2008

Measuring Corporate Environmental Justice Performance

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DEPARTMENT OF ECONOMICS

Working Paper

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Working Paper 2008-16

UNIVERSITY OF MASSACHUSETTS AMHERST

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October 31, 2008

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 low-income people. Applying the measure to 100 major corporate air polluters in the United States, we find wide variation in the extent of disproportional exposures. In a number of cases, minorities bear more than half of the total human health impacts from the firm's industrial air pollution.

Keywords: Corporate social responsibility; corporate environmental performance; environmental justice; air pollution

JEL codes: M14, Q52, Q56

1 Introduction

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

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The difference between CEP and EJ studies is partly methodological: in CEP, the unit of analysis is the source of pollution, the firm or an individual facility; in EJ, the unit of analysis is the receptor, the community or households on the receiving end. They also differ in their audiences and aims. The main audience for CEP research is 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 the responsible government officials, the main aim being to protect communities from disproportionate hazards.

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

In Section 2, we describe the datasets and methodology for matching the exposure and Census data. Our environmental data come from a source-and-receptor model of air-toxics release and exposure from the U.S. Environment Protection Agency (EPA). We merge the EPA data with socioeconomic data from the U.S. 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 (PERI) of the University of Massachusetts, Amherst.

In Section 3, we present the CEJP measure, and report the results of applying it to 100 corporations operating throughout the United States. The corporations are those listed in the latest edition of PERI's "Toxic 100," which uses the same data sources to rank the largest firms in the country on the basis of total human health hazards resulting from air toxics emissions at their facilities.

In Section 4, we present "worst-in-class" and "best-in-class" rankings for firms in two industrial sectors that rank high in their air toxics 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.[1] Whether the exposure patterns at individual facilities can be generalized to overall corporate behavior is seldom evident. Academic EJ researchers generally have focused on the aggregate pollution loads imposed on people of color and low-income communities, rather than identifying specific sources of these burdens.[2] Whatever the overall extent of disproportionate impacts, there is no reason to assume that disparities are constant across firms. We show that the extent to which firms even in the same industrial sector impose disparate pollution burdens on different groups can and does vary substantially.

In Section 5, we examine the relationship between CEJP and the measure of total human health risk for the Toxic 100, with the dual aims of assessing whether a measure of

[1] On the Anniston case, see U.S. Senate Committee on Appropriations [2002] and Bryan [2003].
[2] See, for example, Ash and Fetter [2004], Pastor et al. [2006], and Mohai and Saha [2007].

environmental justice performance adds value to a more conventional measure of CEP, and of testing the hypothesis that performance in these two dimensions, while not identical, is positively correlated.

In Section 6, we conclude by discussing potential uses of these data in research on the determinants and effects of CEJP and in efforts to improve corporate performance.

2 Data and Methods

The underlying data for the CEJP measure come from three sources: the EPA's Risk-Screening Environmental Indicators (RSEI); the 2000 U.S. Census of Population and Housing; and the PERI corporation-facility identification dataset. This section describes these data sources and how we merge them in order to construct our measure of corporate environmental justice performance.

2.1 The RSEI project

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

2.1.1 The RSEI Project and 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). It 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 square kilometer of a 101 km $\times$ 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 one km-sq 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 CEP and EJ literature: CEP 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. But 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 (OPPT) 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) 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 square kilometer within a 101 km by 101 km grid (10,201 sq km) around each facility.

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 (OPP) Reference Dose Tracking Reports; the U.S. Department of Health and Human Services Agency for Toxic Substances and Disease Registry (ATSDR); the California Environmental Protection Agency (CalEPA) Office of Environmental Health Hazard and Assessment (OEHHA); and the EPA's Health Effects Assessment Tables (HEAST). For some chemicals listed in the

[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.

[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].

TRI, no consensus has been reached on the appropriate toxicity weight, and these chemicals are currently excluded from the RSEI public-release data. In recent years, the excluded chemicals have represented about one percent of the total mass of reported toxic air releases nationwide.

Although all TRI chemicals are hazardous, their toxicities 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 (for example, "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 project overlays the grid of toxicity-weighted air pollution concentrations upon a grid of population data drawn from block-level data from the U.S. 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 one-square-kilometer 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.[5]

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

$$\text{RSEI Score}_{fcg} = \sum_a \sum_s \text{Populaton}_{asg} \times \text{IEF}_{as} \times \text{Toxicity}_c \times \text{Concentration}_{fcg} \tag{2.1}$$

where Populaton_{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 from the plume model at cell g for chemical c released by facility f.

The release-cell score, measuring the impact of a given release on a given cell, represents the total human health risk for the population exposed 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

[5]The population-exposure values reflect the cubic meters of air inhaled by a person (roughly 20 cubic meters per 70 kg) per day. Inhalation exposure factors ranging from 0.165 to 0.341 are used to convert toxicity-weighted air concentrations into human exposures, according to the following formula: 0.341×(count of males, aged 0 to 17) + 0.209×(males, 18 to 44) + 0.194×(males, 45 to 64) + 0.174×(males, 65 and Up) + 0.310×(females, aged 0 to 17) + 0.186×(females, 18 to 44) + 0.165×(females, 45 to 64) + 0.153×(females, 65 and Up).

aggregated (across chemicals and cells) on a facility-by-facility basis:

$$\text{RSEI Score}_f = \sum_c \sum_g \text{RSEI Score}_{fcg} \tag{2.2}$$

The facility-wise RSEI scores are made available to government agencies and the public on the RSEI public-release data CD-ROM, 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 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]

2.1.2 The RSEI Geographic Microdata (RSEI-GM)

Because EPA developed the RSEI data for the purpose of prioritizing facilities (that is, sources) for enforcement and clean-up, the public-release data are not designed for examining differences among communities (that is, receptors) in terms of their exposure to industrial toxic releases. The CEJP 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 a cell g is

$$\text{RSEI Score}_g = \sum_f \sum_c \text{RSEI Score}_{fcg} \tag{2.3}$$

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. These studies found statistically significant evidence of disproportionate impacts, both by race and ethnicity (controlling for income) and by income (controlling for race and ethnicity).

To develop corporation-specific measures of EJ performance, we must use the fully disaggregated geographic microdata, which identify impacts by source facility and receptor cell

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

(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 percent 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.

2. Fate, transport, and exposure modeling of all national releases 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.[7] The focus on exposure at the receptor site outflanks the "How near is near?" debate in the environmental justice literature as to what distance best fits the notion of "closeness" to a point source (for discussion, see 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 Global Emissions Monitoring System (GEMS) and other pollution-exposure data based on aggregate levels of pollutants at the receptor site, the RSEI-GM makes it possible to track each exposure to its source. The simultaneous identification of source and exposure is perhaps the most important and distinctive strength of the RSEI-GM.

4. Nearly twenty years of annual data spanning the decennial Censuses of 1990 and 2000. The RSEI-GM time series makes it possible to conduct innovative temporal analysis. Much of the debate over causality and policy in the environmental justice literature has revolved around matters of timing: which came first, the people or the pollution? Longitudinal studies can help us understand the dynamic processes of demographic and environmental change.

5. 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.

6. 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.

In summary, the RSEI-GM database offers a remarkable tool for the analysis of environmental justice issues in the United States. Its fine geographic resolution exceeds that

[7]The 1 square-km resolution of the data does not exhaust the power of the plume model; rather, the trade-off between geographic specificity and database size determines the scale.

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 and improving industrial sectors and processes. The linkage of release and exposure—that is, source and receptor—provided by the RSEI-GM is unparalleled by any other national dataset. The longitudinal character of the 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 environmental justice performance.

2.2 Census of Population & Housing: The Spatial Join

The 2000 U.S. 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.[8] 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 one-square-kilometer cells, of which seven million are within the 101 km $\times$ 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 larger or smaller than one square kilometer. 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 km^2 grid-cell data.[9] For every cell, the crosswalk calculates the fraction of the total area of each block that falls into it. In this way we can count, by age category and sex, the number of poor people, blacks, Latinos, Asian-Americans, Native Americans, and non-Hispanic whites in each of the 1 km^2 cells:

$$\text{Population}_{rasg} = \sum_b \alpha_{gb} \times \text{Population}_{rasb} \tag{2.4}$$

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 share of Census block b that lies in grid cell g. The year 2000 Population_{rasb} of Census

[8] Block groups fully partition Census tracts, the next level of aggregation, which on average contain 4,000 residents.

[9] 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, and the University of California, Berkeley.

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.

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 km^2 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:

$$\text{RSEI Score}_{rfcg} = \sum_a \sum_s \text{Populaton}_{rasg} \times \text{IEF}_{as} \times \text{Toxicity}_c \times \text{Concentration}_{fcg} \quad (2.5)$$

where Population_{rasg} is the race or ethnicity r, age a, and sex s population of 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:

$$\text{RSEI Score}_{rfc} = \sum_g \text{RSEI Score}_{rfcg} \quad (2.6)$$

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

$$\text{RSEI Score}_{rf} = \sum_c \sum_g \text{RSEI Score}_{rfcg} \quad (2.7)$$

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.

2.3 Corporation-facility matching

To develop corporate performance measures, one more step is required: matching individual facilities to their corporate parents. PERI's Corporate Toxics Information Project (CTIP) has developed a dataset for this 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 CTIP matches facilities to their parent companies.

By aggregating the RSEI scores of the facilities owned by individual parent companies, the CTIP produces "The Toxic 100," a ranking of the largest corporations operating in the

[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×(0.209 + 0.186)/2 + 20/47×(0.194+0.165))/2) = 0.190 for persons aged 18 to 64.

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 U.S.-based and 500 foreign-based corporations. The most recent available RSEI data from EPA refer to the year 2005. 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.

3 A Measure of Corporate Environmental Justice Performance

In this section we present our measure of corporate environmental justice performance (CEJP) for the 100 large firms that appear in the latest edition of PERI's Toxic 100. 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 U.S. population. Two CEJP 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.

3.1 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:

$$\text{RSEI Score}_{rF} = \sum_{f \in F} \text{RSEI Score}_{rf} \tag{3.1}$$

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

Our CEJP 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:

$$\text{CEJP}_{rF} \equiv \text{RSEI Score}_{rF}/\text{RSEI Score}_{F} \tag{3.2}$$

CEJP 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. We examine the relationship between the CEJP measure and total pollution impacts in Section 5.

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 this purpose is the share of the group in the national population. In the 2000 Census, racial and ethnic minorities[11] constituted 31.8

[11] We classify as minority all persons reporting either Hispanic for ethnicity or a response other than white

percent of the U.S. population, and people living below the official poverty line were 12.9 percent.

Alternative benchmarks for assessing disproportionality include the share of the group in the population of the specific regions—for example, 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 CEJP measure can be compared to these and other benchmarks. In the tables presented here, we report national population shares as the simplest, and for our purposes most robust, standard for comparison.

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 percent and 15.3 percent, respectively (above their respective national population shares of 31.8 percent and 12.9 percent). 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. To illustrate, we report "best-in-class" and "worst-in-class" CEJP measures for firms in the plastics and oil refining sectors below.

3.2 Results

Table 1 reports the CEJP 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— Exxon Mobil 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 Exxon Mobil, the black share of total human health impacts is 55.5 percent—the highest share of any firm in the Toxic 100.

[INSERT TABLE 1 HERE]

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

for race. The breakout columns for blacks, Asians and Pacific Islanders, Native Americans 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.

the U.S. population. Again, the disproportionate burden borne by blacks is evident: their share of the total pollution burden (18.1 percent) is more than 50 percent greater than their share of the national population (11.8 percent). 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 non-Hispanic whites, but that this effect is moderated in national-level data by the fact that they tend to live in MSAs that have less industrial toxic air pollution than the national average. In the case of blacks, by contrast, Ash and Fetter (2004) found that they 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 CEJP 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 CEJP poverty measure—Exxon Mobil, Arcelor Mittal, and Archer Daniels Midland—also rank in the top ten of the Toxic 100 itself.

[INSERT TABLE 2 HERE]

The Appendix Table 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 (that is, chemical-facility combinations), and total human health hazard (RSEI) score. The firms with the highest shares for Hispanics, Asian/Pacific Islanders, and Native Americans 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.

3.3 Environmental justice performance at the facility level

Two factors enter into a firm's CEJP score. The first is the share of minority or poverty groups in the human health impacts of all its facilities, averaged over the number of facilities. The second is the extent to which its "dirtiest" facilities—that is, the facilities with the highest total RSEI scores—are located in places where these shares are higher (or lower) than average.

To illustrate this point, we examine facility-level measures of environmental justice performance for Exxon Mobil, 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 Exxon Mobil facilities that contribute to the firm's score. 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.

[INSERT TABLE 3 HERE]

4 Best and worst "in class" rankings

This section investigates whether inter-firm differences in environmental justice 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.[12]

Tables 4 and 5 report the CEJP 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.[13]

The firms are ranked from "best-in-class" to "worst-in-class" on the basis of the share of human health impacts borne by minority groups.[14] In the case of the oil industry, Tesoro, Marathon Oil, and Sunoco achieve best-in-class rankings, with minorities accounting for less than 35 percent of the impacts, although Tesoro is the only ranked firm whose minority share of health impacts is below the minority share in the U.S. population at large (31.8 percent). The worst-in-class rankings go to Pasadena Refining, ExxonMobil, and Hess: minorities account for more than 67 percent of the impacts from their oil-refining facilities.

[INSERT TABLE 4 HERE]

In the case of the plastics and synthetic materials sector, Neville Chemical Co., Eastman Chemical, and High Voltage Engineering Corporation achieve best-in-class rankings, with minorities accounting for less than 12 percent 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 percent of the impacts.

[INSERT TABLE 5 HERE]

5 Total Human Health Impact and CEJP

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

First, if the correlation between these two dimensions of performance were extremely high—that is, the biggest polluters also had the biggest shares of minorities and the poor in

[12] 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.

[13] As a cutoff, we use a combined RSEI score of 5,000 for the relevant facilities.

[14] 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.

the resulting health impacts—then the calculation of a separate CEJP measure might not be worth the effort: CEP would tell us all we need to know.

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 is not only the monetary values of costs and benefits but also the power of the parties to whom these accrue. The relationship between CEP and CEJP 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 disproportional impacts were concentrated among relatively minor polluters—then this might mitigate, to some degree, findings of environmental injustice.

To examine this relationship, we looked at plotted total RSEI scores against our CEJP measures for the firms appearing in The Toxic 100. The results are shown in Figures 1 and 2 for the CEJP minority and poverty measures, respectively. In both cases, the results 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.

[INSERT FIGURES 1 & 2 HERE]

Fitting linear regression lines to the 100 observations in each figure, we find that as the minority share rises from 0 to 80 percent, the extent of observed variation, the predicted human health hazard rises by 27 percent. As the poverty share rises from 0 to 30 percent, the small range of variation in poverty shares, the predicted human health hazard rises by 150 percent.

6 Conclusions

The measure of corporate environmental justice performance (CEJP) 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 CEJP 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. Environmental justice—defined in terms of both race/ethnicity and income class—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 U.S. Civil Rights Act. Public and private responses could translate environmental injustice into liabilities that affect the firm's bottom line.

Regular measurement of CEJP 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 CEJP measure is scalable, and as we demonstrated above, it can be used to compare both firms and facilities within firms. It can be readily extended to specific industrial sectors, specific chemicals, or other classifications of industrial point-source pollution.

We believe that the joint measurement of total impact (CEP) and disparate impacts (CEJP) 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 corporate behavior.

References

Michael Ash and T. Robert Fetter. Who Lives on the Wrong Side of the Environmental Tracks? *Social Science Quarterly*, 85(2):441–462, 2004.

Nicolaas W. Bouwes, Steven Hassur, and Marc Shapiro. Information for Empowerment: The EPA's Risk-Screening Environmental Indicators Project. In James K. Boyce and Barry G. Shelley, editors, *Natural Assets: Democratizing Environmental Ownership*, pages 135–150. Washington, DC: Island Press, 2003.

James K. Boyce. *The Political Economy of the Environment*. Edward Elgar, 2002.

James K. Boyce. Inequality and Environmental Protection. In Jean-Marie Baland, Pranab Bardhan, and Samuel Bowles, editors, *Inequality, Collective Action, and Environmental Sustainability*, pages 314–348. Princeton: Princeton University Press, 2007.

Dave Bryan. Minority Groups Mobilize on Pollution: Alabama Towns Battle for PCB Cleanup Reflects Fight Against 'Environmental Racism'. *Associated Press*, 6 April 2003. `http://www.ejrc.cau.edu/washpostejarticle.html`.

J. Chakraborty and M. P. Armstrong. Exploring the use of buffer analysis for the identification of impacted areas in environmental equity assessment. *Cartography and Geographic Information Systems*, 24(3):145–157, 1997.

Paul Mohai and Robin Saha. Racial Inequality in the Distribution of Hazardous Waste: A National-Level Reassessment. *Social Problems*, 54(3):343–370, 2007.

Office of Pollution Prevention and Toxics. *Risk-Screening Environmental Indicators.* U.S. Environmental Protection Agency, Washington, DC, 2004. Accessed February 1, 2008. URL: http://www.epa.gov/oppt/rsei.

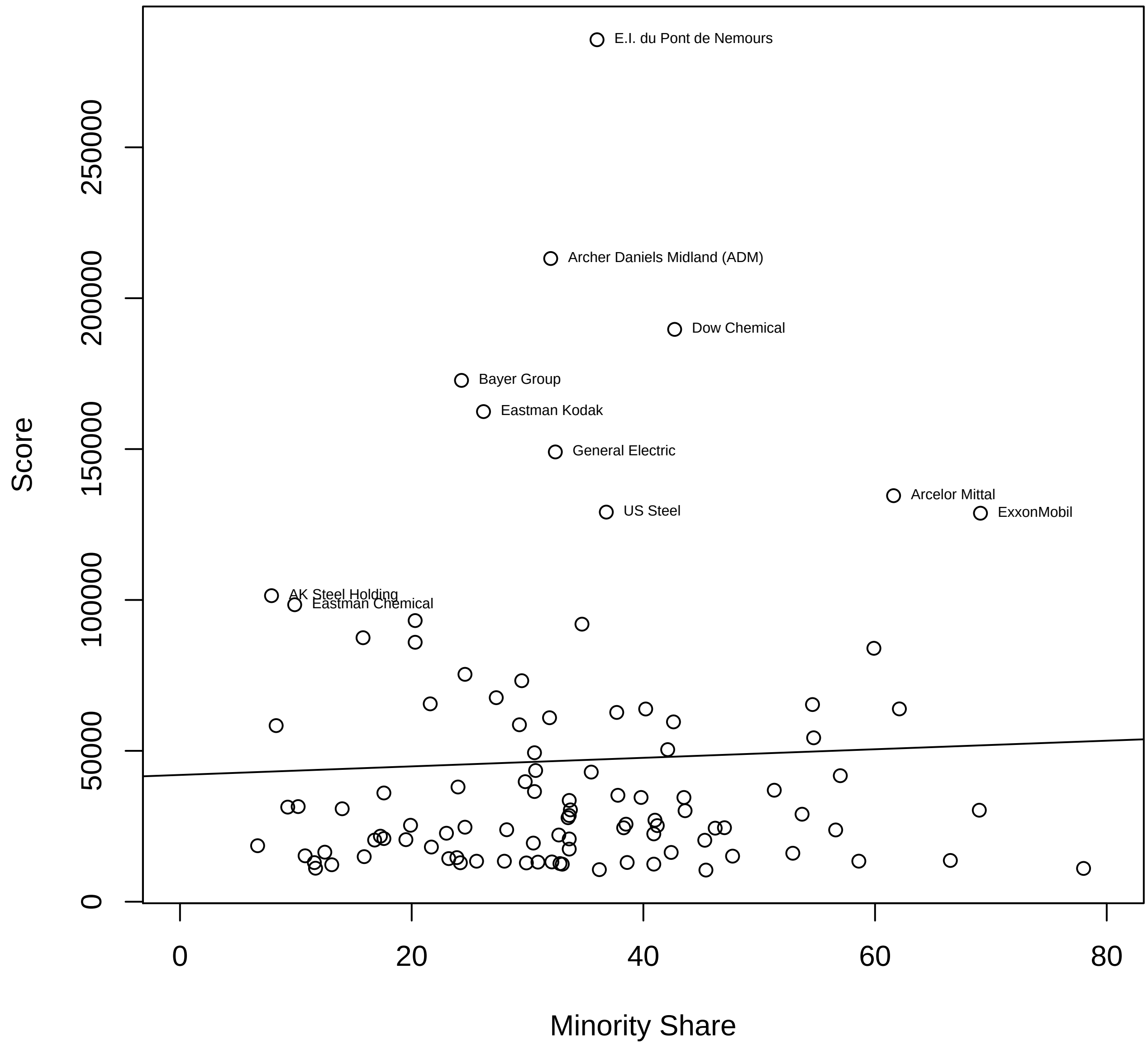
Manuel Pastor, James Sadd, and John Hipp. Which Came First? Toxic Facilities, Minority Move-in, and Environmental Justice. *Journal of Urban Affairs*, 23(1), 2001.

Manuel Pastor, James Sadd, and Rachel Morello-Frosch. The Air is Always Cleaner on the Other Side: Race, Space, and Air Toxics Exposures in California. *Journal of Urban Affairs*, 27(2), 2006.

Robin Saha and Paul Mohai. Historical Context and Hazardous Waste Facility Siting: Understanding Temporal Patterns in Michigan. *Social Problems*, 2005.

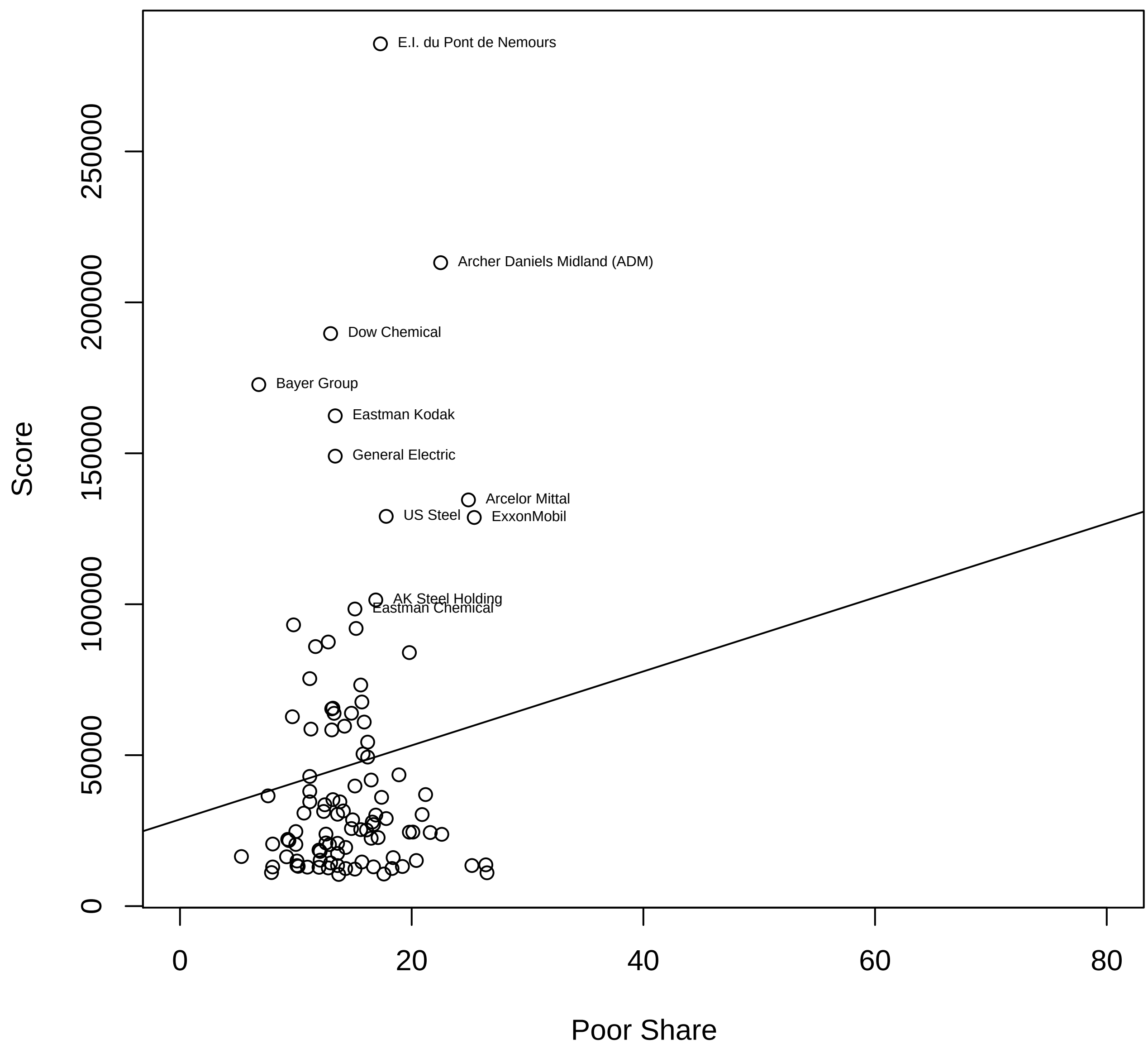
U.S. Senate Committee on Appropriations. *PCB Contamination in Anniston, Alabama.* 107$^{\text{th}}$ Congress, 19 April 2002. Available at http://www.ewg.org/files/AnnistonSenateHearingTrans.pdf.

Figure 1. Total Human Health Impact and CEJP for Minorities: Toxic 100



Source: Toxic 100 Corporate RSEI Score and Appendix Table 1.

Figure 2. Total Human Health Impact and CEJP for Poverty: Toxic 100



Source: Toxic 100 Corporate RSEI Score and Appendix Table 1.

Table 1. Corporate Environmental Justice Performance: Minorities

	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. 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 2. Corporate Environmental Justice Performance: People in Poverty

	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 3. Minority and Poverty Shares of Airborne Human Health Risk: ExxonMobil Facilities

	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
Baton Rouge Refinery (LA)	62269	78.0	75.3	1.1	1.0	0.1	31.1
Baton Rouge Chemical (LA)	24748	73.1	70.0	1.2	1.1	0.1	29.1
Baytown Refinery (TX)	18405	54.6	15.0	35.8	2.6	0.5	15.3
Torrance Refinery (CA)	6710	69.9	10.8	40.9	15.5	0.7	15.1
Joliet Refinery (IL)	6277	33.7	16.5	13.0	2.9	0.2	7.8
50 Additional Facilities	10347	50.8	23.2	23.4	2.6	0.8	17.3
55 Total Facilities	128758	69.1	55.5	10.4	2.2	0.3	25.4

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

	Facilities	Releases	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
ExxonMobil	8	564	115370	65.5	51.9	10.2	2.4	0.3	24.6
ConocoPhillips	17	790	90478	34.8	19.6	10.6	2.3	0.9	15.4
Valero Energy	17	1031	83416	59.8	38.6	18.3	1.8	0.5	19.7
BP	6	386	48841	56.2	16.4	32.6	5.8	0.6	16.3
Citgo Petroleum Corp.	7	314	29364	47.8	28.5	15.7	2.3	0.4	19.4
Pasadena Refining System Inc.	1	36	25291	73.6	12.6	57.7	2.4	0.6	25.1
Sunoco	5	176	24896	34.0	22.9	5.8	3.8	0.3	16.3
Tesoro	6	315	24640	24.5	2.6	11.6	5.9	1.8	10.0
Suncor Energy	1	35	20378	45.3	6.9	33.6	2.5	1.3	12.9
Motiva Enterprises L.L.C.	5	173	14707	42.2	35.6	4.1	1.4	0.3	16.8
Hess	2	110	12564	67.4	14.6	49.8	4.9	0.3	26.9
Sinclair Oil Corp.	3	171	12459	35.3	18.2	6.8	1.1	5.3	20.3
Royal Dutch Shell	6	291	11430	43.5	8.8	25.5	6.0	1.0	12.2
Marathon Oil	7	364	11277	33.8	16.3	13.6	1.9	0.6	14.3
Chevron	7	432	5584	66.2	17.4	31.9	13.3	0.6	18.9
All Oil Refining	163	6836	555298	51.3	27.9	18.8	2.9	0.7	19.0
All Firms	102636	16470	14576982	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

	Facilities	Releases	Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
E.I. du Pont de Nemours	25	732	222229	37.1	31.6	2.8	1.0	0.3	17.9
Eastman Chemical	4	252	98292	9.9	6.4	1.7	0.6	0.2	15.1
Apollo Mgt. (Hexion Specialty Chem.)	23	370	62766	40.3	14.8	22.1	2.1	0.5	13.2
Dow Chemical	23	1181	62806	43.4	17.1	23.9	1.3	0.4	15.0
Neville Chemical Co.	1	22	28498	7.6	4.9	0.6	1.2	0.1	6.6
ExxonMobil	9	289	26770	71.7	66.3	3.4	1.2	0.2	28.3
BASF	13	140	22579	31.3	22.8	4.7	1.4	0.4	13.0
Invista S. A. R. L.	7	106	17580	26.5	20.1	3.8	0.6	0.5	13.7
BP	2	203	14864	77	15.0	44.3	15.4	0.8	20.6
Zeon Chemicals LP	2	23	14759	17	11.5	2.1	1.6	0.2	8.7
Resinall Corp.	2	21	14150	62.5	60.2	1.2	0.3	0.4	32.3
General Electric	8	225	12541	10	5.6	2.0	1.0	0.2	11.5
Stepan Co.	1	25	12345	35.1	18.2	12.8	2.8	0.2	8.2
Georgia Gulf Corp.	3	135	11138	45.7	41.7	1.8	1.3	0.3	22.5
Cytec Industries Inc.	7	108	10957	12.3	6.0	3.2	1.1	0.5	14.1
Lanxess	3	43	10549	17.4	11.7	2.8	1.5	0.2	9.9
Lubrizol Corp.	8	147	10211	21.1	14.7	2.7	1.7	0.3	12.7
Royal Dutch Shell	1	63	8824	48.2	10.3	34.2	2.7	0.5	13.0
U. S. Polymers Accurez LLC	1	10	8397	24.8	17.6	3.0	1.6	0.4	18.3
Rohm and Haas	14	323	7955	25.1	17.1	2.7	3.6	0.3	21.3
Hercules Inc.	5	32	7366	40.2	21.5	15.3	1.7	0.5	20.8
Mitsubishi Chemical	2	20	6906	20.8	12.5	4.3	2.6	0.2	10.6
High Voltage Engineering Corp.	1	4	6555	11.2	3.0	5.5	1.9	0.2	6.2
Witco Corp.	2	62	6553	38.8	34.5	2.3	1.1	0.2	16.9
Westlake Olefins Corp.	4	42	6352	38.3	34.1	2.0	1.2	0.2	16.5
Solutia Inc.	5	72	6336	29	20.5	5.6	0.9	0.9	15.2
Goodyear	2	30	6185	58.6	20.7	33.7	3.3	0.4	18.5
Michelin Group	1	17	5436	35.5	31.5	1.5	0.7	0.2	17.0
Innovene USA LLC	3	69	5404	24.1	19.1	1.9	0.6	0.2	16.7
All Plastics	543	8898	847404	34.1	22.6	8.3	1.6	0.3	16.0
All Firms	102636	16470	14576982	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

	Toxic 100 Rank	Facilities	Releases	RSEI Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
E.I. du Pont de Nemours	1	58	1277	285661	36.0	29.9	3.4	1.0	0.4	17.3
Archer Daniels Midland (ADM)	2	34	211	213159	32.0	25.9	2.7	1.1	0.2	22.5
Dow Chemical	3	41	1415	189673	42.7	15.0	23.6	2.8	0.4	13.0
Bayer Group	4	16	289	172773	24.3	3.2	18.5	1.4	0.4	6.8
Eastman Kodak	5	6	142	162430	26.2	14.2	8.2	2.0	0.3	13.4
General Electric	6	130	828	149061	32.4	11.7	16.1	2.7	0.5	13.4
Arcelor Mittal	7	24	304	134573	61.6	46.6	12.5	1.3	0.3	24.9
US Steel	8	12	281	129123	36.8	29.3	4.6	0.9	0.4	17.8
ExxonMobil	9	55	1452	128758	69.1	55.5	10.4	2.2	0.3	25.4
AK Steel Holding	10	9	124	101428	7.9	5.0	0.9	0.7	0.2	16.9
Eastman Chemical	11	5	284	98432	9.9	6.4	1.7	0.6	0.2	15.1
Duke Energy	12	22	410	93174	20.3	14.7	2.9	1.5	0.3	9.8
ConocoPhillips	13	45	1269	91993	34.7	19.6	10.4	2.5	0.9	15.2
Precision Castparts	14	29	195	87500	15.8	5.0	5.3	2.7	0.6	12.8
Alcoa	15	61	574	85983	20.3	11.1	5.2	1.5	1.2	11.7
Valero Energy	16	36	1442	83993	59.9	38.7	18.3	1.8	0.5	19.8
Ford Motor	17	35	444	75360	24.6	15.4	5.1	2.0	0.3	11.2
General Motors	18	45	662	73248	29.5	17.9	7.3	1.7	0.4	15.6
Goodyear	19	27	211	67632	27.3	19.1	4.3	1.6	0.4	15.7
E.ON	20	10	194	65579	21.6	17.1	1.8	1.1	0.2	13.2
Matsushita Electric Indl	21	4	18	65346	54.6	48.1	3.6	1.4	0.3	13.1
Freeport-McMoran Copper & Gold	22	18	168	63911	62.1	2.9	57.1	0.5	1.6	14.8
Apollo Mgt. (Hexion Specialty Chemicals)	23	35	423	63880	40.2	14.9	21.9	2.1	0.6	13.3
Avery Dennison	24	13	102	62740	37.7	8.3	14.4	12.7	0.2	9.7
BASF	25	45	603	60984	31.9	24.5	4.3	1.1	0.3	15.9
Owens Corning	26	37	143	59609	42.6	14.2	22.0	4.4	0.5	14.2
Dominion Resources	27	19	196	58642	29.3	21.4	3.5	2.2	0.3	11.3
Allegheny Technologies	28	29	168	58375	8.3	5.2	1.2	0.6	0.2	13.1
BP	29	58	1271	54336	54.7	16.9	30.9	5.4	0.7	16.2
Honeywell International	30	57	411	50417	42.1	30.3	8.8	1.9	0.3	15.8
International Paper	31	52	608	49385	30.6	25.5	2.6	1.0	0.4	16.2
Ashland	32	67	646	43492	30.7	20.6	5.9	1.6	0.3	18.9
Constellation Energy	33	14	108	42972	35.5	21.5	10.2	2.1	0.3	11.2
Public Service Enterprise Group (PSEG)	34	9	97	41773	57.0	18.2	26.8	10.1	0.4	16.5
AES	35	14	191	39789	29.8	14.0	13.9	1.2	0.3	15.1
Progress Energy	36	14	234	38027	24.0	12.3	7.7	2.1	0.6	11.2
Nucor	37	29	317	36963	51.3	46.9	2.6	0.7	0.3	21.2
United Technologies	38	42	150	36526	30.6	21.7	5.7	2.0	0.3	7.6
Timken	39	15	79	36047	17.6	12.9	1.1	0.5	0.4	17.4
Berkshire Hathaway	40	62	419	35285	37.8	24.3	10.1	1.5	0.7	13.2
SPX	41	12	49	34559	39.8	19.6	14.6	3.2	0.5	11.2
Toxic 100 Firms	–	2518	30965	4724094	34.2	19.8	10.5	2.1	0.5	15.2
All Firms	–	102636	16470	14576982	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, continued. Minority and Poverty Shares of Airborne Human Health Risk: Toxic 100 Corporations

	Toxic 100 Rank	Facilities	Releases	RSEI Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
Royal Dutch Shell	42	19	609	34556	43.5	17.3	20.4	3.8	0.7	13.8
Southern Co	43	22	306	33577	33.6	26.2	4.2	1.7	0.4	12.5
Allegheny Energy	44	9	159	31539	10.2	7.1	0.8	1.0	0.2	14.1
American Electric	45	20	524	31364	9.3	5.7	1.2	0.7	0.4	12.4
Reliant Energy	46	15	260	30821	14.0	8.1	3.5	1.2	0.2	10.7
Boeing	47	12	113	30453	33.7	12.3	11.1	6.1	1.3	13.6
General Dynamics	48	16	67	30337	69.0	11.1	49.1	6.7	1.0	20.9
Occidental Petroleum	49	21	391	30167	43.6	30.8	9.7	1.6	0.4	16.9
KeySpan	50	4	40	29008	53.7	18.2	24.7	9.1	0.5	17.8
Lyondell Chemical	51	25	501	28591	33.6	11.8	18.5	1.9	0.3	14.9
Sunoco	52	40	774	27851	33.5	22.2	6.1	3.6	0.3	16.6
Anheuser-Busch Cos	53	21	79	27032	41.0	30.1	6.5	2.4	0.4	16.7
Ball	54	30	184	25709	38.5	11.3	21.4	4.1	0.6	14.8
Deere & Co	55	10	67	25346	19.9	6.8	10.2	1.1	0.4	15.6
Procter & Gamble	56	23	108	25238	41.2	36.6	2.4	1.1	0.2	16.1
Tesoro	57	8	361	24708	24.6	2.6	11.6	5.9	1.8	10.0
Temple-Inland	58	19	120	24537	47.0	24.8	21.2	0.5	0.4	20.1
Pfizer	59	17	231	24508	38.3	19.5	13.9	2.5	0.5	19.8
Rowan Cos.	60	2	21	24389	46.2	30.3	13.6	0.7	0.5	21.6
Leggett & Platt	61	36	69	23870	28.2	5.5	18.6	1.8	1.0	12.6
Northrop Grumman	62	14	87	23798	56.6	49.8	3.3	1.8	0.4	22.6
Weyerhaeuser	63	49	476	22708	23.0	15.1	4.0	1.1	1.1	17.1
Rohm and Haas	64	37	584	22489	40.9	15.1	21.4	3.1	0.4	16.5
Tyco International	65	29	215	22115	32.7	16.6	10.6	3.0	0.7	9.3
Terex	66	11	31	21730	17.3	4.9	4.6	4.4	0.6	9.4
Corning	67	6	26	20942	17.6	12.6	2.4	1.2	0.3	12.6
Exelon	68	5	53	20811	33.6	24.2	4.9	3.3	0.2	13.6
Fortune Brands	69	22	103	20583	19.5	8.0	9.4	0.8	0.5	8.0
FirstEnergy	70	7	158	20441	16.8	12.7	1.7	1.1	0.1	10.0
Suncor Energy	71	1	35	20378	45.3	6.9	33.6	2.5	1.3	12.9
Crown Holdings	72	23	137	19447	30.5	8.0	17.9	3.6	0.5	14.3
Masco	73	34	148	18572	6.7	1.3	2.8	1.4	0.4	12.0
ThyssenKrupp Group	74	16	130	18133	21.7	12.0	7.3	1.2	0.5	12.1
Textron	75	13	69	17443	33.6	24.5	4.9	1.6	0.7	13.6
Sony	76	6	36	16426	12.5	7.4	2.1	2.0	0.2	5.3
Mirant	77	9	138	16337	42.4	24.9	10.6	4.6	0.4	9.2
RAG	78	31	252	16080	52.9	45.6	4.2	1.5	0.5	18.4
Alcan	79	11	51	15231	10.8	6.6	2.2	0.6	0.2	12.1
Huntsman	80	17	280	15119	47.7	35.0	9.3	2.2	0.4	20.4
Bridgestone	81	30	155	14952	15.9	8.7	4.0	1.5	0.4	10.1
Danaher	82	22	46	14621	23.9	3.9	15.8	2.1	0.9	15.7
Toxic 100 Firms	–	2518	30965	4724094	34.2	19.8	10.5	2.1	0.5	15.2
All Firms	–	102636	16470	14576982	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, continued. Minority and Poverty Shares of Airborne Human Health Risk: Toxic 100 Corporations

	Toxic 100 Rank	Facilities	Releases	RSEI Score	Minority Share	Black Share	Hispanic Share	Asian/Pacific Share	Nat. Am. Share	Poor Share
PPG Industries	83	30	496	14300	23.2	16.7	3.9	1.1	0.3	13.0
Hess	84	24	457	13687	66.5	15.6	47.6	4.9	0.3	26.4
Akzo Nobel	85	27	371	13453	58.6	44.4	10.4	2.4	0.3	25.2
Dynegy Inc.	86	7	107	13439	25.6	13.2	8.9	2.1	0.3	10.1
Federal-Mogul	87	25	118	13435	28.0	21.5	3.5	1.3	0.3	13.6
Stanley Works	88	8	30	13196	32.1	23.3	5.7	1.7	0.4	10.2
Komatsu	89	2	4	13132	30.9	23.2	4.0	1.0	0.3	19.2
Saint-Gobain	90	55	159	13012	38.6	23.5	10.2	3.0	0.6	16.7
PPL	91	4	83	12972	11.6	4.3	4.6	1.6	0.2	8.0
Caterpillar	92	13	56	12924	24.2	11.9	8.6	1.7	0.2	11.0
Smurfit-Stone Container	93	30	244	12868	29.9	23.1	3.1	1.6	0.7	12.0
Siemens	94	22	66	12649	32.8	18.3	10.5	2.1	0.4	12.8
MeadWestvaco	95	10	214	12465	40.9	34.0	4.0	1.4	0.4	18.3
Marathon Oil	96	37	705	12454	33.0	16.3	12.9	1.9	0.5	14.3
Emerson Electric	97	39	110	12258	13.1	7.2	3.7	0.9	0.3	15.1
Northeast Utilities	98	5	84	11115	11.7	1.4	5.0	1.4	3.1	7.9
National Oilwell Varco	99	7	25	11042	78.0	22.3	53.0	2.0	0.7	26.5
Dana	100	18	49	10638	36.2	29.4	5.3	0.4	0.2	17.6
Chevron	101	48	984	10505	45.4	17.1	17.0	8.3	0.4	13.7
Toxic 100 Firms	–	2518	30965	4724094	34.2	19.8	10.5	2.1	0.5	15.2
All Firms	–	102636	16470	14576982	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