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Is Environmental Justice Good for White Folks?

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Abstract

This paper examines spatial variations in exposure to toxic air pollution from industrial facilities in urban areas of the United States, using geographic microdata from the U.S. Environmental Protection Agency's Risk-Screening Environmental Indicators project. We find that average exposure in an urban area is positively correlated with the extent of racial and ethnic disparity in the distribution of the exposure burden. This correlation could arise from causal linkages in either or both directions: the ability to displace pollution onto minorities may lower the effective cost of pollution for industrial firms; and higher average pollution burdens may induce whites to invest more political capital in efforts to influence firms' siting decisions. Furthermore, we find that in urban areas with higher minority pollution-exposure discrepancies, average exposures tend to be higher for all population subgroups, including whites. In other words, improvements in environmental justice in the United States could benefit not only minorities but also whites.

Keywords: *environmental justice; air pollution; industrial toxics; Risk-Screening Environmental Indicators.*

JEL codes: P16, Q53, Q56, R3.

Introduction

This paper examines exposure to toxic air pollution from industrial facilities in urban areas of the United States. Specifically, we analyze the relationship between spatial variations in the magnitude of pollution exposure and its distribution across racial and ethnic subgroups of the population. To do so, we use geographic microdata from the U.S. Environmental Protection Agency's Risk-Screening Environmental Indicators (RSEI) project, aggregated to the level of the Core Based Statistical Area (CBSA).

Individual exposures to industrial air toxics depend on both the average exposure in the CBSA in which a person resides and the extent to which exposures disproportionately impact specific population subgroups. Consistent with prior research, we find evidence that within any given urban area, racial and ethnic minorities tend to bear greater exposure burdens. The extent of the disparity varies considerably, however, across CBSAs. When wide disparities are found in cities where average exposure is relatively high, the harm to minorities is greater than in cases where disparities are wide but average exposure is low.

We test the hypothesis that average exposure is positively correlated with the extent of racial and ethnic disparity in the distribution of exposure burdens. There are two reasons to expect such a correlation. First, where it is easier to displace pollution onto population subgroups with limited politically effective demand for clean air, firms are likely to pollute more. In effect, the firm faces lower costs of pollution. Second, in urban areas with more industrial air pollution, residents will be likely to invest more political capital in efforts to affect siting decisions, and as a result siting will be more strongly shaped by the distribution of political influence. In effect, politically influential subgroups face higher benefits from pollution shifting.

If the correlation between average burdens and the extent of disparities is sufficiently strong, it is possible that all groups – including whites – would face lower total exposure burdens in urban areas with lower disparities. In other words, environmental justice could be good for white folks, too. Our results provide strong support for this conclusion. We find that in CBSAs with higher minority discrepancies, defined as the difference between the minority share of exposure burdens and the minority share of population, average exposures tend to be higher not only for minorities but for whites, too.

We also examine income effects. Among both whites and minorities, exposures are higher for poor households than for non-poor households. But even among non-poor whites, exposure is lower in cities where the minority discrepancy is lower. Even after controlling for other variables, including average CBSA income and the manufacturing share of CBSA employment, the adverse impact of minority discrepancy on exposure burdens of all groups is statistically significant.

Correlates of Environmental Disparities

Since the publication of the landmark report *Toxic Wastes and Race in the United States* (Commission for Racial Justice, 1987), research and public attention to the topic of environmental justice has grown dramatically in the United States. There is now a substantial body of literature documenting environmental disparities along lines of both race and class: minorities and low-income communities tend to face greater hazards (for reviews, see Mohai and Bryant, 1992; Szasz and Meuser, 1997; Ringquist, 2005; Bullard *et al.*, 2007; Pastor, 2007; and Boyce, 2007).

Explanations for these disparities fall into three general categories: (1) market-based explanations in which environmental hazards lead to lower property values in nearby neighborhoods, inducing in-migration by low-income households (see, for example, Been, 1994; Banzhaf and Walsh, 2006); (2) socio-political explanations in which hazards are sited in communities that lack sufficient social capital and political influence to offer effective resistance (see, for example, Bullard, 1990; Hamilton, 1995; Pastor, 2003; and Saha and Mohai, 2005); and (3) racial discrimination in the siting of hazards and/or in the functioning of housing markets (see, for example, Hurley, 1995; Pellow, 2002; and Bullard *et al.*, 2007; Crowder and Downey, 2010).

In a study of 'which came first' in metropolitan Los Angeles – whether disparities result from siting decisions that followed pre-existing demographics or demographic shifts that followed siting – Pastor *et al.* (2001) found strong evidence of the former and weak evidence of the latter. In a study of disparities in Texas, Wolverton (2009) came to the opposite conclusion. Since most studies rely on cross-sectional data for a single time period, such longitudinal analyses are rare. But the finding in many cross-sectional studies that race and ethnicity are statistically significant predictors of hazard proximity and exposure, even when controlling for income (see, for example, Downey and Hawkins, 2008; Ash and Fetter, 2004; and Morello-Frosch *et al.*, 2002) suggests that insofar as post-siting 'move-in' does contribute to the disparities, lower property values are not the sole mechanism: racial discrimination in housing markets appears to play a compounding role.

Whatever the relative importance of these different explanations, the existence of environmental disparities in the United States along racial and ethnic lines is now well-established. The extent of these disparities is far from uniform across the country, however, as documented in several recent studies (Ash *et al.* 2009; Downey, 2007, 2008). Spatial variation across urban areas in the extent of environmental disparities opens possibilities for quantitative analysis of their correlates – both causes and consequences.

The hypothesis that the extent of disparity is correlated with the overall magnitude of pollution can be based on causal linkages between the two that run in either or both directions. On the one hand, wider disparities may lead to more pollution. Both industry and government are mindful of the relative political influence of communities, as has been documented in several well-publicized cases (see Cerrel Associates, 1986; Horswell, 1989). Some communities may have less ability to engage in what Pargal and Wheeler (1996) term "informal regulation," which they characterize as imposing a "price," or penalty, on polluters. The price varies with "characteristics such as income, education, level of civic activity, legal or political recourse, media coverage, presence of a nongovernmental organization, the efficiency of existing formal regulation," and the magnitude of the existing pollution burden (*ibid.*, p. 1316). Pollution gravitates to locations where its implicit price is lower. When there are wide disparities across communities in the resulting pollution burdens, it becomes easier for those who benefit as producers or consumers from the polluting activities to distance themselves – or, at least, to believe that they have distanced themselves – from the environmental and health consequences (Princen, 1997).

Conversely, more pollution could lead to wider disparities. Assuming that political power, like income, is a scarce resource that is subject to a "budget constraint," one may expect that it will be deployed to what those with power consider its highest-value uses. In urban areas with a large concentration of industrial facilities for exogenous or historical reasons, the value to relatively influential communities of policies that result in disparate burdens may be higher that in urban areas where pollution loads are relatively light. Such settings may be characterized not only by spatially uneven efforts to achieve pollution abatement but also by more vigorous efforts to influence decisions on the siting of new facilities and to perpetuate discriminatory practices in housing markets.

Both lines of reasoning rest on the premise that what economists call "negative externalities" – such as toxic air pollution – are not randomly scattered consequences of missing markets but rather the outcomes of political processes shaped by the distribution of power. Just as purchasing power determines the distribution of effective demand for marketed goods and services, so too political power can be seen as determining the distribution of politically effective demand for clean air and other non-marketed aspects of environmental quality. As a result of this phenomenon, which Boyce (2002, 2007) terms the "power-weighted social decision rule," power inequalities can be hypothesized to affect the magnitude of environmental degradation as well as the distribution of the resulting costs.

In a test of the hypothesis that inequalities in the distribution of power affect the total magnitude of environmental degradation, Boyce *et al.* (1999) analyzed variations among the 50 U.S. states in the distribution of power (proxied by a measure constructed from data on voter participation, educational attainments, tax fairness, and Medicaid access), the strength of environmental protection, and environmental quality. Their results were consistent with the prediction that states with more equitable distributions of power tend to have stronger environmental policies and better environmental quality. International evidence on the impacts on environmental quality of political liberties and civil rights, literacy, and democracy also supports this hypothesis (Torras and Boyce, 1998; Barrett and Graddy, 2000; Harbaugh *et al*., 2002; Torras, 2006).

Model and Data

To test the hypothesis that urban areas with wider environmental racial disparities tend to have higher levels of average pollution exposure for all residents, we estimate the following econometric model:

$$Tox_{ij} = \beta MD_{ij} + \phi \mathbf{X}_{ij} + u_j + \varepsilon_{ij} \qquad (1)$$

where *Tox* is the natural logarithm of average industrial air toxics exposure, *MD* is the measure of minority discrepancy described below, ***X*** denotes a vector of control variables (median household income, its square, white share of the population, manufacturing share of employment, and population density), *u* is the region-specific intercept, *ε* is the error term, and i indexes the city (CBSA), and j indexes the Bureau of Economic Analysis (BEA) region.

To test the hypothesis for specific socioeconomic subgroups of residents, we expand the model as follows:

$$Tox_{ijk} = \beta_k MD_{ij} + \phi_k \mathbf{X}_{ij} + u_{jk} + \varepsilon_{ijk} \qquad (2)$$

where k indexes the subgroup (non-poor white, poor white, non-poor minority, poor minority).

The unit of analysis is the Core Based Statistical Area (CBSA), the U.S. Census-defined successor to the Metropolitan Statistical Area. As were MSAs, CBSAs are clusters of socially and economically linked counties (or county equivalents) around an urban core. CBSAs include micropolitan areas as well as metropolitan areas; the urban core of a metropolitan area has population of at least 50,000, while "micropolitan" describes county clusters with urban cores with population between 10,000 and 50,000. The inclusion of lower-population cores expands the count of CBSAs to more than 900.[1] Although our analysis includes both metropolitan and micropolitan areas, henceforth we also refer to CBSAs interchangeably as metropolitan areas or cities.

Exposure

The exposure indicator, Tox_{ij}, is the average exposure of a CBSA resident, computed as the population-weighted average of neighborhood (Census block group) exposures in the metropolitan area. The average exposures of metropolitan-area residents in specified race and income groups, Tox_{ijk}, are the sub-population weighted averages of neighborhood exposures in the metropolitan area; for example, we calculate the exposure of the average non-poor white resident.

The exposure variables come from the Geographic Microdata of U.S. EPA's Risk-Screening Environmental Indicators (RSEI) for the year 2005, merged with data from the 2000 U.S. Census. Full documentation of the RSEI model is available from the EPA website http://www.epa.gov/oppt/rsei. Here we summarize the RSEI Geographic Microdata and how we used it to calculate exposure and shares (for a more extensive summary, see Ash and Boyce, 2010).

RSEI estimates location-specific exposure to airborne toxics emitted by industrial facilities across the United States. It uses information on annual releases of more than 600 chemicals from more than 20,000 facilities, reported in the Toxics Release Inventory (TRI). The TRI was created at the direction of the Congress under the Emergency Planning and Community Right-to-Know Act (EPCRA) passed in 1986 after the Bhopal chemical plant disaster. EPCRA requires industrial facilities to submit annual data to EPA on deliberate and accidental releases of toxic chemicals into air, surface water, and the ground and on transfers to offsite facilities. TRI data are available on an annual basis starting in 1987. In 2005, almost 17,000 TRI-reporting facilities released a total of 1.5 billion pounds of toxic chemicals into the air; an additional 225 million pounds were

[1] See http://www.census.gov/population/www/metroareas/aboutmetro.html. We drop six micropolitan areas with minimal industrial activity in which average exposure is zero (together these represent 0.05% of the U.S. population), yielding a total of 363 metropolitan areas and 571 mircopolitan areas.

transferred to offsite incinerators.[2]

RSEI incorporates information on the fate and transport of releases using a plume model that takes into account chemical decay rates, stack heights, exit-gas velocities, average temperature and prevailing winds to estimate local concentrations. For each air release (each facility x chemical combination), the RSEI models concentrations in each square kilometer of a 101-km by 101-km grid centered on the releasing facility. The RSEI data on exposure at the receptor grid cells outflanks the "How near is near?" question that arises in environmental justice research based on proximity to pollution sources.[3]

Although all TRI chemicals are toxic, their human health hazards vary widely. RSEI incorporates data on relative toxicity to construct a measure of exposure that is additive across chemicals. Toxicity here refers to chronic human health effects from long-term exposure, including cancer and non-cancer effects such as developmental toxicity, reproductive toxicity, and neurotoxicity. The toxicity weights are based on a peer-reviewed methodology, taking into account the single most sensitive chronic human health endpoint (cancer or non-cancer).[4] The resulting toxicity-weighted concentrations can be added across chemicals from one or more facilities to characterize the total exposure to industrial air toxics at each square kilometer grid cell.

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[2] The TRI data, and hence the RSEI 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.

[3] For more on plume modeling as a tool in environmental justice research, see Saha and Mohai (2005). For further discussion of what distance best fits the notion of "proximity" to a point source, see Boyce (2007).

[4] The EPA's toxicity-weighting system is based on peer-reviewed databases from several sources: the EPA's Integrated Risk Information System (IRIS); the EPA's Office of Pesticide Programs Reference Dose Tracking Reports; the U.S. Department of Health and Human Services Agency for Toxic Substances and Disease Registry; the California Environmental Protection Agency Office of Environmental Health Hazard and Assessment; and the EPA's Health Effects Assessment Tables. For some chemicals listed in the TRI, no consensus has been reached on the appropriate toxicity weight; these chemicals are currently excluded from the fully-modeled RSEI score. In recent years, the excluded chemicals have represented about one percent of the total mass of reported toxic air releases nationwide. The weights do not capture interactive effects of multiple exposures, nor acute effects of short-term exposures. For more details, including strengths and limitations of the RSEI approach to toxicity weighting, see http://www.epa.gov/oppt/rsei/pubs/caveats.html#toxicity.

We merge the toxicity-weighted concentration data at one-square-kilometer resolution from the RSEI Geographic Microdata with 2000 U.S. Census data, converting the RSEI grid cell geography to Census blocks. Details of the spatial join are provided in Ash and Boyce (2010). With block-level toxicity-weighted concentration data, it is possible to characterize exposure and population risk at higher levels of geographical aggregation from block groups to counties and CBSAs.

Population risk in the RSEI exposure model is based on the toxicity-weighted concentration, the number of people exposed, and the age and sex composition of the population. The latter matters because risk varies by the volume of air inhaled per unit of body weight. This variation is captured in distinct inhalation exposure factors (IEF) by age and sex groupings.[5] The population risk for an area is the product of the toxicity-weighted concentration and the population adjusted using IEFs for the age-sex mix. We calculate the average exposure for each metropolitan area by computing the population-weighted average of toxicity-weighted concentrations over all block-groups.

Using Census data on the percentage of specific subgroups in each block, we allocate exposure across subgroups and compute the average burden by subgroup and share of total burden borne by the subgroup. We group all persons other than non-Hispanic whites into the category of "minority." We classify as "poor" all households falling below the federal poverty level in 2000.[6]

Minority discrepancy

The minority discrepancy variable, MD_{ij}, is the share of the total burden of industrial air toxic releases that is borne by members of minority groups less the share of minorities in the population of the metropolitan area:

$$MD_{ij} = 1 - \left[\frac{\sum_{l} \gamma_{lij} \times ToxConc_{lij}}{\sum_{l} \delta_{lij} \times ToxConc_{lij}} \right] - \frac{\sum_{k} Pop_{kij}}{Pop_{ij}} \qquad (3)$$

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[5] The IEFs are intended to reflect biological differences in inhalation uptake by age and sex, although some analysts have criticized them for false precision (Morello-Frosch, personal communication, 2007).

[6] In the Census, income data are available only down to the block-group level. We conduct our analysis at this geographic unit.

where i and j is CBSA and metropolitan region, respectively; k indexes minority sub-group; l indexes block group, γ denotes the white population adjusted using IEFs for the age-sex mix as described above, and δ is the total population adjusted using IEFs for the age-sex mix.

The discrepancy measure is expressed as the amount in percentage points by which the minority share of health risk exceeds the minority share in the population. If members of minority groups are disproportionately more exposed, the variable has a positive sign. Note that our discrepancy measure is purely distributional: it does not reflect the level of risk from pollution exposure, only the extent to which the risk (whatever its level) is borne disproportionately by minorities.

To illustrate the discrepancy measure, we select those metropolitan areas that have both an above-average level of resident exposure and a population large enough to rank among the country's 100 biggest metropolitan communities. Table 1 lists the ten metropolitan areas from this universe that have the largest minority discrepancies. Topping the list is Birmingham, Alabama, where minorities account for 62% of the health risk as compared to 31% of the population, a discrepancy of 31 percentage points. Baton Rouge, Louisiana ranks second, followed by Memphis, Louisville, and Chicago.

[INSERT TABLE 1 HERE]

Control variables

We include four control variables in our analysis. *Median household income* is calculated from 2000 U.S. Census data. In our econometric analysis, we include both income and its square, allowing for the possibility of non-linear effects, including the inverted-U relationship between environmental quality and income found in some studies on the "environmental Kuznets curve" (see, for example, Grossman and Krueger, 1995).

The *white share of CBSA population*, also calculated from 2000 U.S. Census data, is included to capture differences in inter-city differences in racial composition. The direction of the effect is ambiguous: cities with a high percentage minority population may receive less attention from state and federal regulators (Hird and Reese, 1998); but such cities may have disproportionately suffered deindustrialization in recent decades.

The *share of residents employed in manufacturing* in the CBSA is obtained from the 2000 U.S. Census of Population and Housing. This is sometimes used as a control variable in environmental justice analysis (see, for example, Sicotte and Swanson, 2007; Anderton et al., 1994). although it may over-control if initial facility siting is influenced by demographics; that is, the manufacturing share of employment may not, in fact, be a pre-treatment covariate. Including it as a control therefore generates results that are conservative with respect to findings of environmental injustice.

Population density is also obtained from the 2000 U.S. Census of Population and Housing. In common with a number of other studies (Ash and Fetter, 2004; Pastor *et al.*, 2005), we include this as a control. On the one hand, land-use planners may seek to locate polluting facilities in low-density areas to minimize population exposure. On the other hand, high-density areas may have historical patterns of greater industrial activity. The inclusion of population density as a control allows for both possibilities.

Summary statistics for all variables are reported in Table 2. Toxic exposure tends to be higher for minorities (mean of 276, median of 71) than for whites (mean of 198, median of 62) and higher for the poor than for the non-poor, findings that are consistent with an overall pattern of environmental inequality. The high mean values for the exposure variables relative to their medians reflects a significant right-skew, as do the large standard deviations and wide range of values. This motivates our use of natural logarithms in the econometric analysis.

[INSERT TABLE 2 HERE]

The mean value for minority discrepancy is 0.04, indicating that for the average city, the minority share of total health risk from exposure to industrial air toxics exceeds the minority share of the population by 4 percentage points. Since the average minority share of the population is 21 percent (the average white population share is 79 percent), this implies that in the average CBSA, minorities bear roughly 25 percent of the human health risk.[7] The median value for minority discrepancy is 0.02, indicating the majority of U.S. cities are characterized by at least some degree of disproportionate minority exposure to industrial air toxics. However, the range is again large – from negative 0.39 to positive 0.48 – indicating wide variations across cities in this respect, including the existence of some cities where the white share of health risks exceeds their share of the population.

[7] Because minority share of population is positively correlated with city size, the minority share of the average CBSA is less than the share of minorities in the 934 CBSAs in total (total minorities divided by total population), which is 32%.

Results

In Table 3 we present a bivariate analysis of the relationships between average exposure, in aggregate and by population subgroup, and minority discrepancy. For this purpose, we partition cities into three categories by the level of minority discrepancy, that is, the extent to which minorities bear disproportionate risk from industrial toxics. The first column shows exposure for the 75 percent of cities with the lowest minority discrepancy, which together constitute 700 CBSAs with total population of 124 million (slightly less than half of the metropolitan population of the United States). In these cities, the minority discrepancy is smaller than 6 percentage points. The middle column shows exposure for the next 20 percent of cities, 187 CBSAs with 115 million residents, with "medium" minority discrepancy between 6 and 18 percentage points. The final column shows exposure for the 5 percent of cities with the highest minority discrepancy, in excess of 18 percentage points. These 47 CBSAs together have a population of almost 23 million, 8.7 percent of the country's total metropolitan population.

[INSERT TABLE 3 HERE]

Even in the low discrepancy category, average minority exposure exceeds average white exposure. The minority/white exposure ratio rises from 1.1 (208/185) in the low-discrepancy cities to 1.8 in the medium-discrepancy cities and to 2.8 (827/298) in the high-discrepancy cities. The most striking findings, however, are that average toxic exposure of all residents and of each population subgroup, including whites, is lowest in the low-discrepancy cities and highest in the high-discrepancy cities. Comparing these two categories, the high-discrepancy/low-discrepancy ratio for all residents is 2.2 (418/186). The ratio is highest for the poor minority subgroup, for whom average exposure levels are 4.5 times higher (986/219) in high-discrepancy cities than in low-discrepancy cities. But the correlation remains positive among non-poor whites, for whom the ratio is 1.5 (282/184) as well as poor whites, for whom the ratio is 2.1 (419/197).

Figure 1 depicts the findings for minorities and for whites. Toxic exposure for minorities worsens dramatically from low-discrepancy to high-discrepancy cities, but exposure also worsens for whites. These results suggest environmental injustice is bad for white people – and, not surprisingly, even worse for minorities.[8]

[8] The result is all the more striking when we consider that one might expect, *ceteris paribus,* a negative relationship between exposure and discrepancy. The reason is that facilities with a wider geographic

[INSERT FIGURE 1 HERE]

The results of our econometric analysis provide further support for the existence of a positive relationship between minority discrepancy and toxic exposure, both for metropolitan residents as a whole and for subgroups of the population. Table 4 presents the results from estimating our first equation, with toxic exposure of the average CBSA resident as the dependent variable.

[INSERT TABLE 4 HERE]

In column (1), we first estimate the relationship between average exposure and CBSA median income alone. The estimated coefficients on income and its square indicate that exposure to industrial air toxics rises with income up to a point—roughly $40,000 per household, slightly above the sample mean—and then decreases as income rises further beyond that point. This inverted U-shaped relationship, sometimes dubbed “the environmental Kuznets curve,” has been observed in a number of studies (but by no means all) of how pollution varies with income at the national level. One explanation in the present case may be that the upward-sloping portion of the curve reflects a concomitant rise in both pollution and income with increasing industrial activity, while the downward-sloping portion reflects increased post-industrial economic activity, with polluting industries “outsourced” to other cities or countries, coupled perhaps with more effective citizen demand for pollution abatement in cities with above-average incomes. This finding from inter-CBSA variations cannot be generalized, however, to the income-exposure relationship *within* CBSAs. Results reported by Ash and Fetter (2004) indicate that within CBSAs, additional income is negatively correlated with toxic exposure across the observed income range. That is, in any given city, people in wealthier neighborhoods generally breathe less toxic air pollution than people in poorer neighborhoods. The same relationship is suggested by the poor/non-poor comparisons in Table 2.

In column (2), we include minority discrepancy in the estimating equation. Its estimated effect on toxic exposure is positive and statistically significant. That is, places where minorities bear a disproportionate share of the toxic burden also tend to have higher overall levels of toxic pollution. The estimated coefficient implies that a one percentage point increase in minority discrepancy (e.g., from 0.04 to 0.05) is associated with an 8.4%

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impact by virtue of tall stack heights, high exit velocities and/or strong prevailing winds are likely to impact both more people and a more heterogeneous population. By virtue of impacting more people they raise average CBSA exposure, and by virtue of impacting a more heterogeneous population there is less discrepancy.

increase in exposure for the average resident. As shown in columns (3) and (4), the effect remains quite strong even after adding the control variables and regional dummy variables to the equation. This finding is consistent with our hypothesis that the extent of racial and ethnic disparity in the distribution of pollution burdens is positively correlated with the overall level of pollution.

In column (3), we add the control variables. Three variables – the white share of the CBSA's population, the manufacturing share of employment, and population density – are positively correlated with average toxic exposure. The estimated coefficient on the white share implies that a one percentage point increase in this variable (e.g., from 0.79 to 0.80) is associated with a 1.6% increase in exposure for the average resident. In other words, inter-city variations do not mirror the intra-city correlation between race and pollution exposure.

Finally, in column (4) we add dummy variables for the BEA regions. The estimated coefficients represent shifts in the intercept term relative to Region 1 (New England). The results indicate that, all else equal, exposure is lowest in the Rocky Mountain region and highest in the Great Lakes region. Again, most salient from the standpoint of our hypothesis, the estimated coefficient on minority discrepancy remains positive and statistically significant. In this specification, a one percentage point increase in minority discrepancy is associated with a 6.8 percent increase in average toxic exposure. Moving from a city with no minority discrepancy to a city with a minority discrepancy of 6 percentage points, the threshold for the "medium" category in Table 4, thus is associated with a 41 percent increase in toxic exposure.

Table 5 presents the results from estimating our second equation, showing the relationship between minority discrepancy and the average toxic exposure experienced by different race and class subgroups within the population. For this purpose, we use the same set of independent variables as in the final column of Table 4. For comparison, column (1) again shows the results for all residents. In columns (2) to (5), the dependent variables are the average toxic exposure experienced by non-poor whites, poor whites, non-poor minorities and poor minorities, respectively.

The estimated coefficient on minority discrepancy is positive and statistically significant for each subgroup, and the estimated coefficients on the other independent variables are quite stable.[9] Unsurprisingly, we find that minority discrepancy has a greater effect

[9] Among the other independent variables, the largest variation is found in the estimated coefficient on the white share of the CBSA population, which rises from 1.0 for whites to 1.2 for non-poor minorities and 1.3

on the toxic exposure levels of minorities than whites. A one percentage point increase in the minority discrepancy is associated with a 9.5% increase in exposure for non-poor minorities and a 10.6% increase for poor minorities. But a higher minority discrepancy does not translate into better environmental outcomes for whites. On the contrary, a one percentage point increase in the minority discrepancy is associated with a 4.8% increase in exposure for non-poor whites and a 5.9% increase for poor whites. These results again are consistent with the hypothesis that environmental justice is good for white folks: in cities where minorities bear a greater share of the air toxics burden, whites breathe worse air.

Conclusion

An analysis of inter-city variations in exposure to industrial air toxics suggests that the answer to the question posed in the title of this paper is "Yes." Greater minority discrepancy, here defined as the difference between the minority share of exposure hazard and the minority share of the population, is associated with higher exposures not only for minorities but also for whites. A one percentage point increase in minority discrepancy is associated with roughly a 10% increase in exposure for minorities and with a 5% increase in exposure for whites. Within both groups, the increases are somewhat larger for the poor than the non-poor.

The extent of minority discrepancy varies substantially across the United States. In 75% of CBSAs that are home to 47% of the country's total metropolitan population, minority discrepancy is less than 6 percentage points. In 5% of CBSAs that are home to almost 9% of the metropolitan population, the discrepancy is more than 18 percentage points. Average exposures for all residents are more than twice as high in the latter category than in the former. Exposures for whites are 1.6 times higher in the high-discrepancy cities, and exposures for minorities are roughly 4 times higher.

These results are consistent with the hypothesis that greater inequality in the distribution of environmental burdens is associated with higher burdens overall. Plausible causal explanations for this relationship can be posited in both directions: from greater discrepancies to higher exposures, and from higher exposures to greater discrepancies.

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for poor minorities. This implies that minority exposure increases as the minority share of population declines.

The perception that the costs of exposure to air toxics can be shifted onto others may lead to greater acceptance of new polluting facilities as well as to weaker pollution abatement efforts at existing facilities. Insofar as this contributes to the correlation between inequality and pollution, our finding that whites, too, face higher exposures in high-discrepancy cities implies that they have an inordinate belief in the efficacy of pollution shifting, or that they care more about their relative exposure to industrial air toxics than their absolute exposure, or both.

Conversely, higher pollution levels may lead to greater discrepancies in pollution burdens. Cities may have relatively high industrial air toxics emissions for a variety of reasons apart from the presence of wide minority discrepancies, related, for example, to the geography of transportation infrastructure or historical patterns of settlement and economic development. In such settings, more "political capital" may be invested in efforts to reduce pollution, and these efforts may be more effective in some communities than in others owing to differences in political influence. Similarly, more political capital may be invested in efforts to influence siting decisions or to institute and maintain housing market discrimination that reinforces environmental inequities. Future longitudinal studies may shed some light on the relative strength of the causal linkages running in both directions.

The results reported in this study imply the existence of a tight nexus between environmental quality, race, and power in the United States. Whatever the mix of underlying dynamics in the correlation between average exposures and minority discrepancies, the fact that minorities face greater pollution burdens reflects racial disparities in the distribution of power. The evidence presented here suggests that efforts to reduce these disparities could lead to environmental improvements that benefit all Americans.

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Tables and Figures

Table 1: Disproportionate Impacts on Minorities: Top Ten CBSAs

Core based statistical area	Minority share of toxic score	Minority share of population	Minority discrepancy
Birmingham-Hoover, AL	0.62	0.31	0.31
Baton Rouge, LA	0.62	0.38	0.24
Memphis, TN-MS-AR	0.71	0.48	0.22
Louisville/Jefferson County, KY-IN	0.36	0.17	0.19
Chicago-Naperville-Joliet, IL-IN-WI	0.60	0.41	0.19
Harrisburg-Carlisle, PA	0.33	0.15	0.19
Milwaukee-Waukesha-West Allis, WI	0.43	0.26	0.18
Charleston-North Charleston-Summerville, SC	0.53	0.36	0.17
Augusta-Richmond County, GA-SC	0.55	0.40	0.14
Wichita, KS	0.34	0.20	0.14

CBSAs in this table were taken from the group of the top 100 most populous CBSAs that also have a toxic exposure level above the average level for all CBSAs. Values in column 3 may not equal the difference between columns 1 and 2 due to rounding.

Table 2: Summary Statistics

	Mean	Median	SD	Min	Max
Average toxic exposure—all residents	211	65	480	7.3×10^{-09}	9720
Average toxic exposure—white residents	198	62	461	7.4×10^{-09}	9701
Non-poor white	195	61	461	7.0×10^{-09}	10040
Poor white	226	66	489	1.3×10^{-08}	7427
Average toxic exposure—minority residents	276	71	668	6.0×10^{-09}	10300
Non-poor minority	271	70	638	1.2×10^{-09}	10650
Poor minority	302	76	751	1.8×10^{-08}	10690
Minority discrepancy	0.04	0.02	0.07	-0.39	0.48
Median household income	$37,150	$36,380	$7,366	$15,890	$78,610
White share	0.79	0.85	0.18	0.02	0.99
Manufacturing share	0.17	0.16	0.09	0.01	0.48
Population density (pop/km^2)	56	32	85	0.7	1052

n=934 CBSAs. Toxic exposure measures are from 2005 RSEI data. All other variables are from 2000 U.S. Census.

Table 3: Average toxic exposure in low (0-75 percentile), medium (75-95) and high (95-100) minority discrepancy cities

	Minority Discrepancy of the CBSA		
Average exposure of a person in the group listed	**Low** MD below 0.06 *n*=700 CBSAs pop=124.0 million	**Medium** MD 0.06-0.18 *n*=187 CBSAs pop=115.1 million	**High** MD above 0.18 *n*=47 CBSAs pop=22.9 million
Everyone	186	252	418
White	185	223	298
Non-poor white	184	213	282
Poor white	197	286	419
Minority	208	392	827
Non-poor minority	209	374	776
Poor minority	219	441	986

Note: Minority discrepancy, a measure of environmental injustice, is the minority share of a CBSAs toxic score minus the minority share of the CBSAs population. A higher minority discrepancy score indicates greater environmental injustice.

Table 4: Results from OLS estimation; dependent variable is logged average toxic exposure of a CBSA resident

	(1)	(2)	(3)	(4)
Intercept	-6.65**	-6.44**	-5.57**	-6.20**
	(1.29)	(1.25)	(1.12)	(1.25)
Median HH income of CBSA ($000)	0.50**	0.48**	0.30**	0.32**
	(0.06)	(0.06)	(0.06)	(0.06)
Square of CBSA income	-0.0057**	-0.0055**	-0.0039**	-0.0038**
	(0.0008)	(0.0008)	(0.0007)	(0.0007)
➔ Implied income turning point	$44k	$43k	$38k	$42k
Minority Discrepancy		**8.43****	**7.25****	**6.79****
		(1.10)	(0.99)	(0.97)
White share of CBSA			1.61**	1.00*
			(0.45)	(0.50)
Manufacturing share of CBSA			10.64**	7.53**
			(0.80)	(0.89)
Population density of CBSA (1000/km2)			6.61**	5.13**
			(0.96)	(0.99)
BEA Region 2—Mideast				1.20
BEA Region 3—Great Lakes				1.47
BEA Region 4—Plains				1.23
BEA Region 5—Southeast				1.60
BEA Region 6—Southwest				0.12
BEA Region 7—Rocky Mountain				-0.22
BEA Region 8—Far West				0.16
Adjusted R2	*0.065*	*0.120*	*0.314*	*0.358*

* significant at $p<0.05$; **significant at $p<0.01$. n=934 CBSAs.

Notes: "Toxic exposure" is the toxicity-weighted concentration of industrial air toxic chemicals reported in the 2005 TRI, using RSEI fate and transport modeling. "Average toxic exposure" is the mean toxicity-weighted concentration across block groups within a CBSA. Other independent variables were obtained from the 2000 U.S. Census. Coefficients on BEA region dummies indicate increase in exposure relative to BEA Region 1 (CT, ME, MA, NH, RI, VT). BEA Region 2 includes DE, DC, MD, NJ, NY, PA; BEA Region 3 includes IL, IN, MI, OH, WI; BEA Region 4 includes IA, KS, MN, MO, NE, ND, SD; BEA Region 5 includes AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV; BEA Region 6 includes AZ, NM, OK, TX; BEA Region 7 includes CO, ID, MT, UT, WY; BEA Region 8 includes AK, CA, HI, NV, OR, WA.

Table 5: Results from OLS estimation; dependent variable is logged average toxic exposure by race/ethnicity and income

	(1) All	(2) White non-poor	(3) White poor	(4) Minority non-poor	(5) Minority poor
Intercept	-6.20**	-6.34**	-6.01**	-6.25**	-6.21**
	(1.25)	(1.25)	(1.26)	(1.27)	(1.27)
Median HH income of CBSA ($000)	0.32**	0.32**	0.31**	0.31**	0.30**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Square of CBSA income	-0.0038**	-0.0038**	-0.0037**	-0.0037**	-0.0036**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
➔ Implied income turning point	$42k	$42k	$42k	$42k	$42k
Minority Discrepancy	**6.79****	**4.83****	**5.93****	**9.51****	**10.59****
	(0.97)	(0.97)	(0.97)	(0.98)	(0.98)
White share of CBSA	1.00*	1.03*	1.01*	1.24*	1.33**
	(0.50)	(0.50)	(0.51)	(0.51)	(0.51)
Manufacturing share of CBSA	7.53**	7.58**	7.57**	7.91**	7.73**
	(0.89)	(0.89)	(0.89)	(0.90)	(0.90)
Population density of CBSA (1000/km2)	5.13**	5.14**	5.35**	5.20**	5.18**
	(0.99)	(0.99)	(0.99)	(1.01)	(1.00)
BEA Region 2—Mideast	1.20	1.20	1.15	1.26	1.21
BEA Region 3—Great Lakes	1.47	1.48	1.49	1.53	1.51
BEA Region 4—Plains	1.23	1.25	1.21	1.25	1.21
BEA Region 5—Southeast	1.60	1.63	1.50	1.60	1.55
BEA Region 6—Southwest	0.12	0.15	0.04	0.16	0.08
BEA Region 7—Rocky Mountain	-0.22	-0.21	-0.25	-0.20	-0.27
BEA Region 8—Far West	0.16	0.17	0.12	0.19	0.05
Adjusted R2	*0.358*	*0.345*	*0.351*	*0.387*	*0.404*

* significant at p<0.05; **significant at p<0.01. *n*=934 CBSAs.

Notes: "Toxic exposure" is the toxicity-weighted concentration of industrial air toxic chemicals reported in the 2005 TRI, using RSEI fate and transport modeling. "Average toxic exposure" is the mean toxicity-weighted concentration experienced by residents in the group designated in the column headings across block groups within a CBSA. Other independent variables were obtained from the 2000 U.S. Census. Coefficients on BEA region dummies indicate increase in exposure relative to BEA Region 1 (CT, ME, MA, NH, RI, VT). BEA Region 2 includes DE, DC, MD, NJ, NY, PA; BEA Region 3 includes IL, IN, MI, OH, WI; BEA Region 4 includes IA, KS, MN, MO, NE, ND, SD; BEA Region 5 includes AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV; BEA Region 6 includes AZ, NM, OK, TX; BEA Region 7 includes CO, ID, MT, UT, WY; BEA Region 8 includes AK, CA, HI, NV, OR, WA.

Figure 1: Average exposure by race/ethnicity in CBSAs with low, medium and high minority discrepancy scores (Low, Medium and High categories defined as in Table 3)