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DEPARTMENT OF ECONOMICS

Working Paper

**Assessing the jobs-environment
relationship with matched data from US
EEOC and US EPA**

by

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James K. Boyce

Working Paper 2016-03



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Assessing the jobs-environment relationship with matched data from US EEOC and US EPA*

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Abstract

Using matched facility-level data from the US EPA Toxics Release Inventory (TRI) and the US Equal Employment Opportunity Commission EEO-1 database, we assess (1) the trade-off between jobs and environmental quality and (2) the extent to which the distribution of the benefits of employment in industrial production mirrors the distribution of the costs of exposure to hazardous byproducts of industrial activity in the dimension of race and ethnicity. We find no evidence that facilities that create higher pollution risk for surrounding communities provide more jobs in aggregate. The share of pollution risk accruing to ethnic or racial minority groups typically exceeds the share of employment and substantially exceeds the share of good jobs held by members of those groups.

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1 Introduction

This study uses establishment-level data on employment and population exposure to airborne toxic releases to analyze the relationship (and possible trade-off) between facility employment and airborne industrial toxic exposure in order to examine the “jobs versus environment” framework for analysis of regulatory policy. We also explore the relationship at the facility level between the racial/ethnic profile of employment and racial or ethnic disparity in toxics exposure. We consider how the racial and ethnic profile of populations surrounding and affected by polluting industrial facilities compares to the profile of facility workforces.

Firms have employment profiles and environmental profiles that reflect local context, product- and input-market conditions, technological constraints, policy and enforcement, and managerial decisions. We match EEO-1 data from the US Equal Employment Opportunity Commission (EEOC) with Toxics Release Inventory (TRI) and Risk Screening Environmental Indicators (RSEI) data from the U.S. Environmental Protection Agency (2015 and 2004) to operationalize these profiles and analyze the relationship between the EEO-1 data on employment by race/ethnicity and job category at the establishment level provide an employment profile on reporting establishments. The employment profile reports the total number of jobs and their distribution across occupations and across racial and ethnic groups (EEO-1 Joint Reporting Committee, 2006; Edwards et al., 2007).

EPA data on industrial point-source toxic releases and population exposure to releases at the facility level provide the basis for an industrial air toxics exposure profile on reporting facilities. The air-exposure profile describes the total impact in terms of airborne potential chronic human health risk to the population in a 50-km radius surrounding the facility; our profile also describes how the health risk from pollution from the facility is distributed across racial and ethnic groups.

1.1 Research questions

A central policy-relevant question is what is the trade-off, if any, between jobs and the environment? Previous empirical analysis has focused on the economic and employment costs of environmental regulation (Greenstone, 2002; List et al., 2003; Belova et al., 2013; Greenstone et al., 2012). But the employment generation of polluting activity itself has not been widely studied. Population exposure to industrial toxics is often characterized as a social cost that comes with the benefit of both output and employment in industrial production. Some analysts have called the relationship into question. For example, Bezdek et al. (2008) emphasizes employment opportunities in the field of environmental protection and the absence of an association between environmental protection laws and regulation and employment outcomes. Pollin (2015) gives estimates of the additional employment associated with renewable energy and energy efficiency in comparison with fossil-fuel energy, especially during the period of transition from a fossil-fuel economy to a green economy.

The impact of regulation and the impact of polluting activity itself are related yet distinct and independently useful issues. Local decisionmakers in particular may be interested in the employment and pollution potential of new facilities. There is essentially no guidance available on the question of whether a new facility that may provide jobs is worth an addition to the local pollution burden.

In response to a Congressional request, General Accounting Office (2002) examined the employment and other potential benefits, such as contributions to community foundations, local schools, or infrastructure or of volunteer work, of a selection of 15 facilities that were the object of citizen complaints concerning discrimination against protected categories in EPA or State Agency allocation of pollution-disposal permits. The facilities covered in the General Accounting Office study included waste treatment plants, recycling operations, landfills, chemical plants, and packaging facilities. No facility had been required to provide a specified number of jobs to receive its pollution permits.

The pollution costs were characterized by type of pollutant but the pollution impact was not quantified. EPA's Office of Civil Rights recommended an analysis of the effect on property values of proximity to the plants but the analysis was beyond the scope of the inquiry. In addition to the characterization of the pollution and the description of employment and community benefits, General Accounting Office examined other potential costs, such as public subsidies.

The facilities covered in the General Accounting Office study were not required to provide information, although most of them voluntarily provided employment information. General Accounting Office found that the number of full-time equivalent jobs at these 15 facilities ranged between four and 103 workers, with nine of the 15 facilities employing fewer than 25 employees. Most of the facilities also provided some information on the types of jobs at the plant. For example, the ExxonMobil facility at Alsen, Louisiana, reported that "their facility in Louisiana had both hourly and salaried jobs. According to ExxonMobil, its hourly jobs included mechanics, electricians, and laboratory technicians; and its average wage was about \$23 an hour, which is equivalent to \$47,840 per year. 7 Salaried jobs included engineers, a chemist, accountants, and administrative assistants, and the average salary was just under \$70,000 annually."

GAO comments that "the information that the facilities provided was not detailed enough to allow us to determine the numbers for each job type, the salaries for individual jobs, or the number of jobs filled by people from the surrounding communities. The information indicates a wide range of salaries; however, community organizations in some locations told us that, in their view, the majority of the jobs filled by community residents were low paying." General Accounting Office notes that EPA's Office of Civil Rights recommended the collection of more detailed information on the number and types of jobs and on those jobs provided to the communities nearest the facilities.

That a GAO inquiry was necessary to characterize the employment-pollution tradeoff at

only 15 plants and even then with highly limited information on the quality and distribution of employment and the intensity and distribution of pollution points to the need for wider scale quantitative assessment. In this analysis, we directly assess the benefit of industrial activity in terms of employment and the provision of “good jobs” in relation to the environmental and health cost. We do this for more than 700 high-impact facilities, which we can characterize precisely in terms of population human health risk, employment, and the distribution of risk and employment across vulnerable populations.

To what extent does the distribution of the benefits of employment in industrial production mirror the distribution of the costs of exposure to the toxic byproducts of industrial activity, in particular in the dimension of race and ethnicity? The social impact of industrial activity on vulnerable populations is particularly contested, with many claims that employment opportunities warrant excess population exposure.

The analysis of the matched data provides a new and unique lens for assessing the level and distribution of costs and benefits. Where past analysis has focused largely on the impact of environmental regulation on employment and other economic activity, we directly examine the employment impact of pollution itself. Does employment come with the cost of increased pollution. For a local policymaker, the analysis may give guidance on how to consider the prospect of increased pollution with the promise of more or better jobs from a new facility.

Levinson (2015) observes that US manufacturing has substantially reduced its pollution emissions over the past twenty years, roughly the era of the Toxics Release Inventory. The reductions have come in large part through the reduction of pollution intensity of existing manufacturing industries rather than through shifts in composition of on-shore activity.

In 1994 President Clinton signed Executive Order 12898 (William J. Clinton, 1994) requiring all Federal agencies to “develop an agency-wide environmental justice strategy. . . that identifies and addresses disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income popu-

lations.” The direction to agencies specifies actions to “promote enforcement of all health and environmental statutes in areas with minority populations and low-income populations; ensure greater public participation; improve research and data collection relating to the health of and environment of minority populations and low-income populations; and identify differential patterns of consumption of natural resources among minority populations and low-income populations. In addition, the environmental justice strategy shall include. . . consideration of economic and social implications. . . .”

The study provides contextual data related to enforcement that might be useful for targeting educational and other enforcement efforts. The operational context of a facility may be assessed, for instance, not only with the distribution of race and ethnicity in the surrounding population but, in the case of facilities with significant environmental impact, with the distribution of race and ethnicity in population exposure.

These data may help address the question of how decisions by public and private decision-makers affect the relationship between exposure and employment. It should be further possible to address the role played by federal, state, and local policy and implementation; policy simulations are possible. For example: do firms’ local hiring agreements with local administrators or community organizations affect the relationships between employment and environmental impact? how effective would be a requirement that all federal contractors provide social impact statements that report both environmental and employment impacts?

We have previously (Ash and Boyce, 2011; Ash et al., 2013) developed a methodology for assessing gaps between disproportionately risk-exposed populations and the general surrounding population. We now add an alternative comparator for the exposed population, the employment profile of establishments. From a universe of facilities that produce high pollution risk for the surrounding population, we specifically identify facilities with the largest negative gaps between the employment profile of establishments and that of affected populations. Our report to the Equal Employment Opportunity Commission identified the

15 facilities with the largest gaps for African-Americans, the 15 facilities with the largest gaps for Hispanics, the 15 facilities with the largest gaps for Asian-Americans and the 15 facilities with the largest gaps for Native Americans. The facility identifiers are withheld in this article because of EEOC confidentiality requirements.

To inform cost-benefit analyses related to proposed regulations that require knowledge of important variables, our method can provide rigorously derived estimates of the numbers of employees potentially affected by proposed laws or regulations, as well as the number of firms affected by the law and new regulations. The project provides a methodology for assessing the likely employment impact of regulations that affect industrial activity.

2 Data

The EEO-1 employment data are a unique, establishment-level dataset on employment by sex, race/ethnicity, and job category collected and analyzed by Equal Employment Opportunity Commission (2016). The EEO-1 data have high quality firm identifiers which permit aggregation of the sex-race-ethnicity-occupation profile to the firm level. The data permit calculation of employment levels and of the distribution of employment by job category within establishments and firms (EEO-1 Joint Reporting Committee, 2006; Edwards et al., 2007). Previous academic work with the EEO-1 data include research on affirmative action in the 1980s, e.g., Leonard (1984), and, more recently, Kurtulus (2016).

Authorized under Title VII of the Civil Rights Act, EEO-1 requires reporting by all firms with at least 100 employees or, for firms that hold Federal contract, by all firms at least 50 employees. The EEO-1 data are used for compliance and enforcement with Federal contracting rules and rules pursuant to anti-discrimination provisions of Title VII. The key variables are counts of employees by sex, seven ethnicity/race groups (Hispanic; and Non-Hispanic for white, black, American Indian or Alaska Native, Asian, Native Hawaiian or Other

Pacific Islander, and multiple races), and ten categories of occupation (Executive/Senior Level Officials and Managers; First/Mid-Level Officials and Managers; Professionals; and Technicians; Sales Workers; Administrative Support Workers; Craft Workers; Operatives; Laborers and Helpers; and Service Workers) for a total of 140 job counts per report.

We use EEO-1 data for 2010, which were provided by the EEOC with confidentiality provisions. There were approximately 680,000 records in the complete 2010 EEO-1 data, each representing an establishment or other unit among the firms reporting to EEOC. In addition to the occupational distribution as described above, the data identify the industrial sector of the establishment, the relationship between the establishment and the parent firm, Federal contractor status, and geographic identifiers.

The TRI and RSEI data are unique as an establishment-level dataset on toxics release and population exposure that can be aggregated to the firm level, allowing estimation of population exposure to risk and the socio-geographic distribution of population exposure by establishments and firms releasing industrial toxics. As co-directors of the Corporate Toxics Information Project, the principal investigators have more than a decade of experience working with these data. The work has included significant collaboration with the US EPA Office of Pollution Prevention and Toxics of US EPA in its development of the RSEI project and data. Peer-reviewed publications include Bouwes et al. (2003), Ash and Fetter (2004), Ash and Boyce (2011), Ash et al. (2013), and Zwickl et al. (2014).

The TRI was created at the direction of the Congress under the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA) in response to the disastrous leak from Dow Chemical facility in Bhopal, India in 1984. EPCRA requires US-located industrial facilities meeting activity thresholds to submit annual data to EPA on deliberate and accidental releases of some 600 toxic chemicals into air, surface water, and the ground. TRI data are available on an annual basis starting in 1987. In 2010, 14,800 of approximately 18,000 TRI-reporting facilities released a total of 858 million pounds of these toxic chemicals directly

into the air;¹ an additional 178 million pounds were transferred to 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 foremost instance of regulation by “right-to-know” in the US. The TRI data nonetheless 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 covered facilities and processes.

The TRI data capture the largest point-source air pollution emissions in the US but omit emissions from mobile sources, such as trucks, automobiles, ships, and aircraft. The TRI also excludes facilities that are not required to report by dint of the 25-employee threshold 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. The chemicals in the TRI do not include some major pollutants that pose significant health and environmental risks, including particulate matter, sulfur dioxide, nitrogen oxides, ozone, carbon monoxide, and carbon dioxide. Nor is every toxic chemical listed. A complete picture of air pollution and the attendant health risks would include these other modes, sectors, and chemicals.

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. Even so, Hamilton (1995) indicates that these data are taken seriously in

¹Air releases have declined sharply in recent years; in 2000 17,500 facilities released 1.9 billion pounds directly to air, and in 2005 17,000 facilities released 1.5 billion pounds.

terms of estimating the socioeconomic impact of polluting facilities.

The RSEI project was launched by the EPA in the mid-1990s to address several of these limitations (Bouwes et al., 2003). 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 incinerator to which the facility ships waste. The AERMOD Gaussian-plume fate-and-transport model, is used to map how the chemical spreads from the point of release to the surrounding geography, a 50-km radius around each facility.² 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 810m × 810m grid cell within the 50-km radius. Figure 1 provides a schematic of the plume model (a square 101 km × 101 km catchment area in earlier versions was replaced with a 50-km radius in RSEI version 2.3.0).

Although all TRI chemicals are toxic, their hazards to humans vary widely. By multiplying the quantity (mass in pounds or concentration in μg per cubic centimeter) 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

²Transfers of toxic materials for offsite incineration are modeled from the offsite incineration facility with an estimated destruction/removal efficiency prior to plume modeling.

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. At the extreme ends of the resulting toxicity scale for the chemicals on the TRI list, one pound of benzidine is equivalent, in terms of inhalation toxicity, to 3.4 billion pounds of chlorodifluoromethane (HCFC-22), a difference of 9 orders of magnitude. 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 one percent of the total mass of reported toxic air releases nationwide.

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"). EPA has set the equivalence between the non-carcinogenic and carcinogenic scales so that the Reference Concentration for carcinogenic risk is one excess cancer cases per million persons. 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 810m \times 810m grid cell, the RSEI's population weights take into account the age and sex composition of the population,

because risk 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. 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.³ We use RSEI Scores from TRI Reporting Year 2010 reported in RSEI version 2.3.1.⁴ Approximately 15,000 facilities reported air releases or incineration transfers to TRI in Reporting Year 2010.

As an aggregate population measure, the RSEI Score can also be computed for sub-populations (Ash and Boyce, 2011). For example, the “Black RSEI Score” for a facility is the aggregate human health risk borne by the black population in the airshed of the facility, and the Black RSEI Share is the Black RSEI Score divided by the total RSEI Score for the facility.

Firm and establishment name, addresses, and in some cases Dun & Bradstreet identifier (DUNS) allow matching between the EEO-1 data and US EPA data. The principal investigators have developed matching methods with the EPA data that facilitate the match to the EEO-1 data. In some cases, a TRI facility comprises several EEO-1 establishments, representing a distinction in the definitions of facility and establishment. In these cases we aggregate the employment data from all of the subsumed EEO-1 establishments to match it to the single TRI facility.

We focus on high-impact polluters (high ranks in the RSEI data) as the target to match EEO-1 data. Although this focus constitutes a sample selection, it has advantages. First, it contains the cost of matching, much of which, in the absence of common identifiers or

³The RSEI Score expresses potential chronic human health risk from industrial point-source air-toxic releases aggregated for the exposed population. The RSEI Score, which combines risk from carcinogenic and non-carcinogenic sources is unitless, and EPA (2004) recommends against its use for quantitative risk assessment. However, the derivation of the RSEI Score implies that for carcinogens a RSEI Score of 1,000,000 corresponds to a level of population risk with one (1) excess cancer case.

⁴We adjust the RSEI data so that they represent the most current available about the reporting year, in case companies revise earlier TRI reporting. In the case of downward revisions of the mass released, RSEI scores are adjusted on the basis of the linear relation between pounds released and that release’s RSEI score. Upward revisions or new reports are noted but do the RSEI score is not adjusted.

crosswalks, must be done with manual assessment of the results of text- and address-matching algorithms. Second, it concentrates attention where it counts, i.e., where the pollution is; because of disproportionality, the top of the list that we match in fact accounts for a substantial share of all pollution.

Our target sample comprises the 1,000 facilities with the highest air-based RSEI scores, the measure of population potential chronic human health risk coming from industrial toxics released to air either directly or via incineration, among the 15,000 reporting air releases to TRI. We attempted to match these 1,000 facilities to EEO-1 establishments using name, address, industrial sector, and DUNS. The limitation to 1,000 facilities reflects the cost of matching. However, the top 1,000 facilities both cover much of the relevant air toxic risk in the US and include substantial variation between facilities with lower RSEI Scores and those with higher RSEI Scores. The top 1,000 facilities account for almost 95 percent of the national RSEI Score for 2010, i.e., the vast majority of air toxic risk comes disproportionately from the upper tail of the distribution. (Of the 15,000 total facilities reporting air releases, approximately 3,700 have RSEI Scores below one.) Within the upper tail, the distribution remains wide: the lowest RSEI Score among the top 1,000 facilities is 23,877, the seventy-fifth percentile RSEI Score among the top 1,000 facilities is 184,717, and the highest RSEI Score is 20,136,652.

We were ultimately able to match 712 of the top 998 TRI facilities ranked by RSEI Score to establishments in the EEO-1 data.⁵ Appendix Tables A.4, A.5, and A.6 show summary statistics and distributions for the unmatched and matched samples. The matched TRI sample significantly resembles the non-matched TRI sample in terms of distribution across regions and industrial sectors and of average RSEI Score and the variation in RSEI Scores.

⁵Two facilities were dropped from the initial TRI sample of the 1,000 highest risk facilities because they substantially revised their RY 2010 TRI submissions after we completed our matching process.

3 Methods

The analysis proceeds in two stages. First, we examine the level of employment in relation to the level of population risk generated by the facility. The “jobs versus environment” hypothesis argues that there is a common, perhaps even necessary, tradeoff between environmental amenities, such as clean air, and employment opportunities. We examine the level of employment in relation to the level of population risk created by toxic air releases from the facility. We stratify the analysis by the ten US EPA Regions and by the seven industrial sectors (3-digit NAICS Codes) with high representation in the data. We use graphical methods, showing scattergrams of employment versus population risk with a nonparametric curve-fitting to show the relationship. We then use linear regression methods to summarize the relationships.

After presenting the results for the total population and stratified results by sector and region, we then turn to the second stage, environmental-justice component of the analysis, examining the jobs–environment relationship for blacks, Hispanics, and non-Hispanic whites.⁶ We examine the relationship between employment and pollution exposure both with and without controls for the representation of the group in the population.

Then, using the method developed in Ash and Boyce (2011) facilities may be examined on their total population risk, i.e., their RSEI Score, on risk for sub-populations, and on the disparity for sub-populations between risk share and a reference share. In Ash et al. (2009), the reference share is the population share in the city or state containing the facility. In this study, we use instead the disparity for sub-populations between risk share and employment share at the facility. We provide a visual display of the minority share of all jobs at each establishment in relation to the minority share of the total human health risk. In addition to the graphical analysis, we present a list of facilities that rank high on either of these

⁶Sample sizes and population representations were too small to give meaningful results for Asian-Americans and for Native Americans; these groups are included in the later share analysis.

alternative measurements for each of African-Americans, Hispanics, Asian-Americans, and Native Americans.

With the ethnic or racial share of pollution risk on the horizontal axis and ethnic or racial share of employment on the vertical axis, we plot a solid black 45° line to indicate the hypothetical relationship that would obtain if access to employment and exposure to pollution for sub-populations were related equally and exclusively to prevalence in the population. That is, in a population that was 15 percent African-American, we would expect African-Americans to bear 15 percent of risk from pollution exposure and constitute 15 percent of employment, which we call proportionate exposure.

We define the disparity for a facility as the vertical distance between the 45° line and the point representing the establishment, or the difference between the share of the pollution-risk burden and the share of employment. For an establishment below the 45° line, the nonwhite share of pollution exposure exceeds the nonwhite share of employment, and we define this as a positive disparity. For an establishment above the 45° line, the nonwhite share of pollution falls below the nonwhite share of employment, and disparity is negative.

We then focus on job categories that are likely to be good jobs in the sense of having higher pay, career ladders, more job security, or other desirable characteristics. The EEO-1 data track ten broad job categories, and we identify four of these categories as constituting “good jobs”: Executive/Senior Level Officials and Managers; First/Mid-Level Officials and Managers; Professionals; and Technicians. In some cases we assign a fifth job category, Craft Workers, to the “good jobs” grouping, and the major conclusions are not substantively affected. The five job categories excluded from the designation of good jobs are: Sales Workers; Administrative Support Workers; Operatives; Laborers and Helpers; and Service Workers. Table A.1 shows the distribution of jobs and good jobs in the full EEO-1 data, in the EEO-1 data for the industries represented in the Toxics Release Inventory, and in the

EEO-1 data for the establishments in the merged EEO-1 and TRI data.⁷

4 Results

The average facility in the sample had 508 employees with a standard deviation of 1,358 employees. Mean facility employment of African-Americans was 53 (s.d.= 119), of Hispanics was 37 (s.d.= 88), of Asian-Americans was 21 (s.d.= 170) and of Native Americans was 2.5 (s.d.= 14). Appendix Tables A.1, A.2, and A.3 show the geographic, sectoral, and occupational distribution of the facilities in the sample.

We first report some overall figures for impact and then we examine the demographic profile of both risk and employment of the 15 facilities with the highest total population risk exposure and the 15 facilities with the highest cost in population risk per job and per good job. We then examine the tradeoff between total employment and total exposure and repeat this examination by race for non-Hispanic whites, black, and Hispanics. We then report the minority share of all jobs and good jobs in relation to the minority share of the total human health risk.

4.1 Risk from Airborne Industrial Toxics

Figure 2 shows the distribution of 2010 RSEI Scores, the measure of aggregate population risk from toxic air releases from TRI facilities for the matched 712 of the top 1,000 facilities out of approximately 15,000 facilities reporting air releases in 2010. Limiting the sample to the top 1,000 facilities truncates RSEI Scores from above at a score of approximately 23,000. The horizontal axis is on a logarithmic scale, and hence the range of risk exposures in the sample

⁷Throughout we use “good jobs” as a shorthand to designate the following occupations: Executive/Senior Level Officials and Managers; First/Mid-Level Officials and Managers; Professionals; Technicians; and sometimes Craft Workers. Not every job in these occupational categories is in fact good in the sense of having higher pay, career ladders, more job security, or other desirable characteristics, nor are all jobs in the remaining categories necessarily bad in the sense of not having these qualities. Nonetheless, we see the distinction as a reasonable shorthand for these characteristics.

is many orders of magnitude. The mean RSEI Score for the sample is 294,000. The mean log RSEI Score is 11.5 and the standard deviation of log RSEI Score, a scale-invariant measure of dispersion, is 1.2. The standard deviation of log RSEI Score was fairly similar (and equally wide) within each race/ethnic group: 1.8 for African-Americans; 1.9 for Hispanics; 1.7 for Asian-Americans; and 1.5 for Native Americans.

4.2 Is there a jobs versus environment trade-off?

A jobs–environment trade-off implies that more population risk should be associated with more employment, that is, the benefit of additional jobs comes at the cost of additional population risk.

The RSEI Score per job for the facilities in the sample varies across several orders of magnitude among these large polluters as illustrated by the nonparametric density plot in Figure 3 (note that the horizontal scale is logarithmic). Even within the top 15 facilities ranked by RSEI Score per job, that is, facilities creating a high population risk for each job offered, there is substantial variation in the environmental cost per job. The top facility generates 20 times more environmental risk per job offered than the fifteenth facility.

When we limit the analysis to good job (employment in managerial, professional, technical, and craft occupations), the range remains similarly wide. Figure 3 shows the range of environmental impact per good job among these large polluters (again note that the horizontal scale is logarithmic).

In Figure 4 we examine the relationship between total facility employment and total facility risk. Table 1 reports regression results that summarize the relationship. The scattergram, locally smoothed regression, and linear regression together provide strong evidence that comparing among polluting facilities, there is no relationship between employment and population risk. Columns 1 and 2, showing our preferred log-log specification, indicate that the elasticity of employment with respect to facility risk is nearly zero with or without controls

for state and industry.⁸

An alternative linear specification reported in column 5 of Table 1 yields a statistically insignificant negative coefficient, with an increase of 1,000,000 in RSEI Score associated with a loss of 22 jobs; this remains the case with the addition of state and industry indicator dummies as control variables. Similarly a linear-log specification in column 6 yields a small statistically insignificant relationship. These results imply that among polluting facilities, there is no relationship between the degree of environmental risk and the level employment.

Our limitation of the sample to the top 1,000 risk producers truncates the data at a RSEI score of approximately 23,000. It is possible that a trade-off does obtain between population risk and employment at lower levels of population risk. However, the data do span more than four orders of magnitude of population risk (and as noted above account for roughly 95 percent of the total national RSEI score). Thus, where it counts most there is no relationship between additional population risk and additional employment.

The right panel of Figure 4 limits the analysis to employment in good jobs (craft, managerial, professional, and technical occupations) and total facility risk. As with population risk and all employment, there is no relationship between the population risk generated by a facility and its employment in good jobs. A linear regression in lieu of the locally smoothed regression yields a statistically insignificant negative coefficient, with an increase of 1,000,000 in RSEI Score associated with a loss of 16 jobs (in column 5); this remains the case with the addition of state and industry indicator dummies as control variables.

Figure 5 produces the same analysis as in Figure 4 stratified by EPA region. In EPA Region 6, the South Central region (Arkansas, Louisiana, New Mexico, Oklahoma, and Texas), there appears to be a upward-sloping relationship indicating a jobs–environment

⁸We do not have strong prior beliefs about the appropriate functional form and report regression results for log-log, linear-log, and linear specifications. The skew of the data in both dimensions make scatterplots with logarithmic axes more legible than alternatives. In the regressions and scatterplots we added 1 to all employment figures (mean= 508) and 10 to the racially/ethnically specific RSEI Scores to avoid taking log of zero.

tradeoff. In EPA Region 5, the Great Lakes region (Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin), there appears to be a negative relationship indicating that more pollution is associated with fewer jobs. A linear regression summary of the locally smoothed regression, reported in Table 1, yields a nearly identical, statistically significant coefficients of opposite sign for these two regions, with a 1 percent change in RSEI Score associated with a change of 0.18 percent change in employment. With a mean RSEI Score of 300,000 and mean employment of 300, the implied response at the point of means is a RSEI Score change of roughly 6,000 per job.

Figure 6 produces the same analysis as in Figure 4 stratified by industry for the seven industries with at least 40 facilities in the dataset. No industry shows any substantive relationship between employment and population risk. Chemical manufacturing is the most common industry in the sample (see Appendix Table A.2) and on visual inspection may have a slight upward slope (jobs–environment tradeoff). A linear regression in lieu of the locally smoothed regression yields a positive but statistically insignificant coefficient, with an increase — again, statistically insignificant — in RSEI Score of 1,000,000 associated with an increase of 13 jobs (s.e.= 45).

Thus, there is neither a visual nor a statistically significant indication of any relationship between population risk and employment for the full sample. EPA Region 6 appears to have a positive tradeoff, EPA Region 5 a negative tradeoff of identical magnitude. There is little evidence for a jobs–environment tradeoff for the population as a whole.

4.2.1 African-Americans

In Table 3 and Table 4 we repeat the analysis in Table 1 but look only at the pollution risk impact and employment for specific ethnic and racial sub-populations. Columns three and four of each table and The top two panels of Figure 7 show the results for African-Americans. For African-Americans there appears to be a significant tradeoff between environmental

quality for the population and employment. The tradeoff tails off at higher levels of pollution. The coefficient shows that a 1 percent increase in pollution risk to the black population from a facility is associated with an 0.4 percent increase in black employment at that facility. The increase in employment in good jobs associated with a 1-percent increase in pollution risk is somewhat smaller at 0.3 percent.

As the figures indicate, the increase in employment associated with increased exposure to pollution risk is non-trivial, but the domain of the tradeoff is primarily at the lower end of pollution risk among these high-pollution firms. Although the average elasticity of employment over the entire domain of pollution risk is 0.4, much of this occurs at the low end of the domain. In contrast, an increase in the black RSEI Score over the range above 10,000 generates essentially zero additional expected employment. The payoff in terms of good jobs per additional unit of population pollution risk over this domain of pollution risk is even less.

In part, the tradeoff may simply reflect variation in the percentage of African-Americans in the region surrounding the facility. Controlling for the percent black in the State reduces somewhat the apparent tradeoff — results reported in column 4 of Tables 3 and 4, but the tradeoff remains statistically significant even with this local demographic control.

4.2.2 Hispanics

The results for Hispanics are generally similar in direction and magnitude to those for African-Americans, suggesting a jobs–environment tradeoff. These are shown in columns 5 and 6 of Tables 3 and 4 and in the middle two panels of Figure 7. The apparent tradeoff shrinks substantially but remains significant when a control for state Hispanic share is included. As with African-Americans, the tradeoff tails off substantially at higher levels of pollution risk, and the tradeoff is weaker for good jobs. An increase in the Hispanic RSEI Score from 10,000 to 100,000 is associated with fewer than 10 additional jobs for Hispanic persons.

4.2.3 Non-Hispanic Whites

The results for non-Hispanic whites are shown in columns 1 and 2 of Tables 3 and 4 and in the bottom two panels of Figure 7.

Unlike the apparent jobs–environment tradeoff for Hispanics and for African-Americans, there is no evident relationship between employment and population risk for non-Hispanic whites. Indeed the curve is slightly (but not significantly) downward sloping over a substantial share of the domain. The share of non-Hispanic whites in the state does positively correlate with white employment, but differences in exposure of non-Hispanic whites to risk from industrial environmental hazards does not.

4.3 Employment Share *vs.* Pollution Share

In this section of the results, we examine the racial and ethnic shares of toxic pollution risk and of employment for four racial and ethnic groups: African-Americans; Native Americans; Asian-Americans; and Hispanics. This analysis expands on the indication that there is some tradeoff between jobs and environment for African-Americans and Hispanics by examining the terms of the tradeoff.

4.3.1 African-Americans

Figure 8 shows the relationship between share of population risk from toxic pollution exposure and employment share at the facility level for African-Americans. Each point represents an establishment in terms of the share of its toxic pollution risk borne by African-Americans (on the horizontal axis) and the share of its employment held by African-Americans (on the vertical axis). The size of the dot represents the size of employment at the establishment and the shade of the dot indicates the total population risk from airborne toxics emitted by the establishment.

The solid black 45° line indicates the hypothetical average relationship that would obtain if access to employment and exposure to pollution for African-Americans were related exclusively to prevalence in the population. The heavy concentration of points below the 45° line indicates that the vast majority of these establishments impose toxic risk on African-Americans that is greater than proportionate to the share of jobs held by African-Americans.

Because many establishments are concentrated in the region with less than 25 percent shares of both risk and employment, we show a close-up of this region in the upper-right panel of Figure 8. Even in the limited region the disparity between employment and exposure is clear. From the full picture in the upper-left panel of Figure 8, it is clear that there are many establishments for which a significant share of the toxic risk from industrial activity falls upon African-Americans while only a small share of the jobs are held by African-Americans.

At the average facility in this sample of high-impact polluters, African-Americans bear 17.4 percent of the risk but hold only 10.8 percent of the jobs (a disparity of 6.6 percentage points) and a mere 6.9 percent of the good jobs (a disparity of 10.5 percentage points).

In Table 5 we tabulate average facility shares of the toxic risk and of jobs and good jobs for blacks by industry. The table also reports the average facility employment and the average facility RSEI score for each industry. The table, with one row per industry, is in decreasing order by the disparity between the share of the risk burden experienced and the share of jobs held by African Americans.

Table 5 shows that for most industries African American populations experience a share of risk that exceeds the African-American share of jobs. In terms of access to good jobs, the disparity is stronger still. For example, in Petroleum and Coal Products Manufacturing, which includes oil refining and is one of the highest sources of population risk from airborne toxic industrial emissions, African-Americans receive 23 percent of the risk while holding only 11 percent of the jobs and 8 percent of the good jobs.⁹

⁹In the report to EEOC the equivalent table reported these tabulations at the facility level, but they are

The slope of a regression line computed for the upper-left panel of Figure 8 is 0.46 (s.e.= 0.02), which is less than half as steep as the 1.0 slope of the 45° line. That is, one additional percentage point of additional black share of exposure to industrial risk corresponds to only one-half percentage point of additional black representation on the workforce of polluting facilities. The relationship is well below the one-for-one relationship that would be expected based on representation in the population.

When we include the black share of the state population as a control variable, the coefficient on the black share of the RSEI score falls to 0.34 (s.e. = 0.02) with virtually identical results when we use state dummies rather than the state black share of the population. When we instead include the black share of the county as the control variable, the coefficient on the black share of the RSEI score falls to 0.26 (s.e. = 0.03). If population representation functions as the baseline expectation for representation in the workforce, then these regression coefficients that are well below 1 albeit positive, indicate that there is some additional access to industrial employment for African-Americans based on additional pollution exposure but that the addition is well below a one-for-one tradeoff between the jobs share and the environment share. These results are reported in Table 6.

The lower-left panel of Figure 8 shows black access to “good jobs” (craft, managerial, professional, and technical) at polluting facilities as a function of black population exposure to industrial risk. Facilities are very heavily clustered below the 45° line indicating that blacks almost always hold a share of good jobs at smaller than their share of population toxic risk from polluting facilities. The slope of the regression line in for the lower-left panel of Figure 8 is only 0.27 (s.e.= 0.01), a substantially lower implied return of access to good jobs for pollution exposure than for access to any jobs.

In the lower-left panel of Figure 8, Craft Workers are included among the good jobs

suppressed here to maintain confidentiality. In some cases the disparity is very high. Among the highest disparity facilities, the black share of pollution approaching 80 percent and the black share of jobs between 15 and 24 percent.

category. The lower-right panel Figure 8 shows black access to good jobs when craft workers are not included in the definition. The inclusion of craft workers in the definition substantially increases black representation among good jobs. It is very rare for blacks to hold a share of managerial, professional, or technical positions to the same extent that blacks are exposed to risk from the facility.

4.3.2 Hispanics

Figure 9 shows the relationship at the facility level between population toxic-risk exposure and jobs for Hispanics. Each point represents a facility in terms of the share of its toxic pollution risk borne by Hispanics (on the horizontal axis) and the share of its employment held by Hispanics (on the vertical axis). The size of the dot represents the size of employment at the establishment and the shade of the dot indicates the total population risk from airborne toxics emitted by the establishment.

The solid black 45° line indicates the hypothetical average relationship that would obtain if access to employment and exposure to pollution for Hispanics were related exclusively to prevalence in the population or if risk and employment were complementary. The heavy concentration of points below the 45° line indicates that the vast majority of these establishments impose toxic risk on Hispanics that is greater than proportionate to the share of jobs held by Hispanics.

For Hispanics, the relationship between share of population exposure from and share of employment at the facility is somewhat stronger than it is for African-Americans. The regression coefficient for the scattergram in the upper-left panel of Figure 9 is 0.64 (s.e.= 0.02) while it was only 0.46 for African-Americans. The addition of state Hispanic population share reduces the coefficient on Hispanic share of risk to 0.57 (s.e., = 0.04) and to 0.49 (s.e.= 0.04) with the inclusion of state indicator variables. With the inclusion of county Hispanic population share, the coefficient on exposure share is 0.25 (s.e.= 0.06), still indicating

a sizable employment-share return to additional exposure share. These results are reported in Table 8.

Because many establishments are concentrated in the region with less than 25 percent shares of both risk and employment, we show a close-up of this region in the upper-right panel of Figure 9. Even in the limited region the disparity between employment and exposure is clear. From the full picture in Figure 9, it is clear that there are many establishments for which a significant share of the toxic risk from industrial activity falls upon Hispanics while only a small share of the jobs are held by Hispanics.

In the lower-left panel of Figure 9, craft workers are included among the good jobs category. The lower-right panel of Figure 9 shows Hispanic access to good jobs when craft workers are not included in the definition. The inclusion of craft workers in the definition substantially increases Hispanic representation among good jobs. It is very rare for Hispanics to hold a share of the other good jobs, i.e., managerial, professional, or technical positions to the same extent that Hispanics are exposed to risk from the facility.

At the average facility in this sample of high-impact polluters, Hispanics bear 15.0 percent of the risk but hold only 9.8 percent of the jobs (a disparity of 5.2 percentage points) and a mere 6.8 percent of the good jobs (a disparity of 8.2 percentage points).

In Table 7, we report aggregated results by industry ranked from the highest disparity between the Hispanic share of risk from airborne toxic releases and the Hispanic share of employment. As with African-Americans, Hispanics experience a proportion of the toxic risk from pollution that substantially exceeds the Hispanic share of jobs in most cases. Again, Petroleum and Coal Products Manufacturing, of which oil refining is a significant component, has a substantial disparity: 25 percent of the risk burden of industry falls on Hispanics while only 11 percent of jobs and 9 percent of good jobs are held by Hispanics. The aggregation to industry averages masks enormous variation across facilities. Among the highest disparity facilities, the Hispanic share of the risk burdens in the area of 70 percent with 10 to 18

percent of jobs going to Hispanics.

4.3.3 Asian-Americans

Figure 10 shows the relationship at the facility level between population toxic-risk exposure and jobs for Asian-Americans. Each point represents a facility in terms of its share of its toxic pollution risk (RSEI Score) borne by Asian-Americans (on the horizontal axis) and the share of its employment held by Asian-Americans (on the vertical axis). The size of the dot represents the size of employment at the establishment and the shade of the dot indicates the total population risk from airborne toxics emitted by the establishment.

Note that because Asian-Americans compose a relatively small percentage of the US population, we limit both axes in the upper-left panel of Figure 10 from 0 to 0.5 without losing any facilities and from 0 to 0.05 in the close-up in the upper-right panel of Figure 10. For this reason, we also do not report regression results for Asian-Americans.

The solid black 45° line indicates the hypothetical average relationship that would obtain if access to employment and exposure to pollution for Asian-Americans were related exclusively to prevalence in the population. The majority of points fall below the 45° line, which indicates a majority of facilities impose toxic risk on Asian Americans that is greater than proportionate to the share of jobs held by Asian Americans.

The lower-left panel of Figure 10 shows the share of good jobs (craft, managerial, professional, and technical positions) held by Asian-Americans in relation to the share of population risk from toxic exposure. There is no indication of systematic disparity. There is a lot of variation, i.e., some facilities have higher Asian employment share than Asian toxic-risk share and some facilities have higher Asian toxic-risk share than employment share.

4.3.4 Native Americans and Alaska Natives

Figure 11 shows the relationship at the facility level between population toxic-risk exposure and jobs for Native Americans. Each point represents a facility in terms of its share of its toxic pollution risk (RSEI Score) borne by Native Americans (on the horizontal axis) and the share of its employment held by Native Americans (on the vertical axis). The size of the dot represents the size of employment at the establishment and the shade of the dot indicates the total population risk from airborne toxics emitted by the establishment.

Note that because Native Americans are a relatively small percentage of the US population, we limit both axes in the upper-left panel of Figure 11 from 0 to 0.1 without losing any facilities and from 0 to 0.025 in the close-up in the upper-right panel of Figure 11. For this reason, we also do not report regression results for Native Americans.

The lower-left panel of Figure 11 shows the share of good jobs (craft, managerial, professional, and technical positions) held by Native Americans in relation to the share of population risk from toxic exposure. There is no indication of systematic disparity. There is a lot of variation, i.e., some facilities have higher Native American employment share than Native American toxic-risk share and some facilities have higher Native American toxic-risk share than employment share.

5 Discussion

Using matched data from EEOC and EPA we have examined the relationship at the facility level between the exposure of population in the area around the facility to potential chronic human health risk from airborne toxic releases and the employment. The analysis examines data from the matched 712 of the 1,000 facilities generating the highest population risk from airborne toxic releases. This represents a substantial increase in the scale of analysis of the jobs-pollution relationship from General Accounting Office (2002).

To assess environmental disparities by race and ethnicity, we examined the share of a facility toxic risk burden borne by a racial or ethnic group in relation to its share of facility employment, with equal shares as the no-disparity benchmark.

For both African-Americans and Hispanics there are substantial disparities between the risk share and the employment share. Asian-Americans and Native Americans constitute too small a minority of the population to report comparable results. At the average facility in this sample of high-impact polluters, African-Americans bear 17.4 percent of the risk but hold only 10.8 percent of the jobs (a disparity of 6.6 percentage points) and a mere 6.9 percent of the good jobs (a disparity of 10.5 percentage points). At the average facility in this sample of high-impact polluters, Hispanics bear 15.0 percent of the risk but hold only 9.8 percent of the jobs (a disparity of 5.2 percentage points) and a mere 6.8 percent of the good jobs (a disparity of 8.2 percentage points).

The scattergrams of employment share versus risk share imply that there is some tradeoff of environmental quality for jobs for African Americans and Hispanics, but that the tradeoff offers poor terms in which employment gains are far less than proportionate to environmental costs. Furthermore, the tradeoff tails off concavely at higher levels of pollution so that there appears to be little community return, in terms of additional employment, to substantial increases in pollution.

When we examine the tradeoff between total population exposure and employment we find that there is no apparent tradeoff in the sense of there being no employment gradient between less and more polluting facilities. For the most part this is true among facilities in the same industrial sectors, which are more likely to be using similar chemicals and processes, and it is largely true within regions as well.

These are surprising results. The Toxics Release Inventory data are mandatory, self-reported, and, in many cases, based on engineering estimates that associate the process and the scale with an estimated level of release. Alternatives, practiced by a small fraction

of TRI reporters, are methods of actual measurement of pollution release based on either mass-balance methods (accounting for the mass of inputs and outputs to estimate the mass of releases) or continuous or periodic monitoring of stack emissions.¹⁰ The modal method of engineering estimates is likely to associate bigger facilities with more pollution. So there is an almost necessary relationship between the volume of industrial activity and estimated pollution releases. The absence of an association is thus unexpected. Facilities that generate higher population risk provide neither additional employment nor additional employment in good jobs.

There are several possible explanations for the non-association. First, the RSEI method accounts for population exposure; so a bigger facility is not always strictly worse because the facility may be located in a place where the population exposure to its emissions is limited. Second, the industrial sectors may not be finely enough distinguished in the TRI data to compare facilities using the same process at different scales. Finally it is possible that substantial noise in pollution release estimates and that this measurement error attenuates the estimated relationship.

An additional limitation is that we do not have a perfect counterfactual for the employment that would have obtained in the absence of a polluting facility or in the presence of a different polluting facility. A perfect market in amenities with compensating differentials might yield, ex post, the result that communities already have the best pollution-jobs tradeoff available to them with some communities, say those with high human capital, attracting high employment at low pollution cost and other communities, say those with low human capital, required to accept high pollution to attract high-employment facilities. However, many of the toxics in the TRI are not immediately evident to nearby communities — many TRI chemicals, although highly toxic, are low-volume pollutants and not necessarily marked by visible or

¹⁰See http://www3.epa.gov/trimewebhelp/WebHelp/tri_forms_and_instructions6_new_frmr_sec5_column_b_basis_of_estimate_.htm for more detail on the basis of TRI release estimates.

smellable evidence. So it is unlikely that optimal bargaining and compensation are in place.

Despite these potential limitations and concerns, the absence of a clear trade-off between jobs and the environment is striking. There is growing evidence that the cost, in income or jobs, of environmental regulation is often smaller than forecast (Goodstein, 1995; Goodstein and Hodges, 1997) or that the impact of environmental regulation on employment and economic activity is actually positive (Pollin, 2015; Bezdek et al., 2008). In this study, we find little evidence that more pollution itself is associated with more or better jobs in aggregate, a non-trade-off that should inform policymakers and local public and private decision-makers.

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Table 1: Jobs versus Pollution Risk: Linear regression results

	log Employment					Employment	
Intercept	5.67*** (0.41)	5.76*** (1.11)	3.48*** (0.93)	7.60*** (0.81)	3.92*** (0.80)	514.56*** (52.50)	562.50 (503.41)
log(RSEI Score)	-0.01 (0.04)	0.01 (0.04)	0.18* (0.08)	-0.17* (0.07)	0.12 (0.07)		-4.73 (43.61)
RSEI Score/1000000						-21.59 (43.37)	
State Dummies		Yes					
Industry Dummies		Yes					
Adj. R ²	0.00	0.13	0.03	0.03	0.01	0.00	0.00
Subsample			EPA Reg 6	EPA Reg 5	Chem. Mfg		
Num. obs.	712	712	147	195	152	712	712

Each column shows the coefficients from a linear regression of employment on the total population risk for each facility. In columns 1–5 the dependent variable is natural log of employment, i.e., log of the count of total employees in all occupations at the facility. In columns 6–7, the dependent variable is the level of employment. In column 3, the sample is limited to facilities in EPA Region 6, South Central, which comprises Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. In column 4, the sample is limited to facilities in EPA Region 5, Great Lakes, which comprises Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin. In column 5, the sample is limited to Chemical Manufacturing facilities (NAICS code 325). Standard errors are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 2: Good Jobs versus Pollution Risk: Linear regression results

	log Good Jobs					Good Jobs	
Intercept	4.99*** (0.47)	5.13*** (1.24)	2.19* (1.05)	7.34*** (0.91)	3.21*** (0.89)	307.63*** (36.33)	256.64 (348.38)
log(RSEI Score)	-0.02 (0.04)	0.02 (0.04)	0.24** (0.09)	-0.22** (0.08)	0.14 (0.08)		4.04 (30.18)
RSEI Score/1000000						-15.84 (30.01)	
State Dummies		Yes					
Industry Dummies		Yes					
Adj. R ²	0.00	0.14	0.04	0.04	0.01	0.00	0.00
Subsample			EPA Reg 6	EPA Reg 5	Chem. Mfg		
Num. obs.	712	712	147	195	152	712	712

Each column shows the coefficients from a linear regression of employment in managerial, professional, technical, and craft occupational categories on the total population risk for each facility. In columns 1–5 the dependent variable is natural log of employment, i.e., log of the count of employees in good jobs at the facility. In columns 6–7, the dependent variable is the level of employment. In column 3, the sample is limited to facilities in EPA Region 6, South Central, which comprises Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. In column 4, the sample is limited to facilities in EPA Region 5, Great Lakes, which comprises Illinois, Indiana, Michigan, Minnesota, Ohio, and Wisconsin. In column 5, the sample is limited to Chemical Manufacturing facilities (NAICS code 325). Standard errors are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 3: Jobs versus Pollution Risk, by race: Linear regression results

	Non-Hispanic Whites		African-Americans		Hispanics	
Intercept	4.74*** (0.40)	3.85*** (0.43)	-0.75** (0.28)	-0.60* (0.27)	-2.01*** (0.25)	-0.78** (0.25)
log(White Score)	0.04 (0.04)	0.01 (0.04)				
State percent white		1.65*** (0.33)				
log(Black Score)			0.39*** (0.03)	0.31*** (0.03)		
State percent black				4.29*** (0.66)		
log(Hispanic Score)					0.48*** (0.03)	0.27*** (0.03)
State percent hisp						6.16*** (0.51)
Adj. R ²	0.00	0.03	0.19	0.24	0.29	0.41
Num. obs.	712	712	712	712	712	712

Each column shows the coefficients from a linear regression of log employment on log population risk for three race/ethnicity groups. In columns 1–2 the dependent variable is natural log of non-Hispanic white employment, in columns 3–4 African-American, and in columns 5–6 Hispanic. We added 1 to all employment figures and 10 to the racially/ethnically specific RSEI Scores to avoid taking log of zero. Standard errors are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 4: Good Jobs versus Pollution Risk, by race: Linear regression results

	Non-Hispanic Whites		African-Americans		Hispanics	
Intercept	4.52*** (0.43)	4.01*** (0.47)	-0.94*** (0.27)	-0.81** (0.26)	-1.89*** (0.23)	-0.71** (0.23)
log(White Score)	0.01 (0.04)	-0.01 (0.04)				
State percent white		0.95** (0.36)				
log(Black Score)			0.31*** (0.03)	0.25*** (0.03)		
State percent black				3.73*** (0.65)		
log(Hispanic Score)					0.39*** (0.03)	0.19*** (0.03)
State percent hisp						5.86*** (0.47)
Adj. R ²	-0.00	0.01	0.14	0.18	0.24	0.38
Num. obs.	712	712	712	712	712	712

Each column shows the coefficients from a linear regression of log employment in good jobs on log population risk for three race/ethnicity groups. In columns 1–2 the dependent variable is natural log of non-Hispanic white employment, in columns 3–4 African-American, and in columns 5–6 Hispanic. Standard errors are in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5: Industries Ranked by Black Jobs-Environment Disparity

Industry	Black Share			Jobs	Total RSEI Score
	RSEI Score	Jobs	Good Jobs		
Waste Management and Remediation Services	0.373	0.184	0.086	180	61772
Petroleum and Coal Products Manufacturing	0.227	0.111	0.080	524	160542
Chemical Manufacturing	0.226	0.121	0.091	359	321531
Food Manufacturing	0.242	0.150	0.086	893	107296
Wood Product Manufacturing	0.218	0.140	0.048	277	198557
Fabricated Metal Product Manufacturing	0.163	0.088	0.048	272	478009
Utilities	0.151	0.087	0.081	222	96147
Primary Metal Manufacturing	0.152	0.097	0.055	517	214711
Machinery Manufacturing	0.114	0.060	0.036	412	271356
Paper Manufacturing	0.185	0.134	0.072	685	58656
Computer and Electronic Product Manufacturing	0.103	0.070	0.034	937	174418
Plastics and Rubber Products Manufacturing	0.192	0.162	0.077	249	81754
Miscellaneous Manufacturing	0.197	0.169	0.095	490	138168
Professional, Scientific, and Technical Services	0.032	0.024	0.034	41	1309184
Nonmetallic Mineral Product Manufacturing	0.143	0.141	0.069	343	81175
Mining (except Oil and Gas)	0.004	0.003	0.002	549	235290
Transportation Equipment Manufacturing	0.124	0.128	0.080	1676	493727
Support Activities for Transportation	0.102	0.114	0.092	368	192028
Electrical Equipment, Appliance, and Component Manufacturing	0.212	0.246	0.178	864	289203
Furniture and Related Product Manufacturing	0.209	0.248	0.120	685	179809
Pipeline Transportation	0.125	0.167	0.172	30	177970

Source: Authors' computations with EEO-1 and RSEI data.

Table 6: African-American share of jobs versus share of toxics risk: Linear regression results

	Black Share of							
	Jobs					Good Jobs		
Intercept	0.03*** (0.00)	-0.01 (0.01)	-0.00 (0.08)	0.02*** (0.00)	0.02*** (0.00)	-0.00 (0.00)	0.00 (0.06)	0.01*** (0.00)
Black toxic share	0.46*** (0.02)	0.34*** (0.02)	0.31*** (0.02)	0.26*** (0.03)	0.27*** (0.01)	0.19*** (0.02)	0.18*** (0.02)	0.14*** (0.02)
State percent black		0.42*** (0.05)				0.30*** (0.03)		
County percent black				0.33*** (0.04)				0.23*** (0.03)
State Dummies			Yes				Yes	
Industry Dummies			Yes				Yes	
Adj. R ²	0.43	0.48	0.51	0.47	0.35	0.42	0.41	0.45
Num. obs.	712	712	712	712	712	712	712	712

Each column shows the coefficients from a linear regression of the black share of jobs on the black share of risk for each facility. Standard errors in parentheses.

Table 7: Industries Ranked by Hispanic Jobs-Environment Disparity

Industry	Hispanic Share			Jobs	Total RSEI Score
	RSEI Score	Jobs	Good Jobs		
Pipeline Transportation	0.677	0.100	0.103	30	177970
Petroleum and Coal Products Manufacturing	0.252	0.105	0.091	524	160542
Chemical Manufacturing	0.193	0.065	0.054	359	321531
Machinery Manufacturing	0.105	0.047	0.029	412	271356
Furniture and Related Product Manufacturing	0.082	0.025	0.005	685	179809
Support Activities for Transportation	0.810	0.753	0.736	368	192028
Paper Manufacturing	0.063	0.010	0.007	685	58656
Electrical Equipment, Appliance, and Component Manufacturing	0.153	0.101	0.075	864	289203
Transportation Equipment Manufacturing	0.147	0.097	0.070	1676	493727
Mining (except Oil and Gas)	0.184	0.135	0.130	549	235290
Utilities	0.061	0.015	0.015	222	96147
Computer and Electronic Product Manufacturing	0.189	0.151	0.100	937	174418
Nonmetallic Mineral Product Manufacturing	0.117	0.089	0.057	343	81175
Plastics and Rubber Products Manufacturing	0.045	0.018	0.008	249	81754
Waste Management and Remediation Services	0.044	0.017	0.028	180	61772
Food Manufacturing	0.160	0.139	0.069	893	107296
Wood Product Manufacturing	0.049	0.034	0.008	277	198557
Miscellaneous Manufacturing	0.108	0.098	0.068	490	138168
Professional, Scientific, and Technical Services	0.031	0.024	0.000	41	1309184
Primary Metal Manufacturing	0.131	0.127	0.081	517	214711
Fabricated Metal Product Manufacturing	0.153	0.158	0.100	272	478009

Source: Authors' computations with EEO-1 and RSEI data.

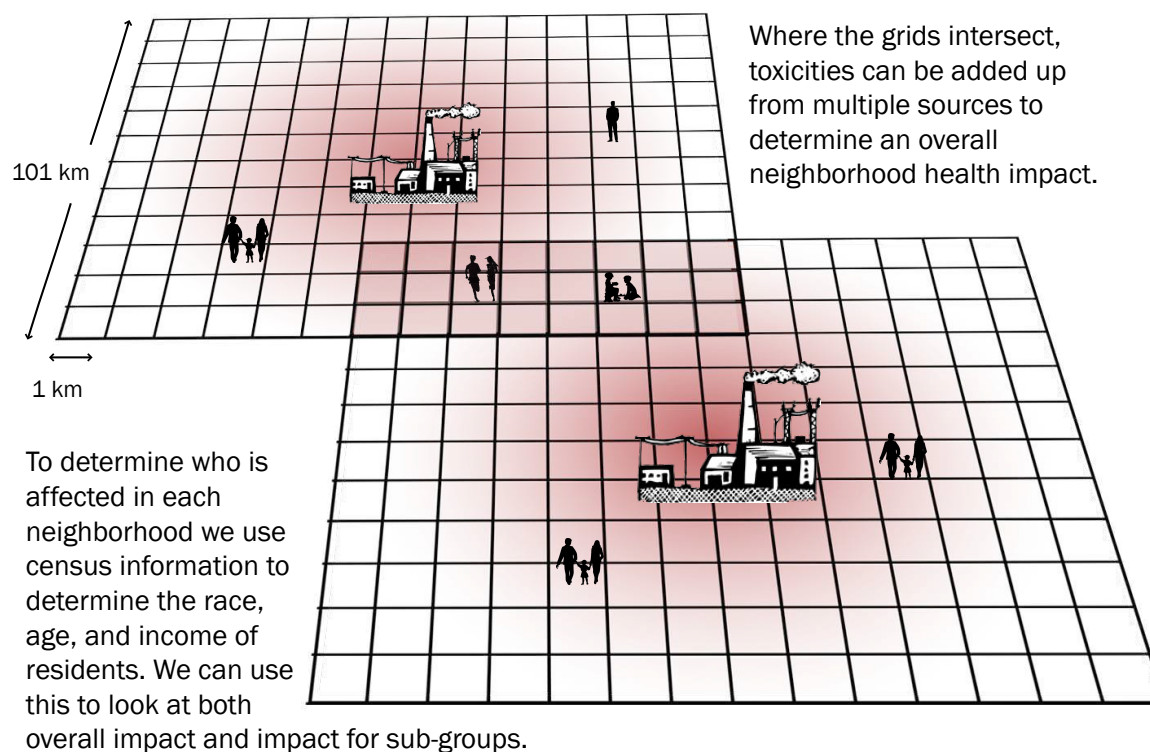
Table 8: Hispanic share of jobs versus share of toxics risk: Linear regression results

	Hispanic Share of							
	Jobs			Good Jobs				
Intercept	0.00 (0.01)	-0.00 (0.01)	0.01 (0.11)	0.00 (0.01)	-0.01 (0.00)	-0.01* (0.00)	0.03 (0.09)	-0.00 (0.00)
Hispanic toxic share	0.64*** (0.03)	0.56*** (0.04)	0.49*** (0.04)	0.25*** (0.06)	0.50*** (0.02)	0.44*** (0.03)	0.39*** (0.03)	0.13** (0.04)
State percent hisp		0.18** (0.07)				0.13* (0.05)		
County percent hisp				0.63*** (0.08)				0.59*** (0.06)
State Dummies			Yes				Yes	
Industry Dummies			Yes				Yes	
Adj. R ²	0.48	0.48	0.53	0.52	0.49	0.49	0.55	0.53
Num. obs.	712	712	712	712	712	712	712	712

Each column shows the coefficients from a linear regression of the Hispanic share of jobs on the Hispanic share of risk for each facility. Standard errors in parentheses.

Figure 1: EPA's Risk Screening Environmental Indicators: Schematic of Air Plume Model

RSEI takes the toxic air release from each industrial source and uses wind and other information to determine where the releases go within a grid around each facility. RSEI attributes higher health impacts to grid cells exposed to higher-toxicity chemicals.



The 101 km × 101 km catchment area with 1-square-kilometer grid cells pictured above was used in earlier RSEI versions and has been replaced with a 50-km radius with 810m × 810m grid cells as of RSEI version 2.3.0). Source: Ash et al. (2009).

Figure 2: Nonparametric Density Plot of RSEI Scores from Highest-Score TRI Facilities

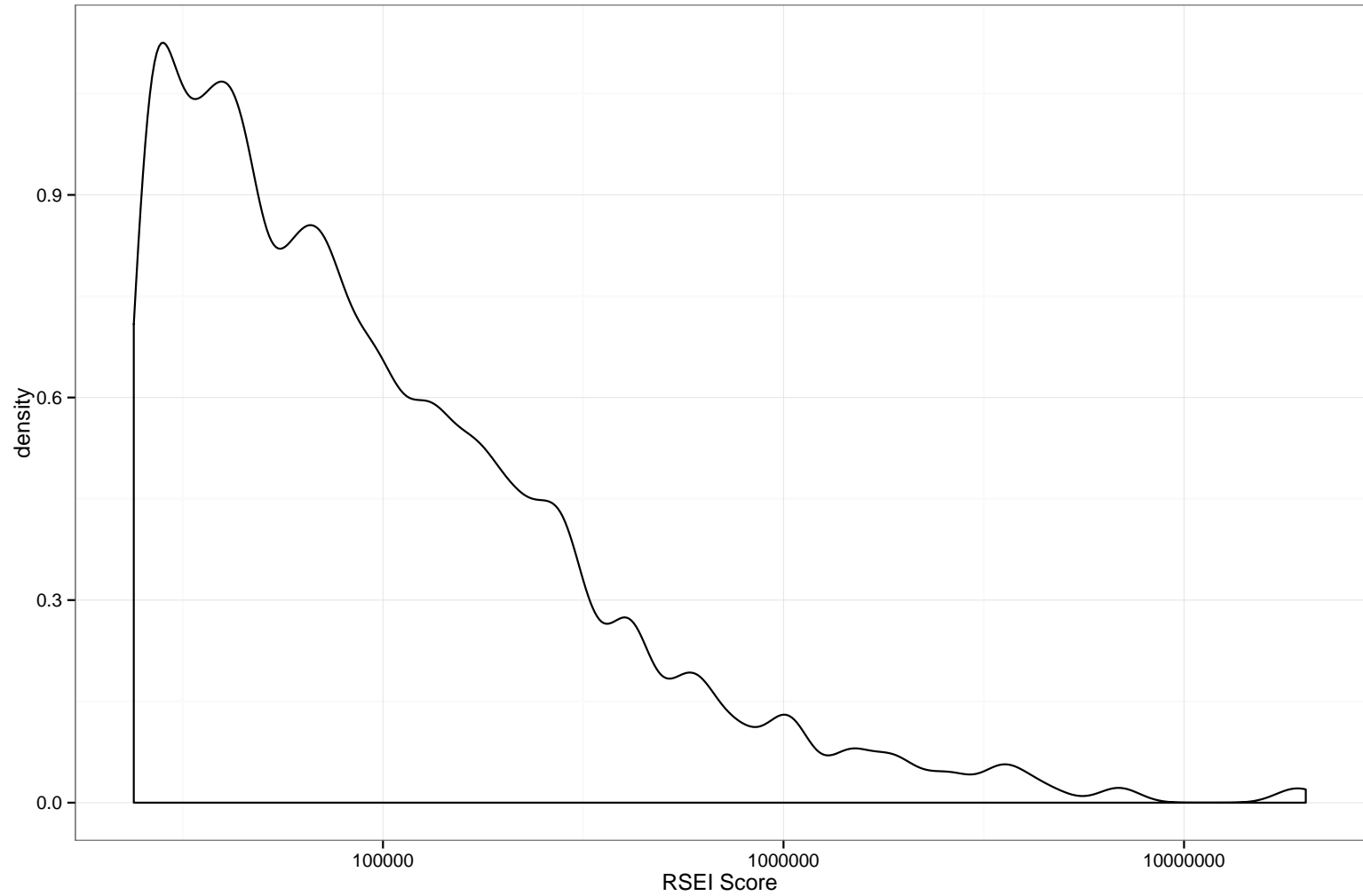
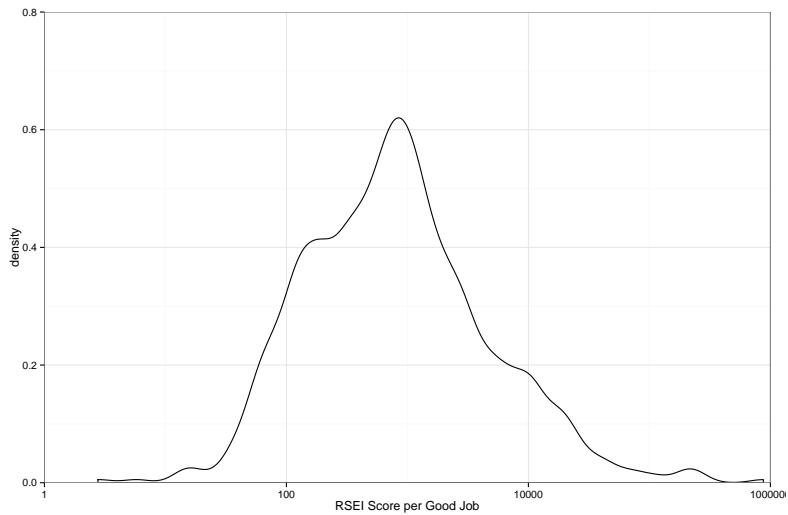
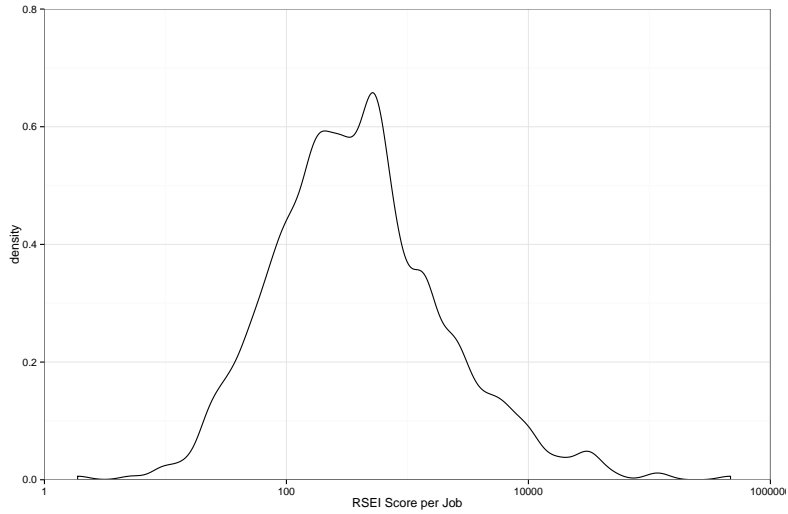
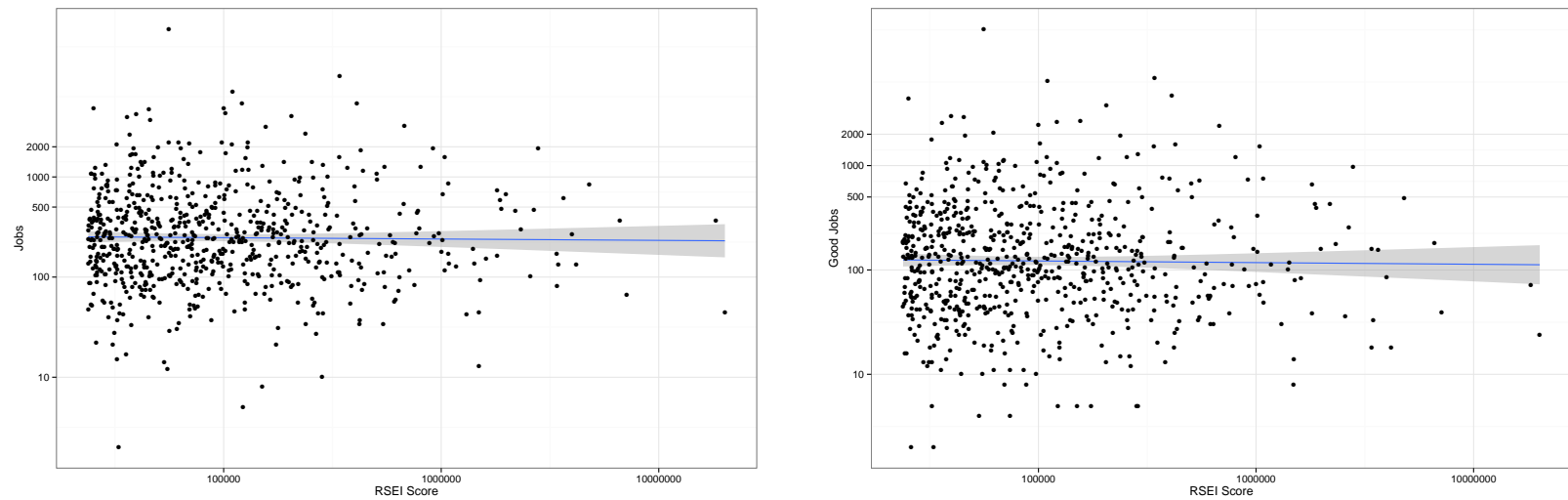


Figure 3: Nonparametric Density Plot of RSEI Score per Job (High Score TRI Facilities)

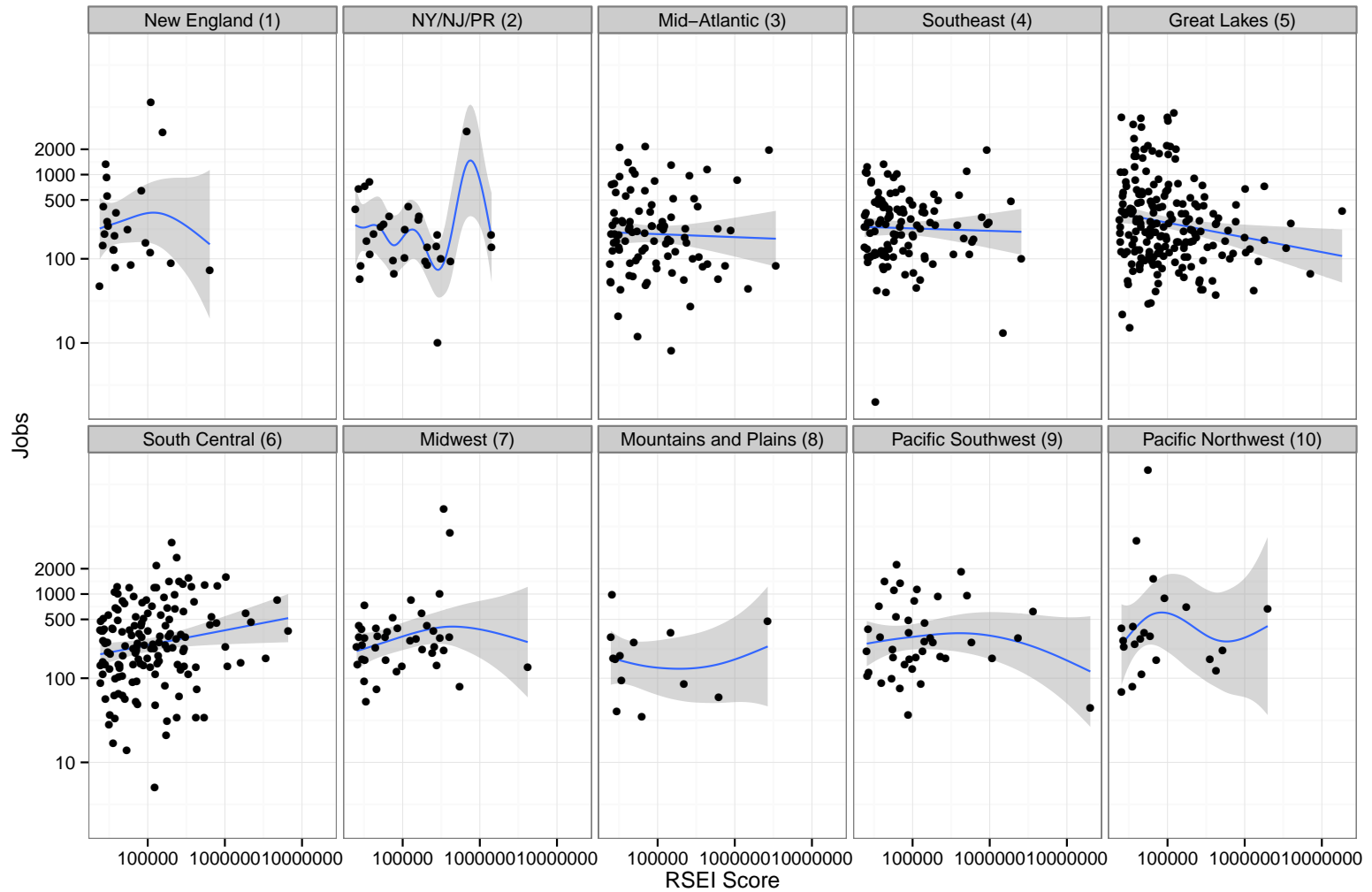


$N = 712$ facilities in matched TRI-EEO-1 sample from the 1,000 TRI facilities with the highest air-based RSEI Scores. Good jobs are defined as managerial, professional, technical, and craft occupations. Source: Authors' computations with EEO-1 and RSEI data.

Figure 4: Jobs versus Pollution Risk

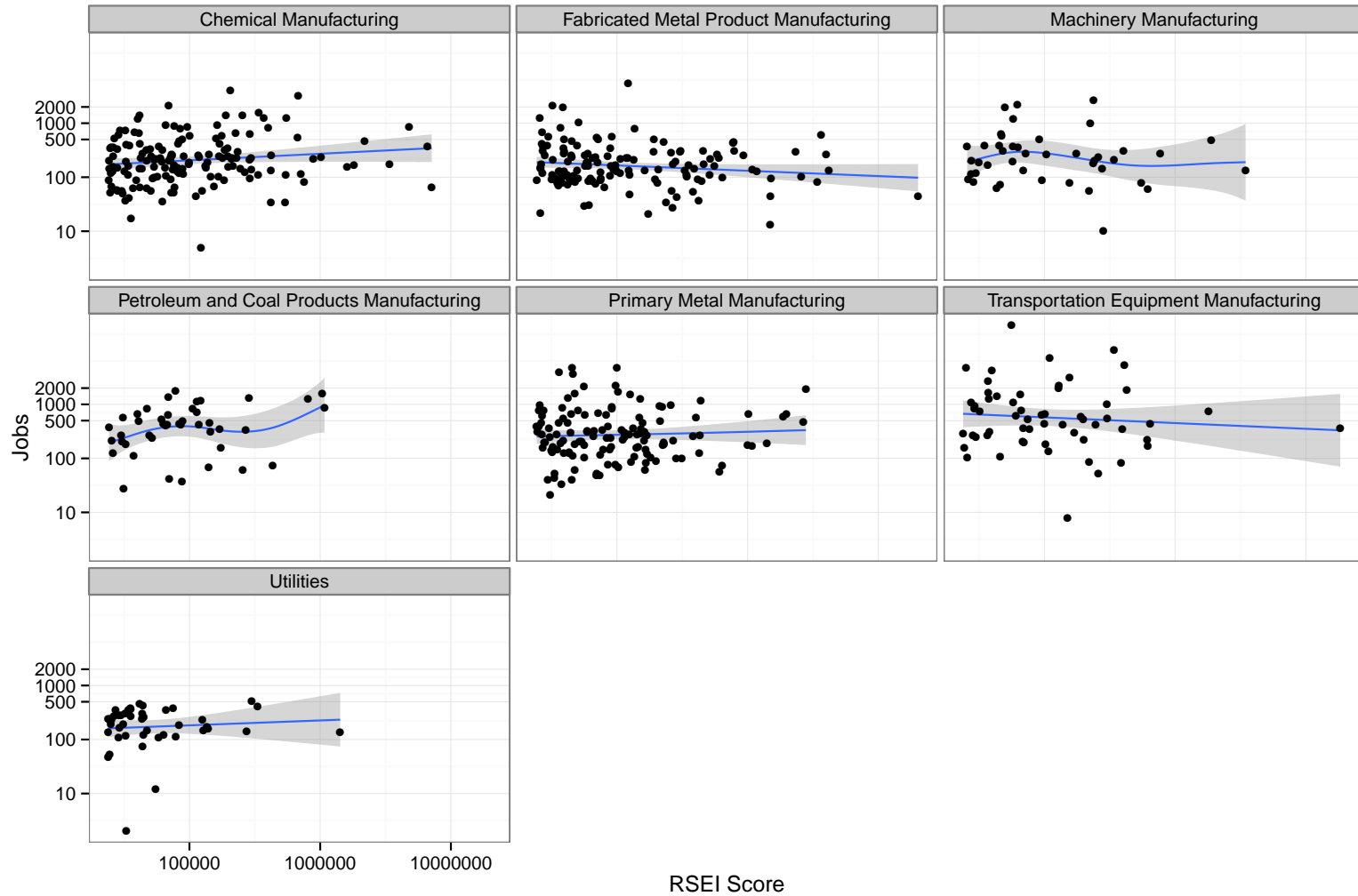
$N = 712$ facilities. The horizontal axis shows the log of RSEI Score, a measure of the potential chronic human health risk from industrial toxic air releases. The vertical axis shows the log of facility employment. The locally smoothed regression function is estimated with general additive model with integrated smoothness estimation using the `mgcv` package in R. The smoothing parameter is selected with the default cross-validation method. Source: Authors' computations with EEO-1 and RSEI data.

Figure 5: Jobs versus Pollution Risk, by EPA Region



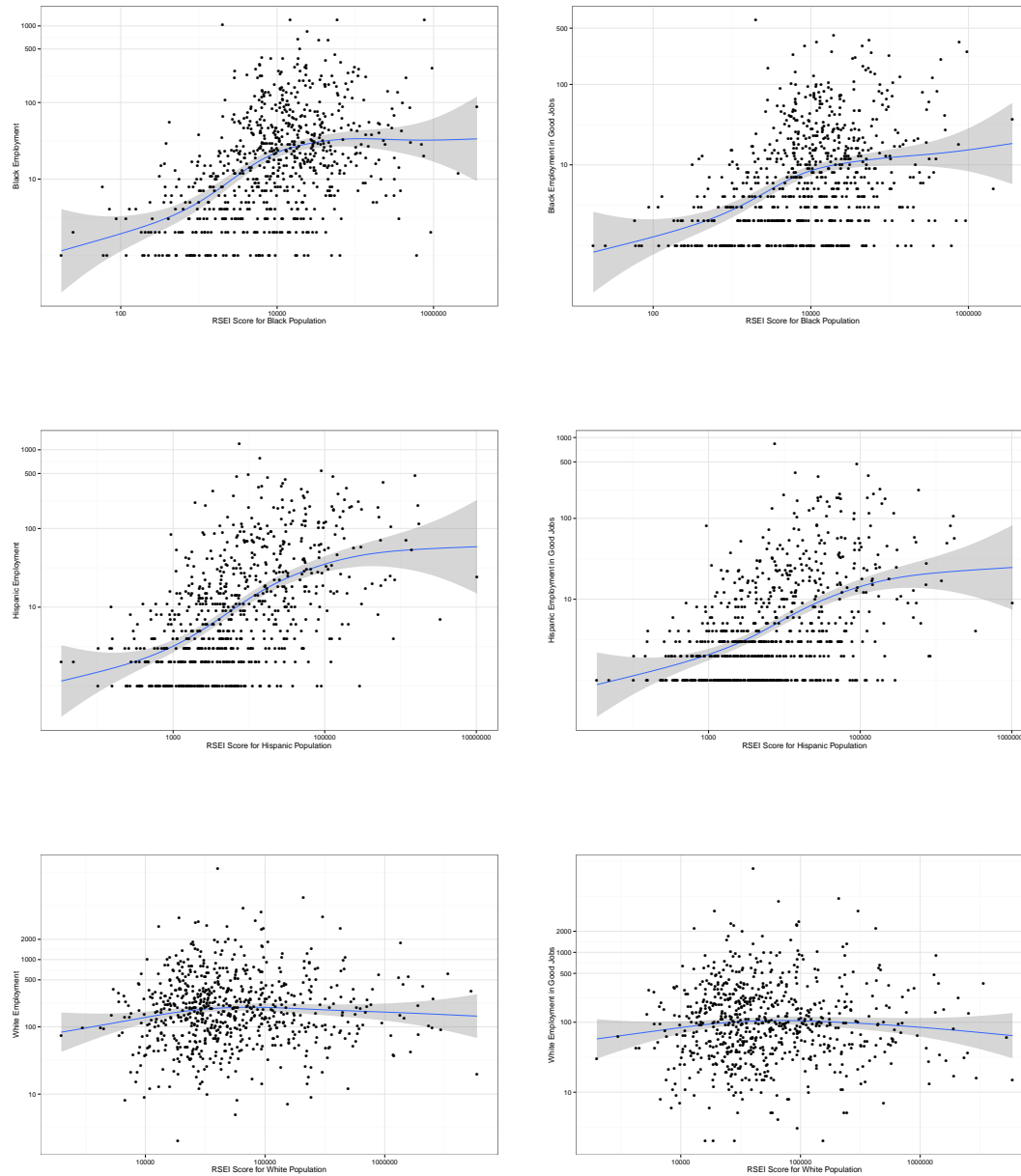
$N = 712$ facilities stratified by 10 EPA Regions. The horizontal axis shows the log of RSEI Score, a measure of the potential chronic human health risk from industrial toxic air releases. The vertical axis shows the log of total employment. The locally smoothed regression function is estimated with the general additive model with integrated smoothness estimation using the `mgcv` package in R. The smoothing parameter is selected with the default cross-validation method. Source: Authors' computations with EEO-1 and RSEI data.

Figure 6: Jobs versus Pollution Risk, by Industry



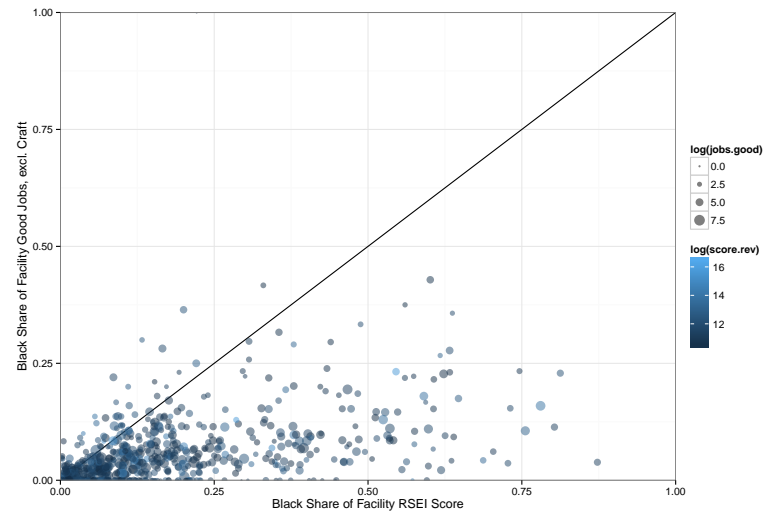
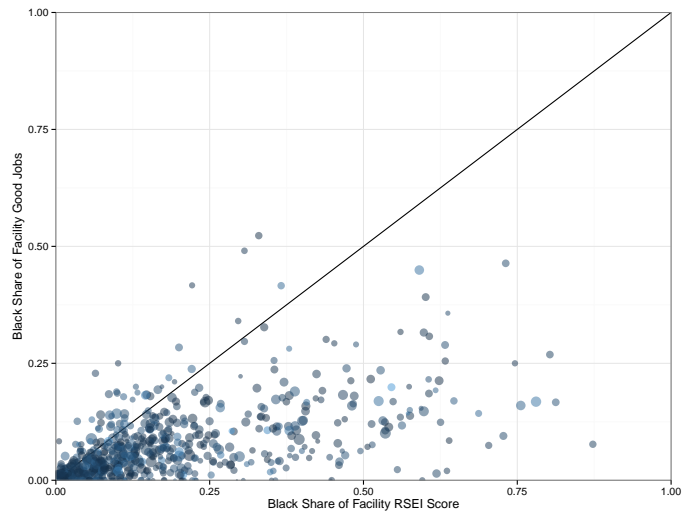
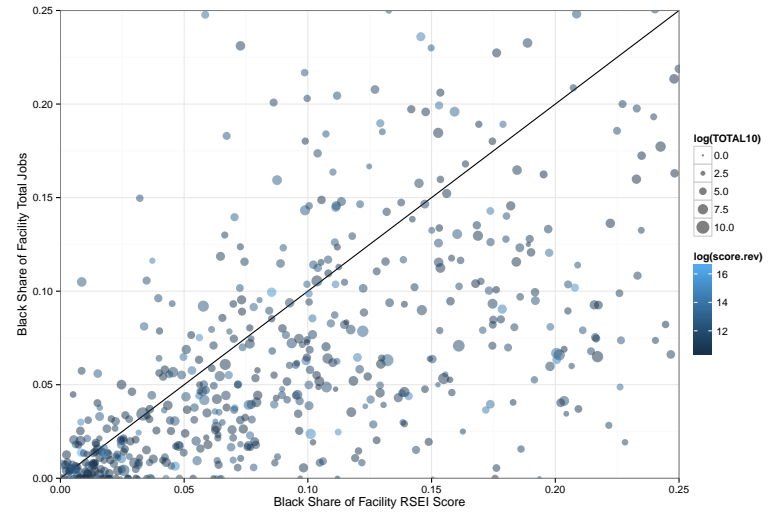
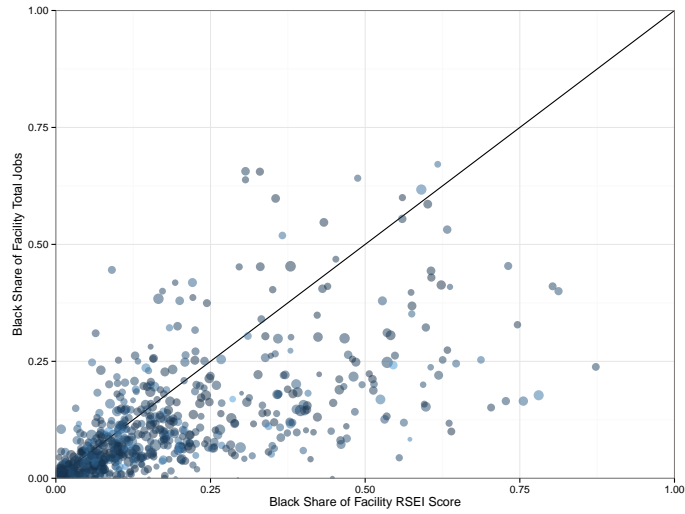
Facilities stratified by 3-digit NAICS code for industries having at least 40 establishments in the data. The horizontal axis shows the log of RSEI Score, a measure of the potential chronic human health risk from industrial toxic air releases. The vertical axis shows the log of total employment. The locally smoothed regression function is estimated with the general additive model with integrated smoothness estimation using the `mgcv` package in R. The smoothing parameter is selected with the default cross-validation method. Source: Authors' computations with EEO-1 and RSEI data.

Figure 7: Jobs versus Pollution Risk, by Race/Ethnicity



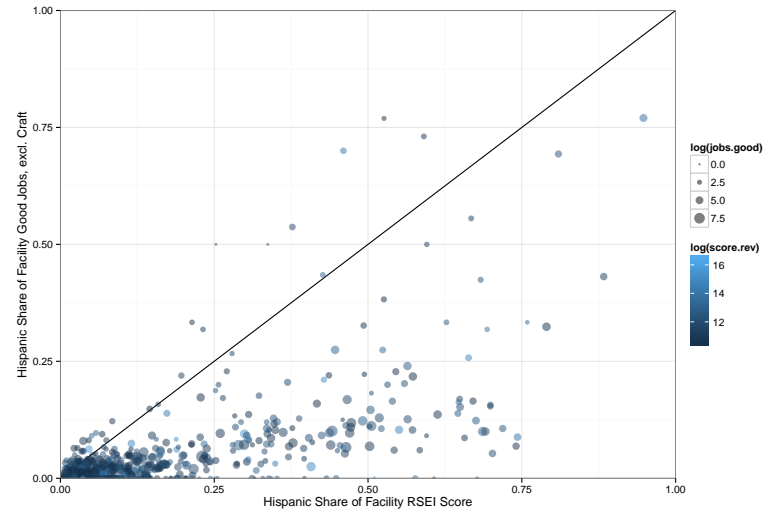
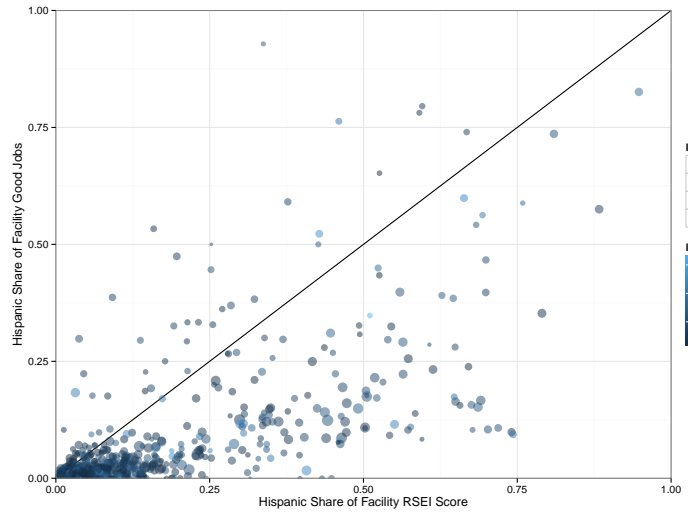
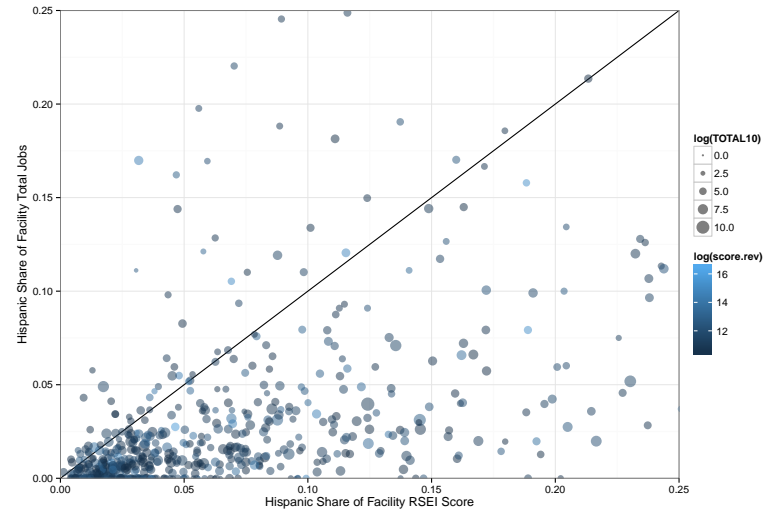
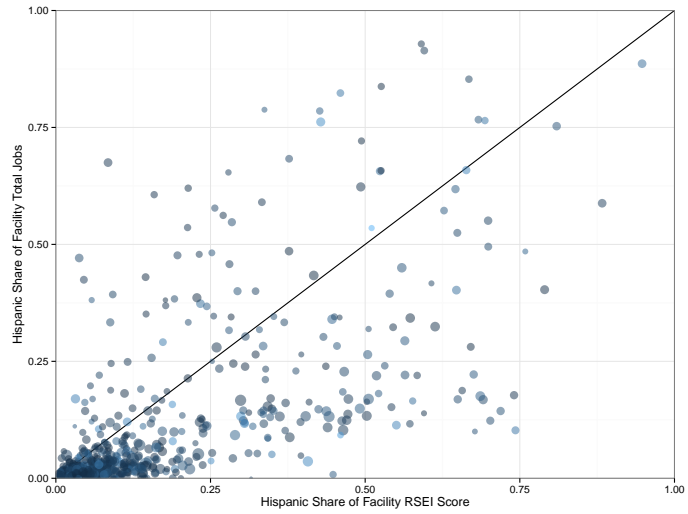
$N = 712$ facilities. The horizontal axis shows the log of RSEI Score, a measure of the potential chronic human health risk from industrial toxic air releases. The vertical axis shows the log of employment. The locally smoothed regression function is estimated with general additive model with integrated smoothness estimation using the `mgcv` package in R. The smoothing parameter is selected with the default cross-validation method. Source: Authors' computations with EEO-1 and RSEI data.

Figure 8: Share of jobs versus share of toxics risk for African-Americans



Source: Authors' computations with EEO-1 and RSEI data.

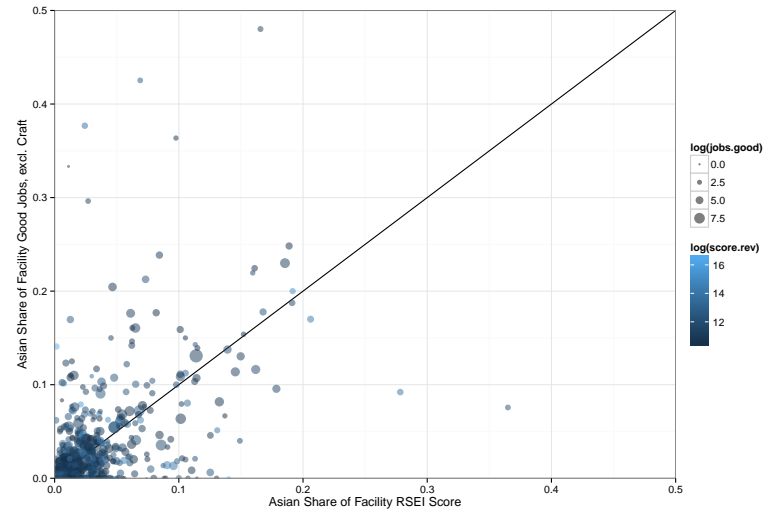
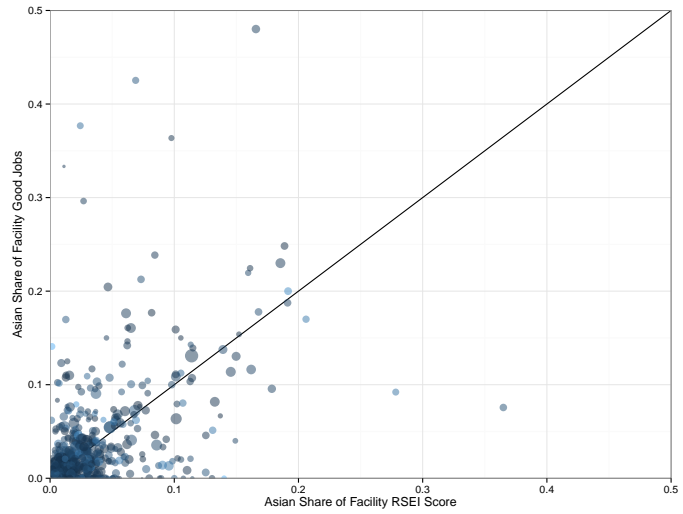
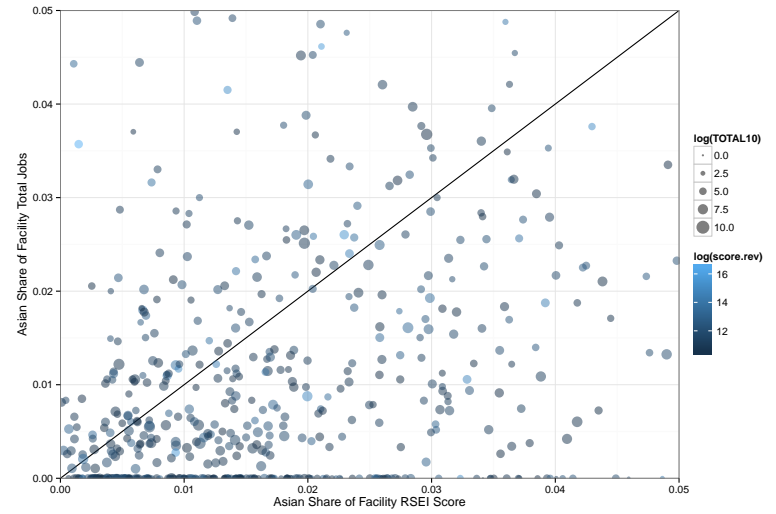
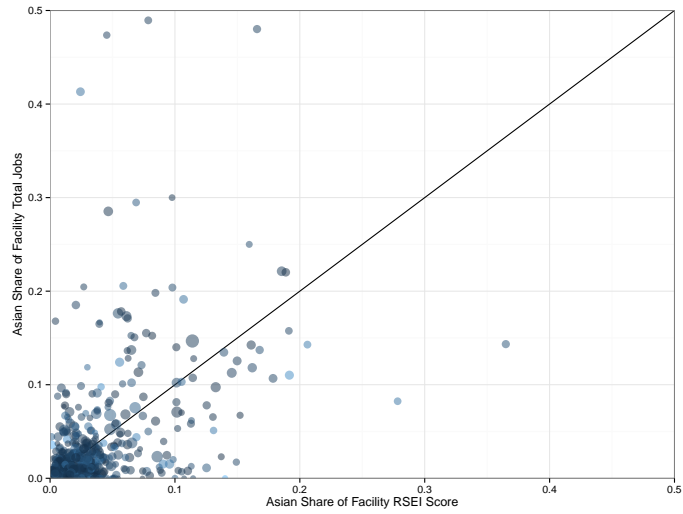
Figure 9: Share of jobs versus share of toxics risk for Hispanics



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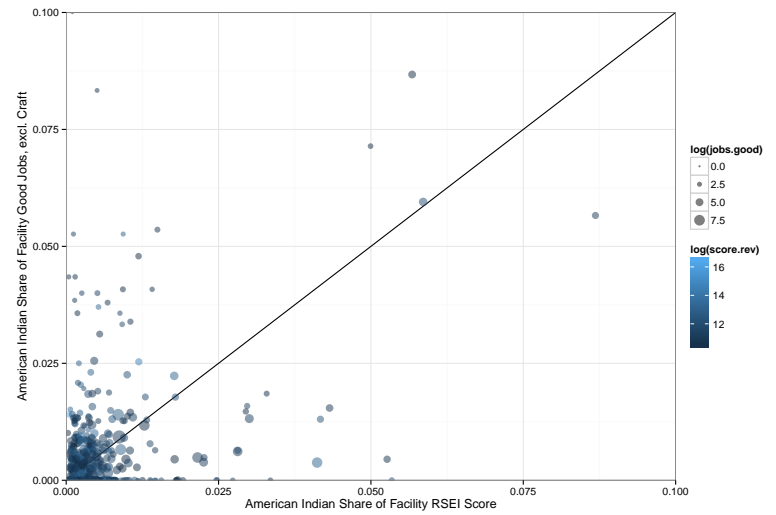
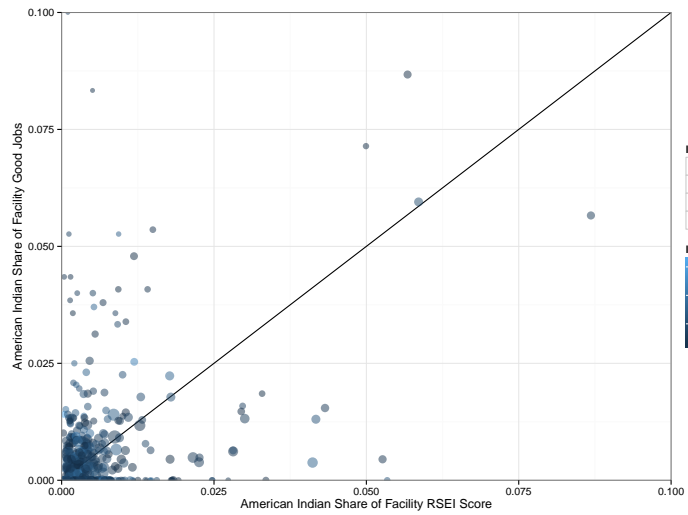
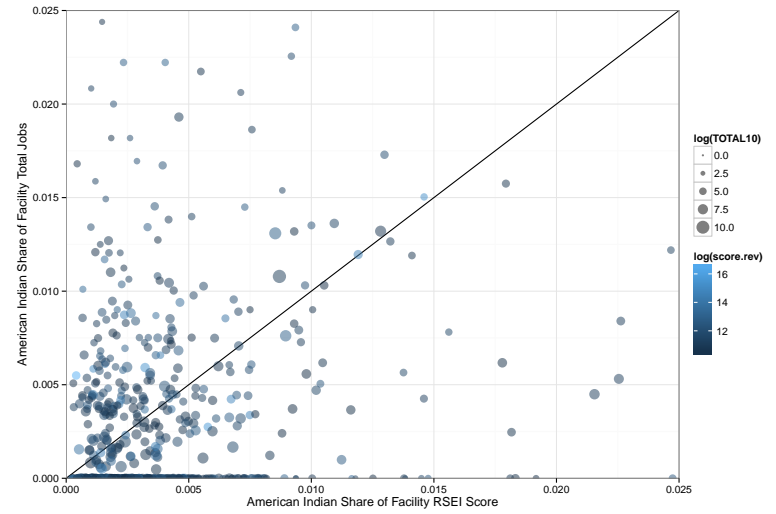
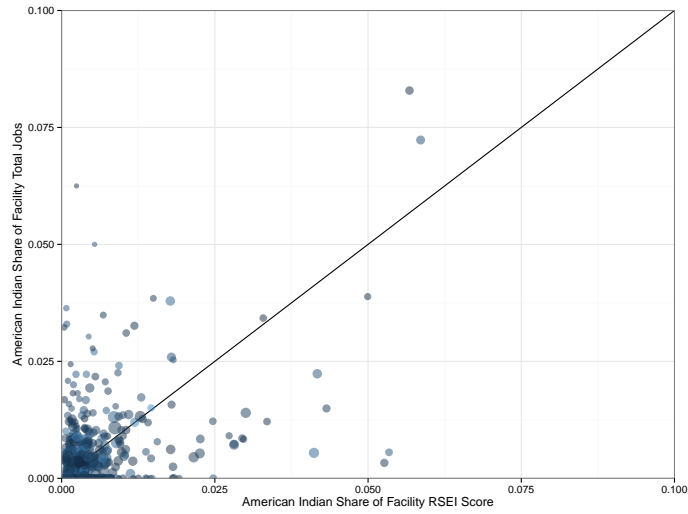
Source: Authors' computations with EEO-1 and RSEI data.

Figure 10: Share of jobs versus share of toxics risk for Asian-Americans



Source: Authors' computations with EEO-1 and RSEI data.

Figure 11: Share of jobs versus share of toxics risk for Native Americans



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Source: Authors' computations with EEO-1 and RSEI data.

Table A.1: Distribution of job categories, by sample

	EEO-1	EEO-1 TRI NAICS	EEO-1 TRI match
Good jobs			
Exec/Sr-Level Officials & Managers (1.1)	0.016	0.022	0.011
First/Mid-Level Officials & Managers (1.2)	0.094	0.109	0.101
Professionals (2)	0.187	0.207	0.176
Technicians (3)	0.058	0.057	0.061
Craft Workers (6)	0.058	0.105	0.247
Other Jobs			
Sales Workers (4)	0.127	0.047	0.010
Administrative Support Workers (5)	0.134	0.114	0.038
Operatives (7)	0.100	0.171	0.308
Laborers & Helpers (8)	0.072	0.099	0.042
Service Workers (9)	0.154	0.068	0.005

The first column contains the distribution of employment by job category for all establishments included in the EEO-1 data. The second column contains the distribution of employment by job category for all establishments in the EEO-1 data limited to the NAICS codes that appear in the Toxics Release Inventory. The third column contains the distribution of employment by job category for all facilities in the EEO-1-TRI matched data. The EEO job category code number is in parentheses following each job category. Source: Authors' computations with EEO-1 and RSEI data.

Table A.2: Distribution of industries

	Establishments (count)	Establishments (percent)	Employment (percent)
Chemical Manufacturing	152	0.213	0.151
Fabricated Metal Product Manufacturing	141	0.198	0.106
Primary Metal Manufacturing	129	0.181	0.184
Transportation Equipment Manufacturing	58	0.081	0.269
Utilities	45	0.063	0.028
Petroleum and Coal Products Manufacturing	43	0.060	0.062
Machinery Manufacturing	43	0.060	0.049
Nonmetallic Mineral Product Manufacturing	21	0.029	0.019
Paper Manufacturing	19	0.027	0.036
Miscellaneous Manufacturing	15	0.021	0.020
Computer and Electronic Product Manufacturing	8	0.011	0.021
Food Manufacturing	8	0.011	0.020
Electrical Equipment, Appliance, and Component Manufacturing	7	0.010	0.017
Plastics and Rubber Products Manufacturing	7	0.010	0.005
Wood Product Manufacturing	6	0.008	0.004
Waste Management and Remediation Services	4	0.006	0.002
Mining (except Oil and Gas)	3	0.004	0.005
Furniture and Related Product Manufacturing	1	0.001	0.002
Support Activities for Transportation	1	0.001	0.001
Pipeline Transportation	1	0.001	0.000
Professional, Scientific, and Technical Services	1	0.001	0.000

The first two columns show the distribution of facilities in the EEO-1–TRI matched data. The third column shows the distribution of employment. Source: Authors’ computations with EEO-1 and RSEI data.

Table A.3: Distribution across EPA Regions

	Facilities	Workers
New England (1)	0.032	0.046
NY/NJ (2)	0.042	0.027
Mid-Atlantic (3)	0.130	0.090
Southeast (4)	0.153	0.103
Great Lakes (5)	0.273	0.302
South Central (6)	0.206	0.179
Midwest (7)	0.058	0.076
Mountains and Plains (8)	0.018	0.009
Pacific Southwest (9)	0.058	0.054
Pacific Northwest (10)	0.029	0.114

The first column shows the distribution of facilities and the second column shows the distribution of workers across US EPA Regions for the EEO-1–TRI matched data. Source: Authors' computations with EEO-1 and RSEI data.

Table A.4: Unmatched and Matched TRI Facilities,
Distribution across EPA Regions

	Unmatched	Matched
New England (1)	0.025	0.032
NY/NJ (2)	0.050	0.041
Mid-Atlantic (3)	0.121	0.130
Southeast (4)	0.160	0.153
Great Lakes (5)	0.281	0.273
South Central (6)	0.164	0.209
Midwest (7)	0.046	0.057
Mountains and Plains (8)	0.036	0.018
Pacific Southwest (9)	0.060	0.057
Pacific Northwest (10)	0.057	0.029

The table shows the distribution of facilities across US EPA Regions. The first column shows the distribution of TRI facilities that were not matched to the EEO-1 data and the second column shows the distribution of TRI facilities that were matched to EEO-1 data. Source: Authors' computations with EEO-1 and RSEI data.

Table A.5: Unmatched and Matched TRI Facilities, Distribution across Industrial Sectors

	Unmatched	Matched
Administrative and Support Services	0.014	0.000
Chemical Manufacturing	0.160	0.211
Computer and Electronic Product Manufacturing	0.000	0.013
Electrical Equipment, Appliance, and Component Manufacturing	0.010	0.011
Fabricated Metal Product Manufacturing	0.265	0.171
Food Manufacturing	0.007	0.011
Furniture and Related Product Manufacturing	0.003	0.003
Leather and Allied Product Manufacturing	0.007	0.000
Machinery Manufacturing	0.066	0.073
Merchant Wholesalers, Durable Goods	0.003	0.000
Merchant Wholesalers, Nondurable Goods	0.010	0.003
Mining (except Oil and Gas)	0.010	0.006
Miscellaneous Manufacturing	0.014	0.020
National Security and International Affairs	0.021	0.000
Nonmetallic Mineral Product Manufacturing	0.031	0.034
Paper Manufacturing	0.000	0.027
Petroleum and Coal Products Manufacturing	0.084	0.064
Plastics and Rubber Products Manufacturing	0.014	0.011
Primary Metal Manufacturing	0.164	0.165
Professional, Scientific, and Technical Services	0.007	0.001
Repair and Maintenance	0.000	0.001
Textile Product Mills	0.000	0.004
Transportation Equipment Manufacturing	0.042	0.095
Utilities	0.045	0.063
Waste Management and Remediation Services	0.010	0.006
Wood Product Manufacturing	0.010	0.007

The table shows the distribution of facilities across 3-Digit NAICS Codes. The first column shows the distribution of TRI facilities that were not matched to the EEO-1 data and the second column shows the distribution of TRI facilities that were matched to EEO-1 data. Source: Authors' computations with EEO-1 and RSEI data.

Table A.6: Unmatched and Matched TRI Facilities, RSEI Scores

	Unmatched	Matched
Mean RSEI Score	278,767	293,898
S.E. of RSEI Score	43,560	43,914
SD log(RSEI Score)	1.20	1.17
Rank among Top 1,000	502	501
Mean Black RSEI Score	51,533	44,325
S.E. of Black RSEI Score	12,587	6,740
Mean Hispanic RSEI Score	47,994	62,747
S.E. of Hispanic RSEI Score	9,533	16,060
Mean Asian RSEI Score	8,316	12,463
S.E. of Asian RSEI Score	1,202	4,144
Mean Native American RSEI Score	1,189	1,159
S.E. of Native American RSEI Score	187	191

The first column shows RSEI Scores of TRI facilities that were not matched to the EEO-1 data and the second column shows RSEI Scores of TRI facilities that were matched to EEO-1 data. Source: Authors' computations with EEO-1 and RSEI data.