Quantifying the distribution of environmental benefits for regulatory environmental justice analysis

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Abstract

Economists have long been interested in measuring distributional impacts of policy interventions. As environmental justice (EJ) emerged as an ethical issue in the 1970s, the academic literature has provided statistical analyses of the incidence and causes of various environmental outcomes as they relate to race, income, and other demographic variables. In the context of regulatory impacts, however, there is a lack of consensus regarding what information is relevant for EJ analysis, and how best to present it. This paper helps inform the discussion by considering the use of inequality indices to quantify the distribution of environmental pollutants. We demonstrate the use of a set of indices using data from the Sulfur-dioxide (SO2) trading program and Heavy Duty Diesel (HDD) rule.

Keywords: environmental justice, ethical index numbers

I. Introduction

Economists have been interested in analyzing the distribution of environmental benefits for almost as long as they have been calculating the benefits themselves. While the tools for conducting benefits analysis are well developed, those for examining equity, or distributional effects, are less so.

Most OECD countries routinely perform a regulatory impact analysis of significant new environmental rules (OECD 2002). These analyses typically contain an estimate of monetized benefits and costs of options under consideration. They may also discuss how these benefits and costs are distributed across various subgroups, economic sectors, or regions. In the U.S. various Executive Orders (EO) require some distributional analysis (e.g., EO 13045 addresses children's health, EO 13211 addresses energy issues). Relevant to this discussion, EO 12898, *Federal Actions to Address Environmental Justice in Minority Population and Low-Income Populations*, requires federal agencies to address disproportionately high and adverse human health or environmental effects on minority populations and low-income populations (Federal Register 1994). To date, however, implementation of EO 12898 has been slow and inconsistent (see GAO 2005, 2007 for critiques of U.S. Environmental Protection Agency (EPA) implementation).

To be useful in the policy-making process, distributional analysis should facilitate the ranking of alternative outcomes. Such rankings are inherently normative, and thus should reflect the views of society as opposed the views of the technical staff preparing the analysis. There is a tradeoff. Purely descriptive analysis such as pollution exposure rates by subgroup may be difficult to digest and interpret in a consistent manner. However, methods for aggregating the data into easily presented rankings have the potential for implicitly reflecting staff value judgments. Ideally, the analysis would be prepared in a manner that is easy to understand yet flexible enough to allow normative judgments to be imposed explicitly.

In addition, for purposes of both decision-making and environmental justice there is a need for consistency and transparency. These concepts are related. Consistency implies that the decision-maker uses a similar framework to make decisions across rules. If a certain distribution of outcomes is preferred to another for one pollutant, then a similar ordering should be preserved for others. For the purposes of EJ, defined by the U.S. EPA to include fair treatment and meaningful involvement, transparency in decision-making is essential (EPA 2010). Interested parties should be able to identify the information and methodology used to make a decision is a way that is clear and accessible. In identifying methods for use in EJ analysis for regulatory policy we are cognizant of the need for both consistency and transparency.

The economics literature has generally had one of two objectives with respect to EJ analysis: to understand whether vulnerable population subgroups (typically defined by race or income) have borne a disproportionate adverse environmental impact or to understand the distributional impact of environmental policy by subgroup. Strategies to achieve the first objective have two components: to find an association between impacts and subgroups and to identify causality. A first step, for example would be to see if vulnerable groups are located in highly polluted areas. If so, the next step might be to determine whether pollution sources located near existing communities, or whether members of vulnerable groups locate near existing sources (see, for example, Been 1994; Been and Gupta 1997; Wolverton 2009).

The second objective typically takes a retrospective look at a policy (such as emissions trading) to determine how it affects different subgroups. A key challenge for this type of analysis is to specify an appropriate counterfactual scenario. In order to know the impact of a policy, one must make an assumption about what the environmental impacts would have been in its absence, all else equal (see Shadbegian, et al. 2007).

Regulatory analysis has a different objective, however. Whether by court order, legislative mandate, citizen petition, etc. a regulatory body such as the U.S. EPA is given a fairly general mandate to control emissions of a particular pollutant, with many implementation options left to the discretion of the agency. In the context of evaluating the relative merits of various options, EJ concerns raise three crucial questions: what is the baseline distribution of the pollutant across subpopulations of interest, what is the projected distribution under each option under consideration, and how might one rank the desirability of the alternate distributions (Maguire and Sheriff 2011).

The statistical tools used in the academic literature are limited in their ability to address these three questions. The primary tool for evaluating the existence of an environmental justice is regression analysis in which emissions or probability of being exposed to emissions is regressed on demographic characteristics and other explanatory variables. Alternatively, at the simplest level, one can calculate correlation or Spearman rank correlation coefficients. Although this type of analysis can be informative about baseline conditions, it offers little in the way of prediction regarding potential regulatory options. Pearson correlation measures the degree to which the relationship can be explained using a linear function, not the strength (slope) of the relationship. Spearman correlation measures the degree to which the relationship can be explained using a monotonic function, not the strength of the relationship. A ranking based on these measures would imply social preferences based on noise rather than pollution exposure since steep relationship with a little noise has lower value than a flat relationship with no noise.

Regressions often use demographic variables such as percent minority in a census block group to predict environmental outcomes such as emissions, ambient pollution levels, or probability of being within a given distance of a pollution source. Regressions have generally been run on data from historic programs. For prospective regulatory analysis, they would need to be run on data generated from pollution dispersion models. It is unclear how to formulate statistical inference from this type of data.

Even ignoring this issue, information generated from this type of regression may be useful, but is not a welfare measure and is problematic for ranking outcomes. As opposed to simple correlations, regressions indicate the strength of a relationship, not just the direction. Caution should be used however, in interpreting the results. If one option weakens the relationship between percent minority and pollution, does this mean that it is better from an EJ standpoint? Not necessarily, since percentages mask the absolute number of people in each geographic unit. In addition, high variance in outcomes for a particular group will tend to drive up standard errors, reducing the likelihood of finding statistically significant effects. However, such variance may be due to hot spots that could be indicative of a potential EJ problem. Pollution, for example, may be highly concentrated in a subset of minority neighborhoods, with the rest having relatively low levels. Such a distribution might be more problematic than a slightly higher average exposure with little variation.

An alternative approach compares the distributions of environmental outcomes across populations under alternative control scenarios including the baseline. From this perspective, for any given level of the total outcome one might posit that the ideal distribution is for every individual to have an identical share of the total. The objective of comparing alternative scenarios is to provide a mechanism by which a policy maker can rank the distributions of policies that fail to meet this ideal.

A similar ranking problem has been faced in the development and public finance literature in the context of comparing distributions of income. Since the 1970s, a rich theoretical literature has described the properties of ethical index numbers (cite). This approach begins with an assumption of individual utility functions that are increasing and convex in the good being analyzed, and independent of all other characteristics. A simple utilitarian social welfare function ranks distributions of the good across the population. Seminal results in this literature have shown that any ranking system involves the implicit choice of a social evaluation function. Since one cannot pursue this line of analysis without making a normative judgment regarding this choice, it is important to choose a set of social preferences that has sensible properties, as we discuss below.

Recently, the public health literature has started to use ethical index numbers to evaluate environmental policy outcomes (cite). This literature has used inequality indices, particularly the Atkinson index, to rank distributions of pollution. It has, however, largely ignored the welfare theory underpinning these measures. Although the Atkinson index has a number of properties that are desirable for environmental justice analysis, particularly its ability to be decomposed into population subgroups, it is not well suited for analyzing distributions of adverse outcomes. Since many environmental outcomes of interest (e.g., emissions, ambient pollution levels, health risk) are “bads”, this use of index numbers implicitly adopts perverse social preferences such that, all else equal, outcomes with more pollution are more highly ranked.

Here, recognizing both the potential usefulness of ethical index numbers as a tool for environmental justice analysis and the potential for their misuse, we suggest use of the Kolm-Pollak family of inequality index, and its associated social evaluation function. Although it has a well-developed theoretical pedigree, this index has been largely ignored in the applied income distribution literature. The Kolm-Pollak index shares the key desirable properties of the Atkinson index, but easily accommodates bad outcome variables, like pollution.

In the next section we discuss in greater detail the theoretical implications of using inequality indices to analyze distributions of bad environmental outcomes focusing on the Atkinson and Kolm-Pollak indices. Next we use the Kolm-Pollak index to evaluate the environmental justice implications of the SO_2 trading program and Heavy Duty Diesel rule.

II. Inequality Indices

An inequality index is a function that translates distributions into a single number. To narrow the field of potential index numbers, researchers have developed a number of useful properties with which to classify them. This axiomatic approach to choosing an appropriate index number begins by selecting a set of desirable properties, then identifying aggregator functions that satisfy them. Some commonly used properties are:[1]

1. *Relative Measure.* Multiplying the outcome variable of all individuals by the same factor does not affect the index value.

[1] Kom (1976a) and Kolm (1976b), among others, provide a detailed treatment of axioms 1-6. Blackorby and Donaldson (1978) and Blackorby and Donaldson (1980) provide a detailed treatment of axiom 7.

2. *Absolute Measure.* Adding the same amount to the outcome variable of all individuals does not affect the index value.

3. *Normalization.* Index equal to zero implies perfect equality.

4. *Transfer Principle.* The inequality index does not increase as a unit of the outcome variable is transferred away from one individual towards another with a lower-valued outcome.

5. *Diminishing Transfer Principle.* A transfer of a unit of a good (bad) outcome between two individuals who have relatively low amounts of the good (bad) affects the index value more (less) than the transfer among two individuals who are the same distance apart, but higher in the distribution.

6. *Welfare Independence.* Society's willingness to trade an increase in one individual's outcome for a decrease in another's does not depend on the unchanged outcome level of a third individual.

7. *Impartiality.* No variable besides the outcome of interest affects the value of the index.

8. *Consistency in Aggregation.* An inequality index can be used to analyze subpopulations such that social evaluations made using the entire population arrive at the same result as those made applying the same preference structure to the collection of sub-populations.

Relative indices are convenient for analyses of income distributions across countries or time since one does not have to account for exchange rates or inflation. As argued by Kolm (1976a), however, relative indexes can be misleading. Suppose the income of both members of a population of two individuals doubles. If prices do not change the difference in purchasing power between the two would also double, thus suggesting that the new distribution is less equal. An absolute inequality index would increase to reflect this change, while relative index would not.

The transfer principle is a fundamental requirement for an inequality index. It states that increasing the dispersion of the outcome across the population should increase the measure of inequality. The diminishing transfer principle is an extension that incorporates the normative belief that an inequality index should be more sensitive to changes in the allocations of people who are less well-off, or in the case of pollution, those who have greater exposure.

The intuition behind welfare independence can be most easily understood in the case of a simple transfer that does not change the average outcome variable for a population. This property implies that the change in the index number arising from a transfer between two individuals is not affected by the distribution of the outcome variables for the rest of the population.

Impartiality means that all individuals are treated symmetrically in calculating the inequality index, regardless of other attributes besides the outcome of interest. Note that this property does not preclude analysis of sub-populations differentiated by such attributes. For example, one could calculate an impartial inequality index for an entire population in which race does not affect the value, and one could re-calculate the same index for various sup-populations.

Finally, for the purposes of EJ analysis we add a final property that the index should accommodate a ranking of "bad" outcomes, such as pollution, whereby those who are most exposed receive greater weight than those with less exposure.

Any ranking system such as an inequality index implicitly relies upon a social evaluation function. Determining that distribution A is less equal than B and consequently A is preferred to B, all else equal, is tantamount to determining that the social welfare generated by distribution A is greater than that generated by B, according to some social evaluation function.

Some orderings require little structure from the social evaluation function. Holding mean outcomes constant for example, the Lorenz partial ordering is consistent with any social evaluation function that is the sum of utility functions that are increasing and concave in the outcome variable (Atkinson 1970). Blackorby and Donaldson (1978, 1980) show how to recover an explicit representation of the social evaluation functions associated with inequality indices that satisfy axioms 1 and 4 and either 2 or 3. The equally distributed equivalent (EDE) value of a distribution is the amount of the outcome variable which, if given equally to every individual in the population, would leave society just as well off as the actual distribution. The EDE thus embodies a set of social and individual preferences and is a measure of social welfare. It also enables rankings of distributions with different means.

The concept of the EDE value is also useful for purposes of analyzing inequality by population subgroups (based on race, income, etc.). Axiom 8 requires that the EDE calculated for the entire population yields the same result as the EDE calculated on the basis of the EDEs of each subgroup (Blackorby and Donaldson 1978, 1980). This property ensures that the same set of preferences is used to rank subpopulations as ranking an entire population. It also guarantees that total inequality for a population can be completely decomposed into within and between group inequalities. Satisfaction of this property is thus necessary for many aspects of EJ analysis where consideration of sub-groups, specifically those defined by race, ethnicity or income categories is important.

Some authors (e.g., Levy, et al. 2007) have advocated presenting inequality indices alongside average outcomes so as not to impose normative assumptions on the efficiency-equity tradeoff. This approach does not avoid the imposition of the analyst's preferences, however, it only encourages the use of logically inconsistent preferences. By using a given inequality index to rank distributions with the same mean, one has already adopted a normative position that implies a specific ranking of distributions with different means. Put another way, if one does not like the ranking of distributions with different means implied by the social evaluation function associated with a given index, one should not be using that index as a measure of inequality in the first place. Kaplow (2005) goes so far as to argue that inequality indices are not particularly useful for comparing distributions with different means; instead all comparisons should be based on the underlying social evaluation function.

Although the EDE may be sufficient for ex post comparisons of total distributions, inequality indices can be useful in the policy-design process. Such information can potentially be of value for fine-tuning policy instruments. Knowing that a particular option results in large average gains with a regressive distribution, for example, may provide a signal to look for ways of modifying the policy to make it more equitable. Such information would be lost by focusing purely on the EDE.

Similarly, with respect to EJ analysis, it can be informative to decompose an inequality index by population subgroups. The index allows the analyst to determine whether a welfare change for a subgroup is due to a change in average outcomes or their distribution. The index may also be useful in identifying the potential for “hotspots” in a subgroup of interest. In principle, this type of information should be directly embedded into a well-specified social welfare function. Due to the technical difficulty of developing an index that does not satisfy impartiality, however, such an approach is not currently feasible.

Within the class of relative indices, Kolm 1976a and Blackorby and Donaldson 1978 show that the Atkinson family of indexes is the only one that satisfies axioms 3-8. Similarly, Kolm (1976a) and Blackorby and Donaldson (1980) show that the Kolm-Pollak family of indexes is the only one that satisfies all other axioms except 1. Consequently, for the rest of this discussion, we focus on these two types of inequality indexes.[2]

Atkinson Index The Atkinson index, I_A, is defined as:

1)
$$I_A = \begin{cases} 1 - \left[\frac{1}{N}\sum_{n=1}^{N}\left[\frac{x_n}{\mu}\right]^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}, \varepsilon > 0, \varepsilon \neq 1 \\ 1 - \prod_{n=1}^{N}\left[\frac{x_n}{\mu}\right]^{\frac{1}{N}}, \varepsilon = 1 \end{cases}$$

Throughout the paper, we employ the notation that N is the population, x_n, is the outcome for individual $n = 1, \ldots, N$, and μ is the mean outcome. For convenience, we suppose that individuals have been ranked such that $x_1 \leq x_2 \leq \cdots \leq x_N$. Atkinson 1970 derived this index based on the underlying assumption that individual preferences are consistent with a utility function that is increasing and concave in the outcome variable and exhibits constant relative risk aversion, $U(x) = A + Bx^{1-\varepsilon}/[1-\varepsilon]$ (with A and B being positive constants). The (constant) elasticity of the marginal social value placed on increasing the outcome variable for any given individual is $-\varepsilon$.

The parameter ε is commonly referred to as the inequality aversion parameter. It allows the analyst to specify the amount society is willing to trade a reduction in the

[2] For a discussion of other index numbers in the context of income distribution, see Chakravarty (1990), in the context of environmental outcomes, see Levy, et al. (2006).

outcome variable for one individual for an increase for another. A value of zero implies that society is indifferent between transfers among any two individuals. The higher the parameter's value, the more weight society places on transfers to individuals with lower outcomes. Since the choice of parameter value is entirely normative, it is common to calculate Atkinson indexes for several values in order to determine how sensitive rankings are to the choice.

It is important to stress that x is a *desirable* outcome variable. The EDE of the Atkinson index for $\varepsilon \neq 0$, as indicated above, is increasing in x. The Atkinson index takes a value between zero and unity (with the interpretation as the percent reduction in a good that society would be willing to give up in order to have a perfectly equal distribution of the rest) since the EDE is necessarily lower than the mean. In contrast, if x were a bad, the EDE would be higher than the mean.

Another consequence of incorrectly using the Atkinson index to measure the distribution of bad outcomes is that the index would violate the diminishing transfers principle since greater weight is placed upon the most well off individuals (those with low outcomes), rather than the worst off.

The Atkinson Index is generally not defined for negative numbers, thus precluding a simple redefinition of bads in that way.[3] Transforming a bad into a good by replacing it with its complement (e.g., parts per billion of an ambient pollutant to parts per billion of "clean" air) may have the undesirable result of rendering an index value so small as to be within rounding error. To put this in perspective, consider the income distribution of a society of billionaires who differed in wealth by only a few dollars. It

[3] Even for examples in which negative values are defined, (Blackorby and Donaldson 1982) show that the Atkinson index generates the perverse result that a progressive redistribution reduces social welfare.

would be almost perfectly equal, with the value of the corresponding Atkinson Index being extremely close to zero. Note that this does not mean that the distributional effects are insignificant. If the good were clean air or probability of not dying from cancer the percent reduction society would be willing to give up for an equal distribution might be quite small, but the value of that reduction might be significant. Nonetheless, presenting the results in a manner such that a regulation changes the Atkinson Index by a miniscule amount may not be informative.[4] This approach also cannot be used if the outcome variable is emissions (e.g., there is no natural complement for tons of SO_2.)

The Atkinson index is commonly used in income distribution analysis and it has recently been used to measure environmental or health outcomes. Waters (2000) used an Atkinson index to analyze distribution of access to health care in Ecuador. Levy, et al. (2007) use the Atkinson Index to evaluate the distribution of mortality risk resulting from alternative power plant air pollution control strategies in the United States. Levy, et al. (2009) use the Atkinson index to analyze reduction in mortality risk from particulate matter reductions from regulating transportation. Fann, et al. (2011) use the Atkinson index to evaluate the distributional impacts of a multi-pollutant air quality regulatory strategy in Detroit. Since the latter three studies used an Atkinson index to measure distributions of bad outcomes, the reported policy rankings are questionable due to their reliance on social preferences that are not well behaved.

Kolm-Pollak index The Kolm-Pollak index, I_K is defined as:

$$I_K = \begin{cases} \frac{1}{\varepsilon} ln \frac{1}{N} \sum_{n=1}^{N} e^{\varepsilon[\mu - x_n]}, \varepsilon > 0 \\ 0, \varepsilon = 0 \end{cases} \tag{2}$$

[4] Some authors (e.g., Levy, et al., 2009, Fann, et al. 2011) have tried to address this problem by replacing a bad outcome variable with its reciprocal. Unfortunately, this approach implies a utility function that is not generally concave in the original outcome variable (e.g., pollution) of interest.

As shown by Blackorby and Donaldson (1980), using this index to rank outcomes is consistent with the utility function developed by Pollak (1971), $U(x) = -e^{-\varepsilon x}$. As with the Atkinson index, ε can be interpreted as an inequality aversion parameter. For the Kolm-Pollak index, the elasticity of marginal social welfare with respect to a change in an individual's allocation is $-\varepsilon x$. Unlike the Atkinson index, this elasticity varies with the outcome variable. Consequently, the inequality aversion parameter needs to be appropriately scaled in order to maintain comparability across different units of measurement. Atkinson and Brandolini (2010) suggest choosing ε such that a desired elasticity is achieved for the mean outcome level.

Since this utility function is increasing and concave in x, it is equally inappropriate to use index values generated from undesirable outcomes with this measure as it is with the Atkinson measure. In contrast with the Atkinson index, however, the Kolm-Pollak index readily accommodates bad outcomes if one simply subtracts them from some arbitrary benchmark value. Such an operation preserves the appropriate welfare ranking and is equivalent to measuring the distribution of a complementary "good." The property of an absolute index that adding the same amount to everyone in the population does not change the value of the index helps in this regard since it ensures that the value of the index is independent of the benchmark.

III. Demonstration: SO_2 Trading Program

The Kolm-Pollak index has been seldom used in the context of income distribution analysis (exceptions include Blackorby, et al. 1981; Atkinson and Brandolini 2010). To our knowledge, it has not been used to evaluate distributions of environmental outcomes. Here we provide an illustration using data from actual and counterfactual sulfur-dioxide

(SO_2) emissions from 1995. The counterfactual emissions data were originally generated by Ellerman, et al. (1997). Shadbegian, et al. 2007 combined the emissions information with demographic data from the U.S. Census to conduct an environmental justice (EJ) analysis.

Here we extend the Shadbegian, et al. (2007) analysis using a Kolm-Pollak index and EDE to describe the effect of the two policy alternatives (command-and-control and cap-and-trade) on population subgroups divided by race and income.

The emissions data are tons of SO_2 from power plants under two scenarios: the observed cap-and-trade policy and a hypothetical continuance of previous command-and-control (CAC) regulation. These data are combined with Census demographic information on surrounding communities at a 25-mile radius.

There are several shortcomings involved in using this type of data. First, SO_2 is not the outcome of interest to the populations affected. SO_2 acts as a precursor to particulate matter, which in turn causes a number of adverse health effects. Ideally, we would be analyzing the distribution of these pollution-induced health impacts. Second, we have demographic information for communities surrounding sources, whereas ideally we would have ambient pollution levels for the communities. If a single community is affected by multiple sources, then this cumulative impact would not be reflected in this data. Third, using a 25-mile radius is unlikely to reflect the true dispersion of the pollutant. Ideally we would use a more sophisticated model that would take factors such as weather conditions, wind direction, and smokestack height into account.

Together, these caveats suggest that the results presented here are at best a very crude proxy of actual EJ impacts. Nonetheless, the data do present the opportunity to conduct a useful proof-of-concept of how an EJ analysis might be conducted using the Kolm-Pollak methodology.

We begin with a generalized Lorenz curve, *GL*, depicting cumulative emissions by population percentile using the formula (Shorrocks 1983):

3) $$GL\left(x, \frac{k}{N}\right) = \sum_{n=1}^{N} x_n$$

Figure 1a presents the generalized Lorenz curves for the entire population, where pollution is arrayed as it would be if it were treated as a good, from the least exposed to the most exposed. As depicted, the baseline curve dominates the trading curve (where the closer a curve is to the 45 degree line the greater the equality), which we attribute to the counter-intuitive ordering of the data. When we multiple pollution by -1 to show pollution as a "bad" we get the opposite result, as shown in Figure 1b. The trading *GL* curve dominates (lies completely above) the CAC curve. This dominance indicates that for a large set of social welfare functions, society prefers the outcomes generated by trading. This ranking is affected by both the average outcome and the distribution of outcomes.

From the generalized Lorenz curve it is useful to derive the traditional (relative) Lorenz curve and the absolute Lorenz curve (Moyes 1987) in order to separate the distributional effects of the two policy options from their average effects. The former divides each x_n in Equation 3 above by μ, while the latter subtracts the mean from each x_n. As shown in Figure 2, the two approaches yield strikingly different implications. Relative Lorenz curves have the intuitive interpretation of illustrating what percent of the total allocation of the outcome variable belongs to a given percentile of the population. Note that unlike relative Lorenz curves for a good, the relative curves for a bad are concave. The 45 degree line represents perfect equality. Since the distribution is ranked in order of increasing welfare, the people at the bottom have relatively more of the bad than people at the top. The relative Lorenz curves for the two policies are virtually indistinguishable from each other. This similarity reflects the fact that the two distributions are close to proportionate to each other. In addition, the curves show that no policy Lorenz dominates the other with respect to equity of distribution, since the two curves cross for every subpopulation.

The absolute Lorenz curves in Figure 3 have the interpretation of indicating the average amount of pollution that would need to be taken away from an individual belonging to a given percentile in order to bring his exposure to the population mean. In contrast, the absolute Lorenz curves show clear differences between the two policies for every subgroup. Moreover, the two policy curves never cross, allowing one to rank the trading policy above CAC in terms of absolute Lorenz dominance for every subpopulation in terms of distributional equity. This dominance reflects the fact that if the trading policy induces a proportional shift downwards in the distribution, then the worse off (those with the highest pollution exposure under CAC) are the ones who receive the greatest benefits in terms of tons of SO_2 reduction.

Now turning to the indices, Table 1 presents three ways of ranking the two pollution control regimes by population subgroups using the Atkinson Index. The first two columns compare the average pollution emissions for each regime. Trading results in a steep decline in emissions for all groups. For the entire population, emissions fall by 18 thousand tons per capita. By subgroup, people below the poverty line had the highest emissions under CAC and experienced the largest average drop from trading, 22 thousand tons. Each other subgroup had a drop of about 19 thousand tons.

In distributional terms, trading resulted in a more equitable distribution for the population as a whole as well as within most subgroups, as indicated by the third and fourth columns in Table 1. The non-white subgroup had the most equitable distribution of emissions under CAC, while the poor had the least equitable. The white and subgroups had the biggest improvement in equity, albeit the changes are virtually indistinguishable. We attribute this result to the fact that the index is giving more weight to transfers among those who are relatively well off to begin with (i.e., have less pollution).

Turning to Table 2, we use these same data to demonstrate the Kolm-Pollak Index. The first two columns are identical to Table 1 showing the mean exposure rates under the two scenarios. In order to calculate the Kolm-Pollak index we multiple emissions by -1 to account for the fact that pollution is a bad. The results for the index are in the third and fourth columns of Table 2. Here we see a more dramatic change in equality between the CAC and trading scenarios. Emissions are distributed much more equitably under the trade scenario for the entire population as well as each sub-group. Combining mean and distributional effects, the EDE shows large improvements in overall welfare attributable to trading. Overall, equivalent emissions fell from 76 to 41 thousand tons per capita in the trade scenario.

The inter-group inequality measure (i.e., between race and between income measures) answers the following question (Blackorby et al. 1981): "How much additional emissions per capita would society be willing to tolerate to move from a distribution in which each member of each population subgroup received its respective *intra*group EDE, to one in which every individual received the EDE for the entire population?"

Let K be the number of mutually exclusive subgroups, indexed by k, with N_k denoting the population of subgroup k, θ_k denoting its EDE, and θ denoting the total EDE. The answer is the weighted sum of subgroup EDEs less the total EDE:

4) $$I_{inter} = \frac{1}{N}\sum_{k=1}^{K} N_k\theta_k - \theta$$

Comparisons of inter-group distributional equity show that trading reduced existing disparities between groups. Even under command and control, between group inequality is small compared to within group measures. This result is unsurprising given that the white and non-poor subgroups are respectively about six and eight times as large as their complementary subgroups. Consequently, the weighted average in Equation 4 is dominated by the EDE for the relatively large subgroups, which in turn is close to the total population EDE. Nonetheless, by this measure intergroup inequality was virtually eliminated by the trading mechanism.

IV. Demonstration: Heavy Duty Diesel Rule

We provide a second demonstration of the Kolm-Pollak index using data from EPA's Heavy-Duty Engine and Vehicle Standards and Highway Diesel Fuel Sulfur Control Requirements (HDD) Rule (U.S. EPA 2000). This rule placed requirements on engines and fuel standards for heavy-duty engines and vehicles to reduce the harmful effects associated with ozone, particulate matter, and other pollutants.[5]

[5] It is important to note that this is a demonstration analysis only; EPA is not revisiting this rule. In addition, the air quality modeling data used in this rule reflect the emissions inventory at the time the rule was written (2000) and do not reflect the current emissions inventory. In addition, the modeling platform EPA uses to estimate changes in air quality has been updated since this rule was published.

For this analysis we have data on demographic data for over 47,000 12x12 kilometer grid cells across the U.S. The air quality modeling is conducted for 36x36 kilometer grid cells over which the demographic data are layered.[6] Grid cells vary greatly in terms of population size, ranging from 0 to over 2 million people in more densely populated areas. For each grid cell we have the baseline and control scenario fine particulate matter (i.e., $PM_{2.5}$) concentrations for the year 2030 as predicted by the modeling results. In addition, we have information on the percent living below the poverty line, the percent Black, White, Asian and Native American, as well as the percent Hispanic in each grid cell. For this analysis we are able to calculate exposure for each sub-group under the baseline scenario as well as the predicted changes to the HDD rule for 2030.[7]

Figure 4 shows the GL for the entire population, with the pollutant depicted in ascending order (i.e., least to most exposed). As with the SO*2* analysis we find that the baseline scenario dominates the control, a result we attribute to the counter-intuitive ordering of pollution.

Next we turn to the Kolm-Pollak index. Table 3 provides the results for the baseline and control scenarios for the entire population as well as sub-groups of interest. We see that average exposures are reduced for the total population under the control scenario, as well as for each sub-group. Exposures decrease by 0.65 micrograms per cubic meter per capita for the entire population. We also see that exposures are greatest for non-whites and the non-poor sub-groups.

[6] The use of grid cell information to examine near-roadway impacts may not be appropriate because the modeling data are likely to imprecise at this level of geographic detail. Therefore, results should be interpreted as a demonstration only.

[7] We present a more limited set of results for the HDD analysis due to time constraints; future work will incorporate a more complete analysis.

Equality also improves for the total population and all sub-groups under the control scenario. PM2.5 is distributed most equally for the White and non-poor sub-groups, although there are greater improvements in equality for the non-White and poor groups. Between race equality improves, but is much higher than the equality across income groups, which is relatively insignificant. The EDE shows that across the entire population 15 micrograms per cubic meter (mg/m^3) per capita of PM2.5 would result in an equal distribution, as compared to the average in the control scenario of 14.09 mg/m^3.

V. Concluding Thoughts

Introducing quantitative tools for examining distributional effects in environmental regulatory analysis is important in order to respond to E.O. requirements, specifically, E.O. 12898 (Federal Register 1994), but also to provide information to the public. While economists have very clear, consistent methods for examining efficiency, less attention has been paid to distributional analysis. The purpose of this paper is to introduce one method for incorporating distribution into regulatory analysis through the use of inequality indices. Such indices have long been used to examine income inequality, but have only recently been used in the public health and environmental fields.

We explore the properties and underlying social evaluation function for two indices, the Atkinson Index and Kolm-Pollak index. The former has long been used in both literatures mentioned above, but violates a key property necessary for environmental regulatory analysis, accommodating "bad" outcomes. Because the underlying social evaluation function for the Atkinson Index assumes that distribution of the good among those with less of it (which is intuitively appealing when discussing income) is preferred, results using this index for the distribution of a bad (where those with less, like pollution, are actually better off) are suspect. The Kolm-Pollak index, while rarely used in empirical analysis is able to accommodate distributions of “bads.”

We demonstrate the Kolm-Pollak index using two regulatory scenarios: the SO_2 trading program and the HDD rule. In both cases we find intuitive results that comport with the regulatory improvements made for both pollutants. In addition, the index provides a way to rank various sub-groups and scenarios according to the distributional outcomes, information that may be useful to both the decision-maker and the public. We stress, however, that the results from these analyses are for demonstration purposes only.

Future research is needed to more fully explore the theoretical and empirical properties of the Kolm-Pollak index under these and other regulatory scenarios. In particular we will further decompose our race sub-groups into the component parts (i.e., Black, White, Asian and Native American, for the HDD rule). This work appears promising for providing transparent, consistent, scientifically appropriate information for both decision-makers and the public regarding the distributional effects of environmental regulations.

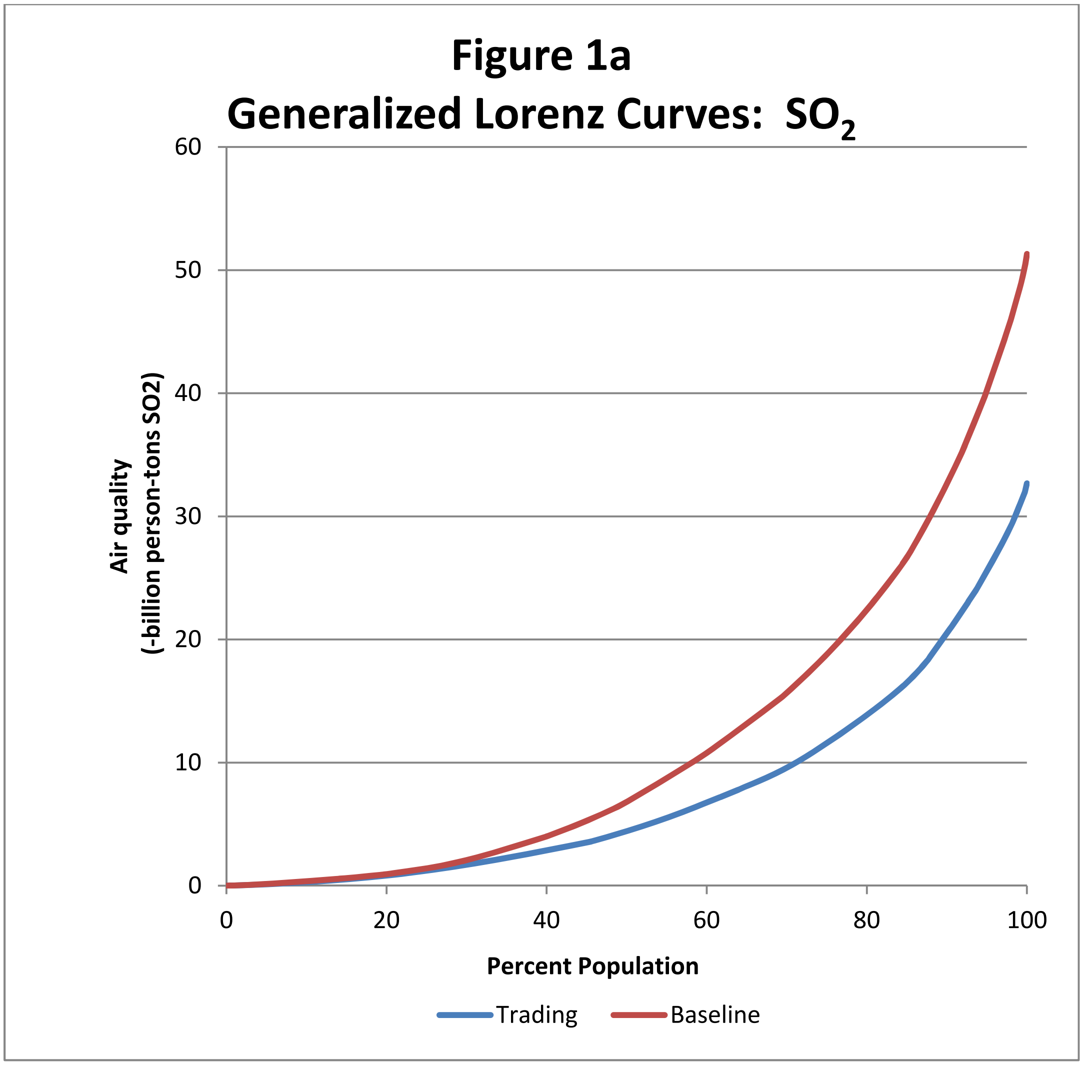
Figure 1a
Generalized Lorenz Curves: SO_2
Air quality
(-billion person-tons SO2)
60
50
40
30
20
10
0
0
20
40
60
80
100
Percent Population
Trading
Baseline

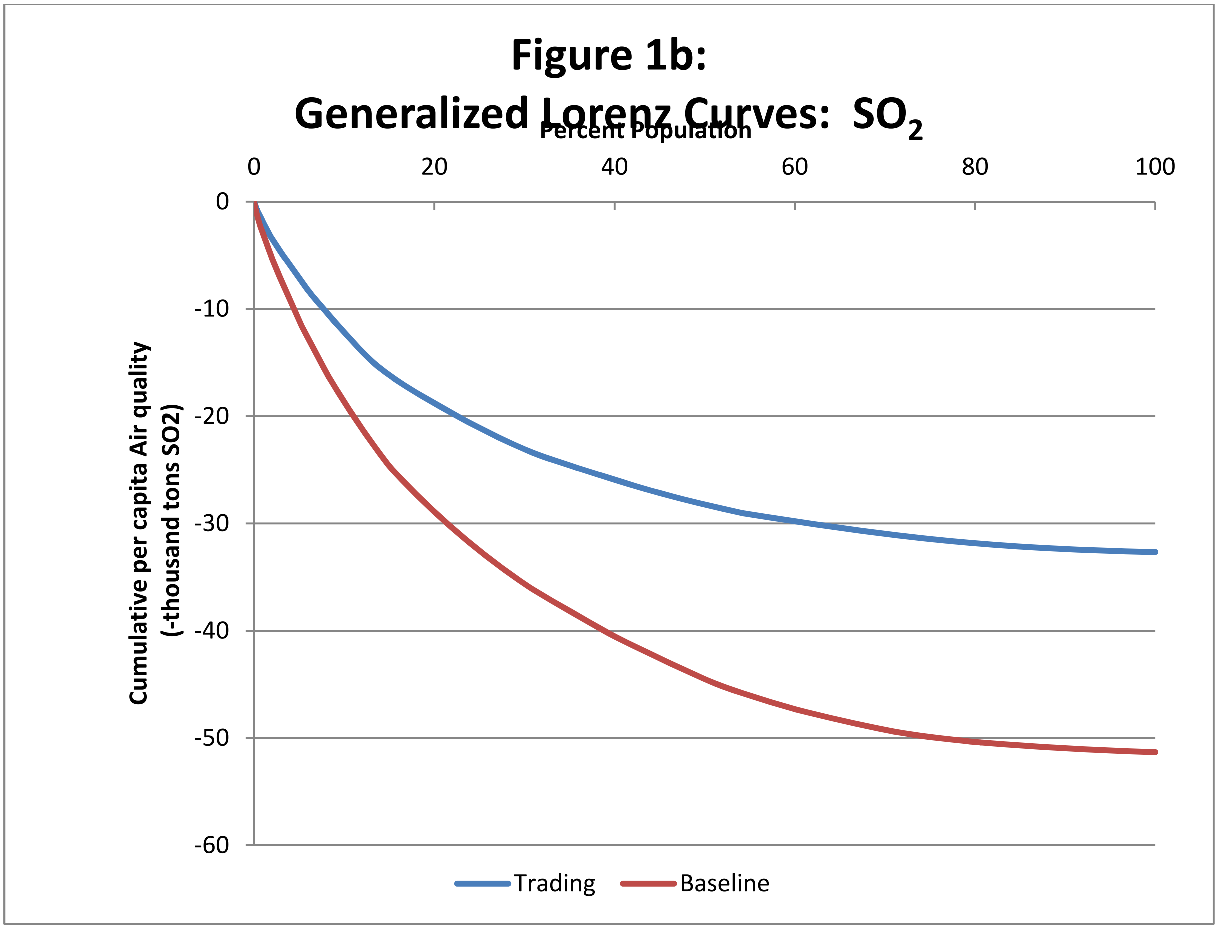
Figure 1b:
Generalized Lorenz Curves: SO_2
Percent Population
0
20
40
60
80
100
0
-10
-20
-30
-40
-50
-60
Cumulative per capita Air quality
(-thousand tons SO2)
Trading
Baseline

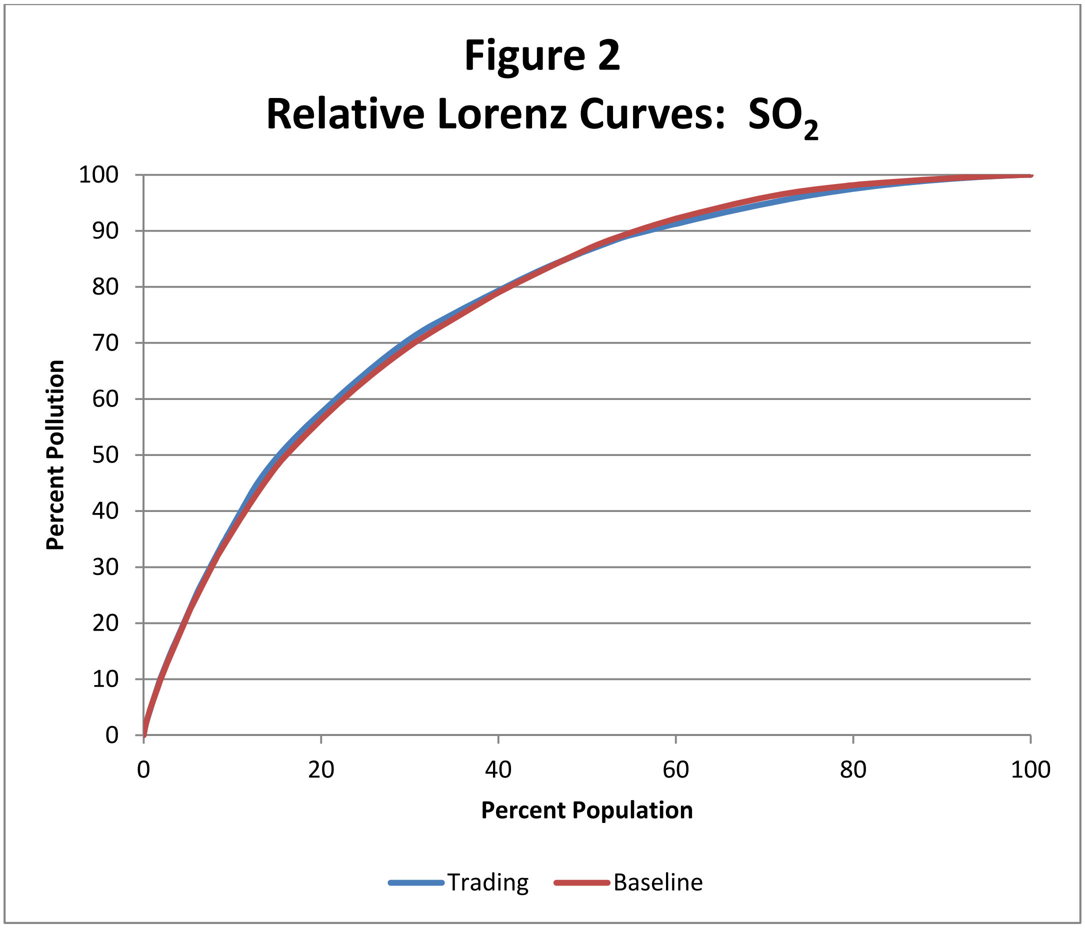
Figure 2
Relative Lorenz Curves: SO_2
100
90
80
70
60
50
40
30
20
10
0
Percent Pollution
0
20
40
60
80
100
Percent Population
Trading
Baseline

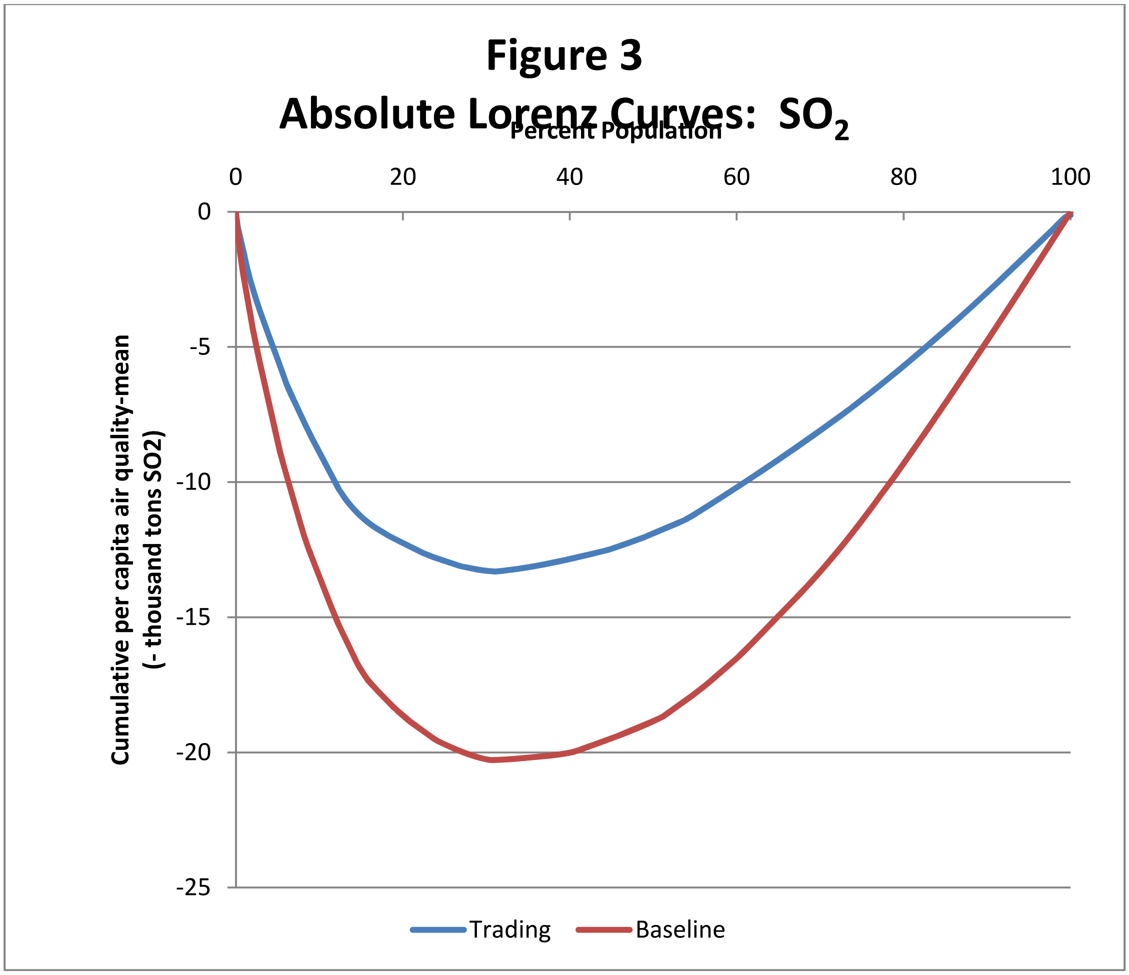
Figure 3
Absolute Lorenz Curves: SO2
Percent Population
0
20
40
60
80
100
0
-5
-10
-15
-20
-25
Cumulative per capita air quality-mean
(- thousand tons SO2)
Trading
Baseline

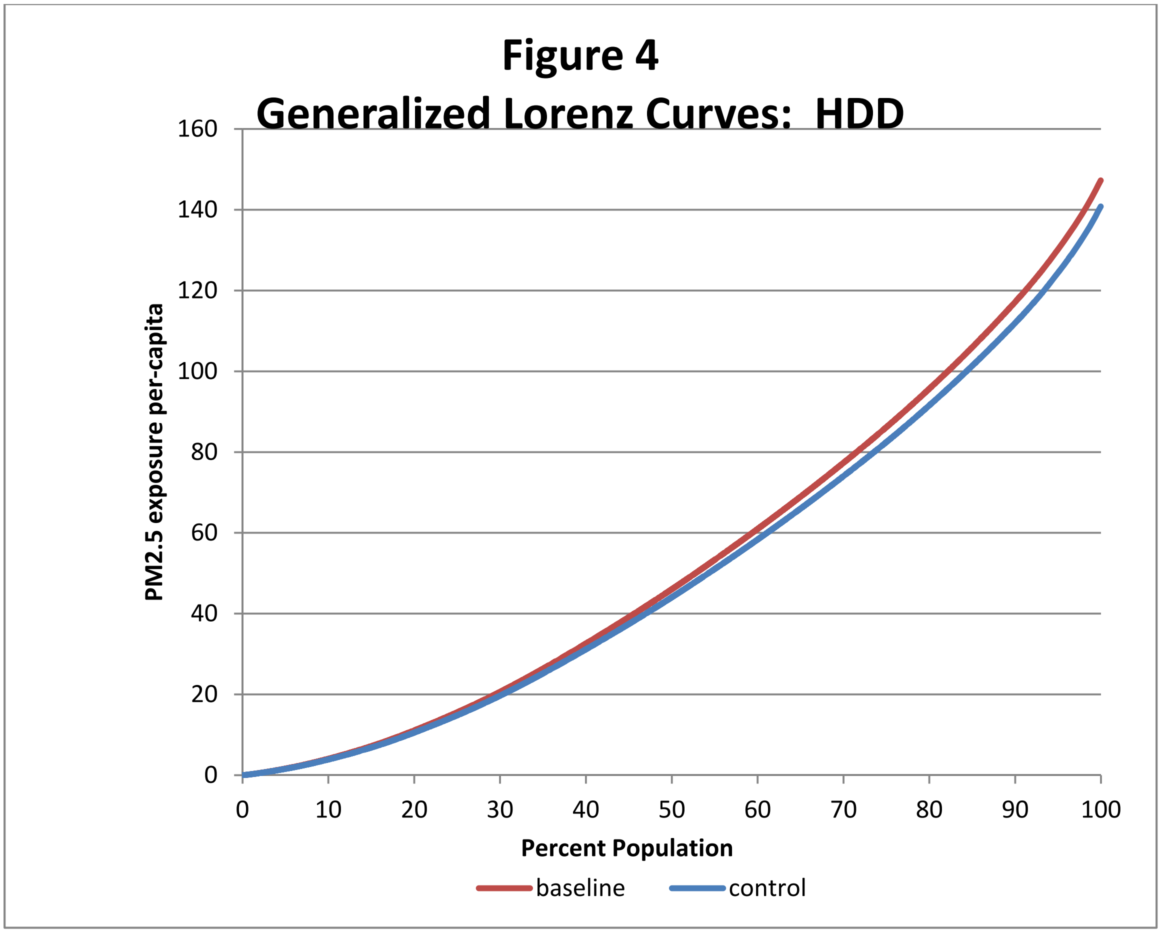
Figure 4
Generalized Lorenz Curves: HDD
PM2.5 exposure per-capita
160
140
120
100
80
60
40
20
0
0
10
20
30
40
50
60
70
80
90
100
Percent Population
baseline
control

Table 1: Atkinson Index (1000 tons SO2 per capita) Epsilon = 0.5						
	Mean		**Index**		**EDE**	
Sub-group	**CAC**	**Trade**	**CAC**	**Trade**	**CAC**	**Trade**
Total	51	33	0.24	0.23	39	25
White	52	33	0.25	0.24	39	25
Non-white	50	31	0.19	0.20	41	25
Non-poor	51	32	0.24	0.24	39	25
Poor	56	34	0.23	0.22	43	27
Between Race			0.00008	0.000002		
Between income			0.0003	0.0001		

Table 2: Kolm-Pollak Index (1000 tons SO_2 per capita) Epsilon = 0.5/51						
	Mean		**Index**		**EDE**	
Sub-group	**CAC**	**Trade**	**CAC**	**Trade**	**CAC**	**Trade**
Total	51	33	25	9	76	41
White	52	33	27	9	78	42
Non-white	50	31	13	6	63	38
Non-poor	51	32	24	9	75	41
Poor	56	34	30	9	86	43
Between Race			0.14	0.01		
Between income			0.07	0.001		

Table 3: Kolm-Pollak Index (mg/m^3 $PM_{2.5}$ per capita) Epsilon = 0.5/15						
	Mean		**Index**		**EDE**	
Sub-group	**Base**	**Control**	**Base**	**Control**	**Base**	**Control**
Total	14.74	14.09	0.99	0.91	15.73	15.00
White	13.98	13.37	0.88	0.80	14.86	13.37
Non-white	17.38	16.61	1.20	1.10	18.58	17.71
Non-poor	14.78	14.13	0.97	0.89	15.75	15.01
Poor	14.46	13.83	1.15	1.06	15.60	14.89
Between Race			4.19	3.99		
Between income			0.00004	0.00003		

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