556	43.5	17.3	20.4	3.8	0.7	13.8
Southern Co	43	22	306	33,577	33.6	26.2	4.2	1.7	0.4	12.5
Allegheny Energy	44	9	159	31,539	10.2	7.1	0.8	1.0	0.2	14.1
American Electric	45	20	524	31,364	9.3	5.7	1.2	0.7	0.4	12.4
Reliant Energy	46	15	260	30,821	14.0	8.1	3.5	1.2	0.2	10.7
Boeing	47	12	113	30,453	33.7	12.3	11.1	6.1	1.3	13.6
General Dynamics	48	16	67	30,337	69.0	11.1	49.1	6.7	1.0	20.9
Occidental Petroleum	49	21	391	30,167	43.6	30.8	9.7	1.6	0.4	16.9
KeySpan	50	4	40	29,008	53.7	18.2	24.7	9.1	0.5	17.8

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	Toxic 100 Rank	Facilities	Releases	RSEI Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Am. Ind. Share	Poor Share
Lyondell Chemical	51	25	501	28,591	33.6	11.8	18.5	1.9	0.3	14.9
Sunoco	52	40	774	27,851	33.5	22.2	6.1	3.6	0.3	16.6
Anheuser-Busch Cos	53	21	79	27,032	41.0	30.1	6.5	2.4	0.4	16.7
Ball	54	30	184	25,709	38.5	11.3	21.4	4.1	0.6	14.8
Deere & Co	55	10	67	25,346	19.9	6.8	10.2	1.1	0.4	15.6
Procter & Gamble	56	23	108	25,238	41.2	36.6	2.4	1.1	0.2	16.1
Tesoro	57	8	361	24,708	24.6	2.6	11.6	5.9	1.8	10.0
Temple-Inland	58	19	120	24,537	47.0	24.8	21.2	0.5	0.4	20.1
Pfizer	59	17	231	24,508	38.3	19.5	13.9	2.5	0.5	19.8
Rowan Cos.	60	2	21	24,389	46.2	30.3	13.6	0.7	0.5	21.6
Leggett & Platt	61	36	69	23,870	28.2	5.5	18.6	1.8	1.0	12.6
Northrop Grumman	62	14	87	23,798	56.6	49.8	3.3	1.8	0.4	22.6
Weyerhaeuser	63	49	476	22,708	23.0	15.1	4.0	1.1	1.1	17.1
Rohm and Haas	64	37	584	22,489	40.9	15.1	21.4	3.1	0.4	16.5
Tyco International	65	29	215	22,115	32.7	16.6	10.6	3.0	0.7	9.3
Terex	66	11	31	21,730	17.3	4.9	4.6	4.4	0.6	9.4
Corning	67	6	26	20,942	17.6	12.6	2.4	1.2	0.3	12.6
Exelon	68	5	53	20,811	33.6	24.2	4.9	3.3	0.2	13.6
Fortune Brands	69	22	103	20,583	19.5	8.0	9.4	0.8	0.5	8.0
FirstEnergy	70	7	158	20,441	16.8	12.7	1.7	1.1	0.1	10.0
Suncor Energy	71	1	35	20,378	45.3	6.9	33.6	2.5	1.3	12.9
Crown Holdings	72	23	137	19,447	30.5	8.0	17.9	3.6	0.5	14.3
Masco	73	34	148	18,572	6.7	1.3	2.8	1.4	0.4	12.0
ThyssenKrupp Group	74	16	130	18,133	21.7	12.0	7.3	1.2	0.5	12.1
Textron	75	13	69	17,443	33.6	24.5	4.9	1.6	0.7	13.6
Sony	76	6	36	16,426	12.5	7.4	2.1	2.0	0.2	5.3
Mirant	77	9	138	16,337	42.4	24.9	10.6	4.6	0.4	9.2
RAG	78	31	252	16,080	52.9	45.6	4.2	1.5	0.5	18.4
Alcan	79	11	51	15,231	10.8	6.6	2.2	0.6	0.2	12.1
Huntsman	80	17	280	15,119	47.7	35.0	9.3	2.2	0.4	20.4
Bridgestone	81	30	155	14,952	15.9	8.7	4.0	1.5	0.4	10.1
Danaher	82	22	46	14,621	23.9	3.9	15.8	2.1	0.9	15.7
PPG Industries	83	30	496	14,300	23.2	16.7	3.9	1.1	0.3	13.0
Hess	84	24	457	13,687	66.5	15.6	47.6	4.9	0.3	26.4
Akzo Nobel	85	27	371	13,453	58.6	44.4	10.4	2.4	0.3	25.2
Dynegy Inc.	86	7	107	13,439	25.6	13.2	8.9	2.1	0.3	10.1
Federal-Mogul	87	25	118	13,435	28.0	21.5	3.5	1.3	0.3	13.6
Stanley Works	88	8	30	13,196	32.1	23.3	5.7	1.7	0.4	10.2
Komatsu	89	2	4	13,132	30.9	23.2	4.0	1.0	0.3	19.2
Saint-Gobain	90	55	159	13,012	38.6	23.5	10.2	3.0	0.6	16.7
PPL	91	4	83	12,972	11.6	4.3	4.6	1.6	0.2	8.0
Caterpillar	92	13	56	12,924	24.2	11.9	8.6	1.7	0.2	11.0
Smurfit-Stone Container	93	30	244	12,868	29.9	23.1	3.1	1.6	0.7	12.0
Siemens	94	22	66	12,649	32.8	18.3	10.5	2.1	0.4	12.8
MeadWestvaco	95	10	214	12,465	40.9	34.0	4.0	1.4	0.4	18.3
Marathon Oil	96	37	705	12,454	33.0	16.3	12.9	1.9	0.5	14.3
Emerson Electric	97	39	110	12,258	13.1	7.2	3.7	0.9	0.3	15.1
Northeast Utilities	98	5	84	11,115	11.7	1.4	5.0	1.4	3.1	7.9
National Oilwell Varco	99	7	25	11,042	78.0	22.3	53.0	2.0	0.7	26.5
Dana	100	18	49	10,638	36.2	29.4	5.3	0.4	0.2	17.6
Toxic 100 Firms	–	2,518	30,965	4,724,094	34.2	19.8	10.5	2.1	0.5	15.2
All Firms	–	102,636	16,470	14,576,982	34.8	18.1	12.6	2.2	0.6	15.3
US Population	–	–	–	–	31.8	11.8	13.7	3.7	0.7	12.9

Appendix Table 1. Minority and Poverty Shares of Airborne Human Health Risk: Toxic 100 Corporations

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