The Distribution of Pollution in the United States: An Environmental Gini Approach

Daniel L. Millimet[1]
Southern Methodist University

Daniel Slottje
Southern Methodist University

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Corresponding Address: Daniel Millimet, Department of Economics, Southern Methodist University, Box 750496, Dallas, TX 75275-0496, USA; E-mail: millimet@mail.smu.edu.

Abstract

The concepts of an environmental Gini coefficient along with a measure of "pollution elasticity" are introduced and used to analyze the distribution of pollution across US. states from 1988–1996. The special properties of the Gini coefficient allow one to decompose overall pollution inequality into several components based on pollution type and predict the effects on overall pollution inequality from stricter regulations on particular types of emissions. In addition, an environmental welfare function – analagous to Sen's social welfare function – is derived and used along with the extended Gini to analyze the impact of tighter environmental regulations on different types of emissions. Finally, Spearman correlations between per capita emissions and state attributes are used to assess whether states at the upper tail of the pollution distribution are randomly assigned. The emissions data is obtained from the US. EPA's Toxic Release Inventory (TRI).

JEL Classifications: Q0, J1, R3, C5, H0

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1 Introduction & Motivation

The notion of "environmental justice" refers to the distribution of environmental hazards across a given population. Many researchers have studied if different segments of the U.S. (e.g., minorities) are differentially burdened by pollution.[1] As an alternative, this paper takes a step backwards and applies the advances made in the study of income distributions to the distribution of pollution emissions across U.S. states. By utilizing and extending the environmental Gini coefficient developed by Heil and Wodon (1999), one can compare the distribution of emissions over time and analyze the effect of policy interventions such as emissions taxes and regulations on this distribution.

This obviously begs the question, "Why should one care about interstate inequality of per capita emissions?" Aside from Gianessi, Peskin, and Wolff's (1979) statement that, "Two key aspects involved in the assessment of any policy are its efficiency and its distributional characteristics," there are two possible reasons why one may incorporate the pollution distribution into one's welfare calculations and assessment of U.S. environmental policy. The first reason – similar to the income inequality literature – pertains to the issue of equity. Although income is a "good" (which increases utility) and pollution is a "bad" (which lowers utility), ceteris paribus, one may wish to distribute the costs of pollution equally among all those in an economy just as one may wish to distribute the benefits of income equally across all individuals. This issue of equity takes on greater significance if, in fact, not only are the costs of emissions distributed unequally across states, but the states at the upper tail of the distribution are not randomly drawn. If the states with a high level of per capita emissions are more heavily populated by minorities or certain other segments of the population, then policies which decrease emissions inequality will also differentially benefit these groups.

Second, from a social welfare perspective, emissions equality potentially minimizes the health costs associated with pollution. There are two reasons for this, although they should be prefaced with the fact that the biological and economic research is not complete. Nonetheless, there are likely to be threshold effects (i.e., a minimum level of toxins to which one can be exposed before suffering any adverse effects)

[1] Refer to Arora and Carson (1999); Brooks and Sethi (1997); Glickman and Hersch (1995); Hamilton (1995); Bullard (1994); Brajer and Hall (1992); Gelobter (1992); GAO (1983); Gianessi, Peskin, and Wolff (1979); Asch and Seneca (1978); Harrison and Rubinfeld (1978); Zupan (1973); Freeman (1972).

in the response by humans and the ecosystem to pollution.[2] As a result, disseminating pollution equally across states increases the probability the threshold is not crossed. Secondly, the dose-response function (e.g., the probability of premature death associated with increasing levels of toxic exposure) is typically assumed to be S-shaped, although in the United States individuals are likely confined to the bottom of the S.[3] This implies, however, that the health effects from higher pollution increase exponentially with the level of per capita emissions.[4] Consequently, spreading out pollution over states may mitigate the individual and social costs of pollution.

The ability to analyze interstate pollution inequality is feasible with the availability of the Environmental Protection Agency's Toxic Release Inventory (TRI). With the passage of the Emergency Planning and Community Right-to-Know Act (EPCRA) in 1986, all manufacturing facilities are required to release information on the emission of over 650 toxic chemicals and chemical categories to air, water, and land.[5] In addition, facilities are required to report the quantities of chemicals which are recycled, treated, burned, or disposed of in any other manner either on-site or off-site. Any facility which produces or processes more than 25,000 pounds or uses more than 10,000 pounds of any of the listed toxic chemicals must submit a TRI

[2] Refer to Butterworth and Bogdanoff (1999); Simpson et al. (1997); Doull (1996); Chestnut et al. (1991).

[3] Refer to Chestnut et al. (1991).

[4] The exact shape of the dose-response function is not known with certainty and varies across pollutants. Most researchers have concentrated on estimating functions of the form

$$\ln(deaths) = \beta X + \delta Emissions_{t-2} + \epsilon,$$

where ln(deaths) is the log of daily deaths and $Emissions_{t-2}$ refers to the level of air emissions two-days prior. Air pollution is the primary pollution studied since it is associated with the largest adverse health effects (Dasgupta, Lucas, and Wheeler (1998)). The limitation of this research is that it implies that an increase in emissions has the same effect on premature mortality regardless of the initial level of pollution. However, Butterworth and Bogdanoff (1999), Williams et al. (1998), Simpson et al. (1997), Saldiva et al. (1995), and Chestnut et al. (1991) document non-linear and increasing dose response functions (at least over some ranges of exposure). In addition, Ostro et al. (1998) and Cropper et al. (1997) estimate the effect of air pollution with and without including outliers (defined as days with the highest 5% of air emissions). The effects of air pollution are positive in both cases, but lower when the outliers are removed (for ages 2–15 in Ostro et al. and ages 15–64 in Cropper et al.). These results also indicate that the dose-reponse function for air pollutants increases exponentially over some range of the data.

[5] Manufacturing facilities are defined as those falling under Standard Industrial Classification (SIC) 20–39. Refer to http://www.scorecard.org.

report.[6] The 1996 TRI data contains information from over 21,500 manufacturing and federal facilities.[7] The data is publicly available after a two-year lag.

While data is available at the chemical level, the data has also been aggregated into several broad categories: two categories for air pollution and one each for land, water, and underground injections. In the majority of the studies utilizing the TRI data, these five pollution categories are aggregated together. Although these aggregations give equal weight to each chemical, some studies have been concerned about forming new aggregates, weighting each chemical by a measure of toxicity.[8] However, as reported by the EPA, most of the widely used chemicals do not vary significantly in their toxicity and many of the less toxic chemicals have not been assigned risk scores by the EPA.[9]

The remainder of the paper is organized as follows: section 2 develops the framework for an environmental Gini coefficient and an environmental welfare function analagous to Sen's social welfare function; section 3 discusses the data; section 4 presents the results for the Gini coefficient and compares it to other measures of inequality, describes the predicted effects of changes in environmental regulation on inequality and welfare, and also explores the effect of reducing inequality on environmental justice; and, finally, section 5 contains some concluding remarks.

2 Empirical Model

2.1 Enviromental Gini Coefficient

To begin, let E^i, $i = 1;:::;51$, represent state i's level of total per capita emissions, which is the sum of different types of emissions.[10] It is convenient to treat the various sources, E^i_k, $k = 1;:::;K$, as distinct, where henceforth the state index i is suppressed. Therefore, E may be re-written as

[6] U.S. EPA (1992).

[7] Refer to http://www.scorecard.org.

[8] Brooks and Sethi (1997); Arora and Carson (1995).

[9] Refer to Arora and Carson (1999) and U.S. EPA (1989).

[10] Washington, D.C. is included as the 51st "state".

$$E = \sum_{k=1}^{K} E_k \quad . \tag{1}$$

In the empirical work, the five emission types considered are: fugitive air releases, stack air releases, water, land, and underground injections (refer to section 3).

Emissions inequality is measured by an environmental Gini coefficient. The Gini coefficient is the best known and most frequently used measure of income inequality. It is convenient to use the covariance formulation of the Gini coefficient:

$$G = \frac{2\,\mathrm{cov}(E, F)}{\mu} \tag{2}$$

where G is the (relative) Gini coefficient of total per capita emissions, F is the cumulative distribution of total per capita emissions, and μ is mean per capita emissions, where

$$\mu = \sum_{k=1}^{K} \mu_k \tag{3}$$

which follows from (1).[11] Using the properties of covariance, (2) can be rewritten as:

$$G = \frac{2\sum_{k=1}^{K} \mathrm{cov}(E_k, F)}{\mu} \quad . \tag{4}$$

Equation (4) is the basis for the decomposition of the overall environmental Gini coefficient into its various components. Dividing by μ and then multiplying and dividing each component k by $\mathrm{cov}(E_k, F_k)$ and μ, where F_k is the cumulative distribution of emission type k, results in the decomposition used below. The decomposition can be written as:

$$G = \sum_{k=1}^{K} \left[\frac{\mathrm{cov}(E_k, F)}{\mathrm{cov}(E_k, F_k)}\right] \left[\frac{2\,\mathrm{cov}(E_k, F_k)}{\mu_k}\right] \left[\frac{\mu_k}{\mu}\right]$$

[11] Refer to Lerman and Yitzhaki (1984, 1985) for the derivation. The cumulative distribution, F, is obtained by ranking the 51 states (including Washington, D.C.) and dividing by 51. Note, whereas in the income inequality literature this procedure yields an estimate of the cumulative distribution, in this case it is exact since we observe all "individuals" in the population (i.e., all of the states).

$$G = \sum_{k=1}^{K} R_k G_k S_k \tag{5}$$

where R_k is the Gini correlation between pollution source k and the rank of total pollution, G_k is the Gini coefficient of pollution source k, and S_k is pollution source k's share of total pollution. The Gini correlation is similar to Pearson's correlation, except the denominator is replaced by (half) the absolute Gini coefficient of E_k.[12] As such, the Gini correlation will take on more extreme value than Pearson's correlation, but is still bound by the absolute value of one.[13]

The primary benefit of the decomposition in (5) is the ability to analyze the impact of marginal changes in emissions of type k on the overall pollution distribution. As in Garner (1993) who examined changes in consumption expenditures, suppose there is an equal increase in emissions across all states such that emissions of type k increase by $\alpha_k E_k$, where α_k is the percentage change. Consequently, the emission's marginal effect relative to the overall Gini coefficient is

$$\begin{aligned} \frac{\frac{\partial G}{\partial \alpha_k}}{G} &= \frac{R_k G_k S_k}{G} - S_k \\ &= I_k - S_k \quad . \end{aligned} \tag{6}$$

This equation indicates that the percentage change in the overall environmental Gini coefficient due to a marginal (uniform) increase in emissions of type k across all states equals the fraction of the overall Gini due to that emission source minus the share of total emissions attributable to that emission source. If $I_k > S_k$, such that the relative marginal impact is positive, then reducing emissions (perhaps by stricter regulations or emissions taxes) of type k is inequality-reducing; if $I_k < S_k$, reducing emissions of type k is inequality-enhancing.

An alternative measure of interest is the "pollution elasticity", η_k. From Yitzhaki (1994),

$$\eta_k = \frac{R_k G_k}{G} = \frac{I_k}{S_k} \quad , \tag{7}$$

which is interpreted in the present context as the elasticity of pollution of type k with respect to overall pollution. As shown in Garner (1993), (7) may be re-written as:

[12] The absolute Gini for emissions of type k, A_k, is $2\,\mathrm{cov}(E_k; F_k)$. Refer to Lerman and Yitzhaki (1985).

[13] Lerman and Yitzhaki (1985).

$$\eta_k = \frac{\mathrm{cov}(E_k;F)}{\mathrm{cov}(E;F)}\frac{\mu}{\mu_k}, \tag{8}$$

where $\mathrm{cov}(E_k;F)/\mathrm{cov}(E;F)$ can be viewed as a regression coefficient from a non-parametric estimation of a Gini regression or as the marginal propensity to pollute emissions of type k.[14]

The pollution elasticity is the key parameter for assessing the distributional effects of environmental regulation. If $\eta_k > 1$, or, in other words, if $I_k > S_k$ (such that type k emissions consitute a greater share of pollution inequality greater than of total pollution), then a decrease in emissions of type k not only reduces the level of overall pollution, but also lowers inequality. If $\eta_k < 1$, then while a decrease in emissions of type k will lower pollution, it will exacerbate interstate inequality. Thus, for inelastic emission types, there is a trade-off between lowering pollution and lowering pollution inequality.

2.2 Environmental Welfare

To balance the goal of improving income and decreasing inequality, Sen (1973) defined an index of social welfare equal to mean income scaled by one minus the income Gini coefficient,

$$SW = \mu(1 - G). \tag{9}$$

This measure allows one to compare social welfare over time, rather than merely income, where social welfare incorporates the level of equality at a point in time. Using the derivation in Lerman and Yitzhaki (1984), (9) reduces to $SW = \mu - A$, where A is the absolute Gini.[15] In a similar spirit, we define a new measure of environmental welfare, EW, such that

$$EW = \frac{1}{\mu}(1 - G), \tag{10}$$

where μ is mean per capita emissions and G is the environmental (relative) Gini coefficient.

Construction of a measure of environmental welfare is useful for the same reason Sen's measure of social welfare is useful: individuals have preferences over not just the size of the pie (of income or pollution, for

[14] For a summary of the properties of (7), refer to Garner (1993).

[15] Whereas the relative Gini is $2\mathrm{cov}(E;F)/\mu$, the absolute Gini is not scaled by 1 over the mean.

example), but also its distribution. Thus, decreases in overall mean per capita emissions will not necessarily improve environmental welfare (according to our definition) if the (level) decrease is accompanied by an increase in emissions inequality across states. In addition, one may use the measure of environmental welfare in (10) to analyze the relative effects of marginal changes in the level of emission type k on overall environmental welfare. Incorporating both the level and distribution of pollution into regulatory decisions - as opposed to solely the level - can ensure that the benefits of environmental policies are "fairly" distributed.

The environmental welfare function contains the reciprocal of μ so that higher values of EW correspond to improvements in environmental welfare. Consequently, the environmental welfare function is not a direct counterpart to Sen's social welfare function. In particular, EW reduces to $(1/\mu) - (1/\mu^2)A$.[16] Certainly, then, there is no reason to expect EW to give the same weight to equality as does Sen's social welfare function. However, since Sen is concerned with a different issue, there is no reason a priori why income inequality should be given the same weight as pollution inequality. Nonetheless, one can alter the weight given to inequality in the environmental welfare function by replacing G in (10) with the extended Gini, G_v, derived in Yitzhaki (1983) and Lerman and Yitzhaki (1984, 1985), where

$$G_v = \frac{-v\,\mathrm{cov}\left[E, (1-F)^{v-1}\right]}{\mu}, \quad v \in (0, \infty). \tag{11}$$

The parameter v reflects preferences for inequality where inequality aversion is increasing in v. When $v = 1$, the distribution of pollution is irrelevant; when $v = 2$, (11) reduces to the typical Gini coefficient in (2); and, when $v \to \infty$, (11) becomes the Rawls max-min criteria, which in this context, implies minimizing the maximum level of per capita emissions across the states.

[16] Despite this difference, EW is still an interesting welfare function. It is trivial to verify that EW is decreasing in per capita emissions as well as pollution inequality just as Sen's welfare function is increasing in income and decreasing in inequality. In addition, relative to Sen's social welfare function

$$\left|\frac{\partial EW}{\partial \mu}\right| < \left|\frac{\partial SW}{\partial \mu}\right|$$
$$\left|\frac{\partial EW}{\partial G}\right| < \left|\frac{\partial SW}{\partial G}\right|$$
$$\left|\frac{\partial EW}{\partial A}\right| < \left|\frac{\partial SW}{\partial A}\right|$$

if $\mu > 1$. Thus, EW is less responsive to changes in both mean per capita emissions and inequality.

To analyze the impact of a change in the emissions of type k, assume (as in the previous section) that there is a uniform percentage increase in emission type k across all states denoted by α_k. The resulting marginal effect relative to overall environmental welfare is given by

$$
\begin{aligned}
\frac{\frac{\partial EW}{\partial \alpha_k}}{EW} &= -\left[\frac{G_v}{1-G_v}(I_k - S_k) + S_k\right] \\
&= -\left[\frac{G_v}{1-G_v} S_k(\eta_k - 1) + S_k\right], \qquad (12)
\end{aligned}
$$

where I_k and S_k are defined previously.[17] The sign of (12) is unambiguously negative if η_k, the pollution elasticity, is greater than or equal to one. In this case, increasing emissions of type k increases both absolute pollution levels as well as environmental inequality; hence, environmental welfare falls.

For the sign of (12) to be positive, $\eta_k > (2G - 1)/G$ must hold. Therefore, if $G \leq 0.5$, $\eta_k > 0$ is necessary, but not sufficient, for environmental welfare to be increasing in the emissions of per capita levels of pollution type k. If $G = 0.5$, then $\eta_k < 0$ is necessary and sufficient for the sign of (12) to be positive. Thus, for relatively equal distributions of per capita emissions across U.S. states, only increases in "inferior" pollution components (i.e., pollution types which decrease as overall emissions increase) lead to higher environmental welfare.[18] As $G \to 1$, the maximum permissible value for η_k such that the sign of (12) is still positive approaches one. This implies that increases in emission types which have less of an inequality-reducing effect increase environmental welfare only if the initial distribution is highly unequal.

3 Data

The data come from the EPA's Toxic Release Inventory spanning 1988–1996.[19] The TRI database was established under Section 313 of the EPCRA. There are five broad categories of pollution utilized from the TRI:

- Stack Air Releases: Releases to air that occur through confined air streams, such as stacks, vents, ducts or pipes. Sometimes called releases from a point source.

[17] For a more explicit derivation of (12), refer to Appendix A.

[18] The concepts of "normal" and "inferior" emissions types are discussed further in section 4.

[19] The TRI data is at http://www.scorecard.org.

- Fugitive Air Releases: Releases to air that do not occur through a confined air stream, including equipment leaks, evaporative losses from surface impoundments and spills, and releases from building ventilation systems. Sometimes called releases from nonpoint sources.
- Water Releases: Releases to water include discharges to streams, rivers, lakes, oceans and other bodies of water. This includes releases from both point sources, such as industrial discharge pipes, and nonpoint sources, such as stormwater runoff, but not releases to sewers or other off-site wastewater treatment facilities. It includes releases to surface waters, but not ground water.
- Land Releases: Releases to land occur within the boundaries of the reporting facility. These releases include on-site disposal in landfills (where wastes are buried), land treatment (where wastes are applied to or incorporated into soil), surface impoundments (which are uncovered holding ponds used to volatilize and/or settle waste materials), and other land disposal (including accidental spills or leaks).
- Underground Injections: Underground injection releases fluids into a subsurface well for the purpose of waste disposal. Wastes containing TRI chemicals are injected into either Class I wells or Class V wells. Class I wells are used to inject liquid hazardous wastes or dispose of industrial and municipal waste-waters beneath the lowermost underground source of drinking water. Class V wells are generally used to inject non-hazardous fluid into or above an underground source of drinking water. Beginning in 1996, TRI reports distinguish between these two types of wells, but this level of detail is not available in EPA's public data release.[20]

Table 1 contains the summary statistics for the five per capita pollution measures across US states.

[20] Definitions are available at http://www.scorecard.org.

Table 1. Summary statistics: Per Capita Emissions across U.S. States, 1988-1996.

Variable	Mean	Std. Dev.	Minimum	Maximum
Stack Air Releases	6.90	8.27	0.00	73.45
Fugitive Air Releases	2.25	1.84	0.00	11.80
Water Releases	1.01	4.28	0.00	49.12
Land Releases	2.87	7.86	0.00	50.89
Underground Injections	2.86	9.36	0.00	98.96
Total	15.89	20.11	0.00	220.93

In addition, Figure 1 shows how mean per capita stack air releases, fugitive air releases, land releases, water releases, underground injections, and total emissions across states (weighted by state population) have changed over time.

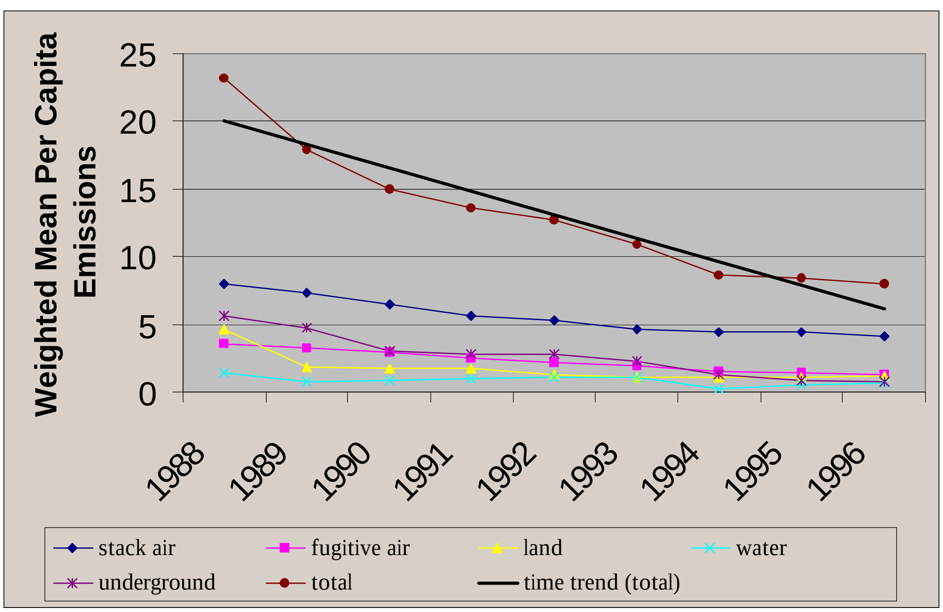

Figure 1. Weighted Mean Per Capita Emissions By Type, 1988-1996.

Table 2 lists the state with the highest level of per capita emissions for each type over the sample period. As is evident, a few states have a particularly negative history in terms of per capita emissions. Louisiana ranks first in terms of per capita water releases over the entire sample period and first for much of the sample period in terms of per capita underground injections and total emissions. In addition, Utah, Tennessee, and Mississippi are the only three states to rank first in per capita levels of either fugitive or stack air releases. Wyoming has the highest level of per capita underground injections since 1994, bypassing Louisiana. Finally, Montana has the highest level of per capita land releases over much of the sample period (with only New Mexico surpassing it in 1991 and 1992). In fact, Montana's per capita land releases are so high that from 1994 through the end of the sample, Montana ranks first in per capita total releases, overtaking Louisiana.

Table 2. States with the Highest Per Capita Emissions, 1988-1996.

Category	1988	1989	1990	1991	1992
Stack Air	Utah	Utah	Utah	Utah	Utah
Fugitive Air	Tennessee	Tennessee	Tennessee	Tennessee	Tennessee
Water	Louisiana	Louisiana	Louisiana	Louisiana	Louisiana
Land	Louisiana	Montana	Montana	New Mexico	New Mexico
Underground Injections	Louisiana	Louisiana	Louisiana	Louisiana	Louisiana
Total	Louisiana	Louisiana	Louisiana	Louisiana	Louisiana

Category	1993	1994	1995	1996
Stack Air	Utah	Utah	Utah	Utah
Fugitive Air	Tennessee	Mississippi	Mississippi	Mississippi
Water	Louisiana	Louisiana	Louisiana	Louisiana
Land	Louisiana	Montana	Montana	Montana
Underground Injections	Montana	Wyoming	Wyoming	Wyoming
Total	Louisiana	Montana	Montana	Montana

4 Results

4.1 Environmental Inequality

While the TRI data set does not span a relatively long time period, it does allow us to compute measures of inequality over nine years (1988–1996) and examine changes in the distribution of pollution across U.S. states. Table 3 shows how various measures of state per capita pollution inequality (weighted by state population) have changed from the late 1980s to the mid-1990s. The (weighted) mean of per capita total emissions is also included.

As stated previously, the Gini coefficient is the most widely used scalar measure of income inequality. A value of zero indicates perfect equality and one signals perfect inequality (i.e., all pollution (income) is located in one state (individual)). The second measure of inequality is referred to as the 90/10 ratio and gives the level of per capita pollution in the state at the 90th percentile as a share of the per capita emissions of the state at the 10th percentile. Thus, a higher 90/10 ratio indicates a widening of the distribution. The next two measures are simply the unconditional variance of per capita emissions and log per capita emissions.[21] Finally, the coefficient of variation (σ/μ) is calculated as well.

[21] Note, it is consistent for the variance to decrease for per capita emissions and simultaneously increase for log per capita emissions if mean emissions have fallen and have a greater concentration between zero and one unit per capita.

Table 3. Weighted Aggregate Pollution Per Capita Inequality Measures, 1988-1996.†

Year	Mean Per Capita Emissions	Gini Coefficient	90/10 Ratio	Variance of Per Capita Total Emissions	Variance of Log Per Capita Total Emissions	Coefficient of Variation
1988	23.11	0.51	13.36	973.91	1.05	1.35
1989	17.92	0.47	16.98	352.89	1.03	1.05
1990	14.93	0.45	14.01	268.85	0.74	1.10
1991	13.64	0.47	10.70	259.46	0.78	1.18
1992	12.73	0.51	13.64	259.08	0.87	1.26
1993	10.89	0.54	17.96	233.31	0.91	1.40
1994	8.64	0.45	15.50	75.41	0.94	1.00
1995	8.36	0.45	15.70	60.23	0.95	0.93
1996	8.00	0.44	14.86	59.63	0.97	0.96

†Weighted by state population.

Although (weighted) mean per capita emissions have fallen monotonically from 1988–1996, the different inequality measures in Table 3 yield different impressions about changes within the distribution of pollution across the states. Column 2 gives the annual environmental Gini coefficient. While it does peak in 1993 and reach its minimum in 1996, variation between years does not follow a meaningful pattern. The 90/10 ratio also indicates a peak in inequality in 1993; however, it shows that the mid-1990s are more unequal than the early 1990s. Given the falling mean per capita emissions, the variance of per capita emissions and the variances of the log of per capita emissions give two different pictures of the distribution. The variance of per capita emissions, along with the mean, has fallen every year in the data, while the variance of log per capita emissions has increased every year since 1990. Finally, the coefficient of variation also points to 1993 as the year with the largest amount of interstate variation in per capita emissions.

4.2 Environmental Regulations and Inequality

To assess the impact of stricter regulation of certain emission types on overall pollution inequality across states, Table 4 decomposes the environmental Gini coefficient for 1996 into its various components utilizing equations (5), (6), and (7). From Table 3, the overall environmental Gini coefficient for 1996 is 0.49. Column 1 gives each emission type's contribution, $R_k G_k S_k$, to the overall Gini coefficient. The largest contributor to overall pollution inequality is stack air emissions (which also constitutes the largest share of total per capita emissions (column 4)). This source constitutes nearly 50% of the overall Gini coefficient (column 5). The remainder is divided fairly evenly between fugitive air releases, water pollution, land releases, and underground injections.

Table 4. Weighted Pollution Inequality Effects by Emission Type, 1996.[y]

Emission Type	Contribution to Total Inequality[z] ($R_k G_k S_k$)	Correlation with Rank of Total Pollution (R_k)	Gini of Component (G_k)	Pollution Share (S_k)	Share of Pollution Inequality[z] (I_k)	Relative Marginal Effect[z] ($I_k - S_k$)	Pollution Elasticity (η_k)
Stack Air	0.21	0.90	0.46	0.51	0.48	0.03	0.94
Fugitive Air	0.06	0.89	0.41	0.16	0.14	0.02	0.88
Water	0.03	0.71	0.56	0.08	0.07	0.01	0.88
Land	0.08	0.81	0.62	0.15	0.18	-0.03	1.20
Underground Injections	0.07	0.92	0.71	0.10	0.16	-0.06	1.60
Total	0.44	1.00	0.44	1.00	1.00	0.00	–

[y]Weighted by state population.

[z]May not add up due to rounding.

Column 2 of Table 4 gives the Gini correlation for each emission type (R_k). A low correlation value implies that increases in overall per capita emissions is not highly correlated with increases in emissions of that particular type. On the other hand, a high correlation indicates that increases in per capital total emissions leads to greater emissions of that type. Of the five pollution components analyzed, both types of air emissions, land pollution, and underground injections all have roughly the same Gini correlation. Only water pollution has a significantly different, and lower, Gini correlation. This is not surprising as states are exogenously endowed with different amounts of water and states with less water are less likely to have increases in pollution be concentrated in water. Thus, one would expect the correlation to be lower.

Inspection of the individual Gini coefficients, G_k, in column 3, indicates that fugitive air releases are distributed most equally across the states, while water, land, and particularly underground injections are extremely unequally distributed. Together the Gini correlation and the Gini coefficient for each emission type determine the elasticity, η_k. Since all of the elasticities are non-negative, all of the emission components are "normal" goods. In other words, as total per capita pollution rises in a given state, this new level of pollution is divided among all five of the pollution types analyzed. A negative elasticity would imply that increases in overall per capita pollution decrease emissions of that particular type, but increase other types of emissions by more than enough to offset the decrease.[22]

Elasticities greater than one indicate that that particular emission type is elastic. For land pollution as well as underground injections, the elasticities are significantly within the elastic range. In addition, the relative marginal effects of a uniform increase in these pollution types (column 7) are positive; negative for both types of air releases and water pollution. Thus, policy interventions which reduce levels of land pollution and underground injections – such as higher taxes or more stringent regulation – are inequality-reducing. Conversely, ceteris paribus, stricter regulations for air and water releases - while reducing overall pollution - are inequality-enhancing.

The fact that reductions in air pollution are inequality-enhancing is quite significant when one interprets the findings from the environmental justice literature. Because air releases combine for over half of all per capita emissions, large reductions in overall per capita levels of pollution are in direct conflict with efforts to reduce emissions inequality across U.S. states. In addition, if (as discussed below) states at the upper tail of the pollution distribution have a higher composition of minorities, for example, then reductions in overall air pollution will increase the racial gap for per capita pollutants. Thus, cross-sectional estimates

[22] This may be somewhat surprising. For example, if the disposal of pollution by firms underground is relatively expensive, then they may only utilize this option if the state is relatively pollution-free and large amounts of, say, air pollution would give the firm a negative reputation. However, as the level of pollution increases, the reputational cost associated with emitting visible air pollution may decrease, allowing the firm to dispose of its pollution into the air or water, thus decreasing its amount of underground injections. However, since all five elasticities are positive, such a cost-saving reallocation of pollution by firms as total per capita pollution rises is ruled out.

of the marginal effect of, say, the proportion of a state which is non-white on per capita emissions will be increasing in absolute value over time as the overall level of air pollution declines. Therefore, only by understanding the interaction between the levels of certain emissions types and the distribution of pollution can one balance the desire for lower pollution with the desire for equity.

4.3 Environmental Social Welfare

Just as Sen's social welfare comparisons balance the desire for higher incomes with preferences for equality, the environmental welfare function in (10) allows one to incorporate the distribution of pollution across states into comparisons of emissions levels over time in the U.S. Table 5 calculates environmental welfare over the range of the data (1988–1996) for three different values of v: 1.5, 2, and 4. Higher values of v give more weight to the distribution of pollution in the calculation of environmental welfare and $v = 2$ corresponds to the typical Gini.

Table 5. Environmental Welfare, 1988-1996.

Year	Mean Per Capita Emissions†	Gini Coefficient†			Environmental Welfare‡		
		$v = 1.5$	$v = 2$	$v = 4$	$v = 1.5$	$v = 2$	$v = 4$
1988	23.11	0.37	0.51	0.71	0.27	0.21	0.13
1989	17.92	0.32	0.47	0.65	0.38	0.30	0.20
1990	14.93	0.29	0.45	0.69	0.48	0.37	0.21
1991	13.64	0.30	0.47	0.70	0.51	0.39	0.22
1992	12.73	0.33	0.51	0.79	0.53	0.39	0.17
1993	10.89	0.36	0.54	0.83	0.59	0.42	0.16
1994	8.64	0.29	0.45	0.73	0.82	0.64	0.31
1995	8.36	0.29	0.45	0.72	0.85	0.66	0.33
1996	8.00	0.28	0.44	0.72	0.90	0.70	0.35

†Weighted by state population.

‡EW from (10) multiplied by 10.

The results in Table 5 show that the trend of improving environmental quality (as measured by per capita emissions level) is altered when the weight given to inequality is relatively significant. As shown in Table 3, the early 1990s and 1993 in particular are characterized by increasing interstate pollution inequality. When the increase in inequality is given relatively more weight in the welfare function (e.g., $v = 4$), environmental welfare declines in 1992 and 1993 despite the decline in overall emissions. Welfare functions based on the typical Gini ($v = 2$) and extended Gini coefficients with $v < 2$, are monotonically increasing over the range of the data.

Table 6 provides estimates of (12) for the same values of v except the results in the table are for a uniform decrease in per capita emissions of type k across all states – as opposed to an increase – since analyzing the effects of a decrease in emissions is more relevant from a policy perspective.

Table 6. Environmental Welfare Effects by Emission Type, 1996.

Emission Type	Pollution Elasticity[y]			Relative Marginal Effect on Environmental Welfare From a <u>Decrease</u> in Emissions		
	$v = 1.5$	$v = 2$	$v = 4$	$v = 1.5$	$v = 2$	$v = 4$
Stack Air	0.93	0.94	0.96	0.50	0.49	0.46
Fugitive Air	0.76	0.88	0.88	0.15	0.14	0.11
Water	0.97	0.88	0.80	0.08	0.07	0.04
Land	1.21	1.20	1.16	0.16	0.17	0.21
Underground Injections	1.56	1.60	1.25	0.12	0.15	0.16

[y]Weighted by state population.

The figures in Table 6 give the percentage change in environmental welfare due to a decrease in per capita emissions of each type. For example, a 10% reduction in per capita stack air emissions across all states will increase environmental welfare by 5.0% if $v = 1.5$ (column 4) and 4.6% if $v = 4$ (column 6). The fact that the increase in environmental welfare is less when $v = 4$ is due to the fact that reductions in stack air releases are inequality-enhancing. Therefore, the welfare improvement due to the decrease in emissions level is partially offset by the increase in pollution inequality. Despite the increase in emissions inequality from reductions in stack air releases, such reductions constitute the largest increase in overall environmental welfare, regardless of the weight given to pollution equality.[23]

After stack air releases, reductions in land releases have the next largest impact on overall environmental welfare. A 10% reduction in per capita land releases across all states will increase environmental welfare by 1.6% if $v = 1.5$ (column 4) and 2.1% if $v = 4$ (column 6). Unlike stack air releases, the improvement in environmental welfare from a reduction in land releases is greater as $v \to 1$ since reductions in land releases are inequality-reducing.

Until now, while the emphasis placed on environmental equality (in terms of the choice of v) changes the magnitude of the effect of reductions on overall environmental welfare, it has not altered the policy conclusions pertaining to which type of emissions should be the focus of environmental regulations: reducing stack air releases increases welfare the most, followed by land releases. However, beyond that, the use of the environmental welfare function can provide useful information for the direction of future environmental policy. If environmental welfare affords less weight to inequality than the typical Gini coefficient (i.e., $v < 2$), then fugitive air releases should be the next target for reductions by regulators. However, if $v \geq 2$ and the distribution of pollution across states enters the decision calculus, then underground injections should be given higher priority since reductions in underground injections are inequality-reducing. Finally, regardless of preferences concerning pollution equality, reductions in water releases affords the least opportunity to increase environmental welfare.

4.4 State Attributes and Inequality

The analysis until this point has documented the degree of interstate inequality in the distribution of pollution and the impact this inequality could potentially have on future environmental regulation if one has preferences over this distribution. In addition, as shown in Table 1, mean per capita emissions decreased monotonically from 1988–1996. As a result, achieving lower per capita pollution levels at any cost (in

[23] This statement implicitly assumes that there are no differences in the welfare gain from reductions in distinct emissions types except for their effect on overall pollution inequality. In other words, there is no attempt to weigh the relative welfare gains from reductions in air pollution versus, say, water pollution in terms of individuals' willingness to pay for one type of reduction as opposed to another.

terms of the distributional effects) is less of an imperative; environmental regulations may be more welfare-enhancing by focusing on interstate pollution inequality. This is particularly true if certain segments of the population are disproportionately represented at the upper tail of the pollution distribution.

Table 7a. Spearman Correlation Coefficients between Per Capita Pollution and Percentage of State Population which is White, 1988-1996.[¤]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1988	0.11 (0.46)	0.10 (0.49)	-0.02 (0.89)	-0.02 (0.89)	-0.43 (0.00)[y]	0.02 (0.90)
1989	0.12 (0.40)	0.03 (0.85)	-0.08 (0.57)	-0.12 (0.42)	-0.31 (0.03)[y]	0.02 (0.87)
1990	-0.13 (0.39)	-0.18 (0.21)	-0.21 (0.15)	-0.03 (0.84)	-0.35 (0.01)[y]	-0.11 (0.44)
1991	-0.13 (0.37)	-0.19 (0.20)	-0.26 (0.07)[z]	-0.02 (0.87)	-0.36 (0.01)[y]	-0.11 (0.43)
1992	-0.13 (0.38)	-0.22 (0.13)	-0.29 (0.04)[y]	-0.10 (0.48)	-0.32 (0.03)[y]	-0.10 (0.51)
1993	-0.14 (0.35)	-0.20 (0.17)	-0.26 (0.07)[z]	-0.10 (0.50)	-0.30 (0.03)[y]	-0.11 (0.46)
1994	-0.07 (0.63)	-0.08 (0.56)	-0.22 (0.12)	-0.07 (0.61)	-0.32 (0.02)[y]	-0.06 (0.70)
1995	-0.08 (0.59)	-0.06 (0.69)	-0.19 (0.18)	-0.14 (0.33)	-0.30 (0.03)[y]	-0.03 (0.85)
1996	-0.09 (0.52)	-0.04 (0.78)	-0.09 (0.53)	-0.06 (0.68)	-0.39 (0.00)[y]	-0.01 (0.96)
All Years	-0.07 (0.13)	-0.11 (0.02)[y]	-0.19 (0.00)[y]	-0.08 (0.07)[z]	-0.35 (0.00)[y]	-0.07 (0.15)

[¤]Probability associated with the t-statistic in parenthesis.

[y]Significant at the 5% level.

[z]Significant at the 10% level.

To provide some evidence that the states with the highest emissions levels are not randomly assigned, Tables 7a through 7f give the Spearman correlation coefficients between per capita emissions (both total as well as decomposed into the five categories of emissions) and selected state characteristics for the period 1988–1996 as well as by year. It should be noted that these results are not intended to prove causation. If certain segments of the population are over-represented in high per capita pollution states, it is irrelevant–for this analysis–why this occurs. However, the fact that certain population sub-groups may differentially benefit from pollution reductions such that "environmental justice" may increase or decrease is relevant.

Tables 7a and 7b provides the correlation coefficients between per capita emission levels and the share of state population which is white (Table 7a) and the share which is black (Table 7b).[24] In Table 7a, while the sign of most of the correlations is negative, few are significant even at the 10% level. Underground injections, however, are always significant at the 5% level as are water releases in the early 1990s. In addition, when the data is aggregated over the nine years, the correlation coefficients for four of the five categories of per capita emissions are negative and significant (with stack air releases being the omitted category). Thus, states at the low end of the distribution for these four groups of pollutants have a significantly higher concentration of whites in the population.

Table 7b indicates a similar and even stronger picture when it comes to the percentage of state population comprised of blacks. The correlation coefficients for all five categories, as well as for total per capita emissions, are positive and significant. In addition, the correlation coefficients are also highly significant and well into the positive range when calculated on an annual basis for stack and fugitive air releases, water pollutants, and underground injections. However, there does appear to be a downward trend beginning in the early 1990s.

[24] Census data includes categories for white, black, Native American, and all others.

Table 7b. Spearman Correlation Coefficients between Per Capita Pollution and Percentage of State Population which is Black, 1988-1996.[¤]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1988	0.33 (0.02)[y]	0.30 (0.04)[y]	0.40 (0.00)[y]	0.02 (0.88)	0.48 (0.00)[y]	0.12 (0.40)
1989	0.31 (0.03)[y]	0.44 (0.00)[y]	0.41 (0.00)[y]	0.12 (0.41)	0.31 (0.03)[y]	0.14 (0.33)
1990	0.32 (0.02)[y]	0.50 (0.00)[y]	0.36 (0.01)[y]	0.10 (0.51)	0.42 (0.00)[y]	0.18 (0.21)
1991	0.31 (0.03)[y]	0.50 (0.00)[y]	0.39 (0.00)[y]	0.08 (0.60)	0.38 (0.01)[y]	0.17 (0.23)
1992	0.32 (0.03)[y]	0.50 (0.00)[y]	0.40 (0.00)[y]	0.19 (0.19)	0.38 (0.01)[y]	0.19 (0.19)
1993	0.34 (0.02)[y]	0.49 (0.00)[y]	0.39 (0.01)[y]	0.14 (0.35)	0.35 (0.01)[y]	0.22 (0.13)
1994	0.25 (0.08)[z]	0.36 (0.01)[y]	0.35 (0.01)[y]	0.13 (0.37)	0.33 (0.02)[y]	0.16 (0.27)
1995	0.25 (0.08)[z]	0.30 (0.03)[y]	0.34 (0.01)[y]	0.17 (0.24)	0.29 (0.04)[y]	0.12 (0.40)
1996	0.25 (0.08)[z]	0.27 (0.06)[z]	0.19 (0.19)	0.16 (0.27)	0.26 (0.01)[y]	0.07 (0.64)
All Years	0.27 (0.00)[y]	0.35 (0.00)[y]	0.34 (0.00)[y]	0.10 (0.03)[y]	0.35 (0.00)[y]	0.13 (0.01)[y]

[¤]Probability associated with the t-statistic in parenthesis.

[y]Signi¯cant at the 5% level.

[z]Signi¯cant at the 10% level.

Table 7c addresses the issue of gender and pollution and reports the correlation coe±cients between per capita emissions and the share of state population which is female. The correlation coe±cients for all nine years combined for total per capita emissions in addition to all of the categories except land releases are positive and signi¯cant. Also, the annual correlation coe±cients for water releases as well as both stack and air releases are positive and signi¯cant. In particular, per capita fugitive air releases are extremely correlated with the gender decomposition of states. As with the correlation between per capita emissions and the share of state population comprised of blacks, the correlations are falling entering the late 1990s.

Table 7c. Spearman Correlation Coefficients between Per Capita Pollution and Percentage of State Population which is Female, 1990-1996.[¤]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1990	0.33 (0.02)[y]	0.55 (0.00)[y]	0.30 (0.03)[y]	0.04 (0.80)	0.18 (0.21)	0.16 (0.26)
1991	0.32 (0.02)[y]	0.56 (0.00)[y]	0.34 (0.01)[y]	0.01 (0.92)	0.16 (0.27)	0.14 (0.32)
1992	0.35 (0.01)[y]	0.55 (0.00)[y]	0.30 (0.04)[y]	0.10 (0.47)	0.19 (0.19)	0.17 (0.25)
1993	0.36 (0.01)[y]	0.57 (0.00)[y]	0.40 (0.00)[y]	0.00 (0.98)	0.18 (0.22)	0.17 (0.24)
1994	0.29 (0.04)[y]	0.42 (0.00)[y]	0.32 (0.02)[y]	0.04 (0.79)	0.14 (0.34)	0.14 (0.34)
1995	0.26 (0.06)[z]	0.38 (0.01)[y]	0.34 (0.01)[y]	0.00 (0.99)	0.09 (0.54)	0.11 (0.44)
1996	0.26 (0.06)[z]	0.31 (0.03)[y]	0.26 (0.06)[z]	0.06 (0.67)	0.10 (0.49)	0.07 (0.64)
All Years	0.32 (0.00)[y]	0.48 (0.00)[y]	0.33 (0.00)[y]	0.05 (0.37)	0.17 (0.00)[y]	0.15 (0.00)[y]

[¤]Probability associated with the t-statistic in parenthesis.

[y]Significant at the 5% level.

[z]Significant at the 10% level.

Finally, Tables 7d through 7f examine the correlation between per capita emissions and the age distribution within states. Specifically, Table 7d and 7e report the correlations for female and male median age, respectively, and Table 7f gives the correlation coe±cients between per capita emissions and the share of the population under the age of ¯ve. The pattern which emerges from the Tables 7d and 7e is that younger states are over-represented in the upper tail of the pollution distribution; especially states with a younger male population. In addition, while the trend in the previous tables indicated a dampening of the correlation between per capita emissions and the gender and racial composition of states, the correlation coe±cients, particularly for male median age, are increasing in absolute value throughout the mid-1990s. The fact the correlation is negative is not surprising since one would expect heavily polluting manufacturing facilities to be intensive in young labor.

Table 7d. Spearman Correlation Coefficients between Per Capita Pollution and Median Female Age, 1990-1996.[¤]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1990	-0.14 (0.77)	0.19 (0.18)	0.13 (0.38)	-0.05 (0.74)	-0.14 (0.32)	-0.17 (0.25)
1991	-0.03 (0.84)	0.19 (0.18)	0.18 (0.21)	-0.04 (0.76)	-0.10 (0.51)	-0.18 (0.21)
1992	-0.02 (0.88)	0.14 (0.32)	0.11 (0.45)	-0.04 (0.79)	-0.06 (0.70)	-0.16 (0.28)
1993	-0.01 (0.86)	0.20 (0.16)	0.27 (0.06)[z]	-0.15 (0.30)	-0.09 (0.52)	-0.15 (0.30)
1994	-0.04 (0.76)	0.09 (0.52)	0.13 (0.37)	-0.15 (0.29)	-0.11 (0.46)	-0.14 (0.33)
1995	-0.06 (0.66)	0.06 (0.70)	0.04 (0.78)	-0.19 (0.18)	-0.10 (0.50)	-0.17 (0.23)
1996	-0.13 (0.35)	-0.09 (0.54)	0.01 (0.96)	-0.18 (0.21)	-0.15 (0.30)	-0.27 (0.05)[y]
All Years	-0.16 (0.00)[y]	-0.07 (0.19)	0.05 (0.31)	-0.17 (0.00)[y]	-0.17 (0.00)[y]	-0.27 (0.00)[y]

[¤]Probability associated with the t-statistic in parenthesis.

[y]Significant at the 5% level.

[z]Significant at the 10% level.

Table 7e. Spearman Correlation Coefficients between Per Capita Pollution and Median Male Age, 1990-1996.[¤]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1990	-0.28 (0.05)[y]	-0.09 (0.53)	-0.00 (0.99)	-0.09 (0.55)	-0.30 (0.04)[y]	-0.34 (0.01)[y]
1991	-0.30 (0.04)[y]	-0.11 (0.45)	-0.01 (0.92)	-0.14 (0.34)	-0.25 (0.08)[z]	-0.37 (0.01)[y]
1992	-0.30 (0.04)[y]	-0.16 (0.25)	-0.07 (0.65)	-0.15 (0.32)	-0.20 (0.17)	-0.35 (0.01)[y]
1993	-0.28 (0.05)[y]	-0.13 (0.36)	0.07 (0.65)	-0.24 (0.10)[z]	-0.23 (0.10)	-0.30 (0.04)[y]
1994	-0.32 (0.02)[y]	-0.22 (0.12)	-0.11 (0.45)	-0.28 (0.05)[y]	-0.22 (0.13)	-0.33 (0.02)[y]
1995	-0.36 (0.01)[y]	-0.25 (0.08)[z]	-0.17 (0.22)	-0.35 (0.01)[y]	-0.23 (0.10)	-0.37 (0.01)[y]
1996	-0.38 (0.01)[y]	-0.36 (0.01)[y]	-0.15 (0.30)	-0.29 (0.04)[y]	-0.32 (0.02)[y]	-0.42 (0.00)[y]
All Years	-0.33 (0.00)[y]	-0.28 (0.00)[y]	-0.08 (0.15)	-0.22 (0.00)[y]	-0.27 (0.00)[y]	-0.38 (0.00)[y]

[¤]Probability associated with the t-statistic in parenthesis.

[y]Significant at the 5% level.

[z]Significant at the 10% level.

Although the fact that prime-age workers are bearing a disproportionate burden of pollution may not be overly troublesome to policymakers, a corollary of this fact, demonstrated in Table 7f, is that per capita emissions (particularly land releases and underground injections) are concentrated in states with a high fraction of children under the age of five. In addition, in the mid-1990s, the trend towards pollution being located in states with a relatively younger overall population (measured by the median age) has been accompanied, not surpisingly, by an increase in the correlation coefficients between per capita emissions of all five categories and the under age five population. Fugitive air releases is the most interesting example of this trend. In only seven years, per capita fugitive air releases have gone from significantly and negatively correlated ($\rho = -0.35$, $p-$value $= 0.01$) with the share of the state population under five to a positive, albeit insignificant, coefficient ($\rho = 0.05$, $p-$value $= 0.72$).

Table 7f. Spearman Correlation Coefficients between Per Capita Pollution and Share of population 5 and Under, 1990-1996.[*]

Year	Stack Air	Fugitive Air	Water	Land	Underground Injections	Total
1990	-0.13 (0.36)	-0.35 (0.01)	-0.15 (0.29)	0.04 (0.78)	0.01 (0.95)	0.06 (0.67)
1991	-0.18 (0.21)	-0.36 (0.01)	-0.22 (0.12)	0.02 (0.89)	0.05 (0.72)	0.02 (0.91)
1992	-0.16 (0.28)	-0.26 (0.07)	-0.11 (0.46)	0.05 (0.74)	0.01 (0.96)	-0.01 (0.94)
1993	-0.15 (0.30)	-0.26 (0.07)	-0.21 (0.14)	0.14 (0.32)	0.10 (0.48)	-0.02 (0.90)
1994	-0.09 (0.52)	-0.17 (0.23)	-0.08 (0.58)	0.22 (0.12)	0.21 (0.13)	0.01 (0.95)
1995	-0.02 (0.86)	-0.14 (0.34)	0.04 (0.77)	0.33 (0.02)[†]	0.23 (0.11)	0.07 (0.63)
1996	0.05 (0.74)	0.05 (0.72)	0.00 (1.00)	0.33 (0.02)[†]	0.32 (0.02)[†]	0.18 (0.21)
All Years	-0.04 (0.44)	-0.09 (0.10)[‡]	-0.09 (0.08)[‡]	0.20 (0.00)[†]	0.17 (0.00)[†]	0.10 (0.05)[†]

[*] Probability associated with the t-statistic in parenthesis.

[†] Significant at the 5% level.

[‡] Significant at the 10% level.

In the end, the data presented provides a valid reason for incorporating the distribution of per capita emissions into decisions regarding environmental regulations. Since reductions in per capita land releases and underground injections are inequality-reducing, tighter regulations of these types of emissions will not only reduce overall pollution, but will also reduce the (relative) burden borne by minorities, women, and children under the age of five. Reducing air and water releases, while improving welfare by lowering pollution, will place a greater share of the environmental hazards on these segments of the population.

5 Conclusion

While analyzing the responsiveness of environmental hazards to the composition of locales has been the focus of much research, this study takes a step backwards and analyzes the distribution of pollution across U.S. states by applying measures of inequality developed for the study of income distributions. By constructing and utilizing the special properties of an environmental Gini coefficient, we have shown how different sources of pollution contribute to overall inequality across U.S. states. The results indicate that there is a substantial amount of inequality in the distribution of total per capita pollution throughout the late 1980s and 1990s despite the decline in mean overall per capita emissions. In addition, the estimated "pollution elasticities" for land releases and underground injections are especially high, indicating that policy interventions which reduce these types of emissions will reduce overall pollution inequality across the states, while reductions in air and water releases will exacerbate pollution inequality. Furthermore, by constructing an environmental welfare function, analogous to Sen's social welfare function, we are able to analyze the impact of different types of environmental regulations on overall environmental welfare. This environmental welfare function allows one to capture the effect of stricter regulations on not only the level of emissions, but also the distribution of emissions across the states. Finally, it is shown that incorporating inequality concerns into decisions concerning environmental regulations is critical to the notion of environmental justice. Because states with a disproportionate share of minorities, women, and children under the age of five are over-represented in the upper tail of the per capita pollution distribution, ad hoc environmental policies - even those which reduce emissions - may exacerbate this inequity.

A Appendix

Environmental welfare is given in (10). Differentiating with respect to α_k, the percentage increase in emission type k across all states, yields

$$\frac{\partial EW}{\partial \alpha_k} = -\mu \frac{\partial G_v}{\partial \alpha_k} + (1 - G_v)\frac{\partial \mu}{\partial \alpha_k} \tag{A1}$$

where

$$\frac{\partial G}{\partial \alpha_k} = G_v(I_k - S_k) = G_v S_k(\eta_k - 1) \tag{A2}$$

from Garner (1993) and

$$\frac{\partial \mu}{\partial \alpha_k} = \mu_k \tag{A3}$$

from (3) and the definition of α_k. Specifically, $\mu = \sum_k \mu_k$, which implies that $\partial\mu/\partial\alpha_k = \partial\mu_k/\partial\alpha_k = \mu_k$ since α_k is the uniform percentage increase in component k across all states. Inserting (13) and (13) into (13), yields

$$\frac{\partial EW}{\partial \alpha_k} = -\mu G_v(I_k - S_k) + (1 - G_v)\mu_k \quad . \tag{A4}$$

Dividing (13) by the environmental welfare function, EW, in (10) simplifies to equation (12) in the text.

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