POLITICAL ECONOMY RESEARCH INSTITUTE
University of Massachusetts Amherst

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James K. Boyce, Klara Zwickl and Michael Ash

February 2015

WORKINGPAPER SERIES

Number 378

POLITICAL ECONOMY RESEARCH INSTITUTE

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James K. Boyce,[1] Klara Zwickl[2] and Michael Ash[3]

23 February 2015

Abstract

Using data on industrial air pollution exposure in the United States, we compute three measures of environmental inequality at the national level and for the 50 states: the Gini coefficient of exposure, the ratio of median exposure of people of color to that of non-Hispanic whites, and the ratio of median exposure of poor households to that of nonpoor households. Comparing Gini coefficients of pollution exposure to those of income, we find that the distribution of pollution exposure is more unequal. Comparing the three measures of environmental inequality, we find that rankings across states vary considerably, and conclude that different measures are most appropriate depending on whether the policy concern is equal fulfillment of the intrinsic right to a clean and safe environment or interactions between environmental inequality and other socioeconomic disparities.

Keywords: Inequality measures, Gini coefficient, environmental justice, air pollution.

JEL codes: I14, Q53, Q56, R11.

Acknowledgements: Research for this paper was supported by the Institute for New Economic Thinking (INET) Grant No. INO13-00028 and by the National Science Foundation Grant No. SES-1060904. We are also grareful to the Research Database Complex (RDC) at Indiana University, funded by Shared University Research grants from IBM, Inc., for hosting the database for this project. An earlier version of this working paper was issued in May 2014 by the Institute of New Economic Thinking (INET) Working Group on the Political Economy of Distribution.

[1] Political Economy Research Institute and Department of Economics, University of Massachusetts Amherst. Email: boyce@econs.umass.edu.

[2] Institute for Ecological Economics, Department of Socioeconomics, Vienna University of Economics and Business. Email: klara.zwickl@wu.ac.at.

[3] Department of Economics and Center for Public Policy and Administration, University of Massachusetts Amherst. Email: mash@econs.umass.edu.

1. Introduction

Pollution in the United States is not an equal opportunity affair. A large body of research has established that racial and ethnic minorities and low-income households 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). However, patterns of environmental inequality have been found to vary substantially across regions and metropolitan areas (Zwickl *et al*., 2014; Downey 2007).

This paper computes and compares three measures of environmental inequality for the 50 U.S. states, 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. Our primary aims are to demonstrate that variations in environmental quality are measurable; to assess its magnitude relative, for example, to income inequality; and to examine the extent to which the different measures are correlated with each other, since a high correlation would imply that policy concerns can be addressed relying on a single measure, whereas a low correlation would imply that different measures are needed for different purposes.

The Gini coefficient is a measure of vertical inequality. It differentiates the population only by the variable in question, in the present case exposure to industrial air toxics, and it summarizes the extent of divergence from a perfectly equal distribution. The other two measures refer to horizontal inequality, comparing differences in exposure across population subgroups that are differentiated on some basis (here minority status and poverty status) other than exposure itself.

We find that exposure inequality rankings vary considerably across these three measures. Because environmental inequalities are likely to be of greatest policy concern in places with high overall pollution burdens, we identify the states that rank in the top half in terms of both median exposure to industrial air pollution and one or more measures of exposure inequality.

Section 2 discusses motivations for measuring environmental inequality – why policy makers and the public may be concerned about the distribution of environmental harm as well as its overall magnitude. Section 3 introduces the data used in our analysis, and section 4 provides details on methods used to calculate the three measures. Section 5 presents results for the states. Section 6 offers some concluding remarks.

2. Environmental quality and environmental inequality

Environmental inequality matters for at least three reasons. The first reason is an intrinsic one, founded on the normative principle that all persons have an equal right to a clean and safe environment. The second reason is that the distribution of environmental quality has important impacts on opportunities to lead a healthy and productive life. The third reason, related to the second, is that the distribution of environmental quality has important impacts on economic outcomes for individuals and communities. In this section we discuss these rationales with a particular focus on air pollution, which the World Health Organization (2014) has characterized as "the world's largest single environmental health risk," currently responsible for one in eight of total deaths worldwide.

(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."[4] Similar language can be found in many U.S. state constitutions, as illustrated by this statement in the constitution of the Commonwealth of Massachusetts: "The people shall have the right to clean air and water."[5]

[4] Similar statements appear in the constitutions of many nations across the world. For example: "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). For discussion of international legal principles on environmental human rights, see Popovic (1996).

[5] Other examples from state constitutions include the following: "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 fundamental legal principles accord an intrinsic value to the distribution of environmental quality. A logical corollary of the principle that all persons have an equal right to a clean and safe environment is that shortfalls in environmental quality likewise should be distributed equally. The environmental rights of some should not take precedence over the environmental rights of others.

The intrinsic value of environmental equity applies to the distribution of environmental quality across communities as well as individuals. The environmental justice movement in the U.S. has drawn attention to the disproportionate environmental burdens often imposed on racial and ethnic minorities and low-income people. Presidential Executive Order 12898, issued by Bill Clinton in 1994, directed all U.S. government agencies 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," inscribing environmental equity into federal policy. In a proclamation marking the order's 20th anniversary, President Barack Obama affirmed "every American's right to breathe freely, drink clean water, and live on uncontaminated land" (Obama, 2014).

To be sure, equity is not all that matters when it comes to environmental quality. A situation in which all people are equally exposed to unacceptably high levels of pollution is arguably inferior than one in which some are exposed to that level and others to lower levels. For any given level of overall pollution exposure, however, a more equal distribution can be regarded as ethically and legally superior to a less equal distribution.

(ii) Equality of opportunity

A second reason for concern about environmental inequalities derives from their implications for equality of opportunity, owing to the vulnerability of children to environmental harm. "Much more important than inequality of outcomes among adults is inequality of opportunity among children," assert the authors of the World Bank's Human Opportunity Index, reflecting a widely held view. "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 susceptible to health and cognitive impacts of pollution, and it has been shown that environmental quality can significantly affect a child's life chances (Currie, 2011). Indeed the impacts extend to the odds of life itself. The reduction in air pollution in the U.S. due to the impact of the 1981-82 recession on economic activity led to a measureable reduction in infant deaths: Chay and Greenstone (2003) found that each one percent decrease in total suspended particulates lowered infant mortality by 0.35 percent. Reductions in carbon monoxide exposure attributable to emissions controls implemented in California in the 1990s are estimated to have prevented approximately 1000 infant deaths (Currie and Neidell, 2005).

Even relatively modest levels of air pollution have been found to have significant adverse impacts on fetal health as well as infant health (Currie *et al.,* 2009). The link between maternal air pollution exposure during pregnancy and fetal growth has led 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 is also linked to neurodevelopmental disabilities including autism, attention-deficit hyperactivity disorder, dyslexia and other cognitive impairments (Grandjean and Landrigan, 2014). Even transitory exposure to high levels of airborne particulates on the day of the exam has been shown to have significant adverse impacts on student performance of high-stakes tests, leading in turn to negative effects on post-secondary education and adult earnings (Lavy *et al.*, 2014).

In addition to neurological impacts, air pollution affects children's educational opportunities by causing 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, controlling for characteristics of schools, years and attendance periods (Currie *et al.,* 2009). 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, after controlling for effects of confounding variables such as average expenditure per student, size of the student body, student-teacher ratio, and percentage of students enrolled in the free lunch program (Mohai *et al.,* 2011). Exposure to airborne toxics has been 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). Similarly, a study in East Baton Rouge, Louisiana, found that proximity to Toxics

Release Inventory (TRI) facilities and high-volume emitters of developmental neurotoxins is significantly related to school performance (Lucier *et al.*, 2011).

(iii) Economic impacts

Pollution also has impacts on economic outcomes, including property values, days lost from work, and health costs. Air pollution has long been known to reduce property values (Nourse, 1967; Anderson and Crocker, 1971). Reductions in total suspended particulates following implementation of the Clean Air Act are estimated to have led to a $45 billion increase in housing values in the 1970s (Chay and Greenstone, 2005). Housing values within a one-mile radius of TRI facilities have been found to decrease by 1.5% when a plant opens and to increase by 1.5% when one closes (Currie *et al.,* 2015).

Air pollution also results in lost work days. An analysis of 1976 U.S. household survey data found that one standard deviation increase in ambient particulate pollution was associated with a 10 percent increase in days lost 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 shown to have statistically significant adverse impacts on worker productivity (Graff Zivin and Neidell, 2011).

Following the publication in 1981 of the landmark report, *Costs of Environment-Related Health Effects,* written by an expert committee of the U.S. Institute of Medicine chaired by economist Kenneth Arrow, a number of studies have estimated the monetary costs of the "environmentally attributable fraction" (EAF) of diseases in the U.S. The annual cost of EAF illnesses among children was calculated by Landrigan *et al.* (2002) to be $54.9 billion in 1997 dollars, with the largest single component coming from lifetime 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 childhood asthma suggests that prior studies have underestimated the health costs of air pollution by measuring only the exacerbation of asthma and not impacts on their prevalence (Brandt *et al.,* 2012).

In December 2011 the U.S. EPA announced Mercury and Air Toxics Standards, the agency's first effort to impose mandatory limits on air toxics. The EPA estimates that the standards will yield annual health benefits valued at between $37 billion and

$90 billion, including prevention of as many as 11,000 premature deaths and 130,000 asthma attacks per year, and notes that these benefits are “especially important to minority and low income populations who are disproportionately impacted by asthma and other debilitating health conditions” (EPA, 2014). 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 used in the present study.

The distribution of environmental quality may contribute the widely observed inverse relationship between health and socioeconomic status (Evans and Kantrowitz, 2002). A study of Bronx borough in New York City found that poor and minority populations are more likely to live in proximity to noxious land uses, including TRI facilities, and that this is associated with a 66% increase in the likelihood of hospitalization for asthma (Maantay, 2007). Interactions among environmental hazards and social vulnerability exacerbate health impacts in minority and low-income neighborhoods (Morello-Frosch *et al.,* 2011). Exposure to multiple hazards has cumulative impacts (Brender *et al.,* 2011).

Whether adverse impacts of pollution exposure could, in principle, be “compensated” by the provision of 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). If access to a clean and safe environment is regarded as an intrinsic right, one can question whether income could adequately compensate for its infringement, on ethical grounds that are analogous to the prohibitions against slavery and trafficking in human organs, namely that human rights cannot be sold. This debate is irrelevant, however, 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 ver. 2.3.1) 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 grid cells, each 810 meters square, in a 50-km radius around each facility. To aggregate across chemicals, RSEI uses toxicity weights based on chronic human health effects from inhalation exposure.

The RSEI data provide the best available measure of exposure to air toxics from industrial facilities, but 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. The industrial point sources in the TRI/RSEI database often loom large, however, in the risks faced by communities with the most severe air pollution (Boyce and Pastor, 2012).

Figure 1 maps median exposure to industrial air toxics by state – that is, the exposure of households at the midpoint of the frequency distribution in their respective states. There are wide interstate variations: the highest median exposure (Utah) is roughly one thousand times greater than the lowest (Vermont).

[insert Figure 1 here]

Here, however, our main focus is the distribution of exposure within states. To examine intra-state variations, we use RSEI geographic microdata to calculate toxicity-weighted exposures for each of the state's RSEI grid cells, aggregated across all industrial facilities that impact the cell. We then map the grid-cell exposures to census blocks, the finest level of geographic resolution in the U.S. Census. We obtain income and demographic variables at the census tract level from the American Community Survey (ACS), using five-year averages for the years 2006-2010. To merge these data, we compute exposure at the census tract level as the area-weighted average of exposure in the tract's constituent blocks.[6]

Figure 2 maps nationwide variation in exposure to industrial air toxics by census tracts. The uneven distribution of exposure is evident within states as well as across them. A number of states include tracts in both the highest and lowest national exposure quintiles, indicating the presence of substantial intra-state exposure inequalities as well as illustrating the importance of spatial disaggregation.

[insert Figure 2 here]

[6] We censor pollution exposure at the nationwide population-weighted 97th percentile (that is, we cap exposure at this value) to reduce the sensitivity of our results to outliers.

4. Three measures of environmental inequality

We compute three measures of environmental inequality from the RSEI data on exposure to industrial air toxics:

(i) Gini coefficient

The Gini coefficient is a measure of vertical inequality, meaning that individuals are differentiated only by the variable in question (in this case, pollution exposure), and the measure summarizes the extent of these differences. It is widely used to measure inequality in the distribution of income, expenditure and wealth (Dorfman, 1979). The Gini coefficient occasionally has been applied to environmental variables, 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).

In the measurement of disparities in income and wealth, the unit of observation is typically the individual or family. When calculating Ginis for spatially based variables, such as pollution exposure, the unit of observation is less straightforward. To minimize the problem of "ecological fallacy," in which conclusions drawn from aggregate spatial data do not apply at a finer level of disaggregation (Ash and Fetter, 2004), it is desirable to base calculations on the smallest unit of observation that is available, in our case 810 meter x 810 meter grid cells. There are almost 15 million grid cells nationwide, 9.7 million of which have exposure to industrial air pollution as estimated by the RSEI). Although grid cells have a fixed area, population density varies greatly across them. Alternatively we can compute Ginis at the census tract level. Tracts are constructed by the US Census Bureau to include around 4000 individuals each,[7] but they vary widely in area due to differences in population density. The United States consists of 74,002 census tracts, so grid cells generally provide a finer spatial resolution. In densely populated urban areas, however, tracts can be much smaller than grid cells. Nationwide the number of grid cells per tract ranges from 0.06-0.07 cells per tract in parts of New York City and Boston to tens of thousands of cells per tract in parts of western states such as Alaska, Nevada, and Wyoming.

Whether it is more appropriate, in assessing environmental inequalities, to partition the country into spatial units by equal area or equal population is an important

[7] Since not every tract includes exactly 4000 individuals, we will additionally population weight the census tract Ginis to account for the remaining variation in population size by unit of observation.

question from the standpoint of environmental policy as well as measurement methodology. Inequality across grid cells of equal area can be reduced by targeting the most polluted grid cells first. The underlying normative premise for such a policy is that every resident, regardless of geographic location, should have equal access to environmental quality; less densely populated areas should not be more polluted, simply because fewer people are affected. Inequality across census tracts of roughly equal population gives more weight to locations with higher population density; the underlying premise is environmental priorities should reflect the number of people who will benefit from environmental regulation and enforcement. This approach is reflected in conventional cost-benefit analyses that show higher benefits when more people are affected by improved environmental quality.

Population weights can also be used in calculating Ginis from grid cell-level data. Because grid cells generally are smaller than tracts, a comparison between tract-based Ginis and population-weighted grid cell-based Ginis can shed light on how much inequality arises from within-tract variations. In the case of income inequality, calculations based on tract-level data versus household-level data show that a substantial part of overall inequality is attributable to within-tract variations (Galbraith and Hale, 2008). In the case of location-based variables such as pollution exposure, however, within-tract variations are likely to be less important. This expectation is confirmed by the results presented in the next section of this paper.

Because the census tract is the finest level of disaggregation available for the income, race and ethnicity variables used in our measures of horizontal inequality, the tract-based Gini is most directly comparable to these other measures of exposure inequality. Moreover, insofar as census tracts roughly correspond to what residents consider to be their "neighborhoods," this measure of inequality is of intrinsic interest.[8]

The Gini coefficient is calculated by the following formula:

$$\text{Gini} = (1/n)\left[n + 1 - 2\sum_{i=1}^{n} (n + 1 - i)\, EXPOSURE_i\right] / \sum_{i=1}^{n} EXPOSURE_i$$

[8] Census tracts have been used as proxies for neighborhoods not only in analyzing environmental disparities (see, for example, Zwickl and Moser, 2014), but also in analyzing housing markets and segregation (Brueckner and Rosenthal, 2009), unemployment (Topa, 2001), and subprime lending (Richter and Craig, 2013).

where $EXPOSURE_i$ = industrial air toxics exposure in census tract (or cell) i, and n = the number of tracts (or cells), indexed in non-decreasing order ($EXPOSURE_i \leq EXPOSURE_{i+1}$). The Gini coefficient lies between the hypothetical values of zero (which would mean that all tracts or cells have the same exposure) and one (which would mean that exposure is confined entirely to a single tract or cell).

(ii) Minority/white exposure ratio

Our other two measures refer to horizontal inequality, also known as group inequality. These measures compare exposure across subgroups of the population that are differentiated by attributes other than exposure itself. To compare exposure of racial and ethnic minorities to that of non-Hispanic whites (hereafter, simply "whites"), we calculate exposure levels for both subgroups:

$$EXPOSURE_{js} = \Sigma_s(EXPOSURE_i * TOTALPOP_k * X_{jk}) / \Sigma_s(TOTALPOP_k * Xj_k) \qquad (2)$$

where subscript j indexes the population subgroup; the subscript s indexes the state; 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 in the state, and term this the "minority/white exposure ratio."

(iii) Poor/nonpoor exposure ratio

Using the same technique, we measure horizontal inequality in the distribution of exposure between poor households (here defined as having incomes below the federal poverty line) and nonpoor households. The "poor/nonpoor exposure ratio" is the ratio of the median exposures of the poor and nonpoor population subgroups within the state.

5. Results

We compute these three measures of inequality in exposure to industrial air toxics for the 50 states plus the District of Columbia. Comparisons of environmental inequalities across states are of interest since states vary not only in the strength of their environmental regulations and enforcement but also in the extent to which their environmental policies explicitly include distributional objectives (Bonorris, 2010).

Vertical inequality: Gini coefficients

Table 1 reports three variants of the environmental Gini – one based on tract-level data, the other two based on grid cell data without and with population weighting. At the national level, the between-tract Gini is 0.76, and it is 0.70 or higher in 29 of the 50 states. The between-cell Gini without population weights is 0.93 at the national level, and higher than the between-tract Ginis in almost every state. With population weighting, however, the between-cell Ginis are nearly identical to the between-tract Ginis. This implies that the difference between the tract-based Gini reported in column 1 and the cell-based Gini reported in column 2 is primarily due to the fact that the latter gives equal weight to all locations regardless of population density, rather than to the difference in the degree of spatial resolution. In other words, there is little intra-tract variation in exposure relative to between-tract variation. If the logic behind population weighting is accepted, therefore, the choice between tracts and cells as a basis for computing the exposure Gini is of little consequence.

[insert Table 1 here]

To compare exposure inequality to income inequality, in the final two columns of Table 1 we present income Ginis. Column 4 reports between-tract Ginis, calculated on the basis of median tract income. Column 5 reports individual income Ginis computed by the Census Bureau from household data from the 2010 ACS. In the case of income inequality, we find a marked difference between these two measures: the national between-tract income Gini is 0.25 compared to an individual income Gini of 0.47, and at the state level the differences generally are even larger. This reflects substantial intra-tract variation in household income, a finding earlier reported by Galbraith and Hale (2008) using data for the year 2000.

At the national level, the Gini coefficient for between-tract and between-cell (population-weighted) exposure inequality is 0.76, compared to 0.25 for between-tract income inequality and 0.47 for individual income inequality. At the state level, between-tract exposure inequality is higher than between-tract income inequality in every case, and higher than the individual income Gini in all but two. We can safely conclude, therefore, that exposure to industrial air toxics in the United States is distributed more unequally than income.

Horizontal inequality: median exposure ratios

Table 2 presents our two horizontal measures of exposure inequality, alongside the between-tract Gini coefficient for ease of comparison. The minority/white exposure ratio is 1.46 nationwide. By this measure, exposure inequality and income inequality are roughly comparable in magnitude: in 2010 the ratio of median white household income to median minority household income was 1.4.[9] The fact that minorities tend to have both higher exposure and lower income suggests that disproportionate pollution burdens often are not offset by higher incomes. The minority/white exposure ratio is less than one in only ten states, and less than 0.67 only in the Dakotas and Montana, where Native Americans, many of whom reside far from industrial facilities, comprise the largest minority group. It exceeds 3.0 in six states: Arkansas, California, Kentucky, Michigan, Minnesota and Wisconsin.

[insert Table 2 here]

The poor/nonpoor exposure ratio nationwide is 1.11, ranging from 0.35 in Idaho to 3.59 in Wyoming. This measure reflects the net balance between two opposing effects. On the one hand, if the presence of industry is correlated with higher incomes as well as more pollution, the exposure of the poor would be expected to be lower than the exposure of the nonpoor, producing a ratio less than one. On the other hand, if more polluting facilities are more likely to be located in low-income neighborhoods, this would yield a ratio greater than one. The ratio is greater than one in 26 states – and greater than 3.0 in two, Virginia and Wyoming – again implying that in many cases higher pollution exposure is not compensated by higher incomes.

Table 3 reports correlation coefficients among the three measures of environmental inequality. The correlations are low, implying that rankings are highly sensitive to the choice of exposure inequality measure. 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, but the fact that it is low (0.185) implies that disproportionate exposure of the poor is not simply an artifact of correlations between race, ethnicity and class.

[insert Table 3 here]

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[9] Calculated from DeNavas-Walt *et al.* (2011), Table A-1, "Income and Earnings Summary Measures by Selected Characteristics: 2007 and 2010."

The correlations between the Gini coefficient and the two horizontal inequality measures are negative, albeit again quite low. *A priori,* one might have expected states with more vertical inequality generally to exhibit more horizontal inequality, too. To illustrate how the contrary can be true, Figure 3 shows percentile-wise exposures for minorities and whites in two states, one (Ohio) with a relatively low Gini but a relatively high minority/white ratio, and the other (Virginia) with the opposite. The contrast between the two states underscores our finding that no single measure suffices to capture the multiple dimensions of exposure inequality.[10]

[insert Figure 3 here]

Inequality and median exposure

The final column in Table 2 presents median exposure levels in the states, which vary considerably as noted above. The relationship between median exposure and exposure inequality is not straightforward. There is a negative correlation (–0.49) between the between-tract exposure Gini and median exposure (see Table 3), indicating that industrial air pollution tends to be more unequally distributed in states with less of it. This is not surprising, since some states (for example, Alaska and Vermont) have low industrial air pollution exposure in many tracts and substantial exposure in a few. Yet other states (for example, Rhode Island and Hawaii) with relatively low median exposure also have relatively low exposure Ginis, as shown in Figure 4.

[insert Figure 4 here]

The positive correlation between the minority/white exposure ratio and median exposure (0.23) implies that pollution tends to be somewhat more concentrated in minority communities in states with higher levels of pollution. This is consistent with the proposition that environmental justice can be "good for white folks," as well as for people of color, in that more equal distribution of exposure between minorities and whites is associated with lower levels of pollution overall (Ash *et al.*, 2013). This may reflect less stringent environmental regulation in states where

[10] Two other features of Figure 3 deserve comment. 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 (the level at which the exposure data are censored, resulting in the flattening the curve). Second, the most exposed decile of whites in Virginia faces considerably higher exposure than the most exposed decile of minorities. As mentioned above, Virginia's poor/nonpoor median exposure ratio is among the highest in the nation; taken together, these observations reflect disproportionately high exposures among poor whites in that state.

pollution burdens fall more heavily 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 linked to the overall magnitude of pollution as both cause and effect.

From a policy standpoint, environmental inequalities are likely to be of greatest concern in places where overall pollution levels are high. The maps in Figures 5-7 partition the states into four groups, based on whether their median exposure and exposure inequality are above or below their average values for all states. Again we see contrasts among the different measures. States with above-average median exposure plus above-average exposure Ginis are concentrated in the south central region, while those with above-average median exposure plus above-average minority/white and poor/nonpoor exposure ratios are concentrated in the northern Midwest.

[insert Figures 5-7 here]

6. Conclusion

Environmental inequality is a multi-dimensional phenomenon. In this study we examined three measures that capture different dimensions: the Gini coefficient of exposure, the median exposure of people of color 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, representing the degree of disparity across the population ranked from least exposed to most exposed. The latter two are measures of horizontal inequality, comparing exposure across groups defined on the basis of minority status and poverty status, respectively.

When we compute these measures for the 50 U.S. states and the District of Columbia, we find that they yield markedly different rankings of environmental inequalities. We find only modest positive correlations between the two horizontal inequality measures, and modest negative correlations between the Gini coefficient and the horizontal measures.

Comparing exposure Ginis to income Ginis, we find that exposure to industrial air pollution is more unequally distributed than income in the United States. Nationwide, the exposure Gini is 0.76 when calculated either between tracts or between cells weighted by population. This is considerably higher than either the inter-tract income Gini (0.25) or the individual income Gini (0.47). When we calculate the exposure Gini based on cells of equal area, without population weights, inequality is even more extreme (0.93 at the national level).

There is no single answer to the question of which type of environmental inequality should be of greatest policy interest and public concern. If we start from the normative premise that every person has an equal right to environmental health and safety, then vertical inequality is arguably most relevant as it measures the extent to which the actual distribution of exposure violates this right. The extent to which exposures exceed a level judged to be "safe" is important, too, and vertical inequality is of most concern when absolute exposure levels are high. Yet even where a state's median exposure is low, vertical inequality may be of interest, indicating the extent to which summary measures mask more serious risks borne by some communities.

Unequal distribution of exposure may be regarded as more objectionable when those who bear disproportionate pollution burdens are disadvantaged in other respects, as well. From this perspective, the extent of horizontal inequalities between people of color and whites, and between the poor and nonpoor, is of particular relevance. The explicit reference to "minority populations and low-income populations" in Presidential Executive Order 12898 reflects this normative principle.

To be sure, inequality is not the only useful criterion for assessing environmental outcomes. Few would claim that social welfare would be improved by increasing pollution in all census tracts until it equals that in the most exposed tract, notwithstanding the fact that this would be one way to eliminate exposure inequality. When the policy question is where to focus pollution abatement efforts or where to site new pollution sources, however, environmental equity may be an important objective. Pursuit of this objective runs counter to any tendency for policymakers to concentrate environmental hazards in "sacrifice zones" that already have high pollution burdens. Measures of environmental inequality not only can be a useful input into policymaking, but also can help to catalyze greater attention among scholars and members of the public to this issue.

Promising avenues for further research on measurement of environmental inequality include the development of comparable measures for mobile-source air pollution and for water pollution, and investigation as to whether variations in these elements of environmental inequality are correlated with the variations in exposure to industrial air toxics reported here. Measures can also be calculated for other spatial units, such as metropolitan areas or Congressional districts. In addition, measurement of environmental inequality opens possibilities for analysis of how it may be related, as both cause and effect, to other variables such residential segregation, voting behavior, and state environmental policies.

References

Anderson, R J, Crocker, T D, 1971, "Air Pollution and Residential Property Values," *Urban Studies* **8**(3) 171-180.

Ash, M, Fetter, T R, 2004, "Who Lives on the Wrong Side of the Environmental Tracks?" *Social Science Quarterly* **85**(2) 441-462.

Ash, M, Boyce, J K, Chang, G, Scharber, H, 2013, "Is Environmental Justice Good for White Folks? Industrial Air Toxics Exposure in Urban America," *Social Science Quarterly* **94**(3) 616-636.

Barros, R P, Ferreira, F H G, Molinas Vega, J R, Saaverda Chanduvi, J, 2009, *Measuring Inequality of Opportunities in Latin America and the Caribbean.* World Bank, Washington, DC.

Bonorris, S, ed, 2010, *Environmental Justice for All: A Fifty State Survey of Legislation, Policies and Cases*, 4th edn. Berkeley, CA: American Bar Association and Hastings College of the Law, University of California.

Boyce, J K, Pastor, M, 2012, "Cooling the Planet, Clearing the Air: Climate Policy, Carbon Pricing, and Co-Benefits." Economics for Equity and the Environment, Portland, OR.

Bouvier, R, 2014, "Inequality in Two Dimensions: An Analysis of the Distribution of Income and Toxic Emissions in Maine," *Ecological Economics* **102** 39-47.

Brandt S J, Perez L, Kunzli N, *et al.*, 2012, "Costs of childhood asthma due to traffic-related pollution in two California communities," *European Respiratory Journal* **40** 363–370.

Brender, J D, Maantay, J A, and Chakraborty, J, 2011, "Residential Proximity to Environmental Hazards and Adverse Health Outcomes," *American Journal of Public Health* **101**(S1) 37-52.

Brueckner, J, and Rosenthal, S, 2009, "Gentrification and neighborhood housing cycles: Will America's future downtowns be rich?" *Review of Economics and Statistics* **91**(4) 725-743.

Bullard, R D, Johnson, G S, Torres, A O, 2011, *Environmental Health and Racial Equity in the United States: Building Environmentally Just, Sustainable, and Livable Communities.* American Public Health Association, Washington, DC.

Chay, K Y, Greenstone, M, 2003, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *Quarterly Journal of Economics* **118**(3) 1121-1167.

Chay, K Y, Greenstone, M, 2005, "Does Air Quality Matter? Evidence from the Housing Market," *Journal of Political Economy* **113**(2) 376-424.

Currie, J, 2011, "Inequality at Birth," *American Economic Review Papers & Proceedings* **101**(3) 1-22.

Currie, J, Davis, L, Greenstone, M, Walker, R, 2015, "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings," *American Economic Review*, **105**(2) 678-709.

Currie, J, Neidell, M, 2005, "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?" *Quarterly Journal of Economics* **120**(3) 1003-1030.

Currie, J, Hanushek, E A, Kahn, E M, Neidell, M, Rivkin, S G, 2009, "Does pollution increase school absences?" *Review of Economics and Statistics* **91**(4) 682-694.

Currie, J, Neidell, M, and Schmeider, J F, 2009, "Air Pollution and Infant Health: Lessons from New Jersey," *Journal of Health Economics* **28** 688-703.

DeNavas-Walt, C, Proctor, B D, Smith, J C, 2011, "Income, Poverty and Health Insurance Coverage in the United States: 2010," Washington, DC: U.S. Census Bureau, Current Population Reports.

Dorfman, R, 1979, "A Formula for the Gini Coefficient", *The Review of Economics and Statistics*, **61**(1) 146-149.

Downey, L, 2007, "U.S. Metropolitan-area Variation in Environmental Inequality Outcomes," *Urban Studies* **44** 953-977.

Druckman, A, Jackson, T, 2008, "Measuring Resource Inequalities: The concepts and methodology for an area-based Gini coefficient," *Ecological Economics* **65** 242-252.

Evans, G W, Kantrowitz, E, 2002, "Socioeconomic Status and Health: The Potential Role of Environmental Risk Exposure," *Annual Review of Public Health* **23** 303-331.

Galbraith, J K, Hale J T, 2008, "State Income Inequality and Presidential Election Turnout and Outcomes," *Social Science Quarterly* **89**(4) 887-901.

Grandjean, P, Landrigan, P J, 2014, "Neurobehavioural effects of developmental toxicity," *Lancet Neurology* **13**(3) 330-338.

Graff Zivin, J S, Neidell, M J, 2011, "The Impact of Pollution on Worker Productivity," WP 17004, National Bureau of Economic Research, Cambridge, MA.

Hausman, J A, Ostro, B D, Wise, D A, 1984, "Air Pollution and Lost Work," WP 1263, National Bureau of Economic Research, Cambridge, MA.

Heil, M T, Wodon, Q T, 2000, "Future Inequality in CO2 Emissions and the Impact of Abatement Proposals," *Environment and Resource Economics* **17** 163-181.

Landrigan P J, Schechter C B, Lipton J M, *et al*., 2002, "Environmental pollutants and disease in American children: estimates of morbidity, mortality, and costs for lead poisoning, asthma, cancer, and developmental disabilities," *Environmental Health Perspectives* **110** 721–728.

Lavy, V, Ebenstein, A, Roth, S, 2014, "The long-run human and economic consequences of high-stakes examinations," WP 20647, National Bureau of Economic Research, Cambridge, MA.

Lucier, C, Rosofsky, A, London, B, Scharber, H, Shandra, J M, 2011, "Toxic pollution and school performance scores: Environmental ascription in East Baton Rouge Parish, Louisiana," *Organization & Environment* **24**(4) 423-443.

Maantay, J, 2007, "Asthma and air pollution in the Bronx: Methodological and data considerations in using GIS for environmental justice and health research," *Health & Place* **13** 32-56.

Millimet, D L, Slottje, D, 2002, "An environmental Paglin-Gini," *Applied Economics Letters* **9** 271-274.

Mohai, P, 2008, "Equity and the Environmental Justice Debate," in *Equity and the Environment*, Eds R C Wilkinson and W R Freudenberg, *Research in Social Problems and Public Policy*, Vol. 15 (Elsevier, Amsterdam) pp 21-50.

Mohai, P. Kweon, B-S, Lee, S, & Ard, K, 2011, "Air pollution around schools is linked to poorer student health and academic performance," *Health Affairs* **30**(5) 852-862.

Morello-Frosch, R, Zuk, M, Jerrett, M, Shamasunder, B, Kyle, A D, 2011, "Understanding the Cumulative Impacts of Inequalities in Environmental Health: Implications for Policy," *Health Affairs* **30**(5) 879-887.

Nourse, H O, 1967, "The Effect of Air Pollution on House Values," *Land Economics* **43**(2) 181-189.

Obama, B, 2014, “Presidential Proclamation -- 20th Anniversary of Executive Order 12898 on Environmental Justice.” Office of the Press Secretary, White House, Washington, DC, February 10.

Ostro, B D. 1990, “Associations Between Morbidity and Alternative Measures of Particulate Matter,” *Risk Analysis* **10**(3) 421-427.

Pastor, M, Sadd, J, Morello-Frosch, R, 2002, “Who’s Minding the Kids? Pollution, Public Schools, and Environmental Justice in Los Angeles,” *Social Science Quarterly* **83**(1) 263-280.

Pastor, M, Jr., Sadd, J, Morello-Frosch, R. 2004, “Reading, writing and toxics: children’s health, academic performance, and environmental justice in Los Angeles,” *Environment and Planning C: Government and Policy* **22** 271-290.

Pedersen, M, *et al.*, 2013, “Ambient air pollution and low birthweight: a European cohort study (ESCAPE), *Lancet Respiratory Medicine* **1**(9) 695–704

Popovic, N.A.F., 1996, “In pursuit of environmental human rights,” *Columbia Human Rights Law Review* **27** 487-620.

Richter, F, and Craig, B R, 2013, “Lending patterns in poor neighborhoods”, *Journal of Economic Behavior & Organization* **95** 197-206.

Szasz, A, Meuser, M, 1997, “Environmental Inequalities: Literature Review and Proposals for New Directions in Research and Theory,” *Current Sociology,* **45**(3) 99-120.

Topa, G, 2001, “Social Interactions, Local Spillovers and Unemployment,” *Review of Economic Studies* **68**(235) 261-295.

Transande, L, Liu, Y, 2011, “Reducing the Staggering Costs of Environmental Disease in Children, Estimated at $76.6 Billion in 2008,” *Health Affairs* **30**(5) 863-870.

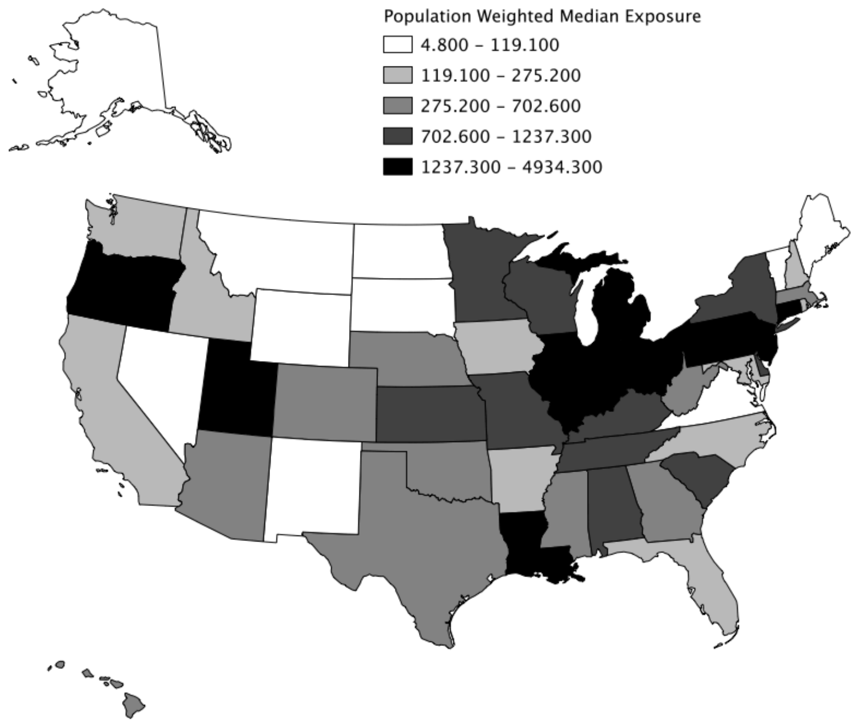
U.S. Environmental Protection Agency (EPA), 2014, “Mercury and Air Toxics Standards (MATS): Healthier Americans,” http://www.epa.gov/mats/health.html. Accessed 9 February 2015.

World Health Organization, 2014, 7 million premature deaths annually linked to air pollution,' http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/. Accessed 23 February 2015.

Zwickl, K, Ash, M, and Boyce, J K, 2014, “Regional Variation in Environmental Inequality: Industrial Air Toxics exposure in U.S. cities,” *Ecological Economics* **107** 494-509.

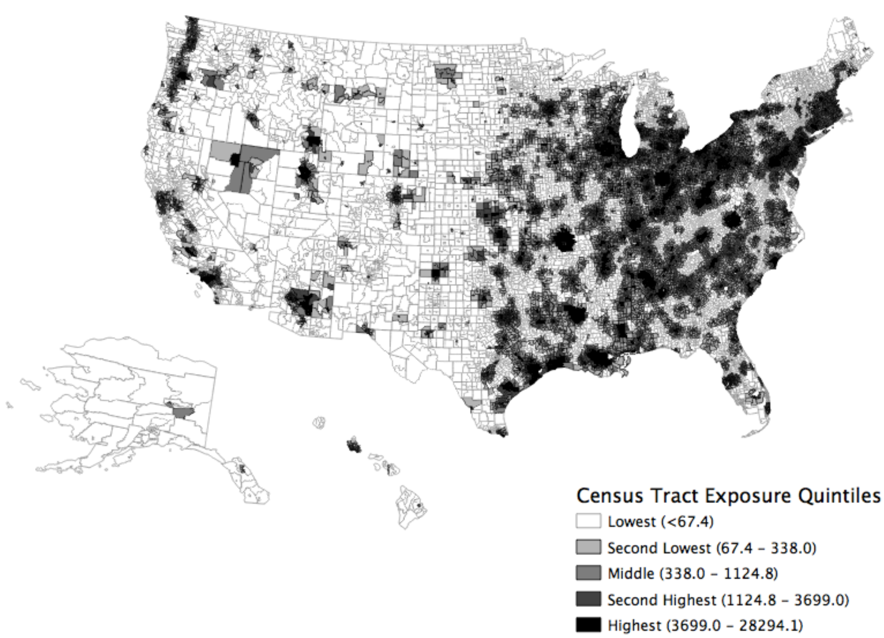
Zwickl, K, and Moser, M, 2014, “Informal environmental regulation of industrial air pollution: Does neighborhood inequality matter?,” Political Economy Research Institute Working Paper 370.

Figure 1: Median industrial air toxics exposure by state



Source: Authors' calculations using 2010 RSEI.

Figure 2: Industrial air toxics exposure by census tract



Source: Authors' calculations using 2010 RSEI.

Table 1: Exposure and income Ginis, 2010

	Between-tract exposure Gini	Between-cell exposure Gini, unweighted	Between-cell exposure Gini, population-weighted	Between-tract income Gini	Individual income Gini
Alabama	0.73	0.80	0.73	0.21	0.47
Alaska	0.91	1.00	0.92	0.17	0.42
Arizona	0.76	0.96	0.75	0.26	0.46
Arkansas	0.81	0.87	0.81	0.18	0.46
California	0.80	0.96	0.79	0.29	0.47
Colorado	0.71	0.95	0.71	0.22	0.46
Connecticut	0.61	0.60	0.60	0.25	0.49
Delaware	0.48	0.70	0.49	0.20	0.44
District of Columbia	0.34	0.38	0.35	0.33	0.53
Florida	0.72	0.78	0.71	0.24	0.47
Georgia	0.70	0.76	0.69	0.23	0.47
Hawaii	0.53	0.92	0.55	0.18	0.43
Idaho	0.81	0.97	0.81	0.16	0.43
Illinois	0.60	0.81	0.59	0.25	0.47
Indiana	0.65	0.73	0.65	0.18	0.44
Iowa	0.82	0.77	0.82	0.15	0.43
Kansas	0.74	0.91	0.73	0.21	0.45
Kentucky	0.71	0.77	0.70	0.20	0.47
Louisiana	0.65	0.83	0.64	0.21	0.48
Maine	0.77	0.86	0.77	0.14	0.44
Maryland	0.69	0.75	0.69	0.22	0.44
Massachusetts	0.63	0.70	0.63	0.21	0.48
Michigan	0.68	0.90	0.68	0.21	0.45
Minnesota	0.69	0.92	0.68	0.19	0.44
Mississippi	0.82	0.85	0.81	0.19	0.47
Missouri	0.77	0.90	0.76	0.20	0.46
Montana	0.83	0.96	0.85	0.14	0.44
Nebraska	0.67	0.85	0.66	0.18	0.43
Nevada	0.85	0.97	0.85	0.22	0.45
New Hampshire	0.63	0.85	0.61	0.14	0.43
New Jersey	0.61	0.73	0.60	0.23	0.46
New Mexico	0.80	0.97	0.81	0.23	0.46
New York	0.59	0.82	0.58	0.29	0.50
North Carolina	0.79	0.81	0.78	0.21	0.46
North Dakota	0.77	0.94	0.79	0.13	0.43
Ohio	0.59	0.68	0.58	0.20	0.45
Oklahoma	0.76	0.88	0.75	0.20	0.45
Oregon	0.64	0.95	0.64	0.18	0.45
Pennsylvania	0.59	0.70	0.58	0.22	0.46
Rhode Island	0.32	0.38	0.34	0.20	0.47

South Carolina	0.71	0.72	0.70	0.21	0.46
South Dakota	0.86	0.92	0.87	0.17	0.44
Tennessee	0.67	0.75	0.66	0.22	0.47
Texas	0.75	0.93	0.75	0.28	0.47
Utah	0.58	0.97	0.57	0.17	0.42
Vermont	0.84	0.87	0.86	0.13	0.44
Virginia	0.85	0.88	0.85	0.24	0.46
Washington	0.72	0.91	0.73	0.21	0.44
West Virginia	0.76	0.83	0.75	0.15	0.45
Wisconsin	0.65	0.80	0.65	0.17	0.43
Wyoming	0.78	0.93	0.82	0.13	0.42
National	**0.76**	**0.93**	**0.76**	**0.25**	**0.47**

Table 2: Three measures of environmental inequality

	Between-tract exposure Gini	Minority/ white exposure ratio	Poor/nonpoor exposure ratio	Population-weighted 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
District of Columbia	0.34	1.13	0.96	112.60
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

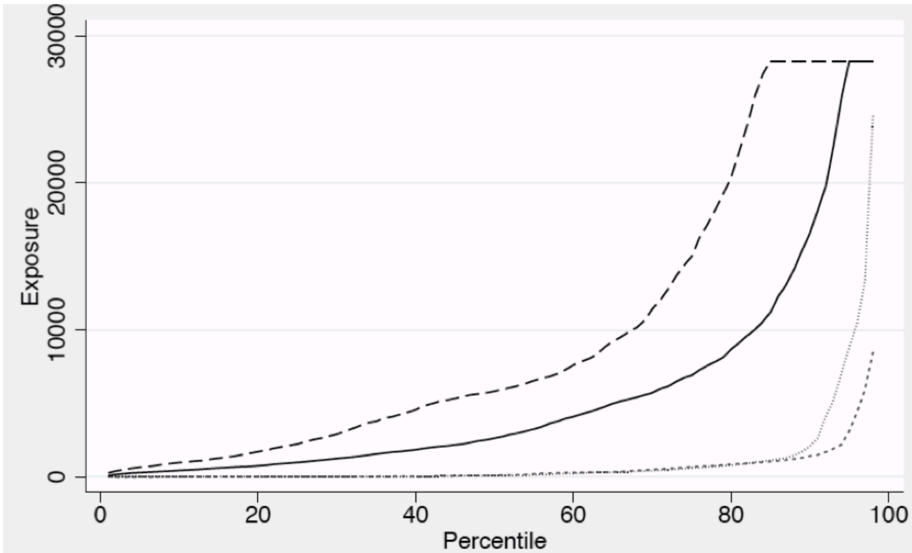
South Dakota	0.86	0.23	0.43	67.07
Tennessee	0.67	2.56	1.17	1149.95
Texas	0.75	1.19	0.82	702.60
Utah	0.58	1.42	0.73	4934.29
Vermont	0.84	1.14	1.00	4.78
Virginia	0.85	1.11	3.17	119.07
Washington	0.72	1.15	1.00	270.76
West Virginia	0.76	0.80	0.74	569.95
Wisconsin	0.65	4.79	1.55	1237.28
Wyoming	0.78	2.09	3.59	93.51
National	**0.76**	**1.46**	**1.11**	**594.92**

Table 3: Correlations*

	Between-tract exposure Gini	Minority/white exposure ratio	Poor/nonpoor exposure ratio	Median exposure
Between-tract exposure Gini	1.000			
Minority/white exposure ratio	-0.199	1.000		
Poor/nonpoor exposure ratio	-0.012	0.185	1.000	
Median exposure	-0.491	0.228	-0.048	1.000

* Excluding Washington, DC.

Figure 3: Minority and white exposure by percentile: Ohio and Virginia



Key:

Ohio minorities

Ohio whites

Virginia minorities

Virginia whites

Figure 4: Scattergram of exposure Gini and median exposure

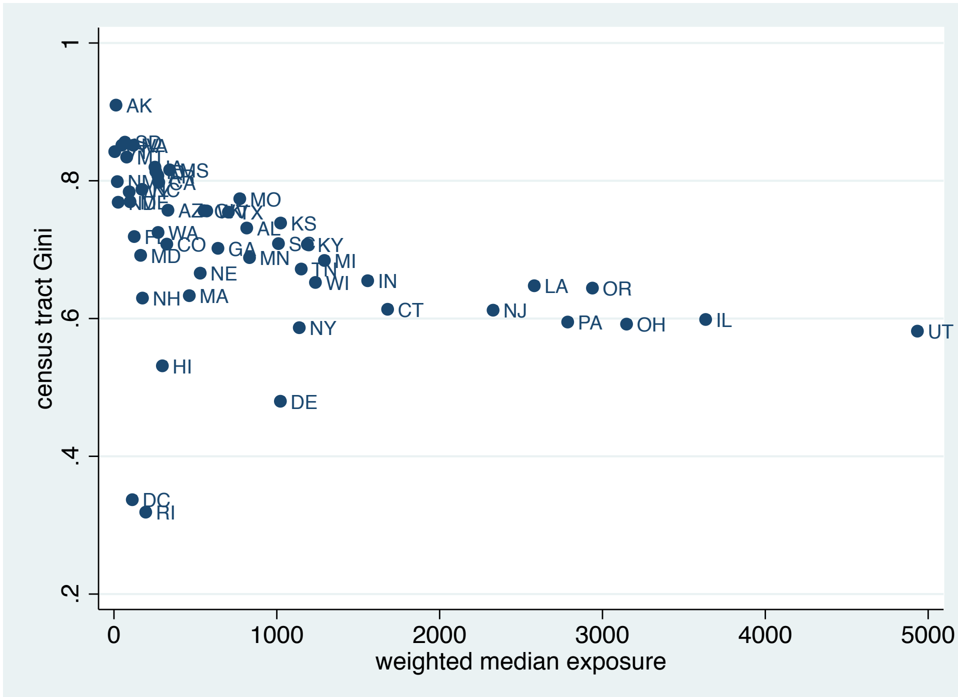


Figure 5: Median exposure and exposure Gini

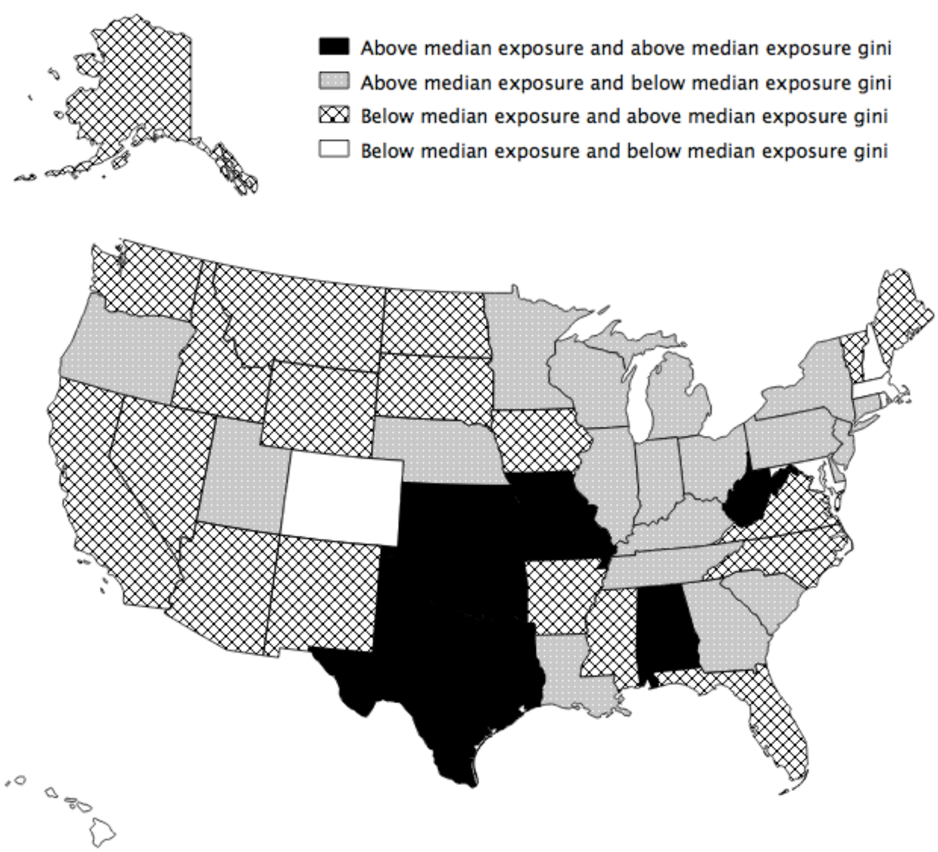


Figure 6: Median exposure and minority/white ratio

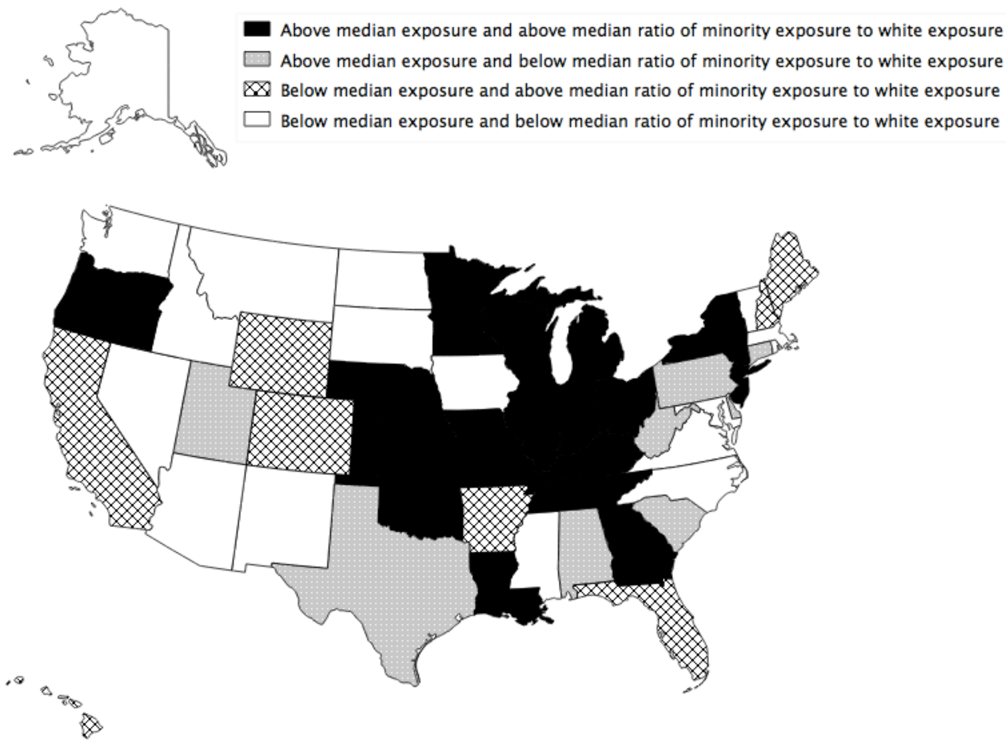


Figure 7: Median exposure and poor/nonpoor ratio