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Analysis

Distribution of income and toxic emissions in Maine, United States: Inequality in two dimensions

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ABSTRACT

Ecological distribution refers to inequalities in the use of environmental sinks and sources. This article explores one such dimension of ecological distribution — that of toxic air emissions. Using data from the Risk-Screening Environmental Indicators model and the United States Census Bureau, I analyze the distribution of both environmental risk and income at the block-group level in the state of Maine. The state of Maine was chosen for its historical dependence upon natural resources as well as its economic and spatial heterogeneity. Results clearly indicate that the toxic air emissions are distributed much more unequally than is income, and that those inequalities are reinforcing. While not in itself an indication of environmental injustice, such analyses may help us to rethink the assumption that there is a tradeoff between income and pollution.

1. Introduction

Sustainability is sometimes said to have three "pillars": economic prosperity, environmental protection, and social equity (General Assembly of the United Nations, 2013). Indeed, the concept of "just sustainability" focuses on four conditions: "improving our quality of life and well-being; on meeting the needs of both present and future generations (intra- and intergenerational equity); on justice and equity in terms of recognition, process, procedure and outcome and on the need for us to live within ecosystem limits" (Agyeman, 2012). Yet despite the seeming emphasis on equity, the most common indices of sustainability include only the distribution of monetary income (or of consumption), not the distribution of environmental quality or well-being. In addition, most such indices include income inequality as a stand-alone concept — in other words, income inequality is not integrated directly in the overall index (European Statistical Library, n.d.; Fordham Institute for Innovation in Social Policy, 2004; Messinger and Coleman, 1998; U.S. Interagency Working Group on Sustainable Development Indicators, 1998), or, at best, discount GDP according to some measure of income inequality (see, for example, Friends of the Earth, n.d.; Hamilton and Saddler, 1997).

Even the consideration of the degree of a society's level of income inequality in indices of sustainability implicitly acknowledges that income inequality is indeed an important concern. However, the distribution of other components of well-being is also crucial. One such distribution is what ecological economist Joan Martinez-Alier calls ecological distribution: the "social, spatial, and temporal asymmetries or inequalities in the use by humans of environmental resources and services, i.e., in the depletion of natural resources (including the loss of biodiversity), and in the burdens of pollution" (Martinez-Alier, 1995, p. 520). Especially in countries where subsets of the population depend greatly on natural resources for their livelihood, then inequalities in the use of resources or the depletion of resources has a direct link to inequality of well-being. A link between inequalities in the burden of pollution and inequality of well-being is less direct, but no less real.

In this article, I will explore one dimension of ecological distribution — the distribution of air pollution. Sudhir Anand argues, in his article "The Concern for Equity in Health" (Anand, 2002), that a person's health holds a special status, as it has both an instrumental value and an intrinsic value: "Health is regarded to be critical because it directly affects a person's wellbeing and is a prerequisite to her functioning as an agent. Inequalities in health are thus closely tied to inequalities in the most basic freedoms and opportunities that people can enjoy" (p. 485). A similar argument could be made for inequalities in pollution.

Pollution, in its many forms, is directly related to an individual's well-being. That fact may be self-evident, as in the polluting of drinking water in Delhi (Lalchanandi, 2013) or the visible smog in China (Staff, 2013), but it also may be more subtle — and, in fact, could affect our well-being in ways of which we are unaware. We are only just beginning, for example, to tease out the links between gene expression and certain pollutants (Steingraber, 2010). Furthermore, the level and type of pollution a person is exposed to could affect that person's ability to

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function both in the economic sphere ("black lung," for example, having prematurely shortened the working lives of many miners in Appalachia and around the world) and in the leisure sphere (asthma affecting a person's ability to participate in sports).

Consequently, inequality in the burden of pollution can be a "double whammy:" pollution does not only affect a person's well-being directly, but also could affect that individual's earning potential, leading to inequality in the realm of income as well. Finally, there is the added complication that productive activity *causes* pollution, implying that while we may be able to reduce pollution inequality, we risk doing so at the expense of decreasing economic growth.

It is important here to make a distinction between *inequality* and *inequity*. Levy et al. (2006) capture the distinction thus: "Equality is … characterized by homogeneity or sameness among individuals or social groups. It is often depicted as uniformity in rights or experiences despite differences in resources, capabilities and backgrounds …. In contrast, the concept of inequity identifies the subset of inequalities that are deemed unjust and unfair by a socially-derived calculus" (p. 3). The authors then provide examples of the distinction: "For example, health inequalities stemming from genetic differences or freely chosen health damaging behavior would *not* be considered inequitable; variations resulting from unknown exposure to unhealthy working conditions or limited social mobility *would* be categorized as inequitable" (p. 3, emphasis mine). While the distribution of income or pollution may be unequal, such inequality is not, by itself, evidence of an inequity.

Various hypotheses have been advanced to help explain the direction and the strength of the relationship between one's income and the quality of the environment in which they live (the environmental justice hypothesis that low-income people tend to live in more polluted areas than the wealthy is one example). Such a relationship may not be one-dimensional, however. For some individuals, inequality in the distribution of income may be reinforced by inequality in pollution, such that those individuals would be disadvantaged both in income and in pollution. For other individuals, the inequalities may be offsetting: whereas an individual may command a low income, they may be advantaged by having cleaner air or a more pristine environment.

This article investigates such a question. I develop a two dimensional index of inequality which allows for us to empirically investigate the question of whether inequality in pollution and inequality in income are reinforcing or countervailing. I then use that index to investigate the distribution (both spatial and demographic) of toxic air pollution in the state of Maine. I focus on the state of Maine for a variety of reasons. First, the small state allows for more careful, detailed analysis than might be the case with whole country-wide analyses or even larger states. More importantly, the state of Maine in some ways can be seen as a microcosm of other parts of the world. Maine has for many years been referred to as "two Maines" — the more populous and urbanized southern section of Maine, and the less economically prosperous and more remote regions of northern Maine (Charles, 1994). While Maine as a whole has been historically dependent on natural resources, southern Maine's economy is now more diverse, whereas much of northern Maine's economy remains disproportionally dependent upon these products. Therefore, Maine offers a convenient case study through which to examine the spatial and economic distribution of pollution and income.

I establish a spatial Gini coefficient for toxic air emissions in the state of Maine, using data from the U. S. Census Bureau and the U.S. Environmental Protection Agency's Risk-Screening Environmental Indicators (RSEI) model. Furthermore, I develop an index of environmentally-adjusted income and calculate the resulting Gini coefficient, thus measuring the inequality in the co-distribution of income and pollution. Results indicate that pollution (in the form of toxic emissions) is distributed much more unequally than the distribution of income. Moreover, a substantial segment of Maine's population is disadvantaged in two dimensions: they experience a lower than average income but a higher than average emission level.

The structure of the remainder of the article is as follows. Section 2 reviews the literature on the distribution of pollution or other measures of risk. Section 3 describes the data and methodology. Section 4 describes the results. Section 5 concludes.

2. Literature Review

2.1. "Distribution Hypotheses" and the Relationship Between Income, Pollution, and Inequality

There are several competing and well-known hypotheses about the relationship between pollution and income at the local level that can be explored using concepts of ecological distribution. The first may be termed the "trade-off hypothesis." In this view of the world, an individual is confronted with various employment and residential locations, all of which vary in terms of their job opportunities and other amenities, including their pollution level. An individual desiring to live in an area with a lower pollution level would theoretically "trade off" a certain amount of her income in order to do so. An individual who is not able or willing to pay that price would then live in the more polluted area with the higher wage. Individuals would sort themselves according to their preference for environmental quality (Cropper and Arriaga-Salinas, 1980). Under such a hypothesis, we would expect inequalities in income and in pollution to be subtractive, rather than additive, as we might expect individuals living in cleaner areas to command less income, and individuals living in more polluted areas to have higher incomes.

The theory of compensating wage differentials just described has its roots in Rosen (Rosen, 1979). Rosen developed a theoretical model demonstrating that an individual living in a low amenity area may, in theory, be compensated for the lack of amenities with a higher income. Although Rosen's theory has been tested for numerous amenities, studies of compensating wage differentials for pollution specifically have been few and far between. Bayless (1982) analyzed the salaries of university professors and concentrations of total suspended particulates (TSP). He found that a one standard deviation increase in TSP was associated with a compensating wage variation of between 1 and 2%. Roback (1982) likewise demonstrates that there is indeed an "implicit price" associated with living in a polluted area — average annual earnings were significantly higher in an area with higher particulate matter (ceteris paribus). More recently, Cole et al. (2009) find that there is a "positive and significant wage premium attached to working in a dirty industry, across a range of pollution exposure measures" (p. 162).

A second hypothesis, which also works through the market but with the opposite result, might be called the market hypothesis. Under this idea, individuals who have a higher level of income might afford to live in a more pristine or unpolluted location, whereas an individual who had lower willingness (or ability) to pay for a location with lower pollution levels would end up in the more polluted locales. Hanna (2007) conducted a hedonic analysis of wages and housing values on emissions. She claims:

> There are also good reasons to expect that pollution levels are influenced by neighborhood incomes. If the willingness to pay for a clean environment is increasing in income, income groups will be sorted into residential locations according to pollution levels, with the rich living in cleaner areas, ceteris paribus (Hanna, 2007, pp. 102–103).

Hanna finds a statistically significant and negative estimate of the relationship between pollution and *non-wage* income, "consistent with an endogenous sorting of income groups by pollution levels" (p. 111) (Contrary to the trade-off hypothesis, however, she finds no evidence that pollution has an influence upon wage and salary incomes). Income sorting such as this would result in wealthy people living in less polluted areas, whereas poorer people would live in more polluted regions. Inequalities in income and pollution would thus be additive. Although the result might appear unjust, some would argue that no injustice has taken place, as individuals are simply expressing their preferences through the market (Banzhaf, 2008).

A third hypothesis, resulting in the same pattern as the market hypothesis but leading to a separate set of policy implications, is the environmental justice hypothesis, familiar to those conversant with the environmental justice literature. Under such a hypothesis, polluting facilities will tend to choose locations based upon the likelihood (or lack thereof) of facing political opposition from residents. As poor (or low power) areas will tend to express less political resistance, for various reasons, polluting firms will tend to locate in low-income areas and/or regions with a large minority population. We would again expect inequalities in income and pollution to be additive, but the policy implications of such a distribution would call for government action (Hamilton, 1995).

2.2. The Environmental Gini Coefficient

The first time the Gini coefficient was applied in an environmental context (at least to this author's knowledge) was in Ruitenbeek (1996). He proposes a Gini coefficient using "ecologically adjusted indices" to account for inequality in other sorts of endowments — inequality in ecological income, or income from traditional ecological uses. His results demonstrate that including non-monetary income in calculations of inequality may in some cases reduce the levels of measured inequality, and thus provide a better indicator of population migration.

Heil and Wodon (2000) use the Gini coefficient to predict the inequality of per capita carbon dioxide emissions, both within and between countries. They predict future emissions per capita by regressing per capita emissions on a quadratic function of GDP, fixed country effects, and fixed year effects. Their estimated results serve as the basis for predicting the growth (or decline) in per capita CO2 emissions and the accompanying change in inequality over time. Results indicate a "convergence" in per capita emissions over time — i.e., even as the level of emissions is predicted to rise, the inequality in per capita emissions is predicted to drop (Heil and Wodon, 2000). Although Heil and Wodon arrive at a measure of ecological inequality, their measure actually determines inequality in *contributions* to pollution (carbon dioxide emissions), rather than inequality in the *burden* of pollution.

Millimet and Slottje (2002) use data from the TRI as well as three measures of state-specific environmental compliance costs to analyze the effects of a uniform national environmental standard on the distribution of per capita emissions across the United States. Using what Heil and Wodon (2000) have termed the "environmental Gini coefficient" to measure inequality in the distribution of emissions, they find that "there is a significant positive correlation between toxic releases and black population share at both the state and county level" (Millimet and Slottje, 2002, p. 94). Moreover, they find that a uniform standard (or, more precisely, a uniform change in compliance costs) exacerbates inequality; that is, that a uniform change in compliance costs would increase the environmental Gini coefficient. Although initially counter-intuitive, they hypothesize that firms previously located in relatively clean areas (that already had high compliance costs) may not be able to afford the still higher compliance costs, and so may shut down or move to more "dirty" areas with lower compliance costs (Millimet and Slottje, 2002). The result would be that previously "clean" areas would become even cleaner, while previously "dirty" areas would become more so.

In 2007, White (2007) applied the Gini coefficient to the then-recently developed concept of a global footprint. He demonstrated that the Gini can be used to measure the inequality of resource use between countries. The intensity of energy use, White found, contributed more than half of the measured inequality in the ecological footprint, a measure of "human demand on bioproductive land" (p. 402).

While the standard version of the Gini coefficient (and other measures of inequality) measures the distribution of income across households, Druckman and Jackson (2008) and Sun et al. (2010) measure the distribution of pollution or resource use across some spatial unit. Druckman and Jackman estimate the average household spending for local areas ("Output Areas," as measured by the UK census), convert that expenditure into resource use, and then measure the inequality in resource use of households. Therefore, the Lorenz curve arising from what they term the AR-Gini is derived by plotting the cumulative resource use of each Output Area against the cumulative percentage of Output Areas in the sample (Druckman & Jackson, 2008, p 247). Sun et al. (2010) use a multidimensional index "reflecting economic, ecological, and social concerns" (Sun et al, p. 603). They use their resulting ECG (environmental Gini coefficient) to determine the allocation of waste discharge permits that would minimize wastewater inequality.

Using a geographic area as the unit of observation is logical from an ecological point of view, as environmental issues are inherently spatial in nature. I develop and use a spatial version of the environmental Gini coefficient, using the U.S. Census block group as the unit of observation, to measure the inequality in toxic emissions across the state of Maine. I then investigate what might be called the "co-distribution" of income and pollution in Maine by combining income and toxic emissions into one index, called the emissions-adjusted income index. The next Section discusses the development of these two measures and the data used.

3. Methodology and Data Description

3.1. The Spatial Gini Coefficient, the Emissions Gini and Emissions-Adjusted Income

The Gini coefficient, perhaps the most common measure of income inequality, is usually measured at the household level (Gastwirth, 1972). Households are first ranked in the order of their household income and then divided into groups containing equal numbers of households. The cumulative percentage of income accounted for by each group of households is then graphed, with the cumulative percentage of households on the horizontal axis and the cumulative percentage of income on the vertical axis. The resulting curve is called a Lorenz curve. The deviation of that curve from the 45 degree line (representing complete equality, where the x-coefficient and the y-coefficient are equal) is a measure of the income inequality within a society. A coefficient of 0 represents complete equality; a coefficient of 1 represents complete inequality.

The standard Gini coefficient can be approximated by the following equation:

$$G = \sum_{i=1}^{n}(X_i - X_{i-1})(Y_i + Y_{i-1}) \tag{1}$$

where X_i is a cumulative measure of population, Y_i is a cumulative measure of income, and i is an index of households from 1 to n, n being the

Table 1
Descriptive statistics.

Variable	Observations (block group)	Mean	Standard deviation	Minimum	Maximum
Toxicity score (2007)	1131	392.06	1585.42	0	45,571.18
Median household income (2000)	1131	$38,009.33	$12,210.68	$9876	$100,966

Correlation between toxicity score and median household income: 0.045.

Table 2
Distribution of median household income.[a]

Inequality measure	Coefficient	Interpretation
Gini coefficient	0.328	A coefficient of zero implies complete equality; a coefficient of 1 implies complete inequality.
Atkinson index ($\theta = 0.5$)	0.087	Atkinson index of inequality. A higher θ indicates a greater weight put on the lower ends of the income distribution.
Atkinson index ($\theta = 1$)	0.173	
Atkinson index ($\theta = 2$)	0.375	
Ratio of 90th percentile to 10th percentile	4.829	The median household income of the 90th percentile was more than 4 times that of the 10th percentile.
Ratio of 90th percentile to 50th percentile	2.208	The median household income of the 90th percentile was more than twice times that of the 10th percentile.

[a] Please recall that the unit of observation is the block group (weighted by population share). Inequality indices calculated by household may be higher or lower than those shown here.

total population of the sample. The data have been ranked in terms of income, with those individuals commanding the lowest income assigned $i = 1$.

I modify the equation in the following way, to take account of the fact that the data are reported by U.S. Census block group, rather than by household or individual. I calculate:

$$SGC = \sum_{j=1}^{n} \left(Z_j - Z_{j-1}\right)\left(V_j + V_{j-1}\right), \tag{2}$$

where SGC is the spatial Gini coefficient, Z_j is a cumulative measure of population in each block group, V_j is the median household income in each block group, and j is an index of block groups from 1 to n, n being the total number of block groups in the dataset.

$$EG = \sum_{j=1}^{n} \left(Z_j - Z_{j-1}\right)\left(P_j + P_{j-1}\right) \tag{3}$$

where EG is the emissions Gini, Z_j is a cumulative measure of population, P_j is a population-weighted measure of toxicity-weighted emissions, and j is an index of U.S. Census block groups from 1 to n, n being the total number of block groups in the dataset. More specifics on the data are given below.

I then develop an index of "environmentally-adjusted income," where block groups subject to a relatively high amount of pollution have their income adjusted downwards to reflect the negative utility associated with pollution, and block groups who enjoy relatively lower levels of pollution have their income adjusted upwards.

An example will help to clarify. Suppose we standardize both the income variable and the pollution variable, so that

$$INC_i = \frac{Income_i - \mu_y}{\sigma_y}, \tag{4}$$

where INC_i is the standardized value of the median household income in block group i, $Income_i$ is the median household income in block group i, μ_y is the arithmetic mean of the median household income, taken over all block groups, and σ_y is the standard deviation of median household income, taken over all block groups, and

$$TOX_i = \frac{\mu_t - ToxCon_i}{\sigma_t}, \tag{5}$$

where TOX_i is the standardized value of the toxicity level experienced by the representative individual in block group i, $ToxCon_i$ is the actual value of the toxicity level in block group i, μ_t is the arithmetic mean of the toxicity level, taken over all block groups, and σ_t is the standard deviation of toxicity level, taken over all block groups. Note that Eq. (5) is constructed so that a block group experiencing a level of toxicity below the mean would have a positive value of TOX_i.

Suppose a representative individual in a certain block group experiences a household income one standard deviation above the mean, and a toxicity score one standard deviation below the mean. That individual would be assigned a "final score" of 1, under equal weights that sum to 1:

$$0.5INC_i + 0.5TOX_i = 0.5(1) + (0.5)(1) = 1. \tag{6}$$

If we took that same individual and simply increased his toxicity level by one standard deviation (to the mean), then his final score would be

$$0.5INC_i + 0.5TOX_i = 0.5(1)–(0.5)(0) = 0.5. \tag{7}$$

Notice that the individual would receive the same score (0.5) if his pollution level remained unchanged from Eq. (5) but his income dropped by one standard deviation. In other words, a one standard deviation increase in pollution is equivalent to a one standard deviation decrease in income, under a scheme with equal weights and standardized data. If INC and TOX were highly correlated, such a weighting scheme might not be warranted, as information would be lost; such is not the case with the data used here, as can be seen in Table 1.

Admittedly, assigning equal weights to components of an index is arbitrarily assigning a specific relationship between those components (a similar critique has been levied against the construction of the Human Development Index; see Noorbakhsh, 1998). While assigning an explicit relationship between a standard deviation of pollution and a standard deviation of income may risk criticism, such an approach is certainly well-precedented, as environmental economists have been attempting to assign a dollar value to pollution for decades (see, for example, Ackerman and Heinzerling, 2001; Cropper, 1981).

I then take the emissions-adjusted income index and calculate the emissions-adjusted Gini coefficient:

$$EAG = \sum_{j=1}^{n} \left(Z_j - Z_{j-1}\right)\left(W_j + W_{j-1}\right) \tag{8}$$

where EAG is the emissions adjusted income Gini, Z_j is a cumulative measure of population, W_j is a population-weighted measure of emissions-adjusted income, described above, and j, as before, is an index of U.S. Census block groups from 1 to n. More specifics on the data are given below.

3.2. Data Description

The data on toxicity used in this study are from the RSEI (Risk-Screening Environmental Indicators) screening tool, made available by the US Environmental Protection Agency (United States Environmental Protection Agency, 2012). It is based on the Toxic Release Inventory (TRI), an annual database comprising a subset of all toxic emissions to land, water, and air as reported by certain industries with 10 or more full-time employees.[2] The TRI was created under the auspices of the

[2] Although the number of reporting facilities and the number of chemicals covered vary from year to year, the latest reporting requirements can be found at http://www.epa.gov/tri/reporting_materials/threshold/index.htm (United States Environmental Protection Agency, 2013a,b).

Table 3
Distribution of concentrations of toxic pollution.[a]

Inequality measure	Coefficient	Interpretation
Gini coefficient	0.803	A coefficient of zero implies complete equality; a coefficient of 1 implies complete inequality.
Atkinson index ($\theta = 0.25$)	0.334	Atkinson index of inequality. A lower θ indicates a greater weight put on the upper ends of the pollution distribution.
Atkinson index ($\theta = 0.5$)	0.571	
Atkinson index ($\theta = 1$)	0.865	
Ratio of 90th percentile to 10th percentile	305.023	The 90th percentile of the distribution was exposed to over 300 times the toxic pollution than that of the block group at the 10th percentile.
Ratio of 90th percentile to 50th percentile	12.647	The block group at the 90th percentile of the distribution was exposed to more 12 times the toxic pollution than that of the block group at the 50th percentile.

[a] Please recall that the unit of observation is the block group (weighted by population share). Inequality indices calculated by household may be higher or lower than those shown here.

Emergency Planning and Community Right-to-Know Act (EPCRA), and had been lauded as an effective tool for those interested in finding out more about the toxic releases in their area (Karkkainen, 2000–2001).

On the other hand, the TRI has also been criticized for not weighting the emissions for toxicity. As the TRI data are reported in pounds, the database gives the same weight to a contaminant such as benzidine as it does to chlorodifluoromethane, even though the former is 3.4 billion times more potent (Political Economy Research Institute, 2013). The RSEI screening tool attempts to correct that, by incorporating data on relative toxicity. In addition, by including data on the fate and transport of a particular contaminant, as well as data on chemical decay rates, wind direction and velocity, stack heights, and exit velocity, the RSEI model is able to calculate the toxic exposure for each square kilometer of a 101 km by 101 km grid surrounding a certain facility. Since the data are weighted for toxicity, and are thus comparable across contaminants, the RSEI model is then able to calculate an additive toxicity weight score for each square kilometer in the continental United States. The 1 km by 1 km grids were converted into Census block groups based on the 2000 Census, in order to more easily determine population and other socio-demographic variables (Although Census block groups themselves vary in their spatial extent, the block group is the finest degree of geographic resolution possible that still allows us to obtain socio-demographic data). The specific data used in this article are based on 2007 emissions reported to the TRI.

Data on population and other socio-demographic characteristics come from the 2000 Census. The subset of the data containing the state of Maine originally contained 1144 observations, each block group comprising an observation. After dropping those block groups with fewer than 3 people and for which Census data were not available, the resulting database consisted of 1131 observations, representing 99.99% of the population.

Descriptive statistics are shown in Table 1. The block groups with the lowest assigned toxicity had a score of zero. A zero score does not imply that no toxic releases affected a particular site; rather, it means that any TRI-covered releases were not associated with a toxicity value. The highest toxicity number was for a block group in York County, Maine, with a toxicity score more than 3 times the next highest value.[3] The mean toxicity score for all block groups in the state of Maine was 391.72; the median was 92.75. The lowest toxicity score, as previously mentioned, was zero; the highest was 45,571.

4. Results

4.1. Spatial Income Inequality

Several measures of spatial income inequality are reported in Table 2: the Gini coefficient, the Atkinson inequality index, and several percentile ratios. The Atkinson inequality index is a member of what has been termed the general entropy class of income distribution measures (Allison, 1978). Unlike the Gini coefficient, the Atkinson index requires the underlying social welfare function to be explicit. Atkinson introduced the idea of the "equally distributed equivalent level of income" (EDI) — that is, the level of (equal) per capita income that would be required to maintain the same level of social welfare as that achieved under the current distribution (Atkinson, 1970, p. 250). In other words, deriving such an index requires the researcher to know the "aversion to inequality" (θ) inherent in the social welfare function. If the society in question had a high aversion to inequality, then a highly unequal distribution of income would result in a relatively low level of aggregated social welfare, and thus a relatively low level of EDI. If, on the other hand, the society in question were highly tolerant of inequality, then a highly unequal distribution of income would require a high level of EDI (Atkinson, 1970). The Atkinson index is reported with $\theta = 0.5$, 1, and 2. All were calculated using user-written programs in Stata (Jenkins, 2010). Results are presented in Table 2.

The toxicity score for each block group was weighted by its share of the total population in the sample and then ranked. The same inequality indices as above were calculated, with one exception. The traditional "inequality-aversion parameter," θ indicates a society's tolerance (or intolerance) of inequality. As θ increases, the calculation will put greater weight on the lower ends of the distribution. Since pollution is a "bad," not a "good," I report the Atkinson index with $\theta = 1$, 0.5 and 0.25, where a smaller θ puts greater weight on the upper ends of the pollution distribution. The Gini coefficient, the Atkinson coefficient for three different inequality aversion parameters, and several percentile comparisons are shown in Table 3.

Lorenz curves were constructed using the author's calculations. The resulting Lorenz curve for the distribution of median household income is shown in Fig. 1; the Lorenz curve for toxic concentration is shown in Fig. 2.

Evidently, the spatial distribution of toxic pollution over the state of Maine is much more unequal than the distribution of median household income. This is not surprising, as pollution is correlated with industrial activity, and much of that activity is concentrated in the southern regions of Maine. From a well-being perspective, the distribution of pollution may be as important as (or more than) the distribution of income, as toxic emissions have a direct impact on an individual's health and welfare. Nonetheless, as some individuals may have chosen to live in a more polluted locale in return for a higher income, the fact that the burden of pollution is distributed *unequally* is not, by itself, evidence of *inequity*.

[3] That dubious distinction belongs to a block group located in North Berwick, in southern Maine, home to a company that manufactures aircraft engines and engine parts. For the past several years, the company has reported releasing Benzo(g,h,i)perylene, a carcinogen, which accounts in part for its high score. In addition, that block group hosts a company that manufactures furniture, as well as a transportation company. Although the value indeed stands out, it is consistent with other block groups that are hosts to similar companies, and with the company's reported emissions in other years (United States Environmental Protection Agency, 2013a,b).

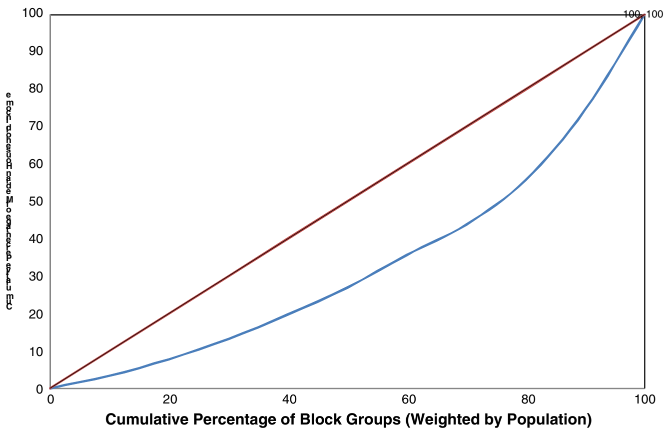

Fig. 1. Lorenz curve showing distribution of median household income by block group (weighted by population).

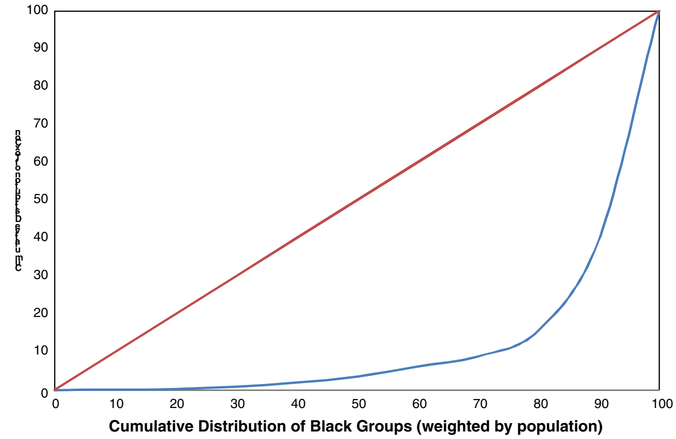

Fig. 2. Lorenz curve showing distribution of ToxCon by population weighted block group.

A deeper question is whether the two inequalities – inequality in pollution and inequality in income – offset each other or are additive. If there is a "tradeoff" between income and pollution, then one would expect to see inequality in the two dimensions counteract each other to a certain extent — richer areas would be expected to have greater levels of pollution, while poorer areas would be expected to have less pollution (as the tradeoff for living in a more pristine environment may be a lesser income). If, on the other hand, poorer areas experience greater pollution, then the inequalities may be reinforcing. The next Section explores this question.

4.2. Emissions-Adjusted Income

As described in Section 3.1, I derive an index of emissions-adjusted income. In this dataset, one standard deviation of income is \$12,210, while one standard deviation in toxicity equals 1585. Therefore, if we were to create an index based on income and toxic pollution, an individual would receive the same final score if she were to experience a \$12,210 decline in income as she would if she were to experience an increase in toxicity level of one standard deviation. Putting a "face" on that, an increase in toxicity level of one standard deviation would be akin to going from a relatively unpolluted block group to a block group located in the middle of Portland, Maine's largest city.

Block groups experiencing higher than average pollution then had their income "adjusted" to

$$ADJINCi = TOX_i(12,210) + Income_i \tag{6}$$

where *ADJINCi* is the adjusted income for individual i.

Of the 1131 block groups in the dataset, 906 (representing approximately 77% of Maine's population) received an increase in "adjusted income," whereas 225 (23%) received a decrease. The average negative adjustment was \$9370, whereas the average positive adjustment was \$2337.

The resulting distribution of adjusted income, Gini coefficient and several ratios percentile ratios are shown in Table 4.

While the new average adjusted income is still \$38,009, the range and standard deviation are both larger. Five block groups now experience negative income, while the block group with the highest adjusted income is \$101,184 (rather than \$100,966). The Gini coefficient (weighted for the block group's share of the population) has increased, showing an increased level of inequality once income is adjusted for pollution.[4] The ratio of the 90th percentile to the 10th percentile has increased, as would be expected. However, the ratio of the 90th percentile to the 50th percentile has decreased, indicating that the median of emissions-adjusted income is closer to the higher end of the distribution than for the distribution of income alone. Once income is adjusted for pollution, a larger percentage of the population is relatively disadvantaged than if income were considered alone — an important and policy relevant finding.

Fig. 3 shows a map of Maine, color-coded to show the different categories of the income-emissions relationship. The block groups colored in black (Category 1, 10% of the population) show those block groups that are disadvantaged in both dimensions — those block groups experiencing both a lower than average income and a higher than average toxicity level. The block groups colored in white (Category 4, representing 37% of the population), on the other hand, experience advantages in both areas — both higher than average income and lower than average toxicity levels. The remainder (53% of the population) experienced either higher than average incomes and higher than average toxicity (Category 2, dark gray), or, lower than average incomes along with lower than average toxicity (category 3, light gray).

Those block groups colored in black could be candidates for the environmental justice hypothesis expressed elsewhere — that low-income and/or minority individuals may be disproportionately exposed to toxic pollution (see, for example, Ash and Fetter, 2004; Brooks and Sethi, 1997; Sicotte and Swanson, 2007, among others). The block groups colored in white are in keeping with the "market hypothesis" (consistent with Banzhaf, 2008; Hanna, 2007), that individuals who have a higher level of income might afford to live in a more pristine or unpolluted location. The remainder could be thought of as experiencing the classic "tradeoff" between income and pollution (see, for example,

Table 4
"Adjusted" median household income.[a]

Mean	Standard deviation	Max	Min
\$38,009.33	\$16,875.82	\$101,184	\$309,723
Number of block groups experiencing an increase in "adjusted income": 906		Number of block groups experiencing a decrease in "adjusted income": 225	
Inequality measure		Coefficient	
Gini coefficient		0.347	
Ratio of 90th percentile to 10th percentile		4.975	
Ratio of 90th percentile to 50th percentile		2.177	

[a] Please recall that the unit of observation is the block group (weighted by population share). Inequality indices calculated by household may be higher or lower than those shown here.

[4] The Atkinson index cannot be calculated for negative values, and so is not reported here.

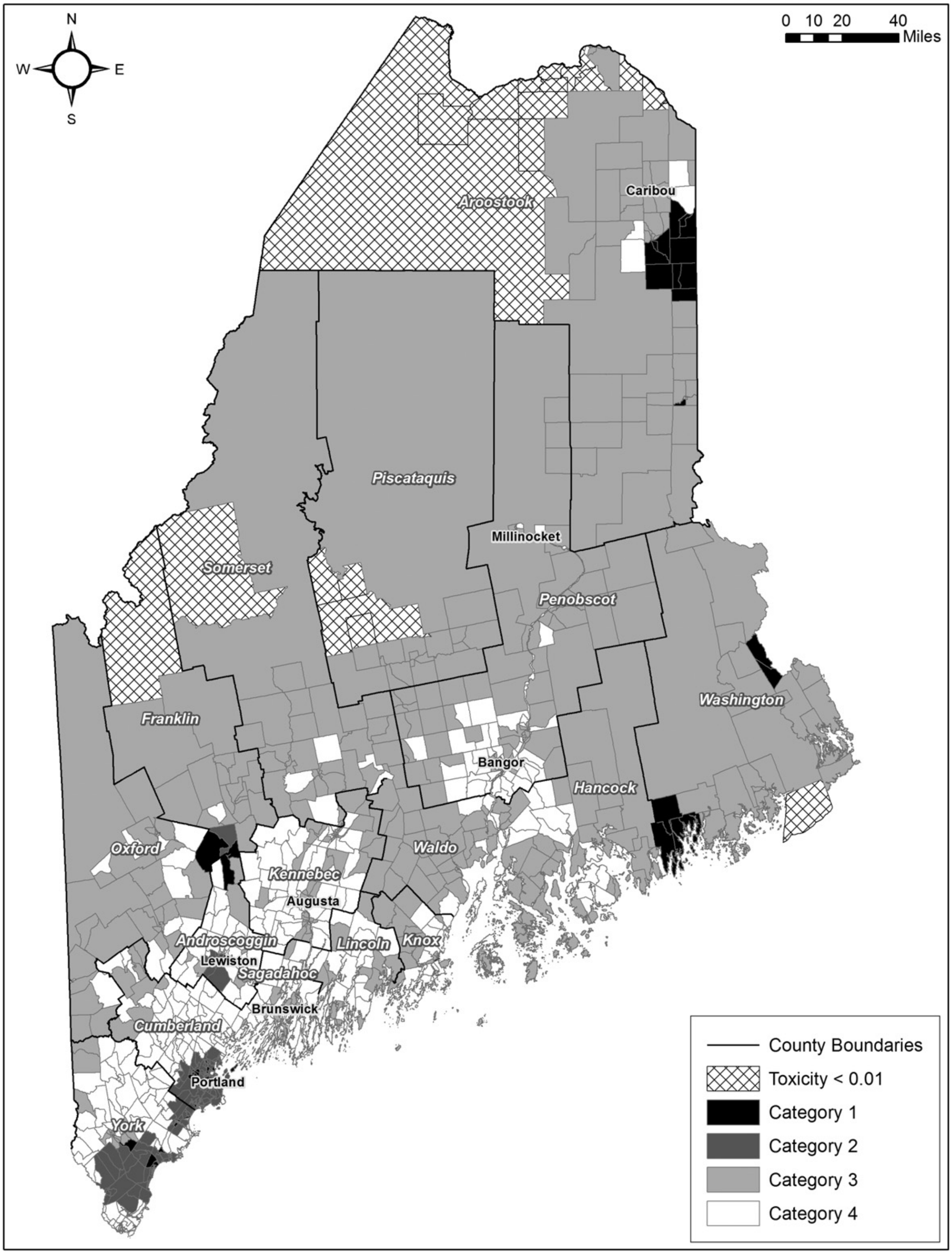

Fig. 3. Map of Maine showing different income–emissions relationship. Category 1 (black): higher than average toxicity score and lower than average income. Category 2 (dark gray): higher than average toxicity score and higher than average income. Category 3 (light gray): lower than average toxicity score and lower than average income. Category 4 (white): lower than average toxicity score and higher than average income.
Source: RSEI (2007) scores; U.S. Census median household income data and block groups, and author's calculations.

Cole et al., 2009; Cropper and Arriaga-Salinas, 1980) — either higher than average incomes and higher than average toxicity, or, lower than average incomes along with lower than average toxicity.

Looking closely at the map, one is struck by the preponderance of light gray (representing both lower than average income and lower than average toxicity) in the northern two-thirds of the state. In the southern third of the state, however, white areas are in evidence, representing higher than average incomes as well as lower than average pollution. It is possible that those areas, which generally have more economic opportunities than the largely rural north, rely on industries and occupations that not only are more lucrative, but also tend to be less polluting (such as finance and real estate). The areas of black and dark gray on the map, representing higher than average pollution, are mainly consolidated around current or former paper mill sites or in urban areas.

In a spatially and economically heterogeneous state such as Maine, different gradients of the income–emissions relationship are bound to arise. This result is consistent with the hypothesis stated by Daniels and Friedman (1999), that "processes such as urbanization and industrial location, which are often treated as control variables, may best be regarded as mechanisms through which disadvantaged residents and toxic pollution come together in space" (p. 244).

This thought experiment indicates that overall income inequality in Maine is exacerbated by, rather than ameliorated by, inequality in pollution. Were that not the case, then assigning a dollar value to a standard deviation of pollution would have resulted in decreased inequality, rather than increased inequality. While assigning a higher (lower) "value" to a standard deviation of pollution would result in increased (decreased) *overall* inequality than that reported in Table 3, the direction of income adjustment would be the same. Therefore, it is clear that inequality in both dimensions (income and pollution) is in evidence for a significant segment of Maine's population, no matter the actual dollar value chosen.

5. Conclusion and Policy Implications

This article explores one dimension of ecological distribution: the distribution of toxic air emissions in Maine. Results imply, overall, that inequality in household income is exacerbated by inequality in toxicity. Furthermore, almost a quarter of the population would experience a decrease in "adjusted" income, were income adjusted for the level of toxicity of airborne emissions. However, we cannot accept (or refute) any of the three hypotheses introduced in Section 2: each of those hypotheses may be supported for different groups of the population. Further research will indicate which groups of the population fall into which category.

In turn, these results point to different sets of policy implications for different sectors of the population. For those who are experiencing the "tradeoff" between income and pollution, policy prescriptions could be followed to ensure that economic development does not take place at the expense of the environment: productivity-enhancing regulations directed at reducing inefficiency and waste, and/or carefully targeted subsidies for research into development of cleaner methods of production. For those who are disadvantaged in both income and pollution dimensions, it may be that some form of procedural environmental injustice has taken place, and so those areas should be targeted for aggressive economic development policies as well as pollution-reduction policies, accompanied by institutional reform.

Environmental pollution occupies an uncomfortable position — it is on the one hand a negative externality that causes harm to individuals and the ecosystem and on the other a by-product of a generally desirable good: economic growth. Even if there is a tradeoff between economic growth and environmental quality for some, that tradeoff may not exist for others in our society, those who – either by circumstance or constrained choice – end up disadvantaged in both the income–pollution dimensions.

As Walker et al. (Walker et al., 2005) pointed out, "polluting industrial sites can never be 'equally' distributed (whatever that might mean) and in this light the pursuit of greater environmental equity or justice must always be partial, relative and brought to bear not on sharing pollution out, but reducing its production at source" (p. 375). It is theoretically possible to decrease the level of pollution *inequality* simply by polluting more in those areas that are "disproportionately underpolluted," without simultaneously lowering emissions in more polluted locales. Of course, such a policy proposal would be absurd, if it did not result in overall decreases in emissions. Lowering overall exposure to toxic pollution – even at the risk of increasing the inequality of such exposure – would be a worthy goal.

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