

# Health Risk, Inequality Indexes, and Environmental Justice

Glenn Sheriff <sup>1,\*</sup> and Kelly B. Maguire<sup>2</sup>

---

Inequality indexes have long been used to analyze distributions of income. Studies have recently begun to use these tools to evaluate the equity of distributions of environmental harm. In response, issues have been raised regarding the appropriateness of using income-based measures in the context of undesirable outcomes. We begin from first principles, identifying a theoretical preference structure under which income-based tools can be appropriate for ranking distributions of “bads.” While some critiques of existing applications are valid, they are not a justification for rejecting the approach altogether. Instead, we show how standard income-based measures can be adjusted to accommodate bad outcomes. Rather than inequality indexes, we argue that equally distributed equivalents (EDEs) are well-suited for this purpose since they account for levels and dispersion of outcome distributions. The Kolm–Pollak EDE is particularly useful, having the advantage of consistently evaluating both bads and their complementary goods (e.g., mortality risk and survival probability). As an illustration, we show how these tools can inform an environmental justice analysis of a proposed Environmental Protection Agency (EPA) rule addressing indoor air pollution.

---

**KEY WORDS:** Distributional analysis; environmental justice; indoor air pollution; inequality indexes

Environmental justice (EJ) refers to a concern that environmental harm is distributed in a manner that disproportionately affects vulnerable demographic groups, typically defined on the basis of race or income. This decades-old concept (United Church of Christ, 1987) has long been an element of U.S. policy (Clinton, 1994). The practical challenge remains, however, of how to quantify policy-induced changes in distributions of environmental outcomes such that a decisionmaker considering various options can objectively identify which is preferable from an EJ perspective (Maguire & Sheriff, 2011).

A recent literature has emerged attempting to fill this gap by using tools developed for evaluating the equity of income distributions for the analysis of distributions of pollution or its implied health impacts. The pioneer in this area is Levy, Chemerynski, and Tuchmann (2006), who consider the merits of several metrics, ultimately recommending the income inequality index developed by Atkinson (1970). The Atkinson index has since been used to evaluate national distributions of mortality risk from power plant and mobile source emissions (Levy, Greco, Melly, & Mukhi, 2009; Levy, Wilson, & Zwack, 2007), a multipollutant risk-based approach to air quality management in Detroit (Fann et al., 2011), ambient NO<sub>2</sub> concentrations (Clark, Millet, & Marshall, 2014), and toxic releases in Maine (Bouvier, 2014). A related literature advocates using welfare weights derived from the Atkinson index to incorporate the monetized value of environmental harm into benefit–cost analysis, effectively placing more value on benefits conferred to low-income people (Farrow, 2011).

<sup>1</sup>School of Politics and Global Studies, Arizona State University, Tempe, AZ, USA.

<sup>2</sup>U.S. Department of Agriculture, Economic Research Service, Washington, DC, USA.

\*Address correspondence to Glenn Sheriff, School of Politics and Global Studies, Arizona State University, P.O. Box 873902, Tempe, AZ 85287-3902, USA; tel: +1 480-727-0708; gsheriff@asu.edu.

In the context of income distributional analysis, a key advantage of the Atkinson index relative to other commonly used income inequality metrics such as the Gini coefficient is that it is *normatively significant* (Blackorby, Bossert, & Donaldson, 1999). That is, one can begin with a sensible well-behaved preference structure and identify the conditions under which one distribution would be more desirable than another based on the Atkinson index values. It is the desirable properties implied by this preference structure that led some to advocate its use in the environmental context (Levy et al., 2006).

Unfortunately, simple substitution of pollution exposure or health risk for income in the formula for the Atkinson index causes the inequality index to lose its desirable normative properties. For example, the Atkinson income inequality index places greater weight on the worse off: people with low values in its argument, income. Fann et al. (2011) recognize that replacing income with something undesirable like health risk places more weight on the better off, those with low risk. Cox (2012) goes further, identifying several shortcomings of the Atkinson index, ultimately concluding that the use of income inequality indexes for purposes of evaluating distributions of health risk is fatally flawed.

We take a more formal approach, first specifying a utility function suitable for evaluating bads (e.g., mortality risk), rather than goods. We then show how this utility function can be used to generate an index of relative inequality analogous to, yet mathematically distinct from, the Atkinson income inequality index. This formulation addresses several of the concerns raised by Cox (2012). Part of the remaining difficulty arises from the fact that while relative inequality indexes have practical advantages in comparing income distributions for populations facing different prices (e.g., from different countries or time periods), these advantages may be liabilities for comparing distributions, for example, exposure to toxic chemicals, in which absolute quantities are meaningful (Harper et al., 2013). In addition, Atkinson-based measures have the undesirable property that they can provide different rank orderings depending on whether an outcome is characterized as a bad or a complementary good (e.g., mortality risk vs. survival probability). To address these issues, we derive an analog of the absolute inequality index proposed by Kolm (1976) that is suitable for evaluating distributions of bad outcomes and is not subject to these two issues.

Although inequality indexes are derived from individual preferences, it is important to recognize that the index values are not normative rankings themselves (Kaplow, 2005). That is, just because a distribution is less equal than another, does not necessarily mean that it is less desirable; total levels are also relevant. Consequently, we advocate use of *equally distributed equivalents* (EDEs) for evaluating distributions. EDEs are derived from the same preference structure as inequality indexes, but take both levels and dispersion into account. The EDE answers the question “What is the level of risk that would make an individual indifferent between a distribution in which everyone received that risk and the actual unequal risk distribution?”

We show how comparisons of EDEs generated by alternative policy options are useful for quantifying the EJ implications of environmental regulations. In particular, they allow the analyst to answer the following questions:

- For a given policy option, did vulnerable demographic groups (e.g., based on income or race) have a worse distribution of a particular environmental risk than the rest of the population?
- Which is the preferred policy option for each demographic group?
- Relative to baseline conditions, which groups benefit most from each option?

The answer to the first question evaluated at baseline levels can be used to provide evidence regarding the presence of a preexisting EJ concern for the specific pollutant that a rule is proposing to regulate. It also allows one to evaluate whether any policy option creates a disparity among demographic groups. The second question allows one to determine whether a particular policy option may make a vulnerable demographic community worse off than under baseline. Although this consideration is less relevant for regulations that reduce risk from all sources, it can be important for regulatory options that change the spatial distribution of risk. Examples could include the choice between market-based versus command-and-control policy mechanisms or the multipollutant versus single-pollutant control strategies evaluated by Fann et al. (2011). The answer to this question can also indicate whether there is a tradeoff between the option chosen by standard benefit–cost analysis and the option that is best for vulnerable populations. The third question can help identify whether a policy option exacerbates preexisting disparities, for example,

by conferring more benefits to groups that had the better baseline outcomes.

Although EDEs can provide useful information for EJ analysis, they do have limitations. The EDE welfare ranking assumes that all individual characteristics besides the outcome of interest are held constant. Consider a comparison of distributions of pollution for low-income and high-income demographic groups. The EDE ranking would be based only on differences in pollution between the two groups, not differences in income. That is, it would compare the expected utility of the two pollution distributions evaluated at a given reference income—not the desirability of having the poor distribution and being poor versus having the rich distribution and being rich. Similarly, it assumes that external factors are constant across the scenarios being evaluated, thus abstracting from possible price changes attributable to differences in pollution.

Here, we focus on EDEs measured in natural units, e.g., cancer risk. Standard benefit–cost analysis in contrast uses monetized values, e.g., willingness to pay to avoid a marginal increase in cancer risk. These marginal willingness-to-pay values are appropriate for approximating the monetized benefit of an incremental change in an environmental outcome. They are less justifiable, however, as a basis for calculating the argument of the EDE function: the total, not marginal, value of an environmental outcome. Moreover, it is unlikely that the preferences assumed in an existing nonmarket valuation study would be consistent with those used to derive the EDE.

An alternative approach proposed by Fleurbaey (2005) could in principle be used to generate a full-health equivalent income. For an individual with a given income and health status, this equivalent income is the smallest income she would be willing to receive in exchange for her actual income if provided with perfect health. Such a measure has the advantage of transforming multidimensional aspects of well-being (various health indicators and income) into a single value. Since equivalent income is a good it could theoretically be adapted for use in standard income inequality measures as well. Unfortunately, the data requirements for such a measure are daunting, and to our knowledge it has not been implemented in practice at the level of detail necessary for an EJ analysis.

In sum, EDEs measured in natural (i.e., not monetized) units offer a middle ground between the statistics (means, variances, and correlations) with no normative content often used in the EJ litera-

ture (Ringquist, 2005), and the Fleurbaey (2005) full-health equivalent income or a complete multidimensional social welfare function over stochastic life histories as proposed by Adler (2012). An advantage of EDEs over the former is that an individual with an appropriately specified set of reasonable well-defined preferences would prefer a distribution with a low EDE over one with a high EDE, whereas the same cannot be said about the other metrics. An advantage of EDEs over the latter is tractability.

The rest of the article is organized as follows. Section 1 describes the microeconomic foundations for applying EDEs to distributions of environmental harm, Section 2 provides a brief illustrative EJ analysis of a U.S. Environmental Protection Agency (EPA) proposal to limit formaldehyde emissions from pressed wood products, and Section 3 offers concluding comments.

## 1. THEORETICAL MODEL

Our policy evaluation framework is explicitly welfarist, being based on individual utility. Any non-welfarist method has the potential of preferring a policy that makes everyone worse off (Kaplow & Shavell, 2001). In particular, we rank pollution distributions based on the preferences of a hypothetical representative individual. We use the veil of ignorance to ensure her impartiality (Harsanyi, 1953; Rawls, 1971). That is, the rankings are based on the *ex ante* preferences of a representative individual who believes she will randomly receive an *ex post* outcome from the distribution.

Formally, under a given policy scenario let  $x_n$  be the adverse environmental outcome such as pollution exposure or health risk experienced by individual  $n$ . For the formaldehyde example in Section 2, for example,  $x$  indicates cancer risk. The vector  $\mathbf{x} = (x_1, x_2, \dots, x_N)' \in \mathbb{R}_+^N$  denotes outcomes for the  $N$  members of the total population. Behind the veil of ignorance, the vector  $\mathbf{x}$  generated by a given policy can be framed as an *ex ante* lottery in which each *ex post* outcome  $x_n$  occurs with probability  $1/N$ . Ranking distributions is then equivalent to determining which lottery would be preferred by the representative individual. To do so requires imposing structure on the individual's preferences.

We first impose the Pareto criterion: increasing pollution for at least one *ex post* outcome while leaving all others unchanged makes a lottery less desirable. Let  $U(\mathbf{x}, \mathbf{y})$  be a twice continuously differentiable function returning the *ex ante* utility

generated by an emissions lottery conditional on a deterministic numeraire good  $y$ , e.g., income. The Pareto criterion can then be expressed as  $\mathbf{x} \geq \bar{\mathbf{x}} \iff U(\mathbf{x}, y) \leq U(\bar{\mathbf{x}}, y)$ .

As is common in the income distribution literature we also impose that  $U$  is Schur concave in  $\mathbf{x}$  (Lambert, 2001). Schur concavity implies that transferring a unit of pollution from a low exposure *ex post* outcome to a high exposure outcome makes a lottery less desirable, i.e., a mean-preserving regressive reallocation of pollution decreases welfare.<sup>1</sup> It is consistent with the representative individual being risk averse.

In addition to evaluating the desirability of an emissions distribution over the total population, we are interested in evaluating the relative desirability of emissions distributions of demographic groups within the population. It is therefore useful to be able to rank the pollution distribution of policy A versus that of policy B for a particular demographic group independently of the outcomes of these policies for some other group. This property requires a separability assumption over demographic groups.

This separability in demographic groups' assumption can be stated as follows. Let  $\mathbf{x}_d$  denote the vector of outcomes corresponding to individuals in demographic group  $d$ , and  $\mathbf{x}_{-d}$  denote the vector of outcomes for individuals outside the group. Then,  $U(\mathbf{x}, y)$  can be expressed  $U(\mathbf{x}_d, \mathbf{x}_{-d}, y)$ . Without further structure, a ranking between alternative distributions for group  $d$  depends upon the distributions of outcomes for the rest of the population. Separability in population subgroups allows us to express  $U(\mathbf{x}, y) = \tilde{U}(U_d(\mathbf{x}_d, y), \mathbf{x}_{-d}, y)$ . That is, we can rank changes in  $\mathbf{x}_d$ , the distribution for group  $d$ , independently of the outcomes for all other individuals (Blackorby, Donaldson, & Auersperg, 1981).

We next impose a restriction that is only implicitly assumed by much of the income distribution literature: separability in utility between consumption of numeraire  $y$  and consumption of the environmental outcome of interest. Separability in consumption implies that the *ex ante* utility function  $U(\mathbf{x}, y)$  can be expressed as  $U^*(u(\mathbf{x}), y)$ . It ensures that the marginal rate of substitution between any two *ex post* realizations  $x_m$  and  $x_n$ , and therefore the ranking of any lot-

teries, is independent of the reference income level  $y$ . The specification is consistent with a marginal utility of  $y$  that is decreasing (multiplicatively separable) or constant (additively separable) in *ex post* pollution exposure (Rey & Rochet, 2004). It is not compatible, however, with preferences in which the marginal utility of  $y$  is increasing in *ex post* exposure, for example, if exposure is equivalent to lost consumption (Hammit, 2013). Evans and Viscusi (1991) use survey data to explore a similar problem of how marginal utility of income is affected by health. Their findings are ambiguous, suggesting that less severe adverse health outcomes may increase the marginal utility of income, while more severe outcomes may decrease it. Multiplicative separability is commonly assumed in the health economics literature (Garber & Phelps, 1997; Murphy & Topel, 2006).

Although  $U(\cdot)$  is measured in utility, preferences over distributions can be represented by a social evaluation function measured in cardinal units of  $x$ , also independently of  $y$ . Let  $\Xi(\mathbf{x})$  be the scalar value of the bad outcome, which if allocated to each individual, would generate the same *ex ante* utility as the actual distribution:

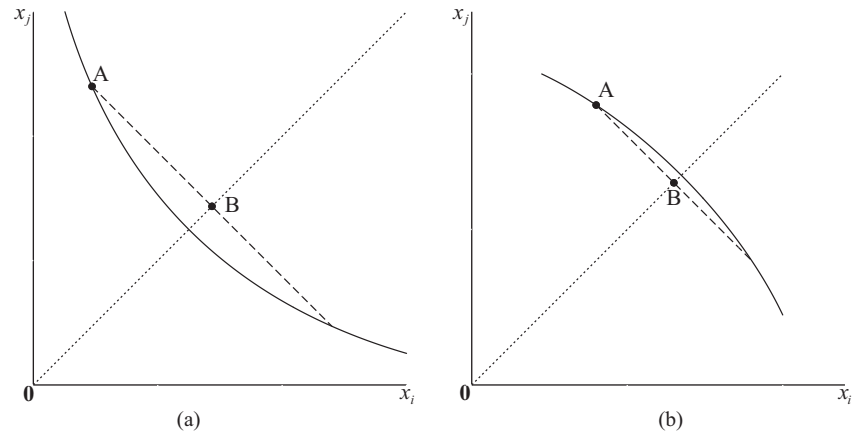
$$\begin{aligned}\Xi(\mathbf{x}) &\equiv \{\xi : U(\xi \cdot \mathbf{1}, y) = U(\mathbf{x}, y)\} \\ &\equiv \{\xi : U^*(u(\xi \cdot \mathbf{1}), y) = U^*(u(\mathbf{x}), y)\} \\ &\equiv \{\xi : u(\xi \cdot \mathbf{1}) = u(\mathbf{x})\}.\end{aligned}\quad (1)$$

The income distribution literature commonly refers to  $\Xi$  as the "equally distributed equivalent" value of  $x$  (Atkinson, 1970). Note that higher values of the social evaluation function  $\Xi(\mathbf{x})$  correspond to less desirable pollution distributions. Schur concavity of  $U(\cdot)$  thus implies Schur convexity of  $\Xi(\mathbf{x})$  since the latter is increasing, rather than decreasing in pollution. Consequently, the EDE for a bad distribution is no lower than the mean outcome, whereas the EDE for income is no higher than the mean.

### 1.1. Atkinson Preferences

In addition to the properties described above, the social evaluation function used to calculate the Atkinson index satisfies homotheticity:  $\Xi(\lambda\mathbf{x}) = \lambda\Xi(\mathbf{x})$  for any  $\lambda \in \mathbb{R}_+^1$  (Blackorby & Donaldson, 1978). This property implies that the rankings of alternative emissions distributions are independent of proportional shifts in  $x$ . Combined with separability in demographic groups, homotheticity implies that  $u(\mathbf{x})$  can be specified as the expectation of the

<sup>1</sup>Let  $\mathbf{Q}$  be a square matrix composed of nonnegative real numbers whose rows and columns each sum to 1. The function  $f(\mathbf{x})$  is Schur concave if  $\mathbf{Q}\mathbf{x}$  is not a permutation of  $\mathbf{x}$  and  $f(\mathbf{Q}\mathbf{x}) \geq f(\mathbf{x})$ . All symmetric quasi-concave functions are Schur concave, although the converse is not true.



**Fig 1.** Schur concave preferences for goods and bads.

Notes: Panel (a) depicts Schur concave preferences for a distribution of a good  $x$  between individuals  $i$  and  $j$ . A mean-preserving reallocation from an unequal distribution A to an equal distribution B improves welfare. Panel (b) depicts Schur concave preferences for a distribution of a bad  $x$  between individuals  $i$  and  $j$ . A mean-preserving reallocation from an unequal distribution A to an equal distribution B improves welfare.

following functions of *ex post* values of  $x_n$  (Blackorby & Donaldson, 1978):

$$u_A(\mathbf{x}) = -\frac{1}{N} \sum_{n=1}^N x_n^{1-\beta}; \beta < 0. \tag{2}$$

The corresponding EDE is

$$\Xi_A(\mathbf{x}) = \left[ \frac{1}{N} \sum_{n=1}^N x_n^{1-\beta} \right]^{\frac{1}{1-\beta}}; \beta < 0. \tag{3}$$

It is instructive to highlight the difference between Equation (2) and the analogous function proposed by Atkinson for the case of an income vector  $\mathbf{y}$ ,

$$v_A(\mathbf{y}) = \frac{1}{N} \sum_{n=1}^N y_n^{1-\epsilon}; \epsilon > 0, \epsilon \neq 1. \tag{4}$$

Note that in Atkinson’s formulation expected utility is increasing in  $y$ , so that Schur concavity requires  $\epsilon > 0$ . For bad outcomes, utility is decreasing in  $x$  such that Schur concavity of  $U$  requires  $\beta < 0$ .

Figure 1 illustrates the implication of this difference. Panel (a) depicts an indifference curve for standard Atkinson preferences when  $x$  is a good, such as income. In this case, the parameter  $\beta$  in Equation (3) is positive. A mean-preserving reallocation of income from an unequal point A to an equal point B increases welfare. Simply substituting health risk for income, however would imply that such a reallocation reduces welfare since, by the Pareto criterion welfare would be decreasing, rather than increasing, in  $x$ . Panel (b) illustrates the impact

of restricting  $\beta < 0$ . Here, a reallocation from A to B increases welfare for a bad  $x$ .

From the EDE, it is straightforward to calculate the corresponding relative inequality index. Letting  $\bar{x} \equiv \sum_n x_n/N$ ,

$$I_A = \frac{\Xi_A(\mathbf{x})}{\bar{x}} - 1 \tag{5}$$

$$= \left[ \frac{1}{N} \sum_{n=1}^N \left[ \frac{x_n}{\bar{x}} \right]^{1-\beta} \right]^{\frac{1}{1-\beta}}; \beta < 0. \tag{6}$$

Again, the difference between this formula and that of the standard Atkinson income inequality index applied to “bads” as proposed by Levy et al. (2006) is the sign of the exponent parameter; here  $\beta$  is non-positive, rather than nonnegative.

### 1.2. Kolm–Pollak Preferences

An implication of the homotheticity assumption imposed by Atkinson preferences is that, like all relative inequality indexes,  $I_A(\mathbf{x}) = I_A(\lambda\mathbf{x})$ . That is, proportional shifts in the distribution do not affect measured inequality. This property is convenient for measuring income inequality across time periods or geographic areas in which the purchasing power of income differs by an exchange rate or inflation index. It is not so useful when measuring distribution of a health or pollution variable in which absolute differences are economically meaningful. As suggested by Cox (2012), it seems unsatisfactory for a distribution with individuals exposed to small levels of

mortality risk, say 0.001 and 0.0002, to be as equitable as one with risks of 1 and 0.2. In this subsection, we consider absolute inequality indexes that do not suffer this drawback. For these indexes, an equiproportional increase in the distribution increases measured inequality (Kolm, 1976).

To construct the absolute index, we impose that the social evaluation function satisfies translatability, rather than homotheticity:  $\Xi(\mathbf{x} + \lambda \cdot \mathbf{1}) = \Xi(\mathbf{x}) + \lambda$  for any  $\lambda \in \mathbb{R}^1$  (Blackorby & Donaldson, 1980). This property implies that rankings of alternative emissions or risk distributions are independent of common shifts in (unobserved) background levels. Combined with separability in demographic groups, translatability requires that  $u(\mathbf{x})$  be specified as a Pollak (1971) function (Blackorby & Donaldson, 1980):

$$u_K(\mathbf{x}) = -\frac{1}{N} \sum_{n=1}^N e^{-\kappa x_n}; \kappa < 0. \tag{7}$$

The corresponding EDE is

$$\Xi_K(\mathbf{x}) = -\frac{1}{\kappa} \ln \left( \frac{1}{N} \sum_{n=1}^N e^{-\kappa x_n} \right); \kappa < 0. \tag{8}$$

Letting  $\bar{x} \equiv \sum_n x_n / N$ , the absolute inequality index is then

$$I_K(\mathbf{x}) = \Xi_K(\mathbf{x}) - \bar{x} \\ = -\frac{1}{\kappa} \ln \left( \frac{1}{N} \sum_{n=1}^N e^{-\kappa [x_n - \bar{x}]} \right); \kappa < 0. \tag{9}$$

Analogously to the case for Atkinson preferences, the specification here differs from the absolute income inequality measures discussed by Kolm (1976) and Blackorby and Donaldson (1980) by the sign of  $\kappa$ . To ensure Schur concavity of  $U$ ,  $\kappa$  must be nonpositive, whereas for a good (like income), the parameter would be nonnegative. Parameter  $\kappa$  can be thought of a measure of the representative individual’s aversion to inequality in adverse environmental outcomes. The elasticity of marginal utility with respect to a change in an individual’s pollution allocation is  $\kappa x_n$ . Preferences vary from no aversion to maximin as this elasticity goes from zero to negative infinity.

### 1.3. The Mirror Property

Cox (2012) discusses an important disadvantage of the Atkinson index in the context of health risk.

An inequality evaluation of alternate policies can generate conflicting rankings based on whether the outcome is good (e.g., survival probability) versus bad (e.g., mortality risk). This quandary has been discussed at length in the health economics literature (Bosmans, 2016; Clarke, Gerdtham, Johannesson, Binglefors, & Smith, 2002; Erreygers, 2009; Erreygers, Clarke, & Van Ourti, 2012; Lambert & Zheng, 2011). Inequality measures which are not vulnerable to this shortcoming satisfy the so-called mirror property.

This mirror property has typically been interpreted as applying to a single functional form of an inequality index. For a bad outcome, commonly referred to as a “shortfall,”  $x$ , with upper bound  $\hat{x}$ , and its complementary good “attainment” outcome,  $\hat{x} - x$ , an index  $I(\cdot)$  would satisfy the mirror property when  $I(\mathbf{x}) > I(\bar{\mathbf{x}})$  if and only if  $I(\hat{x} \cdot \mathbf{1} - \mathbf{x}) > I(\hat{x} \cdot \mathbf{1} - \bar{\mathbf{x}})$  for all permissible  $\mathbf{x}, \bar{\mathbf{x}}$ , and  $\hat{x}$ .<sup>2</sup>

As shown by Lambert and Zheng (2011), this interpretation of the mirror property is incompatible with the diminishing transfer principle, which effectively places more weight on transfers among the worst off. The diminishing transfer principle is widely considered a desirable attribute of an inequality measure and can be satisfied by both Atkinson and Kolm–Pollak preferences. For an attainment, worse off individuals have a relatively low allocation of the good, whereas for a shortfall they have a high allocation of the bad. Thus the contradiction: for both the mirror and diminishing transfer principles to be satisfied a single function would need to evaluate  $x$  and its complement  $\hat{x} - x$  differently.

Consequently, we reframe the standard interpretation of the mirror property in terms of the EDE rather than the inequality index.<sup>3</sup> For a shortfall EDE function  $\Xi_-(\cdot)$  to satisfy the mirror property, we require that there exist some attainment EDE function  $\Xi_+(\cdot)$ , such that the complement of the attainment EDE evaluated at the complement of an arbitrary distribution  $\mathbf{x}$  is equal to the shortfall EDE evaluated at  $\mathbf{x}$ :

**Definition 1. Mirror Property** For any permissible  $\hat{x}$ ,  $\mathbf{x} < \hat{x} \cdot \mathbf{1}$ , and shortfall EDE  $\Xi_-(\cdot)$ , there exists an attainment EDE  $\Xi_+(\cdot)$  such that  $\Xi_-(\mathbf{x}) = \hat{x} - \Xi_+(\hat{x} \cdot \mathbf{1} - \mathbf{x})$ .

<sup>2</sup>This formulation is the weak form of the mirror property, referred to as consistency (Lambert & Zheng, 2011). A stronger form requires that  $I(\mathbf{x}) = I(\hat{x} \cdot \mathbf{1} - \mathbf{x})$  (Erreygers, 2009).

<sup>3</sup>Our definition is thus distinct from other reformulations, e.g., Bosmans (2016).

This definition is both intuitive and logically consistent. If the EDE value of a given vector of mortality risks is  $p$ , it seems clear that the EDE value of the complementary vector of survival probabilities should be  $1 - p$ . It is logically consistent since comparison of any two bad distributions based on the shortfall EDE function generates the same preference ordering as a comparison based on the attainment EDE function of the complementary good distributions. As shown in the following two propositions, Atkinson preferences do not satisfy the mirror property while Kolm–Pollak preferences do.

**Proposition 1.** *The Atkinson EDE does not satisfy the mirror property.*

*Proof.* See the Appendix.

**Proposition 2.** *The Kolm–Pollak EDE satisfies the mirror property.*

*Proof.* See the Appendix.

### 1.4. Practical Implementation

In the preceding subsections, we derived two normatively significant EDE functions that can rank distributions of bad outcomes, explicitly identifying the restrictions each imposes on preferences. Although these functions are analogous to the EDEs associated with the Atkinson and Kolm–Pollak income inequality indexes, they are mathematically distinct. Simply substituting health risk for income in the formula for an income inequality index will cause it to lose its normative significance. That is, one cannot use the resulting index values to determine the relative desirability of a given distribution for some well-behaved preference structure.

Also analogous to the case for income inequality measures, the differences between the two new specifications stem from different assumptions about individual preferences, homotheticity versus translatability. Although there is little *a priori* evidence to suggest which of these properties more closely resembles actual human preferences, translatable preferences have a key practical advantage: only EDE functions with this property are guaranteed to generate a ranking that is insensitive to whether an outcome is expressed as a bad or its complementary good. This attribute is particularly important for analysis of risks that have a natural upper and lower bound.

It is helpful to address two related practical issues regarding implementation of translatable preferences that have been raised in the literature. Both

issues originate from the fact that the elasticity of marginal utility is variable with translatable preferences, rather than constant as is the case for homothetic preferences. From Equations (2) and (7), the respective elasticities are

$$\frac{\partial(\partial u_A/\partial x_n)}{\partial x_n} \frac{x_n}{\partial u_A/\partial x_n} = \beta, \tag{10}$$

$$\frac{\partial(\partial u_K/\partial x_n)}{\partial x_n} \frac{x_n}{\partial u_K/\partial x_n} = \kappa x_n. \tag{11}$$

The elasticities are by definition unit free, being interpretable as the percent change in marginal utility arising from a 1% change in the quantity of  $x$ . Unlike  $\beta$ , the parameter  $\kappa$  is not an elasticity itself, and is not unit free. Rather, it is the percent change in marginal utility per unit of  $x$ . Changing units of  $\mathbf{x}$  without modifying  $\kappa$  effectively changes this elasticity, and hence individual preferences. It could thus cause the social ranking of two distributions to reverse (Zheng, 2007).

Therefore, a change in units of measurement requires a change in units of  $\kappa$ . Fortunately, this operation is quite simple. Consider, for example, a study of distributions of exposure to a pollutant, measured in kg, using a parameter  $\kappa = -0.5$ . If one wanted to calculate the EDE in pounds, it would be necessary to multiply  $\mathbf{x}$  and divide  $\kappa$  by 2.2. This adjustment ensures that the elasticity of marginal utility remain unchanged for each individual at each quantity of  $x$ , and the values of  $\Xi_K$  and  $I_K$  would be 2.2 times larger, as desired.

A related practical issue in applied work is choosing the value of  $\kappa$  that defines the elasticity. Like the  $\beta$  parameter for Atkinson preferences, this parameter can assume any real nonpositive value. The standard approach in the inequality literature is to examine sensitivity of results to a range of values. What constitutes a useful range is an open question.

In the context of income distribution, experiments have found values for the (constant) elasticity of marginal utility of income in the neighborhood of 0.25 (Amiel, Creedy, & Hurn, 1999), and the U.S. Census Bureau often reports results using elasticities of 0.25, 0.5, and 0.75 (DeNavas-Walt, Proctor, & Smith, 2012; Jones & Weinberg, 2000). The only study to our knowledge that has attempted to estimate this elasticity for an environmental good (a hypothetical cleanup program) found higher values, with a mean of 0.72 and median of 2.8 (Cropper, Krupnick, & Reich, 2016).

To present results for a range of  $\kappa$  that generates elasticities comparable to those in the above-cited literature, we first identify a value of  $\kappa$  that is consistent with a given constant elasticity  $\beta$ . To establish a correspondence between an elasticity  $\beta$  and a vector of elasticities  $\mathbf{x}\kappa$ , we choose the value of  $\kappa$  that minimizes the sum of squared differences between the individual elasticities and the constant  $\beta$ :

$$\begin{aligned} \kappa(\beta) &= \arg \min_{\hat{\kappa}} \{[\hat{\kappa}\mathbf{x} - \beta\mathbf{1}]'[\hat{\kappa}\mathbf{x} - \beta\mathbf{1}]\} \\ &= \frac{\beta \sum_{n=1}^N x_n}{\sum_{n=1}^N x_n^2}. \end{aligned} \quad (12)$$

We use  $\kappa(-0.50)$  to calculate the main results, presenting results for  $\kappa(-0.25)$  and  $\kappa(-0.75)$  in the Appendix. Although EDE and index magnitudes vary with different parameter values, the qualitative results remain largely unchanged.

## 2. ILLUSTRATIVE APPLICATION

To our knowledge, an EDE based on Kolm–Pollak preferences has not been used to analyze EJ issues. Here, we provide an illustrative application in the context of evaluating distributional implications policy options to reduce indoor air pollution.

Resins commonly used in pressed wood products can emit significant amounts of formaldehyde. This chemical has been linked to adverse health outcomes including nasopharyngeal cancer. Partly in response to concerns over high levels of formaldehyde in Federal Emergency Management Agency trailers used for temporarily housing people dislocated in the wake of Hurricane Katrina, Congress enacted the 2010 Formaldehyde Standards for Composite Wood Products Act.<sup>4</sup> This legislation amended the Toxic Substances Control Act to set national emissions standards for pressed wood components (hardwood plywood, medium-density fiberboard, and particleboard) common in home construction and furniture.

In 2013, the EPA published a regulatory analysis for a proposed rulemaking to implement the Act.<sup>5</sup> This analysis used a three-stage model to evaluate health impacts of the emissions standards (EPA, 2013). The first-stage generated models of nine housing types in various climate zones, stocking them with a representative selection of pressed wood products.

These engineering models simulated indoor air concentrations of formaldehyde at baseline and under alternative policy scenarios. The second stage introduced epidemiological concentration–response functions to model the impact of formaldehyde concentrations on the probability of incurring fatal cancer. Concentrations varied by home age (due to a decay in emissions rates over time) and other home characteristics such as ventilation, temperature, and humidity. Health responses varied by age of exposed individual. The third stage used data from the American Community Survey and American Housing Survey to populate the model homes and simulate health benefits for various demographic groups. Demographic groups are defined by self-reported race, ethnicity, and income in the American Community Survey. The Hispanic category includes individuals of any race, such that Black, White, Native American, and Other are properly interpreted as non-Hispanic Black, etc. The below-poverty category consists of individuals belonging to households below the U.S. Census Bureau poverty threshold.

Standards introduced by the Act raise several questions in the context of EJ. Formaldehyde emission rates decrease exponentially over time. Concentrations are highest in new or newly remodeled homes with new furniture. Although the legislation was motivated by concern for poor and minority individuals using trailers, these groups may not be the main beneficiaries if they are less likely to live in newer homes with high formaldehyde levels.

We focus on three emission levels considered in the EPA analysis: the baseline absent the legislation (Baseline), the level under the EPA's proposed implementation of the legislated standards (Proposal), and a level corresponding to a hypothetical stricter standard requiring manufacturers to use resins with no added formaldehyde (NAF).

Table I presents average cancer risk for each policy scenario and demographic group. Average baseline risk ranges from 1.1 to 1.6 cases per million. Among racial and ethnic groups, White has the lowest average risk, while Hispanic has the highest. There is also considerable dispersion of risk within groups. Native American has the lowest standard deviation and lowest maximum risk. Black and White share the highest maximum risk, while Hispanic has the highest standard deviation. Minimum risk for all groups is zero.

For all demographics, increased stringency is associated with lower average, standard deviation, and maximum cancer rates. The relative baseline patterns

<sup>4</sup>See, for example, Citizen Petition to EPA Regarding Formaldehyde in Wood Products (<http://www.epa.gov/opptintr/chemtest/pubs/petition3.pdf>).

<sup>5</sup>The final rule was promulgated in 2016.



Table I. Summary Statistics

Demographic	Population (millions)	Mean	Baseline Std. dev.	Max	Fatal cancer cases per million			Mean	NAF Std. dev.	Max
					Proposal Std. dev.	Max	NAF			
Race/Ethnicity										
Black	35.0	1.319	0.856	16.317	1.279	0.774	14.992	1.160	0.543	9.941
Hispanic	45.4	1.426	0.880	16.161	1.384	0.796	14.849	1.256	0.558	9.957
Native American	1.9	1.264	0.764	13.673	1.231	0.699	12.619	1.137	0.532	9.941
White	194.1	1.136	0.823	16.317	1.105	0.765	14.992	1.015	0.602	9.957
Other	19.6	1.342	0.847	14.424	1.302	0.766	13.310	1.178	0.532	9.946
Income										
Above poverty	256.4	1.195	0.840	16.317	1.162	0.776	14.992	1.063	0.596	9.957
Below poverty	38.7	1.353	0.871	16.083	1.313	0.784	14.777	1.194	0.552	9.957
Income unknown	1.0	1.594	0.680	9.734	1.550	0.578	8.534	1.425	0.261	4.474
Total	296.1	1.217	0.845	16.317	1.183	0.779	14.992	1.081	0.592	9.957

Notes: Hispanic includes all races who report Hispanic ethnicity. All others are of non-Hispanic ethnicity.

Source: Author calculations, based on data from U.S. EPA.

are generally preserved under the proposed rule, while the strict NAF limits sharply reduce the differences in maximum risk, and switch the relative position of Hispanic and White in terms of standard deviations.

The table illustrates limitations of using standard summary statistics to evaluate EJ implications of regulatory action. Which distribution is better? Some people may be willing to accept higher average risk, for example, if there was less variance, or better worst-case outcomes. The approach taken here, in contrast, allows us to rank these distributions using explicit well-behaved preference structures and examine sensitivity of rankings to alternative specifications.

The goals of this analysis are to develop an understanding of the baseline distribution (i.e., absent any new regulation) in formaldehyde-induced cancer risk, the way the two policy options affect the distribution, and how the various distributions can be ranked. Table II presents Kolm–Pollak EDEs and inequality indexes,  $\Xi_K, I_K$ , for each policy scenario and demographic group, evaluated at  $\kappa(-0.50)$ . Appendix tables present these statistics evaluated at  $\kappa(-0.25)$  and  $\kappa(-0.75)$ .

Panel A presents EDEs, indicating the additional amount of risk the representative individual would be willing to tolerate if it were to be equally distributed. EDEs can be interpreted as adjusting the average outcomes in Table I for the welfare loss caused by inequality in the distributions. The patterns across demographic groups and policy options observed for mean outcomes are largely preserved for

EDEs. The EDE for the Native American distribution is higher than that for White, however, signifying that the lower variance and maximum risk does not compensate for its higher mean. In addition, although White and Hispanic have, respectively, the best and worst distributions under both Baseline and Proposal, the Proposal results in a larger improvement for Hispanic, thus partially alleviating the disparity. Similarly, although individuals above poverty have better outcomes, the proposal delivers more benefits to individuals below poverty.

Panel B presents the Kolm–Pollak inequality indexes quantifying the equity of the distribution independent of the mean. A higher index value indicates a less equal distribution. Similar to the case with EDEs, Hispanic and below poverty have the most inequitable distributions, but also see the most improvements from the proposed rulemaking. As shown in Tables AI and AII, all results are robust to both lower and higher levels of inequality aversion.

In general, Table II suggests that for this set of policies there is no tradeoff between increased stringency and the equity of the distribution; within each demographic group and across demographic groups lower mean outcomes are associated both with lower inequality indexes and a convergence between the groups with the worst and best outcomes. Thus, concerns that upper income individuals may experience the lion’s share of benefits from the rule due to a higher propensity to purchase new furniture or live in new construction with higher levels of formaldehyde exposure appear to be largely unfounded.

**Table II.** Policy rankings by fatal cancer cases per million

	Baseline (a)	Proposal (b)	NAF (c)	Difference (b)-(a)
<i>Panel A. Equally distributed equivalents</i>				
Race/Ethnicity				
Black	1.457 (0.021)	1.388 (0.016)	1.208 (0.009)	-0.070*** (0.005)
Hispanic	1.584 (0.022)	1.510 (0.009)	1.317 (0.006)	-0.074*** (0.013)
Native American	1.374 (0.005)	1.320 (0.001)	1.186 (0.020)	-0.054*** (0.004)
White	1.263 (0.014)	1.212 (0.004)	1.077 (0.034)	-0.051*** (0.010)
Other	1.474 (0.007)	1.405 (0.008)	1.223 (0.016)	-0.069*** (0.001)
Income				
Above Poverty	1.328 (0.013)	1.272 (0.007)	1.124 (0.026)	-0.055*** (0.006)
Below Poverty	1.500 (0.021)	1.427 (0.013)	1.246 (0.011)	-0.073*** (0.007)
Income unknown	1.682 (0.047)	1.611 (0.051)	1.435 (0.001)	-0.071*** (0.004)
<b>Total</b>	1.352 (0.015)	1.294 (0.008)	1.141 (0.024)	-0.058*** (0.006)
<i>Panel B. Inequality indexes</i>				
Race/Ethnicity				
Black	0.138 (0.007)	0.108 (0.002)	0.048 (0.002)	-0.030** (0.009)
Hispanic	0.158 (0.009)	0.126 (0.002)	0.060 (0.004)	-0.031** (0.011)
Native American	0.110 (0.001)	0.089 (0.002)	0.049 (0.007)	-0.021*** (0.003)
White	0.127 (0.001)	0.107 (0.002)	0.062 (0.003)	-0.020*** (0.004)
Other	0.132 (0.002)	0.104 (0.002)	0.045 (0.001)	-0.028*** (0.004)
Income				
Above Poverty	0.133 (0.003)	0.111 (0.002)	0.061 (0.003)	-0.022*** (0.005)
Below Poverty	0.147 (0.005)	0.114 (0.001)	0.052 (0.002)	-0.033*** (0.006)
Income unknown	0.088 (0.008)	0.061 (0.016)	0.011 (0.001)	-0.027*** (0.008)
<b>Total</b>	0.135 (0.003)	0.112 (0.002)	0.060 (0.003)	-0.024*** (0.005)

<sup>a</sup>Notes: Bootstrapped standard errors in parentheses. Equally distributed equivalents and inequality indexes assume translatable preferences calculated using  $\kappa(-0.50)$ . Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

<sup>b</sup>Source: Author calculations, based on data from U.S. EPA.

### 3. CONCLUSION

EDEs and the associated inequality indexes are useful tools for characterizing distributions of adverse health outcomes. Grounded in an internally consistent set of well-behaved preferences, they provide a transparent method for ranking outcomes of alternative policy options that takes entire distributions into account. They also facilitate comparisons of distributions of outcomes both within and across demographic groups.

The ability to provide normatively meaningful rankings provides clear advantages over other statistics (variance, correlations, regression coefficients, etc.) for regulatory analysis. However, EDEs may also have value as descriptive statistics in other analytical contexts. Empirical studies have begun to examine the effects of environmental quality on residential sorting (e.g., Banzhaf & Walsh, 2008; Gamper-Rabindran & Timmins, 2011). Presentation of EDEs and inequality indexes over time for the analyzed outcomes (e.g., toxic releases or proximity to Superfund sites) could provide the reader with more context as to how distributions within and across groups changed during the period of study.

Similarly, other econometric research has examined the degree to which race or income is a predictor of increased exposure to pollution under alternative policy scenarios (Fowlie, Holland, & Mansur, 2012). In such studies, inclusion of EDEs could provide a sense of which population groups have the least desirable distributions under each policy before controlling for other factors. Inequality indexes for different demographic groups could also provide clues as to the whether exposure generates hotspots under different policies.

Caution should be exercised when applying metrics designed for analyzing the distribution of income to examine harmful environmental or health outcomes. In particular, income inequality indexes lose their desirable properties if used to analyze distributions of bads rather than goods. We have shown how to transform Atkinson and Kolm–Pollak inequality indexes in a manner that permits analysis of distributions of bads. We have also shown that in cases where an outcome can be characterized as either a good or bad (e.g., mortality risk or survival probability), Kolm–Pollak preferences can guarantee distributional rankings that are insensitive to how the outcome is characterized, whereas Atkinson preferences cannot.

As an illustrative example, we apply our approach to evaluate EJ implications of an EPA proposal to limit formaldehyde emissions from composite wood products. This regulation provides an interesting case study since it was partly motivated by concern for poor and minority communities exposed to formaldehyde in temporary housing. Since indoor formaldehyde levels tend to be highest in new and newly remodeled homes, however, less economically advantaged groups may not benefit from the standards.

Using data generated from a hybrid engineering/epidemiological model developed by the EPA, we analyzed the distribution of cancer risk under three scenarios: baseline, EPA proposed emissions standards, and a stricter no-added formaldehyde standard. Baseline EDE values for minority and low-income groups were higher than those for White and high-income groups suggesting that they had relatively undesirable distributions before any policy change. Regarding the two policy options, we found no tradeoffs between health benefits and equity. Stricter standards resulted in lower EDEs, unambiguously benefiting all demographic groups. Moreover, inequality index values were also lower, indicating that the benefits were due not only to reduced average pollution levels but also to reduced inequality within each group. Overall, minority and low-income groups benefited the most from tighter emissions standards. This example serves to illustrate how the Kolm–Pollak EDE and inequality index, appropriately adapted for distributions of bad outcomes, can yield valuable insights about the relative equity of alternative environmental policies options both within and across demographic groups.

**ACKNOWLEDGMENTS**

Matthew Adler, Steve Newbold, Jay Shimshack, V. Kerry Smith, Ann Wolverton, and seminar participants at the Inter-American Development Bank, Resources for the Future, the U.S. Environmental Protection Agency, and the World Bank provided helpful comments. This research was supported in part by the U.S. Department of Agriculture, Economic Research Service.

Disclaimer: The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

**APPENDIX A: PROOFS**

**Proof of Proposition 1.** *The proof has two steps. We first show that any candidate attainment equally distributed equivalent (EDE) that mirrors the Atkinson shortfall EDE must satisfy translatability. We then show that translatability of the attainment EDE requires translatability of the shortfall EDE. Therefore, since it does not satisfy translatability, the Atkinson shortfall EDE does not satisfy the mirror property.*

*Let  $\mathbf{x} < \hat{x} \cdot \mathbf{1}$  and  $\hat{x} \cdot \mathbf{1} - \mathbf{x}$  denote vectors of shortfall outcomes and the complementary attainment outcome. Define  $\Xi_{A-}(\cdot)$  as the Atkinson shortfall EDE defined in Equation (3). The mirror property implies that there exist an attainment EDE function  $\Xi_{A+}(\cdot)$  such that*

$$\Xi_{A+}(\hat{x} \cdot \mathbf{1} - \mathbf{x}) = \hat{x} - \Xi_{A-}(\mathbf{x}); \text{ for any } \hat{x}, \mathbf{x}. \quad (A1)$$

*Suppose  $\mathbf{x} > \mathbf{0}$ .  $\Xi_{A+}(\cdot)$  satisfies translatability since for some arbitrarily small  $\delta > 0$ ,*

$$\Xi_{A+}(\hat{x} \cdot \mathbf{1} - [\mathbf{x} - \delta \cdot \mathbf{1}]) = \Xi_{A+}([\hat{x} + \delta] \cdot \mathbf{1} - \mathbf{x}), \quad (A2)$$

$$= \hat{x} + \delta - \Xi_{A-}(\mathbf{x}), \quad (A3)$$

$$= \delta + \Xi_{A+}(\hat{x} \cdot \mathbf{1} - \mathbf{x}), \quad (A4)$$

*where the second equality follows from Equation (A1). Consequently, also by Equation (A1),*

$$\Xi_{A-}(\mathbf{x} - \delta \cdot \mathbf{1}) = \hat{x} - \Xi_{A+}(\hat{x} \cdot \mathbf{1} - [\mathbf{x} - \delta \cdot \mathbf{1}]), \quad (A5)$$

$$= \hat{x} - [\Xi_{A+}(\hat{x} \cdot \mathbf{1} - \mathbf{x}) + \delta], \quad (A6)$$

$$= \Xi_{A-}(\mathbf{x}) - \delta, \quad (A7)$$

*which is a contradiction since  $\Xi_{A-}(\mathbf{x})$  does not satisfy translatability.  $\square$*

**Proof of Proposition 2.** *Let  $\mathbf{x} < \hat{x} \cdot \mathbf{1}$  and  $\hat{x} \cdot \mathbf{1} - \mathbf{x}$  denote vectors of shortfall outcomes and the complementary attainment outcome. Define  $\Xi_{K-}(\cdot)$  as the Kolm–Pollak shortfall EDE defined in Equation (8). The mirror property requires that there exist an attainment EDE function  $\Xi_{K+}(\cdot)$  such that*

$$\Xi_{K-}(\mathbf{x}) = \hat{x} - \Xi_{K+}(\hat{x} \cdot \mathbf{1} - \mathbf{x}); \text{ for all } \hat{x}, \mathbf{x}. \quad (A8)$$

**Table AI.** Policy Rankings by Fatal Cancer Cases per Million

	Baseline (a)	Proposal (b)	NAF (c)	Difference (b)-(a)
<i>Panel A. Equally distributed equivalents</i>				
Race/Ethnicity				
Black	1.377 (0.019)	1.326 (0.015)	1.182 (0.004)	-0.051*** (0.004)
Hispanic	1.490 (0.013)	1.435 (0.020)	1.281 (0.006)	-0.055*** (0.007)
Native American	1.310 (0.016)	1.269 (0.006)	1.159 (0.004)	-0.041*** (0.010)
White	1.189 (0.020)	1.151 (0.006)	1.043 (0.002)	-0.038 (0.026)
Other	1.399 (0.020)	1.347 (0.011)	1.199 (0.007)	-0.051*** (0.009)
Income				
Above poverty	1.251 (0.021)	1.209 (0.002)	1.089 (0.001)	-0.042* (0.022)
Below poverty	1.414 (0.016)	1.361 (0.011)	1.217 (0.004)	-0.053*** (0.005)
Income unknown	1.632 (0.010)	1.576 (0.088)	1.430 (0.004)	-0.055 (0.078)
<b>Total</b>	1.273 (0.020)	1.230 (0.000)	1.107 (0.002)	-0.043** (0.021)

*Panel B. Inequality indexes*

Race/Ethnicity				
Black	0.058 (0.001)	0.047 (0.007)	0.022 (0.000)	-0.012** (0.005)
Hispanic	0.064 (0.001)	0.051 (0.007)	0.025 (0.001)	-0.012* (0.006)
Native American	0.046 (0.000)	0.038 (0.003)	0.021 (0.000)	-0.008** (0.003)
White	0.053 (0.000)	0.046 (0.003)	0.027 (0.000)	-0.008** (0.003)
Other	0.056 (0.002)	0.045 (0.005)	0.021 (0.000)	-0.011*** (0.003)
Income				
Above poverty	0.056 (0.000)	0.047 (0.004)	0.027 (0.000)	-0.009** (0.004)
Below poverty	0.061 (0.001)	0.048 (0.006)	0.023 (0.000)	-0.013** (0.005)
Income unknown	0.037 (0.004)	0.026 (0.013)	0.005 (0.000)	-0.011 (0.009)
<b>Total</b>	0.057 (0.001)	0.047 (0.004)	0.026 (0.000)	-0.009** (0.004)

Notes: Bootstrapped standard errors in parentheses. Equally distributed equivalents and inequality indexes assume translatable preferences calculated using  $\kappa(-0.25)$ . Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .  
Source: Author calculations, based on data from U.S. EPA.

Consider the candidate function

$$\mathbb{E}_{K+}(\hat{x} \cdot 1 - \mathbf{x}) = \frac{1}{\kappa} \ln \frac{1}{N} \sum_{n=1}^N e^{\kappa[\hat{x} - x_n]}; \kappa < 0, \quad (\text{A9})$$

**Table AII.** Policy Rankings by Fatal Cancer Cases per Million

	Baseline (a)	Proposal (b)	NAF (c)	Difference (b)-(a)
<i>Panel A. Equally distributed equivalents</i>				
Race/Ethnicity				
Black	1.578 (0.030)	1.477 (0.000)	1.244 (0.003)	-0.101** (0.031)
Hispanic	1.737 (0.031)	1.631 (0.000)	1.377 (0.020)	-0.106*** (0.031)
Native American	1.473 (0.020)	1.398 (0.023)	1.228 (0.017)	-0.075* (0.043)
White	1.376 (0.009)	1.305 (0.001)	1.129 (0.021)	-0.071*** (0.010)
Other	1.582 (0.026)	1.486 (0.009)	1.255 (0.008)	-0.096** (0.035)
Income				
Above poverty	1.447 (0.015)	1.369 (0.001)	1.175 (0.018)	-0.078*** (0.016)
Below poverty	1.634 (0.023)	1.525 (0.003)	1.289 (0.003)	-0.108*** (0.026)
Income unknown	1.753 (0.021)	1.657 (0.018)	1.442 (0.000)	-0.096** (0.039)
<b>Total</b>	1.473 (0.016)	1.391 (0.001)	1.192 (0.016)	-0.082*** (0.018)

*Panel B. Inequality indexes*

Race/Ethnicity				
Black	0.259 (0.023)	0.197 (0.003)	0.084 (0.006)	-0.061** (0.019)
Hispanic	0.310 (0.021)	0.247 (0.002)	0.121 (0.017)	-0.064*** (0.019)
Native American	0.209 (0.011)	0.168 (0.016)	0.090 (0.000)	-0.042 (0.027)
White	0.240 (0.004)	0.199 (0.005)	0.114 (0.002)	-0.040*** (0.010)
Other	0.240 (0.016)	0.184 (0.008)	0.077 (0.001)	-0.056** (0.024)
Income				
Above poverty	0.252 (0.009)	0.207 (0.004)	0.113 (0.005)	-0.045*** (0.013)
Below poverty	0.280 (0.019)	0.213 (0.001)	0.095 (0.004)	-0.068*** (0.018)
Income unknown	0.159 (0.020)	0.107 (0.002)	0.018 (0.000)	-0.051** (0.018)
<b>Total</b>	0.257 (0.011)	0.208 (0.003)	0.111 (0.005)	-0.048*** (0.014)

Notes: Bootstrapped standard errors in parentheses. Equally distributed equivalents and inequality indexes assume translatable preferences calculated using  $\kappa(-0.75)$ . Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .  
Source: Author calculations, based on data from U.S. EPA.

$$= \hat{x} + \frac{1}{\kappa} \ln \frac{1}{N} \sum_{n=1}^N e^{-\kappa x_n}. \quad (\text{A10})$$

By Equation (A9),

$$\mathbb{E}_{K+}(\hat{x} \cdot 1 - \mathbf{x}) = \hat{x} - \mathbb{E}_{K-}(\mathbf{x}), \quad (\text{A11})$$

with both  $\Xi_{K+}(\hat{x} \cdot 1 - \mathbf{x})$  and  $\Xi_{K-}(\mathbf{x})$  satisfying translatability, and the mirror property is satisfied.  $\square$

## REFERENCES

- Adler, M. D. (2012). *Well-being and fair distribution: Beyond cost-benefit analysis*. Oxford: Oxford University Press.
- Amiel, Y., Creedy, J., & Hurn, S. (1999). Measuring attitudes towards inequality. *Scandinavian Journal of Economics*, 101(1), 83–96.
- Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory*, 2, 244–263.
- Banzhaf, S. H., & Walsh, R. P. (2008). Do people vote with their feet? An empirical test of Tiebout's mechanism. *American Economic Review*, 98(3), 843–863.
- Blackorby, C., Bossert, W., & Donaldson, D. (1999). Income inequality measurement: The normative approach. In J. Silber (Ed.), *Handbook of income inequality measurement*, Chap. 3 (pp. 133–161). Dordrecht: Springer.
- Blackorby, C., & Donaldson, D. (1978). Measures of relative equality and their meaning in terms of social welfare. *Journal of Economic Theory*, 18, 59–80.
- Blackorby, C., & Donaldson, D. (1980). A theoretical treatment of indices of absolute inequality. *International Economic Review*, 21(1), 107–136.
- Blackorby, C., Donaldson, D., & Auersperg, M. (1981). A new procedure for the measurement of inequality within and among population subgroups. *Canadian Journal of Economics*, 14(4), 665–685.
- Bosmans, K. (2016). Consistent comparisons of attainment and shortfall inequality: A critical examination. *Health Economics*, 25(11), 1425–1432.
- Bouvier, R. (2014). Distribution of income and toxic emissions in Maine, United States: Inequality in two dimensions. *Ecological Economics*, 102, 39–47.
- Clark, L. P., Millet, D. B., & Marshall, J. D. (2014). National patterns in environmental injustice and inequality: Outdoor NO<sub>2</sub> air pollution in the United States. *PLOS One*, 9(4), 1–8.
- Clarke, P. M., Gerdtham, U.-G., Johannesson, M., Binglefors, K., & Smith, L. (2002). On the measurement of relative and absolute income-related health inequality. *Social Science and Medicine*, 55, 1923–1928.
- Clinton, W. J. (1994). Executive Order 12898: Federal actions to address environmental justice in minority populations and low income populations. Retrieved from <http://www.gpo.gov:80/fdsys/pkg/FR-1994-02-16/html/94-3685.htm>
- Cox, L. A., Jr. (2012). Why income inequality indexes do not apply to health risks. *Risk Analysis*, 32, 192–196.
- Cropper, M., Krupnick, A., & Reich, W. (2016). *Preferences for equality in environmental outcomes*. NBER Working Paper No. 22644.
- DeNavas-Walt, C., Proctor, B. D., & Smith, J. C. (2012). Income, poverty, and health insurance coverage in the United States: 2011. In *Current Population Report, P60-243*, (pp. 1–81). U.S. Census Bureau.
- EPA. (2013). *Economic analysis of the formaldehyde standards for composite wood products act implementing regulations proposed rule* Retrieved from <http://www.regulations.gov/#!documentDetail;D=EPA-HQ-OPPT-2012-0018-0484>.
- Erreygers, G. (2009). Can a single indicator measure both attainment and shortfall inequality? *Journal of Health Economics*, 28(4), 885–893.
- Erreygers, G., Clarke, P., & Van Ourti, T. (2012). “Mirror, mirror, on the wall, who in this land is fairest of all?”—Distributional sensitivity in the measurement of socioeconomic inequality of health. *Journal of Health Economics*, 31(1), 257–270.
- Evans, W. N., & Viscusi, K. (1991). Estimation of state-dependent utility functions using survey data. *Review of Economics and Statistics*, 73(1), 94–104.
- Fann, N., Roman, H. A., Fulcher, C. M., Gentile, M. A., Hubbell, B. J., Wesson, K., & Levy, J. I. (2011). Maximizing health benefits and minimizing inequality: Incorporating local-scale data in the design and evaluation of air quality policies. *Risk Analysis*, 31, 908–922.
- Farrow, S. (2011). Incorporating equity in regulatory and benefit-cost analysis using risk-based preferences. *Risk Analysis*, 31, 902–907.
- Fleurbaey, M. (2005). Health, wealth, and fairness. *Journal of Public Economic Theory*, 7(2), 253–284.
- Fowlie, M., Holland, S. P., & Mansur, E. T. (2012). What do emissions markets deliver and to whom? Evidence from Southern California's NO<sub>x</sub> trading program. *American Economic Review*, 102, 965–993.
- Gamper-Rabindran, S., & Timmins, C. (2011). Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. *American Economic Review*, 101(3), 620–624.
- Garber, A. M., & Phelps, C. E. (1997). Economic foundations of cost-effectiveness analysis. *Journal of Health Economics*, 16(1), 1–31.
- Hammit, J. K. (2013). Admissible utility functions for health, longevity, and wealth: Integrating monetary and life-year measures. *Journal of Risk and Uncertainty*, 47(3), 311–325.
- Harper, S., Ruder, E., Roman, H. A., Geggel, A., Nweke, O., Payne-Sturges, D., & Levy, J. I. (2013). Using inequality measures to incorporate environmental justice into regulatory analyses. *International Journal of Environmental Research and Public Health*, 10, 4039–4059.
- Harsanyi, J. C. (1955). Cardinal utility in welfare economics and in the theory of risk-taking. *Journal of Political Economy*, 61(5), 434–435.
- Jones, A. F., Jr., & Weinberg, D. H. (2000). The changing shape of the nation's income distribution 1947–1998. In *Current Population Reports, P60-204*, (pp. 1–11). U.S. Census Bureau.
- Kaplow, L. (2005). Why measure inequality? *Journal of Economic Inequality*, 3, 65–79.
- Kaplow, L., & Shavell, S. (2001). Any non-welfarist method of policy assessment violates the Pareto principle. *Journal of Political Economy*, 2, 281–286.
- Kolm, S.-C. (1976). Unequal inequalities I. *Journal of Economic Theory*, 12, 416–442.
- Lambert, P. (2001). *The distribution and redistribution of income*. Manchester: Manchester University Press.
- Lambert, P., & Zheng, B. (2011). On the consistent measurement of attainment and shortfall inequality. *Journal of Health Economics*, 30(1), 214–219.
- Levy, J. I., Chemerynski, S. M., & Tuchmann, J. L. (2006). Incorporating concepts of inequality and inequity into health benefits analysis. *International Journal for Equity in Health*, 5, Art. 2.
- Levy, J. I., Greco, S. L., Melly, S. J., & Mukhi, N. (2009). Evaluating efficiency-equality tradeoffs for mobile source control strategies in an urban area. *Risk Analysis*, 29(1), 34–47.
- Levy, J. I., Wilson, A. M., & Zwack, L. M. (2007). Quantifying the efficiency and equity implications of power plant air pollution control strategies in the United States. *Environmental Health Perspectives*, 115(5), 743–750.
- Maguire, K., & Sheriff, G. (2011). Comparing distributions of environmental outcomes for regulatory environmental justice analysis. *International Journal of Environmental Research and Public Health*, 8, 1707–1726.

- Murphy, K. M., & Topel, R. H. (2006). The value of health and longevity. *Journal of Political Economy*, 114(5), 871–904.
- Pollak, R. A. (1971). Additive utility functions and linear Engel curves. *Review of Economic Studies*, 38(4), 401–414.
- Rawls, J. (1971). *A theory of justice*. Cambridge, MA: Harvard University Press.
- Rey, B., & Rochet, J.-C. (2004). Health and wealth: How do they affect individual preferences? *Geneva Papers on Risk and Insurance Theory*, 29(1), 43–54.
- Ringquist, E. J. (2005). Assessing evidence of environmental inequities: A meta-analysis. *Journal of Policy Analysis and Management*, 24(2), 223–247.
- United Church of Christ. (1987). *Toxic wastes and race in the United States: A national report on the racial and socio-economic characteristics of communities with hazardous waste sites*. Public Data Access.
- Zheng, B. (2007). Unit-consistent decomposable inequality measures. *Economica*, 74, 97–111.