

Three Measures of Environmental Inequality

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Working Paper No. 12

ABSTRACT

Using data on industrial air pollution exposure in the United States, we compute three measures of environmental inequality: the Gini coefficient of exposure, the ratio of median exposure of minorities to that of non-Hispanic whites, and the ratio of median exposure of poor households to that of non-poor households. Comparing inequalities in states and Congressional districts, we find that relative rankings by the three measures vary considerably. We conclude that different measures of environmental inequality may be appropriate for different analytical purposes.

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JEL Codes: No. I14, Q53, Q56, R11

Research for this study was supported by grants from the Institute for New Economic Thinking (Grant No. INO13-00028) and the National Science Foundation (Grant No. SES-1060904).

1. Introduction

Pollution is not an equal opportunity affair. A large body of research has established that racial and ethnic minorities and low-income households in the United States tend to face higher pollution burdens than non-Hispanic whites and higher-income households (see, for example, Szasz and Meuser, 1997; Ash and Fetter, 2004; Mohai, 2008; Bullard *et al.* 2011). Patterns of environmental inequality vary substantially across regions of the country, however (Zwickl *et al.*, 2014).

This paper compares three measures of environmental inequality for the 50 U.S. states and 435 Congressional districts, using data on exposure to industrial air toxics from the Risk-Screening Environmental Indicators (RSEI) of the U.S.

Environmental Protection Agency (EPA): (i) the Gini coefficient of exposure; (ii) the ratio of the median exposure of minorities to that of non-Hispanic whites; and (iii) the ratio of the median exposure of poor households to that of nonpoor households.

The Gini coefficient is a measure of vertical inequality: differentiating the population only by exposure to industrial air toxics, it summarizes the extent of divergence from a perfectly equal distribution. The two ratios are measures of horizontal inequality: they compare exposure across population subgroups defined on the basis of minority status and poverty status, respectively.

We find that exposure inequality rankings based on these measures vary considerably from each other, and conclude that which measure is most appropriate

depends on the question being posed. Regardless of the measure, environmental inequalities are likely to be of greatest policy concern in places with the highest overall pollution burdens. We therefore identify the states and Congressional Districts that rank in the top half in terms of both median exposure and exposure inequality.

Section 2 discusses reasons for measuring environmental inequality. Section 3 introduces the data used in the analysis. Section 4 provides details on the calculation of the three measures. Section 5 presents results for the states level and section 6 presents results for Congressional districts. Section 7 concludes.

2. Environmental quality and environmental inequality

Environmental inequalities matter for at least three reasons. The first is intrinsic, based on the normative principle that all individuals have an equal right to a clean and safe environment. The second is that environmental quality has important impacts on the distribution of opportunities to lead a healthy and productive life. The third is that environmental quality has economic impacts on individuals and communities.

(i) Intrinsic value of environmental equity

The normative principle that every person has the right to a clean and safe environment is widely asserted in the most fundamental of legal documents, national constitutions. The post-apartheid constitution of the Republic of South Africa declares, for example, “Every person shall have the right to an environment which is not detrimental to his or her health or well-being.” Similar statements appear in the constitutions of many nations across the world: “All residents enjoy the right to a healthy, balanced environment” (Argentina); “Every person shall have the right to a wholesome environment” (Belarus); “All citizens shall have the right to a healthy and pleasant environment” (Republic of Korea); “Everyone shall have the right to a healthy and ecologically balanced human environment and the duty to defend it” (Portugal).¹

Similar language can be found in many state constitutions in the United States, as illustrated by the following extracts: “The people shall have the right to clean air and water” (Massachusetts); “The people have a right to clean air, pure water, and the preservation of the natural, scenic, historic and esthetic values of the environment” (Pennsylvania); “All persons are born free and have certain inalienable rights. They include the right to a clean and healthful environment” (Montana); “Each person has the right to a clean and healthful environment” (Hawaii).

These constitutional principles put an intrinsic value on the distribution of environmental quality. A logical extension of the principle that all people have an

¹ For discussion, see Popovic (1996).

equal right to a clean and safe environment is that any shortfalls in environmental quality should be distributed equally as well. That is, the environmental rights of some people should not take precedence over the environmental rights of others.

The intrinsic value of environmental equity applies not only to the distribution of environmental quality across individuals, but also to its distribution across communities. The environmental justice movement has drawn attention to disproportionate environmental burdens often imposed on racial and ethnic minorities and low-income people in the U.S.

Recognition of these disparities led to Executive Order 12898, issued by President Bill Clinton in 1994, which directed every federal agency to take steps to identify and rectify “disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income populations.” This Executive Order inscribed environmental equity into federal law. In a proclamation marking its 20th anniversary, President Barack Obama reaffirmed “every American's right to breathe freely, drink clean water, and live on uncontaminated land” (Obama, 2014).

Of course, equity is not all that matters when it comes to environmental quality. An environment in which all people are equally exposed to high levels of pollution is arguably worse than one in which some are exposed to that level and others to lower ones. For any given level of overall exposure, however, a more equal

distribution can be regarded as ethically superior and legally preferable to a less equal distribution.

(ii) Equality of opportunities

A second reason for concern about environmental inequalities rests on their implications for equality of opportunity. “Much more important than inequality of outcomes among adults is inequality of opportunity among children,” according to the authors of the World Bank’s Human Opportunity Index. “The debate should not be about equality (equal rewards for all) but about equity (equal chances for all), because the idea of giving people equal opportunity early in life, whatever their socioeconomic background, is embraced across the political spectrum” (Barros *et al.*, 2009, p. xvii).

Children are especially vulnerable to the health and cognitive impacts of pollution, and environmental quality can significantly affect a child’s life chances (Currie, 2011). Indeed the impacts can include life itself. A study of the effects of reduced air pollution during the 1981-82 recession in the U.S. found that each one percent decrease in total suspended particulates resulted in 0.35 percent lower infant mortality (Chay and Greenstone, 2003). Reductions in carbon monoxide emissions in California in the 1990s are estimated to have prevented approximately 1000 infant deaths (Currie and Neidell, 2005). Even levels of air pollution that are

historically low have been found to have significant adverse impacts on fetal health and infant health (Currie, Neidell and Schmeider, 2009).

Maternal exposure to air pollution during pregnancy is linked to restricted fetal growth, leading researchers to conclude that “a substantial proportion of cases of low birthweight at term could be prevented in Europe if urban air pollution was reduced” (Pedersen *et al.*, 2013). Fetal exposure to industrial chemicals has been linked to neurodevelopmental disabilities including autism, attention-deficit hyperactivity disorder, dyslexia, and other cognitive impairments (Grandjean and Landrigan, 2014).

Apart from neurological impacts, air pollution can affect a child’s education by increasing school absences due to illness. A study of elementary and middle-school children in Texas found that air pollution had significant adverse effects on school attendance (Currie *et al.*, 2009). Similarly, a Michigan study found that schools located in neighborhoods with the highest industrial air pollution levels had the lowest attendance rates and the highest proportions of students who failed to meet state educational testing standards (Mohai *et al.*, 2011).

Exposure to airborne toxics was found to have a statistically significant negative effect on academic test scores in metropolitan Los Angeles, after controlling for other socioeconomic predictors of school performance (Pastor *et al.*, 2002, 2004). A study in East Baton Rouge, Louisiana, similarly found that proximity to Toxics Release

Inventory facilities, high concentrations of toxic emissions, and high-volume emitters of developmental neurotoxins are significantly related to school performance (Lucier *et al.*, 2011).

(iii) Economic impacts

Pollution also has economic impacts on property values, days lost from work, and health costs.

Air pollution has long been recognized to reduce property values (Nourse, 1967; Anderson and Crocker, 1971). Conversely, reductions in total suspended particulates in the 1970s as a result of implementation of the Clean Air Act are estimated to have led to a \$45 billion increase in housing values over the decade (Chay and Greenstone, 2005). An analysis of industrial plants in the Toxics Release Inventory in five large states found that housing values within one mile decreased by 1.5% when plants opened, and increased by 1.5% when they closed (Currie *et al.*, 2013).

Air pollution also results in lost work days. An analysis of 1976 household survey data in the U.S. found that one standard deviation increase in ambient particulate pollution was associated with a 10 percent increase in work days lost due to illness (Hausman *et al.*, 1984). A 12.8% increase in exposure to sulfates in U.S. metropolitan areas in 1979-1981 was associated with 4800 extra days of

respiratory-related restrictions per 100,000 work days (Ostro, 1990). Air pollution has also been found to have significant adverse effects on worker productivity (Graff Zivin and Neidell, 2011).

Since the publication of the 1981 report, *Costs of Environment-Related Health Effects*, which was produced by an expert committee convened by the U.S. Institute of Medicine and chaired by economist Kenneth Arrow, a number of studies have sought to estimate the monetary costs of the “environmentally attributable fraction” (EAF) of diseases in the U.S. The annual cost of EAF illnesses among children was estimated by Landrigan *et al.* (2002) at \$54.9 billion (in 1997 dollars), with the largest single component coming from lifelong productivity losses attributable to early exposure to neurotoxins. Updated estimates by Transande and Liu (2011) put the annual cost at \$76.6 billion (in 2008 dollars). Recent research on the impacts of air pollution on childhood asthma suggests that prior studies may have underestimated the associated health costs by measuring only the exacerbation of existing asthma and not impacts on its incidence (Brandt *et al.*, 2012).

The EPA estimates that Mercury and Air Toxics Standards announced in December 2011 – the agency’s first effort to impose mandatory limits on air toxics – will yield annual health benefits valued at between \$37 billion and \$90 billion, including the prevention of 4200-11000 premature deaths (EPA, 2011). The standards, which were upheld by a federal appeals court in April 2014, apply only to power plants – a subset of the industrial facilities whose air toxics releases are the basis for the

exposure data we use in this study. The EPA (2014) notes that these benefits are “especially important to minority and low income populations who are disproportionately impacted by asthma and other debilitating health conditions.”

The distribution of environmental quality may contribute the widely observed gradient in which health varies inversely with socioeconomic status (Evans and Kantrowitz, 2002). A study of Bronx borough in New York found that proximity to noxious land uses, including Toxics Release Inventory facilities, is associated with a 66% increase in the likelihood of hospitalization for asthma, and that poor and minority populations are more likely to live within specified distance buffers (Maantay, 2007). Exposure to multiple environmental hazards has cumulative impacts (Brender *et al.*, 2011). Interactions among environmental hazards, individual biological susceptibility, and social vulnerability often exacerbate impacts in minority and low-income neighborhoods (Morello-Frosch *et al.*, 2011).

Whether the adverse impacts of pollution exposure could be “compensated,” in principle, by other amenities is a matter of debate. It has been argued, for example, that individuals may be willing to tradeoff environmental quality for income, and hence that people living in more polluted locations who have higher incomes than those in less polluted locations may be no worse off (Millimet and Slottje, 2002). However, if access to a clean and safe environment is regarded as an intrinsic right, one can question whether income can adequately compensate for its infringement on ethical grounds akin to the prohibitions against slavery and trafficking in human

organs. Human rights cannot be sold. This debate is irrelevant insofar as environmental inequalities mirror disparities in socioeconomic status rather than operating in the reverse direction.

3. Mapping exposure to industrial air toxics in the United States

To measure industrial air toxics exposure we use geographic microdata from the EPA's Risk Screening Environmental Indicators (RSEI) model for the year 2010. The RSEI model covers air releases of more than 400 chemicals from more than 15,000 industrial facilities that are required to report to the Toxics Release Inventory (TRI). RSEI models the dispersion of these releases in the environment, incorporating information on stack heights, exit gas velocities, wind patterns, and chemical decay rates to estimate ambient concentrations in more than 10,000 grid cells, each 810 meters square, around each facility. To aggregate across chemicals, RSEI uses toxicity weights based on chronic human health effects from inhalation exposure.

Although the RSEI data provide the best available measure of exposure to air toxics from industrial facilities, they only capture one component of overall air pollution. The data do not include pollution from mobile sources, or from small point sources such as dry cleaning establishments. Industrial point sources often loom large, however, in the risks faced by those communities with the most hazardous air pollution (Boyce and Pastor, 2012).

Using RSEI geographic microdata, we calculate toxicity-weighted exposures for each grid cell, aggregated across all industrial facilities with releases that impact that cell. We then map the grid cell exposures to census blocks, the finest level of geographic resolution in U.S. Census data. We obtain income and demographic variables at the census tract level from the American Community Survey, using the five-year averages 2006-2010. To merge these two data sets, we calculate exposure at the census tract-level as the area-weighted average of exposure in the tract's constituent blocks. To control for the influence of outliers, we censor the resulting tract-level exposure variable at the 97th percentile nationwide.

Figure 1 maps nationwide variations in exposure to industrial air toxics, partitioning census tracts into national exposure quintiles. The uneven distribution of exposure is evident not only across states but also within them. A number of states include tracts that rank in both the highest and lowest quintiles, suggesting the presence of substantial intra-state exposure inequalities.

[insert Figure 1 here]

4. Three measures of environmental inequality

We compute three measures of environmental inequality:

(i) Gini coefficient

The Gini coefficient is widely used to measure inequality in the distribution of income and assets. It is a measure of vertical inequality: individuals are differentiated only by the measured attribute, such as income, and the Gini coefficient summarizes the extent of the differences. The Gini coefficient has been applied to environmental variables, too, including carbon emissions (Heil and Wodon, 2000), resource use (Druckman and Jackson, 2008), and industrial air toxics exposure in the state of Maine (Bouvier 2014).

The Gini coefficient is calculated by the following formula:

$$\text{Gini} = (1/n)[n + 1 - 2\sum_{i=1}^n (n + 1 - i) \text{EXPOSURE}_i] / \sum_{i=1}^n \text{EXPOSURE}_i$$

where EXPOSURE_i = industrial air toxics exposure in Census tract i , and n = the number of tracts, indexed in non-decreasing order ($\text{EXPOSURE}_i \leq \text{EXPOSURE}_{i+1}$). The Gini coefficient was calculated using Stata's *ineqdec0* package, including tracts with zero exposure and weighting tracts by total population. The Gini coefficient lies between the hypothetical values 0 and 1. Here 0 would mean that all tracts in the state or Congressional district have the same exposure, and 1 would mean that the state's or district's exposure is entirely confined to a single tract.

(ii) *Minority/white exposure ratio*

Our other two measures refer to horizontal inequality: they compare exposure across population subgroups differentiated by attributes apart from exposure itself. To compare exposure of racial and ethnic minorities to that of non-Hispanic whites (hereafter, simply “whites”), we calculate exposure levels for the two subgroups as follows:

$$EXPOSURE_{js} = \frac{\sum_s (EXPOSURE_i * TOTALPOP_k * X_{jk})}{\sum_s (TOTALPOP_k * X_{jk})} \quad (2)$$

where subscript j indexes the population subgroup; the subscript s indexes the state (or Congressional district); and X_{jk} is the share of subgroup j in the population of census tract k .

We then calculate the ratio of the median exposures for the minority and white population subgroups. We refer to this as the “minority/white exposure ratio.”

(iii) Poor/nonpoor exposure ratio

Using the same method, we measure horizontal equity in the distribution of exposure between the poor (defined as households below the federal poverty line) and nonpoor. For this purpose we calculate median exposures of the poor and nonpoor population subgroups and again compute their ratio. We refer to this as the “poor/nonpoor exposure ratio.”

5. Environmental inequality in the states

The three measures of environmental inequality for the 50 U.S. states (plus Washington, DC) are reported in Table 1. The Gini coefficients are 0.70 or higher in 29 of the 50 states, indicating a high degree of vertical inequality in industrial air pollution exposure. They range from 0.32 in the smallest state, Rhode Island, to 0.91 in the largest state, Alaska. The relationship between the Gini and physical area is not surprising given that pollution is concentrated in particular locations, so that smaller states tend to show less spatial variation in exposure.

[insert Table 1 here]

How does exposure inequality compare to income inequality? State-level Gini coefficients of income distribution calculated from the census tract data (thereby omitting intra-tract variation, as in the case of our exposure data) range from 0.13 to 0.33. Intra-tract variation in income is likely to be considerably greater, however, than intra-tract variation in air pollution exposure. State-level income Ginis calculated from individual household-level data for the year 2010 range from 0.54 to 0.68 (Frank 2014). Tract-level exposure Ginis in the majority of the states therefore exceed the highest household-level income Gini in any state. We conclude that exposure to industrial air toxics in the United States in general is distributed more unequally than income.

The minority/white exposure ratio ranges from 0.03 in North Dakota to 4.79 in Wisconsin. It is below one in only ten states, and less than 0.67 only in the Dakotas and Montana where Native Americans, many of whom live far from industrial facilities, comprise the largest minority. The minority/white exposure ratio is above 3.0 in several states, including California, Michigan, Minnesota and Wisconsin.

The poor/nonpoor exposure ratio ranges from 0.35 in Idaho to 3.59 in Wyoming. This ratio reflects the balance between two opposing forces. On the one hand, if the presence of industry is correlated with higher incomes as well as more pollution, exposure of the poor would be expected to be lower than exposure of the nonpoor, yielding a ratio less than one. On the other hand, if polluting facilities are more likely to be located in low-income neighborhoods, this would yield a ratio greater than one. The ratio is greater one in 26 states – and above 3.0 in Virginia and Wyoming – indicating the latter effect often outweighs the former.

Table 2 reports correlation coefficients among the three measures of exposure inequality. The low correlations imply that rankings of states in terms of exposure inequality are highly sensitive to the specific measure used.

[insert Table 2 here]

The correlation between the two horizontal inequality measures – the minority/white ratio and the poor/nonpoor ratio – is positive, as one would expect

given higher poverty rates among minorities. More notable is the fact that it is quite low ($r=0.19$), implying that disproportionate exposures among the poor are not simply an artifact of correlations between race and class.

The correlations between the Gini coefficient and the two horizontal inequality measures are negative, albeit again low. This is surprising, in that one might expect states with greater vertical inequality generally to have greater horizontal inequality, as well. To show how the contrary may be true, Figure 2 depicts percentile-wise exposures for minorities and whites in two states, Ohio and Virginia. Ohio has a relatively low Gini but a relatively high ratio of median minority exposure to median white exposure, while Virginia has the opposite. The contrast between them illustrates why distinct dimensions of environmental inequality require distinct measures.²

[insert Figure 2 here]

To examine the relationship between exposure inequality and overall exposure levels, we also report in Table 2 the correlations between our inequality measures and median exposure in the state. The correlation is negative in the case of the Gini

² Two further observations from Figure 2 warrant mention. First, more than 15% of Ohio's minority population lives in census tracts with industrial air toxics exposure at or above the 97th percentile nationwide (where the exposure data are censored, flattening the curve). Second, the most exposed decile of whites in Virginia face considerably higher exposure than the most exposed decile of minorities. As noted above, Virginia's poor/nonpoor median exposure ratio is among the highest in the nation; together these observations imply disproportionately high exposures among poor whites in that state.

coefficient, positive in the case of the minority/white ratio, and near zero in the case of the poor/nonpoor ratio.

The negative correlation between the Gini coefficient and median exposure (-0.49) implies that industrial air pollution tends to be more unequally distributed in states with less of it. Again, this result is not surprising. A state with little industrial air pollution exposure in most tracts, but substantial exposure in a few, will have low median exposure and a high exposure Gini, as in the cases of Alaska and Vermont.

The positive, although modest, correlation between the minority/white ratio and median exposure (0.23) implies that pollution tends to be somewhat more concentrated in minority communities in states with more pollution. This may reflect less stringent environmental regulation in states where pollution burdens fall more disproportionately on disadvantaged groups, or more vigorous efforts to shift exposure burdens onto disadvantaged communities in states with more pollution. That is, environmental justice may be related to overall environmental quality as both cause and effect. The positive correlation is consistent with the view that environmental justice can be “good for white folks,” too, in that more equal distribution of exposure is associated with lower pollution levels overall (Ash *et al.*, 2013).

From a policy standpoint, environmental inequalities are likely to be of greatest concern in states where overall pollution levels are high. The maps in Figures 3a-3c

partition the states into four groups, based on whether their median exposure and exposure inequality are above or below the average values for all states. We again see a contrast between our different measures. States with above-average exposure and above-average Ginis are concentrated in the south central region, while those with above-average exposure and above-average minority/white and poor/nonpoor ratios are concentrated in the northern Midwest.

[insert Figures 3a-3c here]

6. Environmental inequality in the Congressional districts

Table 3 reports the top ten Congressional districts by each of our three environmental inequality measures among all districts that have median exposure above the national median.³ Although three states – Illinois, Ohio and Pennsylvania – account for 40% (12 of 30) of the top-ten rankings in Table 3, no individual district ranks in the top ten by more than one measure, further evidence that exposure inequality’s multiple dimensions cannot be captured adequately by a single measure.

[insert Table 3 here]

³ The data here refer to Congressional districts as demarcated at the time of the 2012 elections.

In the full set of 435 Congressional districts, Gini coefficients of exposure range from 0.04 in New York's 15th district to 0.96 in Michigan's 1st district.⁴ The former, located in the Bronx, is the smallest Congressional district in the nation, illustrating the sensitivity of exposure Ginis to physical area. The latter, comprised of Michigan's Upper Peninsula and the northern tier of the Lower Peninsula, is a large area with relatively little industrial air pollution, as reflected in the district's low median exposure.

The minority/white exposure ratio varies from 0.03 in North Dakota's at-large district (comprising the entire state) to 31.56 in Colorado's 3rd district and more than 67,000 in Florida's 25th district. These extremely low value for North Dakota reflects exceptionally low median exposure among minorities (most of whom are Native Americans) in that state. The very high value for Colorado's 3rd district, a large territory in western and south-central portions of the state with relatively little industrial pollution, reflects very low median exposure among whites. In Florida's 25th district, stretching from the western suburbs of Miami to the Everglades, where the minority share of population in the average census tract exceeds 80%, the median exposure of whites is extremely low. The minority/white exposure ratio is greater than one in 65% (284) of the nation's Congressional districts, and it is 2.0 or higher in 13.8% (60) of them.

⁴ Complete data for all Congressional Districts available from the authors on request.

The poor/nonpoor exposure ratio ranges from 0.04 in Utah's 3rd Congressional District to 24.37 in Colorado's 3rd. As noted above, this ratio reflects the balance between two opposing forces: the tendency for industrial activity to be associated with higher incomes as more pollution, and the tendency for polluting facilities to be located in lower-income communities. The ratio is greater than one in the majority of Congressional districts (229), and it is 2.0 or higher in 5.5% (24) of them.

Table 4 reports correlation coefficients among the three measures across Congressional districts. The low correlations again imply that the different measures capture distinct dimensions of exposure inequality. Consistent with our findings at the state level, we again see a significant negative correlation between the Gini and the district's median exposure.

[insert Table 4 here]

The Gini coefficient of exposure is sensitive to physical area, as we have noted: larger spatial units tend to have higher Ginis. Exposure to pollution from industrial point sources is unevenly across the landscape (which is why we are interested in exposure inequality), and larger spatial areas provide more room for variation. We also find a negative correlation between the Gini coefficient and median exposure: when most tracts have low exposure, high exposure in a few tracts can produce a high Gini. Controlling for these effects, we find a modest positive correlation (significant at the 5% level) between the Gini coefficient and the poor/nonpoor ratio

for Congressional districts, but still no statistically significant correlation between the Gini and the minority/white ratio.⁵

Figures 4a-4c partition the nation's Congressional districts into four groups, again based on whether exposure inequality and median exposure are above or below average values. Comparing these to state-level patterns, we see considerable diversity within states. Michigan, Wisconsin and Minnesota, all of which are in the high exposure and high minority/white ratio quadrant, have some Congressional districts with both low exposure and a low minority/white ratio. Exposure inequality is sensitive to jurisdictional scale, as well as to the choice of measure.

[insert Figures 4a-4c here]

7. Conclusions

Environmental inequality is a multi-dimensional phenomenon. When examining how inequality in exposure to industrial air toxics varies across the United States,

⁵ To control for the effects of area and median exposure, we estimated the following econometric model:

$$\text{Gini} = \alpha + \beta_1 \ln \text{AREA} + \beta_2 \text{MEDEXPOSURE} + \beta_3 \text{HI} + \mu$$

where $\ln \text{AREA}$ = the natural logarithm of the physical area of the Congressional district; MEDEXPOSURE = the exposure of the median resident; HI = horizontal inequality, measured by the minority/white exposure ratio or the poor/nonpoor exposure ratio; and μ is an error term. Results available from the authors on request.

we must choose the dimension on which to focus as well as the spatial units to be compared.

Three dimensions of environmental inequality are examined in this study: the Gini coefficient of exposure, the median exposure of racial and ethnic minorities relative to that of non-Hispanic whites, and the median exposure of the poor relative to that of the nonpoor. The first is a measure of vertical inequality. The latter two are measures of horizontal inequality.

The three measures yield markedly different rankings of environmental inequalities in the states and Congressional districts. We find a modest positive correlation between the two horizontal inequality measures (0.2 for states; 0.3 for Congressional districts), as would be expected given the link between minority status and poverty status. The correlations between the Gini coefficient and the other two measures are much weaker, and negative for states.

Which type of inequality is of greatest concern? There is no across-the-board answer to this question. If we start from the normative principle that every individual has an equal right to a clean and safe environment, then vertical inequality is relevant as it measures the extent to which the distribution of exposure is inconsistent with an "equal right." To be sure, it can be argued that the extent to which exposures exceed what is "clean and safe" is most important here. Even where median exposure is low, vertical inequality may be of interest since it reveals

the extent to which summary measures for a population may mask more serious risks borne by some individuals. Vertical inequality is of most concern, however, when absolute exposure levels are high.

An unequal distribution of exposure can be regarded as more objectionable when the communities with higher exposure are disadvantaged in other respects as well. Starting from this normative premise, horizontal inequality between minorities and whites, and between the poor and nonpoor, is particularly relevant. The explicit reference “minority populations and low-income populations” in Executive Order 12898 translates this principle into federal government policy in the United States.

Of course, inequality is not the only useful criterion for assessing environmental outcomes. Few would claim that welfare would be improved by increasing pollution until exposure in every census tract in the state or district equals that in the most exposed tract, notwithstanding the fact that in principle this is one way to eliminate exposure inequality. But when the policy choice is where to concentrate pollution abatement efforts, or where to locate new pollution sources, environmental inequality may be a relevant objective.

Promising avenues for further research on environmental inequality include the following. It would be interesting to develop measures of inequality in exposure to mobile-source air pollution and water pollution, and to explore whether spatial variations in these aspects of environmental inequality are correlated with

variations in exposure to industrial air toxics. The development of measures that combine absolute levels of exposure together with exposure inequality could be useful for policy makers in prioritizing sites for remedial actions. In addition, measurement of environmental inequality makes it possible to analyze how this is related to socioeconomic variables such as income distribution and residential segregation, and to political variables such as voting behavior and state environmental policies.

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Figure 1: Industrial air toxics exposure by U.S. Census tract, 2010

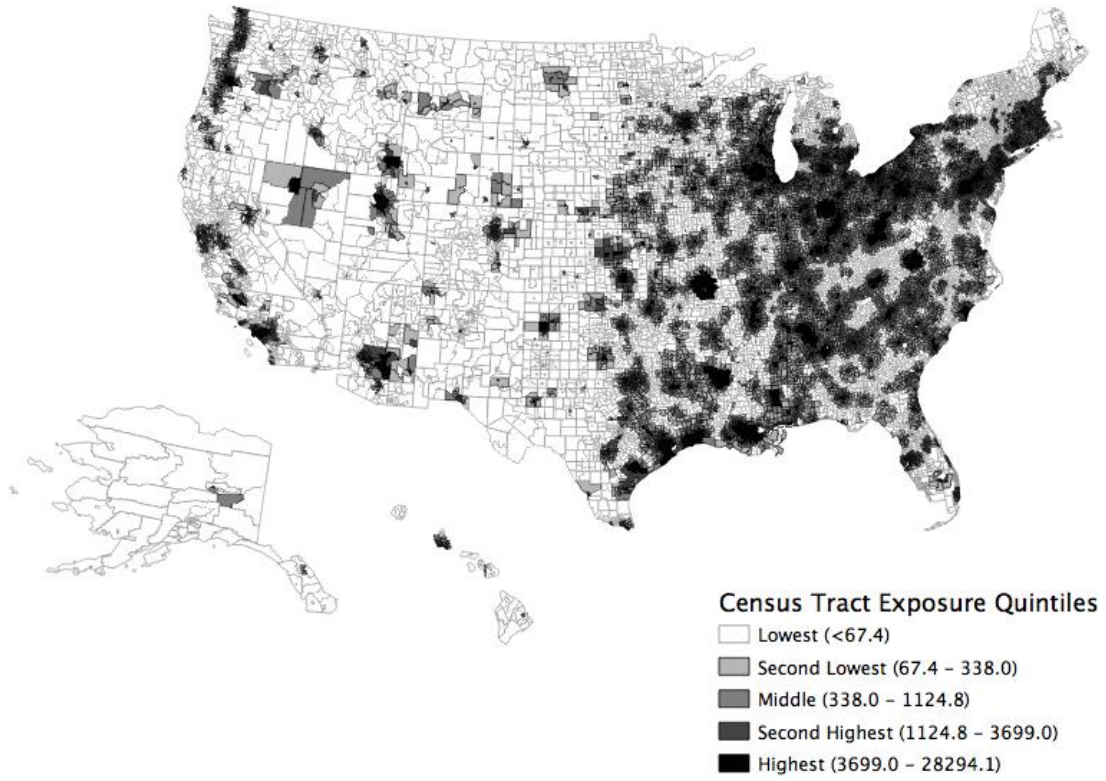
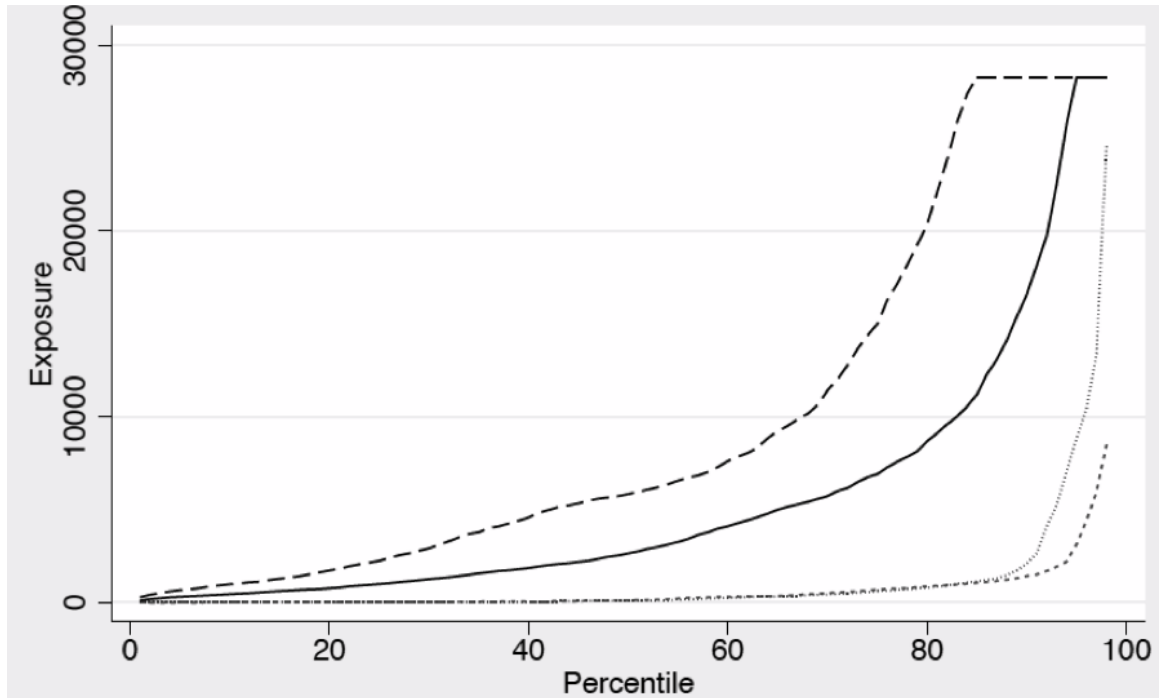


Figure 2: Minority and white exposure by percentile, Ohio and Virginia

Key:

- Ohio minorities
- Ohio whites
- Virginia minorities
- Virginia whites

Figure 3a: Median exposure and exposure Gini in the states

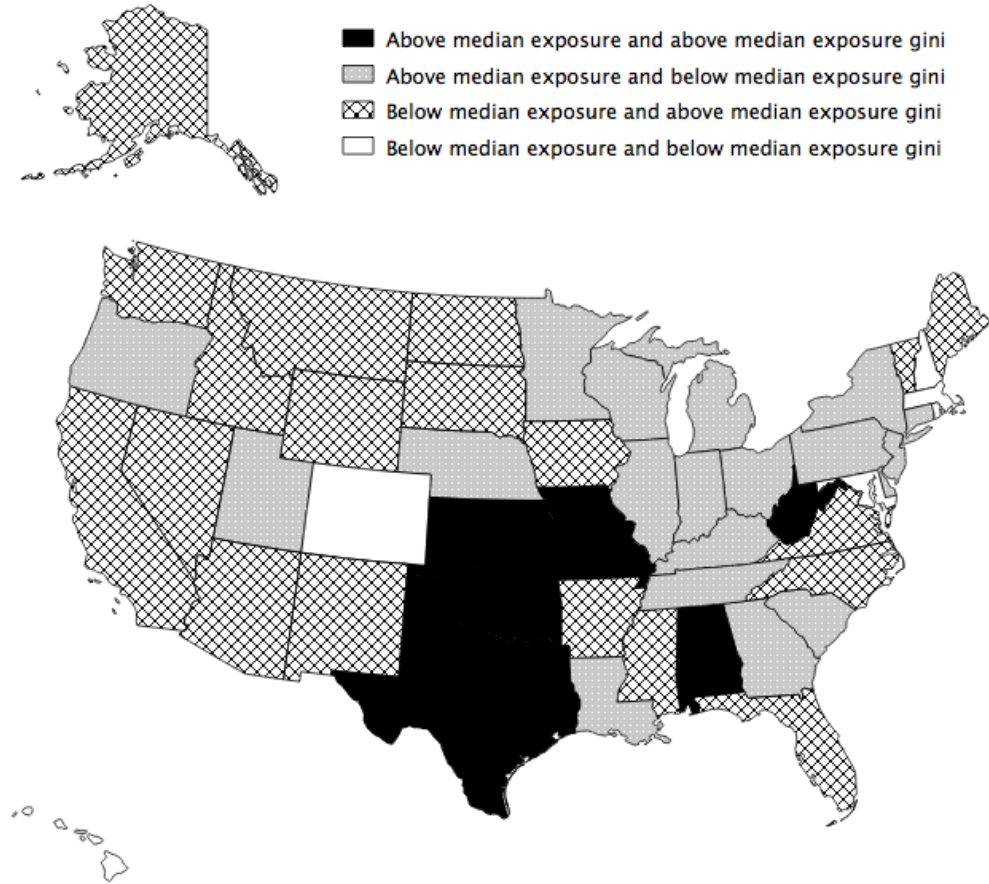


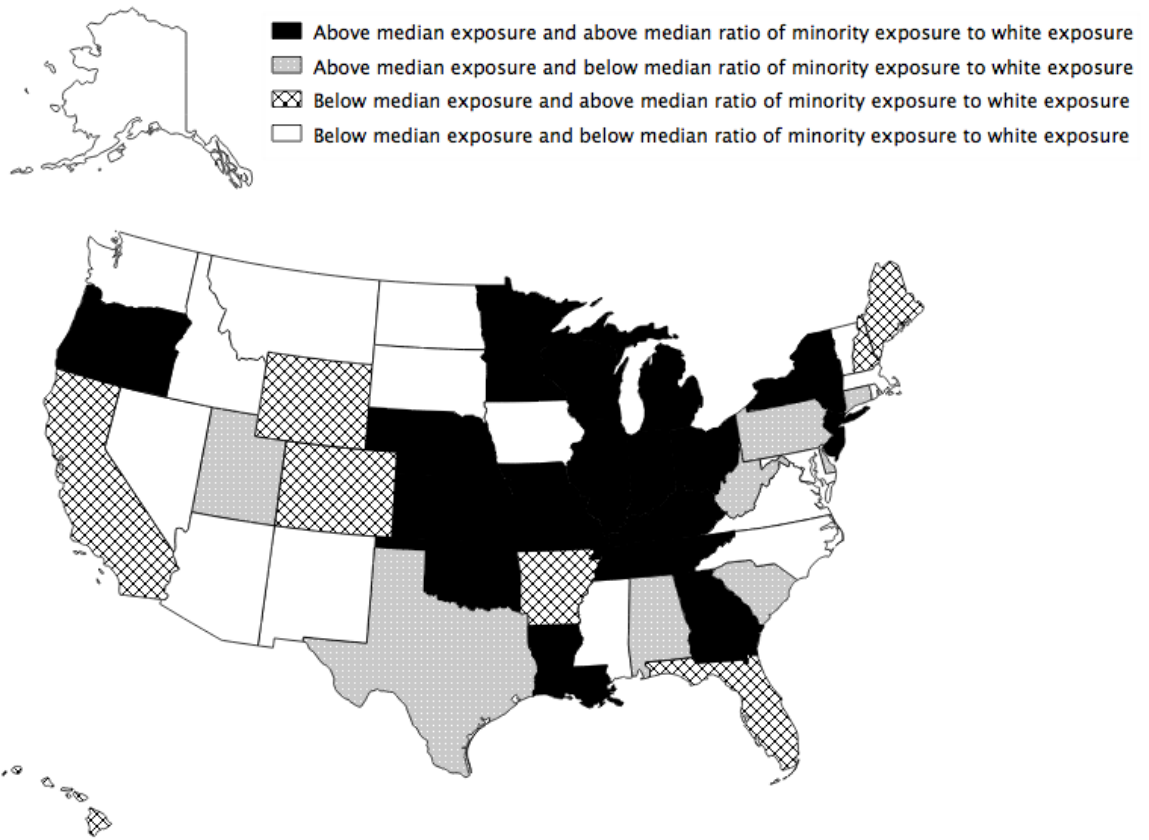
Figure 3b: Median exposure and minority/white ratio in the states

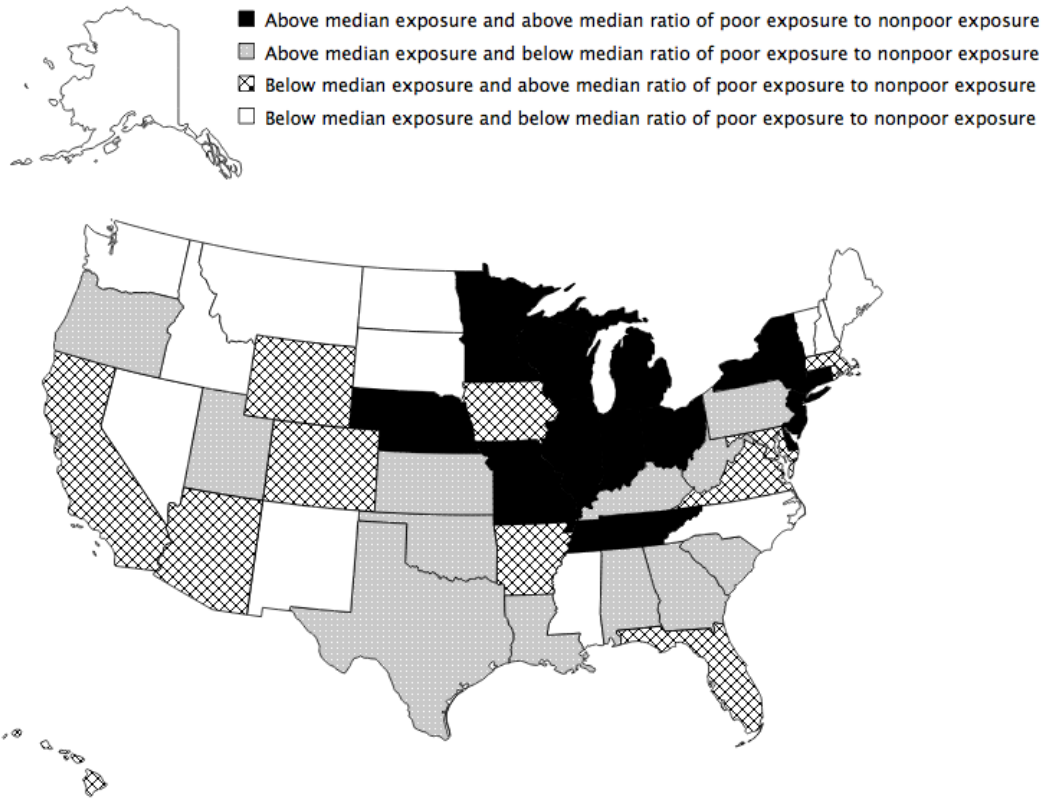
Figure 3c: Median exposure and poor/nonpoor ratio in the states

Figure 4a: Median exposure and exposure Gini in Congressional districts

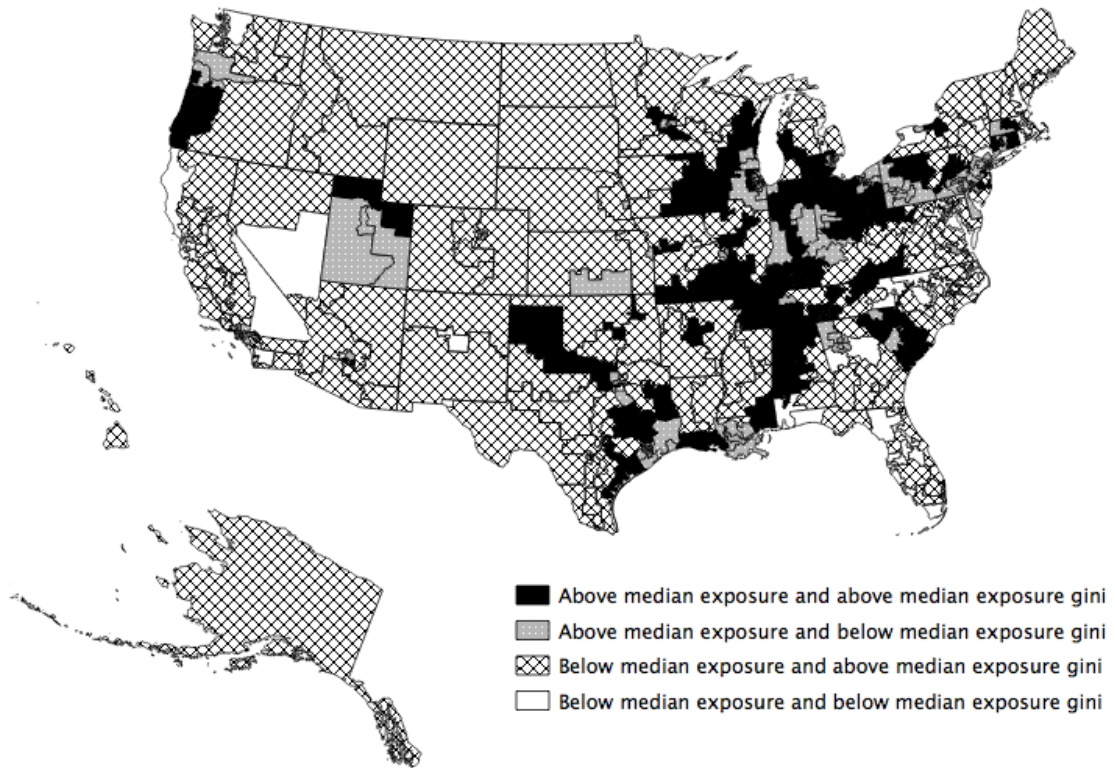


Figure 4b: Median exposure and minority/white ratio in Congressional districts

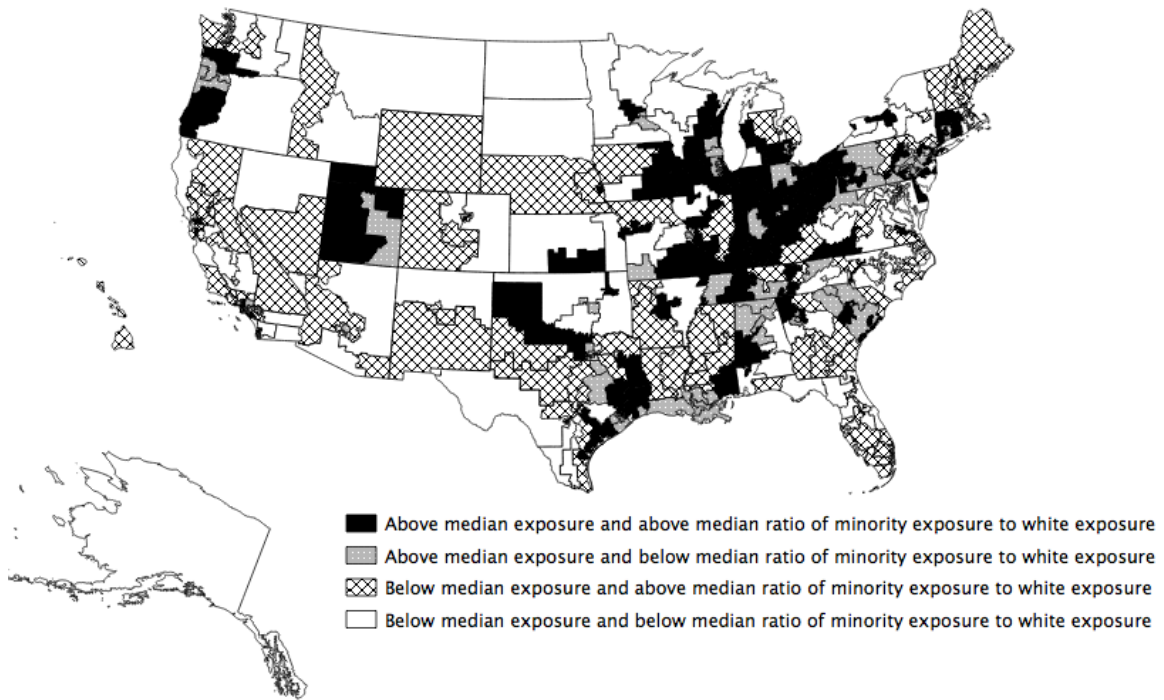


Figure 4c: Median exposure and poor/nonpoor ratio in Congressional districts

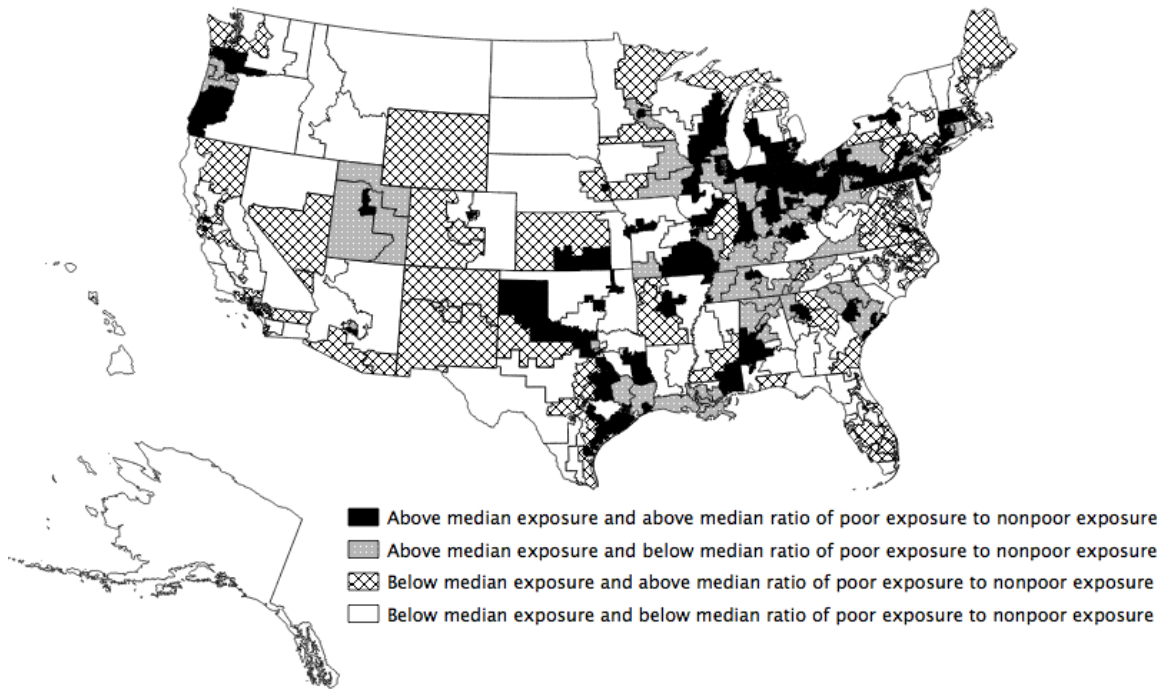


Table 1: Environmental inequalities by state

State	Gini coefficient of exposure	Minority/white exposure ratio	Poor/nonpoor exposure ratio	Median exposure
Alabama	0.73	0.94	0.86	815.33
Alaska	0.91	1.00	0.89	12.49
Arizona	0.76	1.10	1.07	331.61
Arkansas	0.81	3.24	1.02	269.70
California	0.80	3.48	1.25	275.23
Colorado	0.71	1.76	1.32	324.45
Connecticut	0.61	1.06	1.17	1680.44
Delaware	0.48	1.36	1.07	1022.00
Florida	0.72	1.88	1.19	124.58
Georgia	0.70	1.89	0.94	638.59
Hawaii	0.53	2.02	1.12	297.34
Idaho	0.81	1.05	0.35	257.17
Illinois	0.60	2.92	1.73	3633.57
Indiana	0.65	2.01	1.36	1558.14
Iowa	0.82	1.22	1.19	251.68
Kansas	0.74	2.20	0.57	1023.45
Kentucky	0.71	3.66	0.50	1187.81
Louisiana	0.65	1.76	0.84	2581.43
Maine	0.77	1.45	0.95	99.01
Maryland	0.69	0.67	1.80	163.73
Massachusetts	0.63	1.05	1.10	462.68
Michigan	0.68	3.10	1.28	1292.35
Minnesota	0.69	4.59	1.12	832.43
Mississippi	0.82	0.85	0.76	341.85
Missouri	0.77	2.48	1.52	772.55
Montana	0.83	0.46	0.92	78.03
Nebraska	0.67	2.07	1.16	529.72
Nevada	0.85	0.78	0.95	48.59
New Hampshire	0.63	2.15	0.95	175.10
New Jersey	0.61	2.05	1.25	2328.42
New Mexico	0.80	1.03	0.81	20.67
New York	0.59	2.41	1.54	1137.93
North Carolina	0.79	1.06	0.93	171.75
North Dakota	0.77	0.03	0.94	25.88
Ohio	0.59	2.20	1.48	3148.11
Oklahoma	0.76	1.81	0.58	553.12
Oregon	0.64	1.61	0.72	2938.53
Pennsylvania	0.59	0.98	0.91	2786.53

Rhode Island	0.32	0.97	1.06	195.10
South Carolina	0.71	1.03	0.78	1010.19
South Dakota	0.86	0.23	0.43	67.07
Tennessee	0.67	2.56	1.17	1149.95
Texas	0.75	1.19	0.82	702.60
Utah	0.58	1.42	0.73	4934.29
Vermont	0.84	1.14	1.00	4.78
Virginia	0.85	1.11	3.17	119.07
Washington	0.72	1.15	1.00	270.76
Washington, DC	0.34	1.13	0.96	112.60
West Virginia	0.76	0.80	0.74	569.95
Wisconsin	0.65	4.79	1.55	1237.28
Wyoming	0.78	2.09	3.59	93.51
National	0.76	1.46	1.11	594.92

Table 2: Correlations for states

	Gini coefficient	Minority/white ratio	Poor/ nonpoor ratio	Median exposure
Gini coefficient	1			
Minority/white ratio	-0.20	1		
Poor/nonpoor ratio	-0.01	0.19	1	
Median exposure	-0.49	0.23	-0.05	1

Table 3:
Top ten Congressional districts by environmental inequality measure

Gini coefficient of exposure		Minority/white exposure ratio		Poor/nonpoor exposure ratio	
Texas, District 1	0.77	Pennsylvania, District 3	5.41	Kentucky, District 3	3.54
Pennsylvania, District 5	0.77	California, District 33	4.11	New York, District 25	3.18
Illinois, District 12	0.75	New York, District 25	3.76	Kansas, District 3	2.42
Iowa, District 1	0.75	Texas, District 36	3.64	Pennsylvania, District 16	2.26
Tennessee, District 4	0.74	New Jersey, District 3	3.56	Illinois, District 7	2.05
Mississippi, District 4	0.74	Ohio, District 7	3.54	Illinois, District 2	2.04
Indiana, District 9	0.73	Ohio, District 2	3.31	Ohio, District 11	2.01
Virginia, District 9	0.73	New York, District 24	3.06	Ohio, District 3	2.01
Tennessee, District 7	0.73	Illinois, District 2	3.00	Michigan, District 3	2.00
Indiana, District 4	0.72	Illinois, District 17	2.97	Oklahoma, District 1	2.00

Note: Top ten among all districts with median exposure higher than national median.

Table 4: Correlations for Congressional districts

	Gini coefficient	Minority/white ratio	Poor/nonpoor ratio	Median exposure
Gini coefficient	1			
Minority/white ratio	0.14	1		
Poor/nonpoor ratio	0.01	0.30	1	
Median exposure	-0.42	0.04	0.07	1

Note: Excluding Florida's 25th and Colorado's 3rd district.