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ARTICLE

Toxic Inequalities

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Abstract
Environmental pollution often affects the most disadvantaged people the most. In this paper, we argue that benefit–cost analyses of policies and programs designed to alleviate such inequalities should incorporate distributional considerations while respecting individual preferences. The concept of equivalent income offers a theoretically sound approach for defining distributional weights that does not rely on the comparison of well-being measures such as subjective utility, happiness or life satisfaction. We demonstrate how this concept can be used to analyze the implications of exposure to neurotoxic substances, which requires us to explicitly consider the endogenous relationship between neurodevelopment and income in the derivation of welfare weights. Through a simulation exercise, we show the difference between standard and inequity-aware welfare analysis and highlight the profound effect on program choice that accounting for unequal exposure to pollution has. Based on our results, we discuss why policymakers concerned with environmental health and safety should seek to factor fairness considerations into their decision-making processes.

> The percentage of children with elevated blood lead levels [in Flint, MI] increased after water source change, particularly in socioeconomically disadvantaged neighborhoods. Water is a growing source of childhood lead exposure because of aging infrastructure. (Hanna-Attisha *et al.*, 2016)

1. Introduction

Research documenting that disadvantaged groups of society are disproportionately exposed to environmental pollution is abundant (e.g., Mohai *et al.*, 2009; Laurent, 2011; Banzhaf, 2012; Banzhaf *et al.*, 2019). The causes of such "toxic inequalities" are numerous and often intertwined. Two prominent factors contributing to environmental injustice are regulatory failure and intergenerational transmission of poverty.[1] They pose challenges for policymakers who seek to alleviate environmental inequalities while respecting people's

[1] Banzhaf *et al.* (2019) discuss other factors such as profit-maximizing decisions by polluting firms, Coasean negotiations between firms and communities, as well as Tiebout-like utility-maximizing decisions by households.

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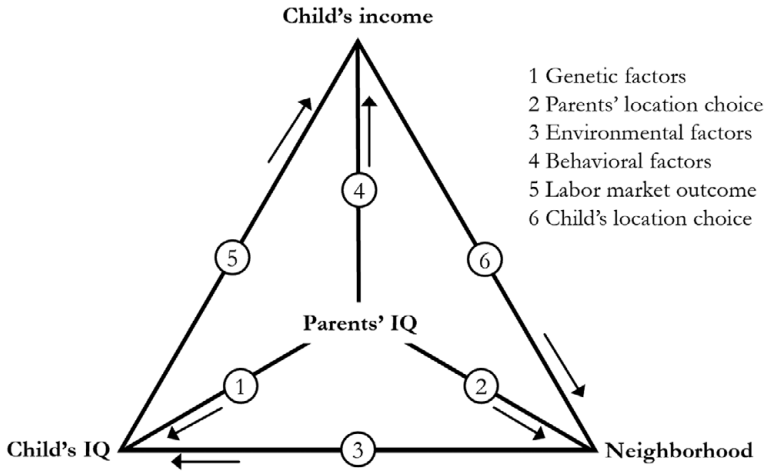


Figure 1. Pyramid of toxic inequalities (adapted from *Banzhaf and McCormick* (2012)).

preferences for health and safety (Fleurbaey *et al.*, 2013; Adler, 2016; Sheriff & Maguire, 2020). One particularly startling example is inequalities caused by exposure to neurotoxic substances – lead in drinking water or mercury in the vicinity of coal-fired power plants are salient examples – that impair the cognitive development of children. The impacts are often irreversible, affecting exposed individuals throughout their lives (Grönqvist *et al.*, 2020), and are predominantly borne by children who grow up in disadvantaged neighborhoods (Currie, 2011).

Exposure to neurotoxic substances often coincides with and amplifies existing social inequalities. For instance, Aizer *et al.* (2018) find that disadvantaged children in Rhode Island are more likely to be exposed to lead, which may be one of the reasons for the observed disparities in math and reading test scores among students from different socioeconomic backgrounds. In the long run, toxic inequalities create a vicious circle in which the cognitive ability of parents impacts their disposable income and, through that, determines in which neighborhood their children are raised (see Figure 1). Children's cognitive ability becomes the joint outcome of genetic and environmental factors, which in turn affects their future earnings and, through that, their own location choices. Thus, social inequalities tend to be passed on from generation to generation (Bowles & Gintis, 2002).[2]

The traditional economics approach to neighborhood location choices has been based on hedonic pricing, which holds that non-market goods and services are bundles of attributes that are fully internalized in the housing market (Bishop *et al.*, 2020). All else being equal, the presence of toxic substances in a neighborhood should lower housing prices in that area. However, in the context of environmental pollution, we see at least two problems with the hedonic approach. First, pollution will not be adequately reflected in the housing prices that prevail *before* the public becomes aware of the threat. Second,

[2] Things get further complicated by the fact that cognitive ability tends to regress toward the mean. Thus, children in disadvantaged neighborhoods may well be more intelligent than their parents but still less intelligent than they could have been, had they grown up in an unexposed neighborhood.

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even if the potential for exposure to toxic substances is (partially) internalized by the housing market (Currie *et al.*, 2015), prices do not reflect the intergenerational effects identified above unless home buyers are explicitly considering them.

Since housing prices are unlikely to accurately reflect exposure to neurotoxic substances and other invisible pollutants, economists have come up with alternative approaches to assess the benefits of cleanup projects and pollution prevention policies. The standard practice is to measure the pollution-induced harm in terms of IQ loss and convert it to the expected lifetime earnings loss faced by affected individuals (Grosse *et al.*, 2002). However, this approach fails to capture distributional aspects of environmental pollution and ignores that the income elasticity of demand for the provision of environmental goods – or the avoidance of environmental bads – is commonly found to be substantially smaller than unity (Baumgärtner *et al.*, 2017; Drupp *et al.*, 2018). In other words, standard benefit–cost analysis (BCA) is silent about inequalities in exposure to harmful substances, and these "toxic inequalities" are further compounded by income inequalities.

In theory, the marginal willingness-to-pay (WTP) to avoid the loss of one IQ point should be proportional to the expected income gain *and* any other utility derived from avoiding this loss. This implies that the burden of neurotoxicity as measured by unweighted WTP is lower if poorer people bear the brunt of pollution. Accordingly, if one is solely interested in efficiency, then programs aimed at restoring the environmental status of poorer neighborhoods are comparatively less desirable than those targeted at better-off neighborhoods (Harberger, 1978). Such a strong focus on efficiency is at odds with fairness considerations widely recognized by BCA scholars (Adler, 2016; Fleurbaey & Abi-Rafeh, 2016; Banzhaf, 2023; Fleurbaey & Hammitt, 2024). Moreover, the efficiency argument is only valid under the assumption that costless lump-sum transfers are feasible (Johansson-Stenman, 2005), and it depends on the numéraire chosen for the analysis (Hammitt, 2021). Lastly, unweighted BCA has also been criticized for violating democratic principles as it favors some people systematically over others (Nyborg, 2014).

This paper presents a non-welfarist approach to analyzing unequal exposure to toxic pollutants that incorporates fairness considerations while respecting individual preferences. To fix ideas, we introduce the tale of Janusville – a fictional town where the poorer half of the population live on the B side and the richer half reside on the A side. Income in Janusville is approximately lognormally distributed. Intelligence would be normally distributed (with a mean IQ of 100 points and a standard deviation of 15 points), if it were not for the contamination of drinking water that causes children growing up on the B side to have two IQ points less than they would have otherwise. As suggested by Figure 1, the labor market outcome of these children will be determined by both their intelligence and the support they receive from their parents. Together these factors imply that the prospective income of children growing up on the B side of Janusville is lower than that of children growing up on the A side.

Let us assume that the town council gathers to decide whether they should invest in a cleanup project benefiting children on the B side only or spend the money on an educational program to help children across town to grapple with life. Both programs are thought to provide the same aggregate IQ gain for future generations and entail the same costs.[3]

[3] One may argue that educational programs are unlikely to achieve substantial gains in IQ. However, as the Perry Preschool Program has demonstrated, disadvantaged children can achieve remarkable results when given proper support (Heckman *et al.*, 2010).

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The council debates which program is better. This is a thorny question as it relates to how the distribution of intelligence will eventually affect aggregate income, and what that means. Taking efficiency as the core criterion, the town should strive for the IQ distribution that maximizes aggregate income. However, it seems ethical to demand the town council consider fairness aspects in its evaluation.

In the remainder of the paper, we seek to advise the town council of Janusville on the program choice considering different ethical principles for dealing with distributive justice. Our approach is based on the concept of equivalent income, which we define as the hypothetical income that makes an individual indifferent between their current well-being endowment (in terms of consumption, health, social status, work-life balance, etc.) and a well-being endowment that fixes all but the individual's income to specific reference levels (Fleurbaey, 2016). Equivalent income is an attractive concept for making interpersonal comparisons because it accounts for differences in resource endowments while respecting individual preferences.

Unlike previous applications of the equivalent income concept in the health domain (e.g., Fleurbaey *et al.*, 2013; Samson *et al.*, 2018), we explicitly consider the interdependence of health and wealth (Fuchs, 2004; Deaton, 2008). This is particularly relevant for the relationship between IQ and income as more intelligent individuals tend to earn more than less intelligent ones. In Section 2, we set out the theoretical background and present a welfare model that accounts for the feedback effect between IQ and income. Section 3 introduces equivalent income as a non-welfarist measure of individual preferences and shows how it may be used to obtain theoretically sound welfare weights that can be employed in applied BCA. In Section 4, we apply the concept to the question of program choice faced by the town council of Janusville, contrast it to the results obtained with standard BCA, and highlight the normative challenges with each approach. Section 5 concludes.

2. Theoretical background

We start with a simple model in the spirit of Fleurbaey *et al.* (2013) to address unequal exposure to neurotoxic substances in Janusville.[4] The situation of individual $i = 1, \ldots, n$ is described by the tuple $(y_i(g_i), g_i)$, where g_i denotes i's intelligence (typically measured in IQ) and $y_i(g_i)$ is their prospective income, which itself is a function of intelligence. Building on Bergson (1938) and Samuelson (1947), our model evaluates the vectors $(y_1(g_1), g_1), \ldots, (y_n(g_n), g_n)$ in terms of a real-valued social welfare function (SWF): $W(u_1(y_1(g_1), g_1), \ldots, u_n(y_n(g_n), g_n))$, where u_i expresses individual i's preferences. W is thus a numerical representation of society's preference ordering, which we assume to respect the Pareto principle. This implies that W assigns the same value to those states of the world in which everyone is equally well-off.

Since we attempt to model the situation in Janusville, we focus on the welfare effect of a marginal gain in intelligence dg_i but abstract from other factors that affect prospective

[4] We ignore the time gap between exposure to neurotoxic substances during childhood and labor market outcomes in adulthood. Instead, we characterize individuals based on their intelligence and prospective lifetime earnings.

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income y_i. Taking the full differential of W, we define an infinitesimal change to the initial situation as follows:

$$dW = \sum_i \frac{\partial W}{\partial u_i}\frac{\partial u_i}{\partial y_i}\left[\frac{\partial y_i}{\partial g_i}dg_i + \frac{\partial u_i}{\partial g_i}\frac{\partial y_i}{\partial u_i}dg_i\right]. \tag{1}$$

The right-hand side of Equation (1) can be further decomposed. Using customary notation, $\beta_i \equiv \frac{\partial W}{\partial u_i}\frac{\partial u_i}{\partial y_i}$ accounts for the marginal welfare that society derives from individual i being marginally better off. The terms in square brackets represent i's willingness-to-pay (WTP) for obtaining the marginal gain in intelligence dg_i. Specifically, $\frac{\partial y_i}{\partial g_i}dg_i$ is the expected change in prospective income due to the gain in intelligence, while $\frac{\partial u_i}{\partial g_i}\frac{\partial y_i}{\partial u_i}dg_i$ captures the gain in utility (converted into a money equivalent) and thus represents the hedonic value of intelligence.

With this in mind, we may rewrite Equation (1) as a weighted sum of individual WTPs:

$$dW = \sum_i \beta_i \mathrm{WTP}_i. \tag{2}$$

As discussed in detail by Fleurbaey *et al.* (2013), Equation (2) incorporates both empirical and ethical considerations. WTP_i may be derived from market observations or elicited by stated preference methods, while β_i is a parameter that measures how a gain in i's prospective income should be compared with similar gains accruing to other individuals (Boadway, 2006). By definition, β_i consists of (i) an ethical component, $\frac{\partial W}{\partial u_i}$, that reflects how much society values an extra unit of utility accruing to person i; and (ii) an empirical component, $\frac{\partial u_i}{\partial y_i}$, that reflects i's marginal utility from income. Based on common fairness arguments, society should give more weight to those individuals whose starting point is less favorable, for example, because of unequal exposure to pollution.

Three broad arguments have been made against the use of distributional weights in BCA (Boadway, 2006; Adler, 2016; Acland & Greenberg, 2023): (i) the focus of BCA should be on efficiency; (ii) according to the Kaldor–Hicks compensation, principle income could, at least in theory, be distributed in a Pareto-efficient way; and (iii) everyone can expect to be better off in the long-run, since eventually positive net payoffs from various policy changes will even out among individuals. In a first-best world, the efficiency argument has merit because government can redistribute income without affecting labor supply choices (Boadway & Keen, 1993; Kaplow, 1998). We will briefly discuss the first-best solution before turning to the more realistic second best in which authorities have limited power over the tax schedule. Typically, local authorities cannot levy and redistribute taxes independently, but they may still seek to address equity concerns in public projects while respecting citizens' preferences.[5]

2.1. First-best solution

To establish a benchmark, we first apply the logic of standard BCA, which ignores distributional concerns entirely and evaluates policies solely based on aggregate, unweighted WTP

[5] In the Appendix, we also discuss the case in which authorities may levy and redistribute taxes, but transfers remain imperfect as taxpayers respond by adapting their labor supply to the tax schedule.

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(Banzhaf, 2023). In keeping with this logic, the first-best solution refers to a situation in which government can redistribute income without constraints. In other words, any post-transfer income distribution $(y_1, \ldots, y_n)$ that preserves the total sum of income is feasible (Adler, 2016). Ignoring differences in the marginal utility of income across individuals, and under the maintained assumptions of costless redistribution and a fully monetized welfare metric, the socially optimal solution is to maximize total income $Y = \sum_i y_i$ and redistribute it so that $\beta_i = \beta$ for all i. This allows us to normalize β to unity without loss of generality.

Under these assumptions, a policy that seeks to reduce detrimental impacts on population-level intelligence should maximize aggregate WTP for the attainable increase in IQ:

$$\max \sum_i \left[\frac{\partial y_i}{\partial g_i} x_i + \frac{\partial u_i}{\partial g_i} \frac{\partial y_i}{\partial u_i} x_i \right] - C \text{ s.t.} X = \sum_i x_i, \tag{3}$$

where x_i refers to the absolute IQ gain that individual i can expect from a policy whose cost is C; accordingly, X is the achievable population increment in IQ (i.e., the total IQ points gained across the population). In order to be meaningful, the allocation of X needs to come from a feasible set (i.e., we exclude all allocations that would result in some individuals having an extraordinary IQ).

Equation (3) suggests that government should prioritize those with the highest WTP for IQ changes and the terms in brackets are decisive for the choice of policy. If we presume that average income increases with IQ and the marginal rate of substitution between intelligence and income is also increasing in income, then WTP_i is higher for wealthier people. Applying this result to Janusville suggests that an educational program targeting both sides of town (or just the A side) would be preferable to a cleanup project that benefits only the B side. This is because the additional gains in prospective income from the educational program could, in theory, be re-distributed to the less well-off. This argument, widely known as the potential Pareto test, was devised by Kaldor and Hicks precisely to circumvent distributional issues in BCA (Banzhaf, 2023).

2.2. *Second-best solution*

Readers may object to this advice on ethical grounds since the first-best solution disregards inequalities in exposure to neurotoxic substances. Moreover, the assumption of perfect redistribution is unrealistic for most real-world applications. Instead, we now consider that Janusville has no discretionary powers to levy and redistribute taxes and must finance public projects from a given budget. This assumption allows us to study the implications of limited redistribution without explicitly modeling labor-leisure responses (see Johansson-Stenman *et al.*, 2002). However, it also breaks the first-best equivalence and motivates the search for a second-best solution.

Given the constraint on income transfers, the town should maximize the weighted sum of individual WTPs:

$$\max \sum_i \beta_i \left[\frac{\partial y_i}{\partial g_i} x_i + \frac{\partial u_i}{\partial g_i} \frac{\partial y_i}{\partial u_i} x_i \right] - C \text{ s.t.} X = \sum_i x_i, \tag{4}$$

where the notation is the same as in Equation (3); accordingly, $\beta_i \left[\frac{\partial y_i}{\partial g_i} + \frac{\partial u_i}{\partial g_i} \frac{\partial y_i}{\partial u_i} \right]$ is i's weighted WTP for an IQ increment of exactly one point. In contrast to the first best, β_i depends on

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individual *i*'s initial endowment of income and IQ. The big question is now *how* the weights should differ between individuals with different initial endowments. Any answer to this question involves ethical considerations regarding how society ranks gains in utility to different individuals and empirical considerations related to how individuals' utility changes when their income or intelligence increases.

Since the weight β_i given to individual *i* can be broken down into $\frac{\partial W}{\partial u_i}$ and $\frac{\partial u_i}{\partial_{y_i}}$, we can study how different ethical considerations affect the weights. Whereas utilitarians assume $\frac{\partial^2 W}{\partial u_i^2} = 0$ and thus apply the same weight to all utility changes, prioritarians maintain that more weight be given to those in less favorable circumstances, that is, $\frac{\partial^2 W}{\partial u_i^2} < 0$.[6] Regardless of one's ethical view, less weight should thus be given to a person with a higher initial endowment, and vice versa. The weights affect how BCA accounts for the terms in brackets in Equation (4), where the first term captures the expected change in income from a one-point gain in IQ. Because labor economists find that gains in income increase with concurrent IQ (e.g., Lin *et al.*, 2018), we assume that this term is marginally increasing in g_i. The second term describes the marginal rate of substitution between IQ and income and may hence be seen as the WTP for a one-point gain in IQ.

To implement this second best, the town council needs advice on how to (i) construct meaningful welfare weights and (ii) estimate the income demand elasticity for IQ points. Distributional weights are typically larger for poorer individuals, reflecting diminishing welfare gains to society from improving people's well-being. Yet, in absolute terms, wealthier individuals may be willing to pay more for health-related goods than poorer ones. This is reflected by Equation (4), where the two terms in brackets go in opposite directions as wealth increases. This implies that optimal program choice is primarily an empirical problem.

3. Distributional weights based on equivalent income

While Section 2 provided pragmatic solutions for program choice under different constraints, they both hinge on the weights assigned to individual WTPs. In this section, we discuss how these weights can be calibrated *without* making interpersonal comparisons of subjective well-being. To start with, suppose that interpersonal comparisons of subjective well-being were meaningful, and that marginal changes in subjective utility due to IQ changes could be readily measured. As Adler (2022) discussed, these assumptions can be combined in a prioritarian SWF with an Atkinson transformation function that displays constant elasticity of substitution in utilities:

$$W(u_1,\ldots,u_n) = \frac{1}{1-\rho}\sum\nolimits_i u_i(y_i(g_i),g_i)^{1-\rho}, \tag{5}$$

so that $\beta_i = \frac{\partial W}{\partial y_i} = \frac{\partial u_i}{\partial y_i} u_i(y_i(g_i),g_i)^{-\rho}$ can be interpreted as a distributional weight that captures society's aversion to inequality governed by the parameter ρ.[7] However, because this weight

[6] Marginal utility of income is assumed to decrease with increasing income, that is, $\frac{\partial^2 u_i}{\partial y_i^2} < 0$, reflecting the well-established fact that a marginal dollar is more worth to the poor than to the wealthy.

[7] The assumption of a CES function is convenient since, depending on the choice of ρ, it can capture both utilitarian and prioritarian preferences.

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is based on interpersonal utility comparisons, it raises both practical and ethical concerns. It is simply unclear how subjective utility could be meaningfully compared between individuals.

One approach to addressing this issue is to assume that all individuals derive the same utility from income. This can be modeled by a constant elasticity function so that $u_i(y_i) = \frac{y_i^{1-\varepsilon}}{1-\varepsilon}$, with ε being a constant coefficient of relative risk aversion (CRRA). Inserting the CRRA utility function into Equation (5) yields after some algebra:

$$W(u_1,\ldots,u_n) = \frac{1}{1-\sigma}\sum\nolimits_i y_i^{1-\sigma}, \tag{6}$$

with $\sigma = \varepsilon + \rho - \rho\varepsilon$ (see Nurmi & Ahtiainen, 2018). Accordingly, the distributional weight attached to individual i's income becomes $\beta_i = y_i^{-\sigma}$, where the parameter σ combines diminishing marginal utility of income (as expressed by the relative risk aversion of individuals) with society's relative inequality aversion. As noted by Kaplow (2010), the SWF given by Equation (6) may be interpreted as (i) a utilitarian welfare function with constant relative risk aversion, (ii) an egalitarian SWF with risk-neutral individuals or (iii) a combination of such preferences.[8]

The weights implied by Equation (6) avoid interpersonal comparisons, but they also ignore other resources that the individual is endowed with, such as their baseline IQ. To capture differences in resource endowments, we assume that for every individual i there exists a compensating variation z_i such that $(y_i(g_i), g_i) \sim ((y'(g') - z_i), g')$, where g_i and $y_i(g_i)$ are i's IQ and prospective income, respectively, g' is a chosen reference level of IQ, and $y'(g')$ is the after-tax income corresponding to that reference level.[9] In other words, individual i is willing to pay (or receive) the compensating variation $z_i = \int_{g_i}^{g'} \left[\frac{\partial y_i}{\partial g_i} + \frac{\partial u_i}{\partial g_i}\frac{\partial y_i}{\partial u_i}\right] dg$, where the first term in brackets captures the change in expected income when moving from the current IQ to the reference IQ. Below, we will denote this income change by $\Delta y_i(g_i \to g')$. The second term in brackets corresponds to the hedonic value of intelligence, which we will denote by $\mathrm{WTP}_i(g_i \to g' | y_i)$.[10]

There is a crucial difference between our setup and that of Fleurbaey *et al.* (2013). Namely, z_i captures both the direct effect of IQ on well-being and the feedback effect that IQ has on well-being via increased consumption potential (Fuchs, 2004; Deaton, 2008). It allows us to formally define individual i's equivalent income as follows:

$$y_i^*(y_i(g_i), g_i, y', g') = y'(g') - z_i. \tag{7}$$

In the special case where $\frac{\partial u_i}{\partial g_i}\frac{\partial y_i}{\partial u_i} = 0$, the compensating variation simplifies to $z_i = y'(g') - y_i(g_i)$ and the corresponding equivalent income becomes $y_i^*(y_i(g_i), g_i, y', g') = y_i(g_i)$.[11] In other words, the inverse of the prospective income distribution is used to determine the distributional weights (Nurmi & Ahtiainen, 2018).

[8] In line with the literature, we will refer to σ as inequality aversion parameter, even though it technically combines individual and societal preferences. See Kaplow (2010) for a discussion of the difference between σ, ρ, and ε.

[9] For practical reasons, we assume a reference level of g' = 100 IQ points. However, we stress that an alternative reference level would simply rescale all equivalent incomes and thus shift all weights proportionally. In this sense, g' merely serves as a normalization, and the reference IQ level does not affect program choice.

[10] We note that WTP_i can be negative, that is, a willingness-to-accept, if i's current intelligence is higher than the chosen reference level.

[11] Note that this is the case if individuals are risk neutral, that is, if $\varepsilon = 1$.

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Up to this point, we have defined the compensating variation z_i in terms of individuals' marginal rates of substitution between income and intelligence. In this sense, the construction remained consistent with a welfarist perspective. Now, we impose additional structure by assuming a common relationship between income and the hedonic value of intelligence across individuals. As Fleurbaey *et al.* (2013) discuss in detail, with this assumption, y_i^* is *not* a welfarist measure anymore since it does not measure subjective utility, even though it satisfies the Pareto principle. To appreciate this point, consider two individuals who have the same income and IQ but value their resource endowment differently. In a welfarist framework like the one given by Equation (5), their different preferences would justify weighing these two individuals differently. Under the equivalent-income approach, however, both individuals are assigned the same equivalent income. Therefore, we can rewrite Equation (5) as $W\left(y_1^*,\ldots,y_n^*\right)$.

Upon inserting into Equation (7), the welfare change due to a change in population intelligence becomes:

$$dW = \sum\nolimits_i \frac{\partial W}{\partial y_i^*}\frac{\partial y_i^*}{\partial y_i}\left[\frac{\partial y_i}{\partial g_i}+\frac{\partial y_i^*}{\partial g_i}\frac{\partial y_i}{\partial y_i^*}\right]dg_i. \tag{8}$$

This welfare change consists again of two factors – individual i's total benefit of a specified gain in intelligence, $\left[\frac{\partial y_i}{\partial g_i}+\frac{\partial y_i^*}{\partial g_i}\frac{\partial y_i}{\partial y_i^*}\right]dg_i$, and the corresponding weight $\beta_i = \frac{\partial W}{\partial y_i^*}\frac{\partial y_i^*}{\partial y_i}$, which indicates how society values this specific gain in comparison with the gains accruing to other individuals. Importantly, when using the equivalent-income approach, the weight assigned to each individual is a combination of ethical considerations captured by society's valuation of equivalent income, that is, $\frac{\partial W}{\partial y_i^*}$, and empirical facts reflected by the expected change in equivalent income from a change actual income, that is, $\frac{\partial y_i^*}{\partial y_i}$.

Using the chain rule, we can break down Equation (8) further and rewrite the distributional weight as $\beta_i = \frac{\partial W}{\partial u_i}\frac{\partial u_i}{\partial y_i^*}\frac{\partial y_i^*}{\partial y_i}$. This decomposition makes clear that the weight captures three elements: society's valuation of an individual's utility, the curvature of individual utility in equivalent income, and the way changes in actual income translate into changes in equivalent income. If one takes the stance that intelligence per se is not part of an individual's resource endowment and has only instrumental value in obtaining a larger income, then $\frac{\partial y_i^*}{\partial y_i}=1$ and thus $y_i^*(y_i(g_i),g_i)=y_i(g_i)$. Similarly to the steps in Equations (5) and (6), one obtains an Atkinson SWF function where the applicable weight boils down to $\beta_i = y_i^{-\sigma}$.[12]

Conversely, if intelligence is considered to be more than just a means to an end, the welfare weight becomes $\beta_i = \frac{\partial y_i^*}{\partial y_i}\left[y_i^*(y_i(g_i),g_i)\right]^{-\sigma}$, where $y_i^*(y_i(g_i),g_i)=y_i(g_i)-\mathrm{WTP}_i(g_i\rightarrow g'|y_i)$ and $\frac{\partial y_i^*}{\partial y_i}=1-\frac{\partial \mathrm{WTP}_i(g_i\rightarrow g'|y_i)}{\partial y_i}$. In words, the welfare weight now reflects the individual's valuation of intelligence captured by their WTP; the income dependence of this valuation through the mapping from actual income into equivalent income; and society's distributive preferences over equivalent income expressed through the inequality aversion parameter σ. Note that also in this case the parameter σ captures both the diminishing marginal utility of income and social aversion to inequality.

[12] The same result holds if the monetary valuation of intelligence is income invariant, that is, $\frac{\partial \mathrm{WTP}_i}{\partial y_i}=0\rightarrow\frac{\partial y_i^*}{\partial y_i}=1$.

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To assess the interplay of these dimensions, we can rewrite $\frac{\partial y_i^*}{\partial y_i}$ in terms of income elasticity of WTP. Define $\eta_i = \frac{y_i}{\text{WTP}_i} \frac{\partial \text{WTP}_i}{\partial y_i}$, then $\frac{\partial y_i^*}{\partial y_i} = 1 - \eta_i \frac{\text{WTP}_i}{y_i}$. This expression is convenient as it allows us to distinguish three cases (Nurmi & Ahtiainen, 2018): (i) if $\eta = 1$, then $\frac{\partial y^*}{\partial y}$ is constant; (ii) if $\eta > 1$, then $\frac{\partial y^*}{\partial y}$ falls with income; and (iii) if $\eta < 1$, then $\frac{\partial y^*}{\partial y}$ rises with income. Assuming constant income elasticity means the factor $\frac{\partial y_i^*}{\partial y_i}$ assigns relatively more weight to the poor (rich), whenever benefits are distributed progressively (regressively). When the income elasticity exceeds one, benefits are disproportionately valued by the rich, and the equivalent-income mapping further tilts the weights in favor of the poor. Conversely, when the income elasticity is below one, the mapping partially offsets the prioritarian tilt. Intuitively, when the non-income attribute is valued disproportionately more by poorer individuals, less additional reweighting toward the poor is required. Conversely, when richer individuals value the same attribute disproportionately more, stronger reweighting is warranted. Importantly, this adjustment does not reflect an ethical judgment but corrects for the income dependence of monetary valuation. Distributive preferences remain solely governed by the inequality aversion parameter σ.

4. Application

We now return to the challenge of advising the town council of Janusville and apply the framework developed above to evaluate the different policy options laid out in the introduction section. To facilitate this exercise, we need to make assumptions about the relationship between childhood IQ and future earnings. Fortunately, the impact of childhood IQ on future earnings has been widely studied (Lin *et al.*, 2018). While existing studies differ with regard to outcome age, measure of income, extent to which non-cognitive factors were accounted for and the inclusion of other control variables, they all find a strong link between IQ and future earnings. For example, Cunha and Heckman (2016) find a convex relationship between productivity and both genetic and acquired cognitive abilities, implying that people with higher cognitive abilities are disproportionately rewarded by the labor market.[13]

The direct change in utility from a gain in IQ expressed in monetary terms – that is, the hedonic value of a higher IQ – is less studied, since it cannot be readily inferred from market observations. The most relevant research we are aware of is a recent survey study by Mourato *et al.* (2023) in which 13,200 respondents from 11 OECD countries were asked to state their WTP for avoiding a specific IQ point loss in their children. Importantly, respondents were explicitly instructed not to focus on future income of their offspring but rather on how well their children would do in school. Mourato and her co-authors found that the WTP per IQ point increased with income, but not proportionately. In other words, IQ appeared to be a necessity rather than a normal good.

4.1. Janusville

We draw on these empirical findings to simulate the population of Janusville. Our simulation seeks to account for the causal relationships that influence a child's labor market outcome as

[13] A convex relationship is consistent with normally distributed IQ and lognormally distributed income across society.

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displayed by Figure 1. The starting point of our simulation is parental IQ and income, which together determine on which side of town a child will grow up. Neighborhood choices affect a child's prospects because children living on the B side will be exposed to neurotoxic substances, while children living on the A side will not. Parental IQ also impacts a child's IQ, which we capture by imposing a positive correlation between IQ and parents' income. Eventually, a child's IQ will determine their lifetime earnings via labor market outcomes.

We capture these relationships through 1,000 draws from a multivariate normal distribution with partial correlations between parents' income, children's IQ and expected lifetime earnings. We then use parental income as a sorting variable so that the poorer half of the population lives on the B side of Janusville and the richer half on the A side. Because parental income is positively correlated with both children's IQ and expected lifetime earnings in the simulated distribution, this sorting induces systematic differences across neighborhoods not only in income but also in cognitive endowments. As a result, the B side is disadvantaged both in terms of income and IQ already prior to the pollution shock, capturing intergenerational persistence in social inequality.

For simplicity, we assume that each child growing up on the B side will lose two IQ points compared to a world in which no toxic inequalities existed. Consistent with findings by Lin *et al.* (2018), we assume a reduction of two IQ points will reduce the lifetime earnings of these children by about 3%. Based on this setup, we derive the IQ and expected lifetime earning distributions shown in Figure 2, with a mean IQ of 94.4 on the B side and of 103.8 on the A side, respectively. Normalized to average lifetime earnings, income has a mean of 0.81 on the B side and 1.19 on the A side, respectively. The assumed correlation between parents' income and their offspring's IQ offspring is $\rho = 0.3$, which is broadly consistent with findings in the intelligence literature (e.g., Von Stumm & Plomin, 2015).

4.2. Distributional weights in practice

Implementing the equivalent income weights introduced in Section 3 requires knowledge of the equivalent income for each individual, which is determined by the program choice as well as by the choice of the inequality aversion parameter σ. While future lifetime earnings

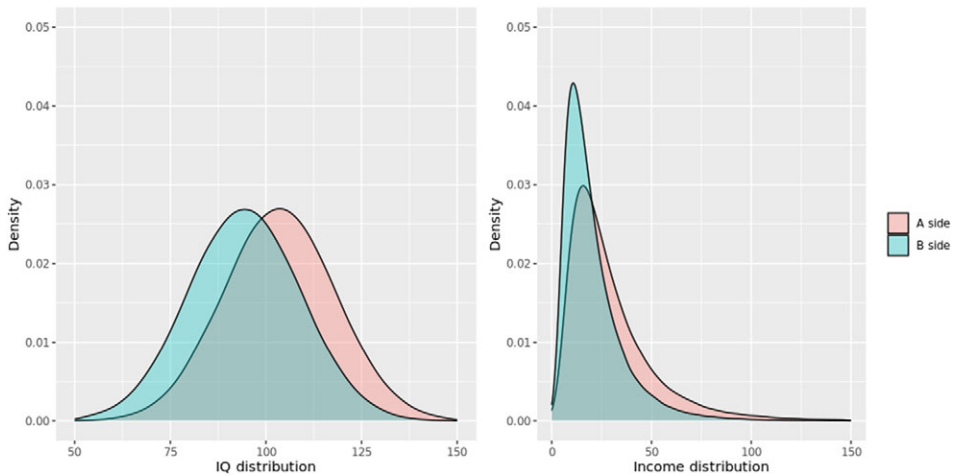


Figure 2. *Initial IQ and income distributions on both sides of Janusville.*

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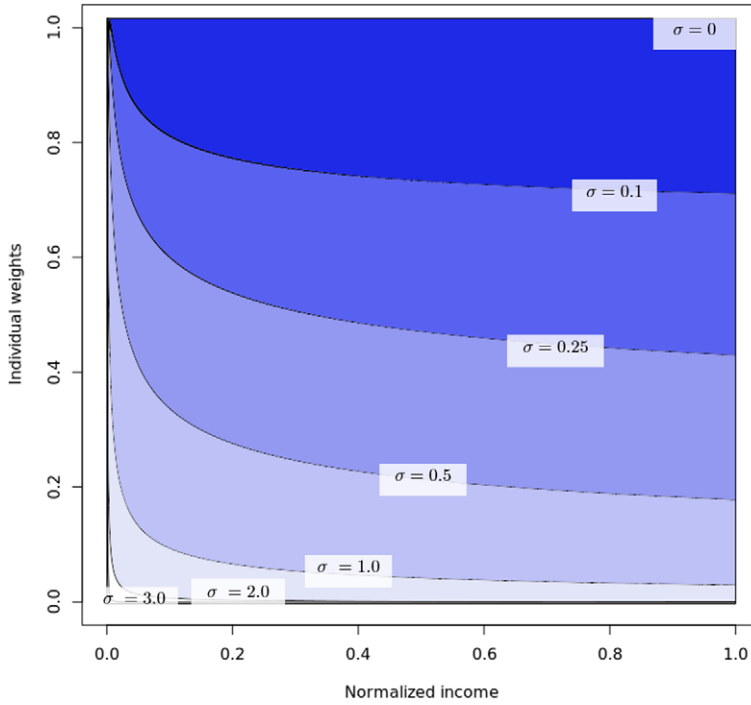


Figure 3. *Contour plot for different values of income and inequality aversion.*

are calibrated to empirical data in our simulation, σ is a policy parameter. There is a stream of literature discussing plausible values of σ based on both empirical findings (Dasgupta, 1998; Johansson-Stenman *et al.*, 2002) and ethical considerations (Anthoff *et al.*, 2009; Hallegatte *et al.*, 2016). Most studies suggest values of σ between 0.5 and 2 but recommend conducting a sensitivity analysis. Below, we explore values of σ between 0 and 3, noting that these extremes may be ethically less desirable.

To calculate the individual weight β_i, we normalize the equivalent income y_i^*. Typically, this is done by dividing through a specific reference income. While this normalization has neither an effect on the relative weights nor on the eventual choice of program, it does affect the aggregate scaling of a unit increase in monetized welfare. We, therefore, set the reference income equal to the minimum lifetime earnings in the simulated population so that the weight given to the worst-off individual equals unity. Figure 3 shows how the chosen inequality aversion parameter affects the relative weights. Note that with increasing inequality aversion, the weights become ever more sensitive to income.

4.3. Results of the simulation

Our simulations explore two distinct scenarios: redistribution of program benefits is possible (first best), and redistribution of benefits is not possible (second best).[14] For comparing the

[14] In the Appendix, we sketch out the solution to an intermediate case where partial redistribution via non-optimal income taxes is possible. In this case, a menu of policy options needs to be assessed with respect to all feasible

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optimal solutions under each of these scenarios, we consider programs of continuous nature so that the attainable increase in aggregate IQ points can be distributed across the population in many ways. In reality, programs are not continuous but discrete proposals. This limits the choice problem to few policy options. We, therefore, modify the solutions obtained in Section 2 to a discrete choice among competing projects. Concretely, consider $j = 1, \ldots, m$ mutually exclusive programs. Then, the first-best solution is given by:

$$\max_j \left\{ \sum_i^n \text{WTP}_{i,1} - C_1, \ldots, \sum_i^n \text{WTP}_{i,m} - C_m \right\}, \tag{9a}$$

while the second-best solution is attained by:

$$\max_j \left\{ \sum_i^n \beta_i \text{WTP}_{i,1} - C_1, \ldots, \sum_i^n \beta_i \text{WTP}_{i,m} - C_m \right\}. \tag{9b}$$

We apply Equations *(9a)* and *(9b)* to two discrete programs that are expected to result in the same aggregate gain in IQ points. Program ***A*** is an educational project that seeks to benefit all children in Janusville and is expected to result in a one IQ point increase for every child. Program ***B*** is a cleanup project that seeks to restore the counterfactual IQ distribution on the B side of town by eliminating inequalities in exposure to neurotoxic substances for future generations. Based on findings by Lin *et al.* (2018), we assume that each IQ point gained will increase a child's lifetime earnings by 1.45%. For simulating the hedonic value of intelligence, we rely on the results of Mourato *et al.* (2023). Specifically, we model WTP based on their estimates of (i) the income elasticity of WTP ($\widehat{\eta} = 0.4$), and (ii) their mean WTP per IQ point, which corresponds to approximately 1% of a person's income. By solving the first-order linear differential equation that results from assumption (i), we obtain a WTP estimate for every individual in the population while respecting the initial condition of assumption (ii).

Table 1 summarizes the results of our simulation. The unweighted net present value (NPV) of the cleanup project (program ***A***) is 20.5 average lifetime earning equivalents, whereas the unweighted NPV of the educational project (program ***B***) amounts to 24.1 average lifetime earning equivalents.[15] This difference is brought about by lower income expectations on the B side of town. Thus, from a pure efficiency view, program ***A*** should be chosen. However, if equity considerations are considered, program ***B*** is preferred for any inequality aversion parameter $\sigma > 0.78$ and the margins become larger the more inequality averse the decision maker is. As discussed above, the literature on inequality aversion supports values of $\sigma > 1$. In our context, this may be further justified by the fact that exposure to pollutants is often caused by negligence, which advocates for inequality aversion being considered in BCA, since living in a polluted area may no longer be an economic choice but the consequence of knowing better.

Could income taxes be adjusted in such a way that the educational project would Pareto dominate the cleanup project? The NPV of the education program for people living on the A

combinations of tax schedules, distributional weights, and distortionary effects of taxes. If the decision maker can find a Pareto-dominant option by adjusting the tax transfer schedule, this option should be chosen (Adler, 2016).

[15] The simulations use the concept of lifetime income which has the advantage that the reader can scale it to any place and time of interest. For example, Tamborini *et al.* (2015) analyze lifetime earnings in the United States for different educational attainments and find average lifetime earnings close to $2 million.

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Table 1. Results of the simulation

NPV in mean lifetime earning equivalent	Increase in income per IQ point	$\sigma = 0$	$\sigma = 0.78$	$\sigma = 1$	$\sigma = 2$	$\sigma = 3$
Program ***A*** (education)	24.1	24.1	18.4	16.3	11.2	8.4
Program ***B*** (cleanup)	24.1	20.5	18.4	17.2	14.1	11.6
Program ranking	$\boldsymbol{A \sim B}$	$\boldsymbol{A \succ B}$	$\boldsymbol{A \sim B}$	$\boldsymbol{B \succ A}$	$\boldsymbol{B \succ A}$	$\boldsymbol{B \succ A}$

The results in Table 1 reflect both the direct and indirect effects of a change in IQ on WTP. If one instead considers that intelligence is not in and of itself a source of individual well-being, then the weight for $\sigma = 1$ becomes $\beta_i = \frac{\bar{y}}{y_i}$, and the corresponding weighted change in welfare is given by $\text{WTP}_i^* = \frac{\bar{y}}{y_i}\text{WTP}_i$. Under these alternative assumptions, income has a proportionate effect on i's WTP for a change in IQ, whereas the weighted WTP is the same for all individuals as $\text{WTP}_i = 1.045 y_i \rightarrow \text{WTP}_i^* = 1.045\bar{y}$. In this case, the weighted WTP per IQ point gained is the same across individuals, and any distribution of IQ gains results in the same aggregate welfare. As soon as WTP for a direct change in utility from IQ is accounted for, Program ***B*** becomes more favorable because the incremental income from gaining two IQ points is slightly higher than the incremental income expected from two consecutive gains of one IQ point each.

side of Janusville is approximately 13.6 mean lifetime earning equivalents, whereas it generates 10.5 lifetime earning equivalents on the B side. If the A side could be subjected to an aggregate tax of at least 10.5 which would subsequently be transferred to the B side, then the educational project Pareto dominates the cleanup project (presuming taxes and transfers are distributed in a suitable manner). However, only geographically targeted taxes and transfers can achieve this. As Figure 2 shows, there are some individuals on the B side with expected lifetime earnings higher than the population mean income. If taxes are based on income rather than location, these individuals will suffer from both the program choice and the change in the tax-transfer schedule. We may, therefore, conclude that environmental injustice can only be fully resolved with spatially exclusive taxes and transfers that bear minimal administrative costs.[16]

We can compare the program ranking in Table 1 to the standard practice of valuing IQ changes, which takes the average increase in expected lifetime earnings per IQ point gained to evaluate the benefit of a project (Grosse *et al.*, 2002). Using this approach, the ranking of the two programs is always the same regardless of how the 1,000 IQ points are distributed. Just like unweighted BCA, the standard approach is agnostic as to who will benefit from a program. Yet, as the aggregate WTP per IQ point on either side of Janusville is assumed to be the same, the standard approach ranks projects akin to a weighted BCA that displays a weak form of inequality aversion. Given the assumptions of our simulation, the inequality aversion parameter that would make both projects equally good and thus correspond to the standard approach in applied BCA corresponds to $\sigma = 0.78$, meaning that even a modestly inequality-averse decision maker should give significantly more weight to the cleanup project.

In the introduction, we pointed out that environmental externalities are often not fully reflected in the housing market; that is, lower housing prices only partly compensate for

[16] Hendren (2020) estimates that transferring an additional $1 from the top to the bottom of the income distribution through increased redistribution is 1.5–2 times more costly than transferring $1 from the bottom to the top through reduced redistribution. For the town council of Janusville, this complicates matters as it implies that the benefit of either program cannot be fully redistributed. Even with best intentions, the welfare gain across individuals will never be equal. And while the educational program may be more efficient, Hendren's result implies that redistributing its gains could be so costly that it might still be more efficient to implement the clean-up program instead.

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expected future losses from pollution. We can do a sensitivity analysis that relaxes this assumption. Suppose instead that the externalities are at least partially internalized so that residents on the B side of Janusville are compensated through lower housing costs not only for the expected earning loss but also for the hedonic value of the associated IQ loss. Let this compensation be denoted by ϑ_i. The equivalent income of individual i on the B side is thus given by $y_i^*(y_i(g_i), g_i) = y_i(g_i) + \vartheta_i - \text{WTP}_i(g_i \to g' | y_i)$. For a moderately inequality-averse decision maker this means that, although the housing market accounts to some degree for toxic externalities, the results of a weighted BCA change only slightly because the compensation ϑ_i will be negligible compared to income $y_i(g_i)$. In our simulation, for instance, the cleanup project remains preferred to the education program, even for $\sigma = 1$.

In addition, the extent to which negative externalities are internalized in the housing market has important implications for both the sorting of the population and the ranking of policy options. If externalities occur unexpectedly, housing prices will not have adjusted, and affected households bear the full welfare loss. In contrast, if externalities are anticipated prior to residential sorting, housing prices should reflect the disamenity, implying that individuals exposed to pollution are already compensated through lower housing costs. In our framework, this distinction can be captured by varying the degree of internalization in the simulation. The effective welfare loss associated with pollution decreases with increasing internalization, which in turn reduces the desirability of policies that primarily benefit disadvantaged groups. Conversely, when externalities are not internalized, policies targeted at the affected population receive relatively greater weight.

5. Conclusions

In this paper, we set out to provide advice to the town council of Janusville, a fictional town where people face very unequal exposure to neurotoxic substances. The Janusville fable serves three purposes. First, it allows us to keep the analysis tractable. Second, it helps us to abstract from the institutional settings of a specific case and focus on results that can be generalized across environmental health and safety concerns. Third, it enables us to compare two concrete programs under different assumptions about the preferences and premises of the decision maker and to thereby trace out which assumptions drive the conclusions on the program choice.

Our results suggest that implementing a program which benefits all children of Janusville rather than the ones exposed to toxic pollution is only the better option if the focus is solely on efficiency. However, if the town council considers equity a crucial factor in the program choice, they should implement the cleanup project because geographically targeted taxes or other transfers that would compensate exposed individuals seem neither practically feasible nor theoretically desirable. The standard BCA practice of valuing each IQ point gained by the average increment in expected lifetime earnings (Grosse *et al.*, 2002) provides a certain tradeoff between efficiency and equity aspects. However, it does so at the cost of being completely agnostic as to how the gains in IQ are distributed. We hence deem it a poor man's approach to address toxic inequalities. Weighted BCA is arguably more complex but, as we demonstrate, the equivalent income concept is a promising approach for defining welfare weights that capture unequal exposure to toxic pollutants.

One novel result of our paper is that accounting for the correlation between wealth and neurodevelopmental health in the derivation of equivalent incomes will result in relatively

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more weight being given to the most disadvantaged people. This is of particular importance because racial segregation and other factors discussed in the environmental justice literature have led to low-income communities being disproportionately exposed to toxic pollutants and other environmental disamenities (Mohai *et al.*, 2009). At the same time, the same communities are often disadvantaged in terms of access to health care (Deaton, 2008). Applying the equivalent income approach without considering feedback effects between wealth and health may thus underestimate the actual benefit of addressing toxic inequalities.

Another aspect we shed light on is how welfare weights can account for both income-affecting and hedonic aspects of a higher IQ. Accounting for the former seeks to express society's concern for the worse-off, whereas accounting for the latter means that one corrects for differences caused by diminishing marginal utility of income. We show how both elements can be usefully integrated into the equivalent income approach and demonstrate that, for Janusville, doing so attenuates the relative attractiveness of the cleanup project. Some BCA scholars (e.g., Acland & Greenberg, 2023) have argued that it is better to keep equity and utility weighting separated so as not to conflate welfare and equity impacts of programs and policies. However, we believe that combining different policy objectives into a coherent BCA framework is a promising idea, provided that decision makers are informed of the moral values reflected in the resulting rankings.

Finally, we emphasize that neurodevelopment is only one of many health dimensions affected by environmental pollution. Common health effects linked to environmental pollutants include cancer and cardiovascular diseases, endocrine disruption, reproductive toxicity, respiratory and dermal sensitization, and many more. Although the link between wealth and some of these health dimensions may be less straightforward as for the exposure to neurotoxic substances, the same principles apply. Therefore, we see ample opportunity to apply the equivalent income approach in situations characterized by unequal exposure to pollutants. Indeed, this approach can be applied to any policy context in which an intervention that affects some dimension of health targets two or more groups that are either spatially or demographically separated and for which the analyst has distributional information.

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References

Acland, D. J. and D. H. Greenberg. 2023. "Distributional Weighting and Welfare/Equity Trvfs: A New Approach." *Journal of Benefit-Cost Analysis*, *14*(1): 68–92. https://doi.org/10.1017/bca.2023.5.

Adler, M. D. 2016. "Benefit-Cost Analysis and Distributional Weights: An Overview." *Review of Environmental Economics and Policy*, *10*(2): 264–285. https://doi.org/10.1093/reep/rew005.

Adler, M. D. 2022. "Theory of Prioritarianism." In: Adler, M. D. and O. F. Norheim (Eds.) *Prioritarianism in Practice*. Cambridge University Press. 10.1017/9781108691734.002.

Aizer, A., J. Currie, P. Simon, and P. Vivier. 2018. "Do Low Levels of Blood Lead Reduce Children's Future Test Scores?" *American Economic Journal: Applied Economics*, *10*(1): 307–341. https://doi.org/10.1257/app.20160404.

https://doi.org/10.1017/bca.2026.10053 Published online by Cambridge University Press

Anthoff, D., C. Hepburn, and R. S. Tol. 2009. "Equity Weighting and the Marginal Damage Costs of Climate Change." *Ecological Economics*, *68*(3): 836–849. https://doi.org/10.1016/j.ecolecon.2008.06.017.

Banzhaf, H. S. 2012. *The Political Economy of Environmental Justice*. Stanford University Press.

Banzhaf, H. S. 2023. "Distribution and Disputation: Net Benefits, Equity, and Public Decision-Making." *Journal of Benefit-Cost Analysis*, *14*(2): 205–229. https://doi.org/10.1017/bca.2023.30.

Banzhaf, H. S., L. Ma, and C. Timmins. 2019. "Environmental Justice: Establishing Causal Relationships." *Annual Review of Resource Economics*, *11*(1): 377–398. https://doi.org/10.1146/annurev-resource-100518-094131.

Banzhaf, H. S. and E. McCormick. 2012. "Moving beyond Cleanup." In Banzhaf, H. S. (Ed.) *The Political Economy of Environmental Justice*. Stanford University Press. https://doi.org/10.2307/j.ctvqsdxmz.7.

Baumgärtner, S., M. A. Drupp, J. N. Meya, J. M. Munz, and M. F. Quaas. 2017. "Income Inequality and Willingness to Pay for Environmental Public Goods." *Journal of Environmental Economics and Management*: 35–61. https://doi.org/10.1016/j.jeem.2017.04.005.

Bergson, B. A. 1938. "A Reformulation of Certain Aspects of Welfare Economics." *Quarterly Journal of Economics*, *52*(2): 310–334. https://doi.org/10.2307/1881737.

Bishop, K. C., N. V. Kuminoff, H. S. Banzhaf, K. J. Boyle, K. von Gravenitz, J. C. Pope, V. K. Smith, and C. D. Timmins. 2020. "Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality." *Review of Environmental Economics and Policy*, *14*(2): 260–281. https://doi.org/10.1093/reep/reaa001.

Boadway, R. 2006. "Principles of Cost-Benefit Analysis." *Public Policy Review*, *2*(1): 1–44.

Boadway, R. and M. Keen. 1993. "Public Goods, Self-Selection, and Optimal Income Taxation." *International Economic Review*, *34*(3): 463–478. https://doi.org/10.2307/2527177.

Bowles, S. and H. Gintis. 2002. "The Inheritance of Inequality." *Journal of Economic Perspectives*, *16*(3): 3–30. https://doi.org/10.1257/089533002760278686.

Cunha, F. and J. J. Heckman. 2016. "Decomposing Trends in Inequality in Earnings into Forecastable and Uncertain Components." *Journal of Labor Economics*, *34*(S2): S31–S65. https://doi.org/10.1086/684121.

Currie, J. 2011. "Inequality at Birth: Some Causes and Consequences." *American Economic Review*, *101*(3): 1–22. https://doi.org/10.1257/aer.101.3.1.

Currie, J., L. Davis, M. Greenstone, and R. Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *American Economic Review*, *105*(2): 678–709. https://doi.org/10.1257/aer.20121656.

Dasgupta, P. 1998. "Population, Consumption and Resources: Ethical Issues." *Ecological Economics*, *24*(2–3): 139–152. https://doi.org/10.1016/S0921-8009(97)00138-9.

Deaton, A. 2008. "Income, Health, and Well-Being around the World: Evidence from the Gallup World Poll." *Journal of Economic Perspectives*, *22*(2): 53–72. https://doi.org/10.1257/jep.22.2.53.

Drupp, M. A., J. N. Meya, S. Baumgärtner, and M. F. Quaas. 2018. "Economic Inequality and the Value of Nature." *Ecological Economics*: 340–345. https://doi.org/10.1016/j.ecolecon.2018.03.029.

Fleurbaey, M. 2016. "Equivalent Income." In Adler, M. D., and M. Fleurbaey (Eds.) *The Oxford Handbook of Well-Being and Public Policy*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199325818.013.15.

Fleurbaey, M. and R. Abi-Rafeh. 2016. "The Use of Distributional Weights in Benefit–Cost Analysis: Insights from Welfare Economics." *Review of Environmental Economics and Policy*, *10*(2): 286–307. https://doi.org/10.1093/reep/rew003.

Fleurbaey, M. and J. K. Hammitt. 2024. "The Right Numeraire or the Just Weights? How to Make BCA Rational and Fair." *Journal of Benefit-Cost Analysis*, *15*(S1): 6–25. https://doi.org/10.1017/bca.2024.1.

Fleurbaey, M., S. Luchini, C. Muller, and E. Schokkaert. 2013. "Equivalent Income and Fair Evaluation of Health Care." *Health Economics*, *22*(6): 711–729. https://doi.org/10.1002/hec.2859.

Fuchs, V. R. 2004. "Reflections on the Socio-Economic Correlates of Health." *Journal of Health Economics*, *23*(4): 653–661. https://doi.org/10.1016/j.jhealeco.2004.04.004.

Grönqvist, H., J. P. Nilsson, and P. O. Robling. 2020. "Understanding how Low Levels of Early Lead Exposure Affect Children's Life Trajectories." *Journal of Political Economy*, *128*(9): 3376–3433. https://doi.org/10.1086/708725.

Grosse, S. D., T. D. Matte, J. Schwartz, and R. J. Jackson. 2002. "Economic Gains Resulting from the Reduction in Children's Exposure to Lead in the United States." *Environmental Health Perspectives*, *110*(6): 563–569. https://doi.org/10.1289/ehp.02110563.

https://doi.org/10.1017/bca.2026.10053 Published online by Cambridge University Press

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2016. "Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters." In *Climate Change and Development Series*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1003-9.

Hammitt, J. K. 2021. "Accounting for the Distribution of Benefits and Costs in Benefit–Cost Analysis." *Journal of Benefit-Cost Analysis*, *12*(1): 64–84. https://doi.org/10.1017/bca.2020.29.

Hanna-Attisha, M., J. LaChance, R. C. Sadler, and A. Champney Schnepp. 2016. "Elevated Blood Lead Levels in Children Associated with the Flint Drinking Water Crisis: A Spatial Analysis of Risk and Public Health Response." *American Journal of Public Health*, *106*(2): 283–290. https://doi.org/10.2105/AJPH.2015.303003.

Harberger, A. C. 1978. "On the Use of Distributional Weights in Social Cost-Benefit Analysis." *Journal of Political Economy*, *86*(2, Part 2): S87–S120. https://doi.org/10.1086/260696.

Heckman, J. J., S. H. Moon, R. Pinto, P. A. Savelyev, and A. Yavitz. 2010. "The Rate of Return to the HighScope Perry Preschool Program." *Journal of Public Economics*, *94*(1–2): 114–128. https://doi.org/10.1016/j.jpubeco.2009.11.001.

Hendren, N. 2020. "Measuring Economic Efficiency Using Inverse-Optimum Weights." *Journal of Public Economics*: 104198. https://doi.org/10.1016/j.jpubeco.2020.104198.

Johansson-Stenman, O. 2005. "Distributional Weights in Cost-Benefit Analysis – Should we Forget about them?" *Land Economics*, *81*(3): 337–352. https://doi.org/10.3368/le.81.3.337.

Johansson-Stenman, O., F. Carlsson, and D. Daruvala. 2002. "Measuring Future Grandparents' Preferences for Equality and Relative Standing." *Economic Journal*, *112*(479): 362–383. https://doi.org/10.1111/1468-0297.00040.

Kaplow, L. 1998. "A Note on the Optimal Supply of Public Goods and the Distortionary Cost of Taxation." *National Tax Journal*, *51*(1): 117–125. https://doi.org/10.1086/NTJ41789316.

Kaplow, L. 2010. "Concavity of Utility, Concavity of Welfare, and Redistribution of Income." *International Tax and Public Finance*, *17*(1): 25–42. https://doi.org/10.1007/s10797-008-9097-5.

Laurent, E. 2011. "Issues in Environmental Justice within the European Union." *Ecological Economics*, *70*(11): 1846–1853. https://doi.org/10.1016/j.ecolecon.2011.06.025.

Lin, D., R. Lutter, and C. J. Ruhm. 2018. "Cognitive Performance and Labour Market Outcomes." *Labour Economics*: 121–135. https://doi.org/10.1016/j.labeco.2017.12.008.

Mohai, P., D. Pellow, and J. T. Roberts. 2009. "Environmental Justice." *Annual Review of Environment and Resources*, *34*(1): 405–430. https://doi.org/10.1146/annurev-environ-082508-094348.

Mourato, S., G. Atkinson, D. Dussaux, C. Sotis, S. Georgiou, and D. Contu. 2023. "Valuing the Avoidance of IQ Losses in Children." In *OECD Environment Working Papers*, Vol. *219*. Paris: Organisation for Economic Co-operation and Development. https://doi.org/10.1787/71574eb4-en.

Nurmi, V. and H. Ahtiainen. 2018. "Distributional Weights in Environmental Valuation and Cost-Benefit Analysis: Theory and Practice." *Ecological Economics*: 217–228. https://doi.org/10.1016/j.ecolecon.2018.04.021.

Nyborg, K. 2014. "Project Evaluation with Democratic Decision-Making: What Does Cost-Benefit Analysis Really Measure?" *Ecological Economics*: 124–131. https://doi.org/10.1016/j.ecolecon.2014.07.009.

Samson, A. L., E. Schokkaert, C. Thébaut, B. Dormont, M. Fleurbaey, S. Luchini, and C. Van de Voorde. 2018. "Fairness in Cost-Benefit Analysis: A Methodology for Health Technology Assessment." *Health Economics*, *27*(1): 102–114. https://doi.org/10.1002/hec.3515.

Samuelson, P. A. 1947. *Foundations of Economic Analysis*. Harvard University Press.

Sheriff, G. and K. B. Maguire. 2020. "Health Risk, Inequality Indexes, and Environmental Justice." *Risk Analysis*, *40*(12): 2661–2674. https://doi.org/10.1111/risa.13562.

Tamborini, C. R., C. Kim, and A. Sakamoto. 2015. "Education and Lifetime Earnings in the United States." *Demography*, *52*(4): 1383–1407. https://doi.org/10.1007/s13524-015-0407-0.

Von Stumm, S. and R. Plomin. 2015. "Socioeconomic Status and the Growth of Intelligence from Infancy through Adolescence." *Intelligence*: 30–36. https://doi.org/10.1016/j.intell.2014.10.002.

Appendix

One crucial assumption of the first-best solution is the separability of preferences for public and private goods, which enables government to change the tax schedule without distorting labor supply decisions (Boadway & Keen, 1993). However, under more realistic assumptions, taxes and transfers do create distortions. To account for such distortions, the model may be extended by assuming that income is a function of labor supply and tax schedule (Johansson-Stenman, 2005).

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Formally, let individual utility from income y_i, intelligence g_i and leisure l_i be given by $u_i(y_i(g_i,t_i),l_i(t_i),g_i)$, where t_i denotes the applicable tax rate. Individuals have a fixed time budget τ such that leisure is determined by their labor supply decision, that is, $l_i(t_i)=\tau-L_i(t_i)$, which in turn hinges on how the tax rate t_i affects working hours L_i. Net income is given by $y_i=y_i^g-t_i(y_i^g)$, where t_i applies to gross income $y_i^g\equiv\omega_i(g_i)L_i(t_i)$ and $\omega_i(g_i)$ stands for the hourly wage rate that a person with an IQ of g_i receives. Differentiating the utility function with respect to L_i and plugging in income results in the optimal labor supply decision:

$$\frac{\partial u_i}{\partial y_i}\omega_i\left(1-\frac{\partial t_i}{\partial y_i^g}\right)=\frac{\partial u_i}{\partial l_i}\leftrightarrow\omega_i\left(1-\frac{\partial t_i}{\partial y_i^g}\right)=\mathrm{MRS}_{l_i,y_i}. \tag{A1}$$

As income depends on the marginal tax rate $\frac{\partial t_i}{\partial y_i^g}$, which we assume to increase with income, the individual chooses the amount of labor supply L_i to equate the marginal utilities from both leisure and income. If the substitution effect is larger than the income effect (i.e., the opportunity cost of giving up one hour of leisure is high compared to the additional income gained from one hour of work), then taxation decreases the supply of labor L_i, and vice versa.

When we differentiate endogenous income with respect to t_i, we obtain the following optimality condition: $\partial y_i/\partial t_i=\omega_i\frac{\partial L_i}{\partial t_i}-1$, which implies that $\partial y_i/\partial t_i<-1$ and $\partial y_i/\partial^2 t_i<0$ for all i.[17] That is, as the tax rate goes up, individual income falls by more than the incremental tax and additional labor gets discouraged. In this second-best setting, government maximizes the modified welfare problem:

$$\max W\left(u_1\left(y_1\left(g_1',t_1\right),l(t_1),g_1'\right),\ldots,u_n\left(y_n\left(g_n',t_n\right),l(t_n),g_n'\right)\right)\text{ s.t.}$$

$$g_i'=g_i+x_i,X=\sum\nolimits_i x_i,\sum\nolimits_i t_i=C, \tag{A2}$$

where C stands for the cost of the program. The maximization problem yields the Lagrangian $\mathcal{L}=W(u_1,\ldots,u_n)-\left[\lambda\left(\sum_i x_i-X\right)-\mu\left(\sum_i t_i-C\right)\right]$ with the following first-order conditions:

(i) $\lambda=\frac{\partial W}{\partial u_i}\frac{\partial u_i}{\partial y_i}\left[\frac{\partial y_i}{\partial g_i}+\frac{\partial u_i}{\partial g_i}/\frac{\partial u_i}{\partial y_i}\right]=\beta_i\left[\frac{\partial y_i}{\partial g_i}+\mathrm{MRS}_{g_i,y_i}\right]$, so that the social marginal utility from the intelligence of individual i equals the shadow price of intelligence in society.

(ii) $\mu=\frac{\partial W}{\partial u_i}\frac{\partial u_i}{\partial y_i}\frac{\partial y_i}{\partial t_i}=\beta_i\frac{\partial y_i}{\partial t_i}$, so that the social marginal (dis-)utility from taxing individual i equals the shadow value that corresponds to a marginal change in the tax rate.

This solution can be directly compared to the first best, which is characterized by $\partial y_i/\partial t_i=-1$ for all i. From the discussion above, it follows that now $\partial y_i/\partial t_i<-1$ and $\partial t_i/\partial^2 y_i>0$. Moreover, if we assume that substitutability between work and leisure is stronger than the income effect and maintain that meaningful weights in BCA are inversely related to income

[17] Similar to the generalized feasibility constraint assumed by Fleurbaey *et al.* (2013), this set of constraints ensures that reducing income inequality reduces total income. However, the assumptions we need to make are less strong as we do not impose a relationship between total income and the IQ distribution in the population.

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(Nurmi & Ahtiainen, 2018). Under these assumptions, taxes are a monotonically increasing function of income. At the optimum, we, therefore, have $\beta_i < \beta_j$ for any $y_i > y_j$, which reflects that, in contrast to the first-best solution, the social planner cannot redistribute income freely because of the behavioral rebound effect of taxes and transfers on labor market choices.

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