On the measurement of environmental inequality: Ranking emissions distributions generated by different policy instruments

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Adapting results from the income distribution literature, we develop a normatively significant metric with which to rank emissions distributions from alternative policy options in a manner consistent with an explicit well-behaved preference structure. This approach allows one to determine which policy has the most desirable outcome for a given demographic group as well as which groups benefit most from a given policy. Applying these methods to Southern California's NO_x pollution-trading program and a counterfactual command-and-control policy suggests that in this case trading benefited all demographic groups and generated a more equitable overall distribution of emissions, even after controlling for lower aggregate emissions. Upper-income and white demographics had more desirable distributions relative to low-income and some minority groups under the trading program, however, and population shifts over time may have undermined anticipated gains for African Americans.

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Tension can exist between the goal of environmental protection and concern for individuals in historically disadvantaged communities. Initially, environmental justice concerns focused on the question of whether permits for facilities generating hazardous waste were more likely to be issued in poor or minority neighborhoods (e.g., United Church of Christ, 1987). More recently, focus has shifted to policy mechanisms themselves (Fann et al., 2011; Fowlie et al., 2012).

Traditional performance-based command-and-control air pollution regulations

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typically allow a regulated source to emit pollution per unit of input or output up to the amount written in its permit. In efforts to reduce the cost of environmental protection, recent decades have seen the introduction of programs that would allow individual sources to increase emissions if they pay a tax or purchase credits from other sources that reduce emissions (Stavins, 2003).

The distributional question is whether such market-based mechanisms cause low income and minority populations to be worse off than a system in which each source has to comply with its own permit. In principle, market-based mechanisms could cause a reallocation of pollution to low income or minority neighborhoods for several reasons. It may be economically efficient to do so if marginal control costs in these areas are relatively high. Alternatively, the flexibility inherent in market mechanisms could allow plant managers to make pollution control decisions on the basis of informal political or discriminatory, rather than purely economic, motives. More affluent neighborhoods may be more effective at pressuring plant managers to reduce emissions, for example (Hamilton, 1993; Gray and Shadbegian, 2004). Or, managers may experience greater disutility from increasing emissions in white versus minority neighborhoods (Hamilton, 1995).

There is a large literature showing a correlation between pollution exposure and demographic characteristics such as racial minority or low income status (see, for example, Ringquist, 2005; Banzhaf et al., 2019). Less evidence exists regarding the relationship between exposure and environmental policy design. Early work compared anticipated air quality improvements from command-and-control policies to baseline levels, generally finding that low income and minority populations tended to receive larger benefits (Harrison and Rubinfeld, 1978; Gianessi et al., 1979). Fowlie et al. (2012) found no evidence that emissions sources surrounded by minority and low income populations emitted more under a nitrogen oxides (NO_x) emissions trading program than in a counterfactual command-and-control policy. Using the same emissions data, but looking at air pollution dispersion models rather than simple circles around facilities, Grainger and Ruangmas (2018) find limited evidence suggesting that facilities "upwind" from African American communities may have higher emissions with a market based instrument.

The question is not merely academic, particularly in light of recent policies to reduce CO_2 emissions. One of the most cost effective means of reducing emissions is to move production from more to less carbon intensive sources, e.g., shifting electricity generation from coal to natural gas burning power plants. Although CO_2 itself is not toxic in atmospheric concentrations, fossil fuel combustion typically generates local co-pollutants such as fine particulate matter ($PM_{2.5}$) and nitrogen oxides (NO_x) that are. Thus, the concern is that the facilities that increase production may disproportionately affect poor or minority communities. A California court temporarily stayed the state's fledgling carbon emission trading program due to a suit on such grounds.[1]

The literature uses many descriptive statistical tools (group means, correlations, etc.) to consider whether a particular distribution of environmental harm poses an environmental justice problem (Maguire and Sheriff, 2011). None of these measures are normatively significant, in the sense that there is not a relationship between a distributional ranking based on their mathematical value and the way that a "reasonable" human being would rank them (Blackorby et al., 1999).

The main contribution of this paper is to rank alternative environmental policy instruments from an environmental justice perspective by adapting approaches commonly used in the income distribution literature (e.g., Lambert, 2001). Beginning with an explicit well-behaved preference structure, we derive a mathematical function for a given distribution of environmental outcomes such that its value is consistent with the underlying preference ordering. In contrast to the techniques predominantly used in the environmental justice literature, the key advantage of this normative approach is that it allows us to make statements such as distribution A is better than B based on a transparent set of explicit value judgements.

[1]Superior Court of California Case CPF-09-509562, Association of Irritated Residents et al. vs. California Air Resources Board.

The methodological approach relies on three key empirical ingredients: a counterfactual emissions profile, a geographical emissions dispersion model, and a model of how emissions exposure translates into health impacts. Our contribution is not to advance the state of the art in calculating any of these ingredients, but rather to illustrate how existing off-the-shelf estimates can be used to generate normatively significant rankings. As the literature progresses, the methods we describe can easily accommodate new estimates to generate improved rankings.

We apply these methods to analyze the environmental justice implications of Southern California's Regional Clean Air Incentives Market (RECLAIM) program. RECLAIM replaced command-and-control regulations for stationary sources of oxides of nitrogen with an emissions trading program. More specifically, we analyze the distribution of short run changes in facility emissions, rather than long run questions of entry and exit. Although the methods are generalizable to other trading programs, the empirical results regarding the relative performance of trading to traditional regulation are clearly limited to RECLAIM. Nonetheless, RECLAIM's environmental justice implication has a broader policy relevance since it has featured prominently in the debate over California's carbon trading program (see discussion in Farber, 2012; Fowlie et al., 2012, and its online appendix).

Comparative assessment of distributional implications of policy alternatives is complicated by the lack of counterfactual emissions. As in Fowlie et al. (2012), we use matching techniques to generate counterfactual emissions outcomes. Using data collected by Fowlie et al. (2012) for both RECLAIM participants and firms operating under a traditional command-and-control regime we predict the counterfactual emissions of participating firms.

Our main dispersion model uses the "centroid containment" method (Mohai and Saha, 2006). We construct a 3 km radius buffer around each facility and consider exposed individuals to be those residing in the facility's census block group and all other block groups whose centroids fall within the buffer. Similar buffers are commonly used in a variety of contexts (e.g., Chakraborty and Armstrong, 1997;

Greenstone and Gallagher, 2008; Fowlie et al., 2012). Recognizing the limitations of such a basic model, we consider two alternatives: a simple "west wind" in which emissions travel farther east than west, and the more sophisticated air quality dispersion model used by Grainger and Ruangmas (2018) that predicts the transport of emissions particles through the atmosphere. Our health impacts model assumes that an individual's utility is a simple function of NO_x pollution in her census block group. We discuss limitations to this approach and alternative assumptions in Section II.

Our approach provides answers to the following types of questions. At baseline, did disadvantaged demographic groups have a worse distribution of NO_x pollution from regulated facilities than the population as a whole? Did the distribution for these groups improve after the RECLAIM program came into effect? Would they have been better off under traditional command-and-control regulation? Did population sorting over time undermine benefits of RECLAIM for disadvantaged demographic groups? In short, did the efficiency of the RECLAIM program come at the expense of historically disadvantaged socio-economic groups?

Previous research has applied income inequality measures to environmental policy issues, without considering environmental justice considerations.[2] To evaluate the equity of proposals to limit GHG emissions, for example, Heil and Wodon (2000) calculated Gini coefficients for projected country-level per capita CO_2 emissions under various mitigation scenarios. A related literature (e.g., Fankhauser et al., 1997; Anthoff and Tol, 2010) combines equity weights with integrated assessment models to calculate international damage from climate change. Millimet and Slottje (2002) calculated Gini coefficients for state and county-level per capita toxic release exposures to understand whether uniform federal environmental standards ameliorate disparities in environmental outcomes.

More recently, indexes originally developed for measuring income inequality

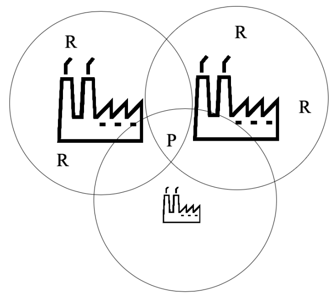
[2]Many studies use the related concept of concentration indexes to rank joint distributions of health attributes and socioeconomic status. This approach, however, only applies to cases in which the latter can be clearly ranked (e.g., income). It less useful for analyzing distributions across categorical variables, such as race, that lack a natural ordering (Fleurbaey and Schokkaert, 2011).

have been used to compare distributions of pollution outcomes across individuals at a relatively fine level of spatial disaggregation, typically calculated at the U.S. Census Block Group level. The most common measure has been the Atkinson inequality index (Levy et al., 2007, 2009; Fann et al., 2011; Clark et al., 2014), although studies have also employed other measures such as Gini coefficient (Bouvier, 2014; Boyce et al., 2016; Holland et al., 2019) and Generalized Entropy indexes (Boyce et al., 2016). Unlike our approach, using inequality indexes to compare distributions with different means has the disadvantage that they are not welfare measures, and consequently lack normative significance (Kaplow, 2005). In other words, a person with well-behaved preferences would not necessarily prefer a pollution distribution that has a lower Gini coefficient or Atkinson index.

We find little evidence to suggest an environmental justice concern regarding the distribution of emissions from RECLAIM facilities during the 1990–1993 baseline period. The distributions of exposures for whites and individuals from households above twice the poverty line are worse than the distributions for all other demographic groups. Both the counterfactual command-and-control policy and RECLAIM changed the relative ordering of demographic groups. Although the black demographic has the most desirable exposure distribution under all three scenarios, under RECLAIM the distribution for whites is preferable to that for Hispanics. With respect to income, under RECLAIM the wealthiest group has the most desirable distribution.

Despite this shift in relative positions across groups, each individual group is better off under RECLAIM than at baseline or command and control. This improvement is due to both a reduction in average exposure levels as well as a reduction in the inequity of the dispersion in exposure levels within groups. That is, there is no evidence to suggest that the gains accruing to RECLAIM for one demographic group came at the expense of any other group, nor that average improvements within a group came at the expense of increased “hotspots” within the group.

Figure 1. Facility versus individual as unit of analysis



Source: Authors. Factory icon made by Vectors Market from www.flaticon.com.

The paper is organized as follows. Section I describes the microeconomic foundation for the social evaluation functions used to rank emission distributions. Section II provides a brief description of the RECLAIM policy setting (for a more detailed description, see Fowlie et al., 2012). Section III describes the raw emissions and demographic data as well as the calculation of counterfactual emissions. Section IV presents empirical results, and Section V offers concluding comments.

I. Theoretical model for ranking distributions of environmental disamenities

The fundamental question of interest is determining the relative desirability of distributions of environmental harm arising from different policy scenarios. In a break from the current environmental justice literature, we employ a welfarist policy evaluation framework. This change in perspective is important since any non-welfarist ranking can potentially prefer a policy that makes everyone worse off (Kaplow and Shavell, 2001).

A key implication of this approach is that the unit of analysis is the individual. In contrast, much of the literature (e.g., Wolverton, 2009; Fowlie et al., 2012; Grainger and Ruangmas, 2018) focuses on facility observations. Although the facility approach is useful for examining impacts of a policy or neighborhood characteristics on plant emissions, in order to measure direct welfare implications, we need to examine policy impacts on individuals.

Figure 1 illustrates the potential importance of this distinction in the context of environmental justice. Consider three facilities, two identical large emitters and one small. Let the circles represent a 3 km radius from each facility, and "P" and "R" represent predominantly poor and rich census blocks of equal population size. Using a facility-level unit of analysis might suggest there is no environmental justice concern; large emitters are surrounded by rich communities, while the small emitter is be surrounded by the poor community. Using the individual as the unit of analysis would identify the potential hotspot in which individuals in the poor community are exposed to over twice the cumulative emissions as those in rich communities.

We make the standard assumption that individuals attach utility to the outcome (pollution exposure) not the magnitude of the change in outcomes between policy scenarios (Bernoulli, 1954). In particular, we rank pollution distributions based on the preferences of a hypothetical representative individual, using the veil of ignorance (Harsanyi, 1953; Rawls, 1971) to ensure her impartiality. 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.

For purposes of ranking the desirability of emissions distributions we assume all individual characteristics, both internal and external, are held constant. We thus abstract from questions of differing vulnerability to pollution based on race or income (Hsiang et al., 2019). Similarly, we assume that external factors are constant across the scenarios being evaluated, thus abstracting from possible hedonic adjustments à la Roback (1982) to wages and housing prices arising from differences in pollution.

Under a given policy scenario let x be an individual's exposure to the environmental outcome of interest. Ideally, this variable could be an indicator of health outcomes. Data limitations, however, might limit the analysis to individual exposure levels, local ambient pollutant concentrations, or nearby facility emissions.

In our main specification, the outcome variable is the sum of annual emissions from all RECLAIM facilities within a 3 km radius of the census block centroid containing the individual. The vector $\mathbf{x} \equiv (x_1, x_2, ..., x_n, ..., x_N)' \in \mathbb{R}^N_+$ represents exposures in the N census block groups. Behind the veil of ignorance, the vector $\mathbf{x}$ generated by a given policy can be framed as an ex ante lottery in which the representative individual has an equal chance of receiving the outcome for any individual in the population. Thus, the probability assigned to each ex post outcome x_n is π_n, census block group n's share of the population.

Suppressing the probability vector, π, let $U(\mathbf{x}, y)$ be the ex ante utility generated by an emissions lottery conditional on a deterministic numeraire good (income) y. Ranking distributions is equivalent to determining which lottery would be preferred by the representative individual. As detailed below, doing so requires imposing structural assumptions on the individual's preferences.

We begin with a standard assumption ensuring that pollution is bad.

ASSUMPTION 1: *Pareto Criterion. Increasing pollution for at least one ex post outcome, leaving all others unchanged makes a lottery less desirable.*

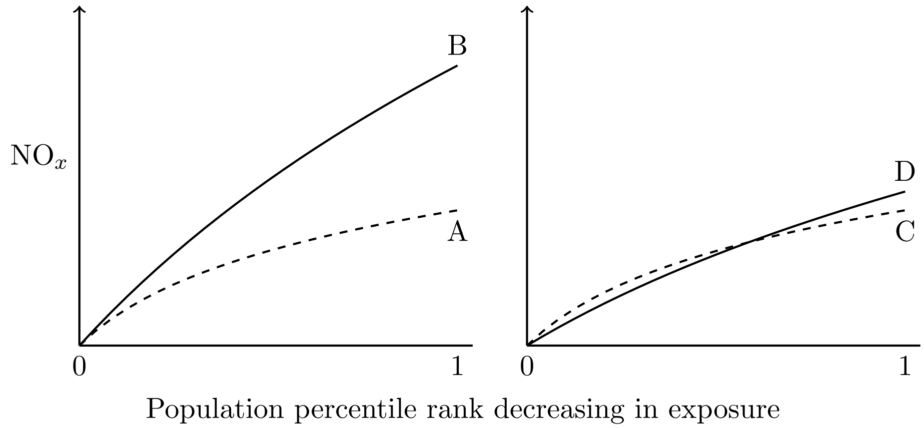
As is common in the income distribution literature (e.g., Lambert, 2001) we also impose that U is Schur concave in $\mathbf{x}$.

ASSUMPTION 2: *Schur Concavity. (i) The pollution lottery is symmetric; permutations of* $\mathbf{x}$ *do not change the desirability of a lottery. (ii) Transferring a unit of pollution from a low exposure outcome to a high exposure outcome makes a lottery less desirable.*[3]

The next assumption allows one to rank the pollution distributions of policies A and B for a specific demographic group independently of the outcomes of these policies for another group.

[3]Formally, let $\mathbf{Q}$ be a square matrix composed of non-negative real numbers whose rows and columns each sum to 1. The function $f(\mathbf{x})$ is Schur concave if $\mathbf{Qx}$ is not a permutation of $\mathbf{x}$ and $f(\mathbf{Qx}) \geq f(\mathbf{x})$. All symmetric quasiconcave functions are Schur concave, although the converse is not true (Dasgupta et al., 1973).

Figure 2. Illustrative generalized Lorenz curves for pollution exposure



Notes: Distribution A GL dominates B. GL curve A is nowhere above B, indicating that each population percentile in A has weakly less NO_x exposure than the corresponding percentile in B. Distribution C does not GL dominate D. The higher population percentiles C have less exposure than D, while the lower percentiles in C have more exposure.

ASSUMPTION 3: *Separarbility in population subgroups. Distributional rankings for a demographic subgroup are insensitive to outcomes for the rest of the population.*

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. Separability in population subgroups implies $U(\mathbf{x}, y) \equiv \tilde{U}(U_d(\mathbf{x}_d, y), \mathbf{x}_{-d}, y)$. This property ensures that ranking alternative vectors (lotteries) $\mathbf{x}_d$ for group d is independent of outcomes for all other individuals (Blackorby et al., 1981).

These three assumptions are sufficient to allow partial distributional rankings based Generalized Lorenz (GL) curve dominance (Shorrocks, 1983), both for the population as a whole and each demographic group. The vertical axis is similar to that of a Lorenz curve. Rather than plotting cumulative percentage of total exposure, however it plots the cumulative percentage multiplied by the population mean exposure. The horizontal axis of the standard Shorrocks (1983) GL curve requires a minor modification, however, to ensure suitability for ranking bad outcomes. For goods, such as income, the horizontal axis represents the population percentile ranked in increasing order of x, i.e., from worst to best off. For pollution, in contrast, the horizontal axis of the GL graph is ranked in decreasing order of x. As with the income GL curve, the height the curve at 100 percent of the population equals the mean exposure and a ray from the origin depicts a perfectly equal distribution. Unlike for income, the GL curve for an unequal pollution distribution is bowed upwards from this ray, not downwards. As illustrated in Figure 2, distribution A dominates distribution B if A's GL curve is somewhere below and nowhere above B's. This dominance ensures that A has both lower overall levels of pollution and a more equitable distribution. This condition is analogous to second order stochastic dominance (Thistle, 1989).

GL dominance is a partial ordering since it cannot rank distributions whose GL curves cross, like distributions C and D in the right panel of Figure 2. To evaluate such distributions it is necessary to impose further preference structure. We begin with an assumption that is only implicitly imposed by much of the income distribution literature: separability in utility between consumption of numeraire y and consumption of the environmental outcome of interest.

ASSUMPTION 4: *Separability in consumption. The reference income level y does not affect the ranking of any two pollution lotteries.*

Separability in consumption implies $U(\mathbf{x}, y) \equiv U^*(u(\mathbf{x}), y)$. It ensures that the marginal rate of substitution between two ex post pollution exposure outcomes is independent of income. This assumption is satisfied by utility functions with a marginal utility of y that is decreasing (multiplicatively separable) or constant (additively separable) in ex post pollution exposure (Rey and Rochet, 2004). It is violated by utility functions in which marginal utility of income increases with ex post exposure (Hammitt, 2013). Using survey data, Evans and Viscusi (1991) evaluate how marginal utility of income is affected by health, with ambiguous results. They find that less severe adverse health outcomes may increase the marginal utility of income, while more severe outcomes may decrease it. Nonetheless, the health economics literature commonly assumes multiplicative separability (e.g., Garber and Phelps, 1997; Murphy and Topel, 2006).

Atkinson (1970) showed how preferences over distributions can be represented by a social evaluation function measured in cardinal units of x. The "equally distributed equivalent" (EDE) value of x is the scalar value of pollution exposure $\Xi(\mathbf{x})$ that, if allocated to each individual, would be as desirable as the original distribution:

$$\Xi(\mathbf{x}) \equiv \{\tilde{x} : u(\tilde{x} \cdot \mathbf{1}) = u(\mathbf{x})\}\,. \tag{1}$$

The next assumption implies that distributional rankings are unaffected by parallel shifts in all outcomes. In practical terms it ensures that rankings of alternative pollution distributions are insensitive to some common unknown background level of exposure.

ASSUMPTION 5: *Translatability.* $\Xi(\mathbf{x} + \lambda \cdot \mathbf{1}) = \Xi(\mathbf{x}) + \lambda$ *for any* $\lambda \in \mathbb{R}^1$.

Translatability, combined with separability in population subgroups, implies that $u(\mathbf{x})$ is the expectation of Pollak (1971) functions (Blackorby and Donaldson, 1980):

$$u(\mathbf{x}) = -\sum_{n=1}^{N} \mathrm{e}^{-\kappa x_n} \pi_n; \kappa < 0, \text{with} \tag{2}$$

$$\Xi(\mathbf{x}) = -\frac{1}{\kappa} \ln \sum_{n=1}^{N} \mathrm{e}^{-\kappa x_n} \pi_n. \tag{3}$$

This EDE differs from that used in the income distribution literature by the sign of κ. For income κ would be positive, whereas Schur concavity of $U(\cdot)$ requires that κ be negative for a "bad" x. The representative individual's aversion to inequality in adverse environmental outcomes is decreasing in κ.

These assumptions also imply that the social evaluation function satisfies consistency in aggregation, i.e., rankings of distributions do not change if the EDE is calculated for the entire population versus calculated for each demographic group then aggregated (Blackorby and Donaldson, 1980).

GL dominance and EDEs rank distributions in a way that takes into account both overall pollution levels and the equity of the distribution across the population. It may also be of interest to compare the equity of distributions independently of the overall pollution levels. Suppose, for example, it were found that historical market-based mechanisms tended to result in emissions distributions that are less equitable than command-and-control regulations. This result might suggest that future market-based policies should be designed to have greater overall pollution reduction than a command-and-control alternative in order to generate similar benefits.

To evaluate equity in a way consistent with translatability, we employ absolute Lorenz (AL) curves (Moyes, 1987). AL curves effectively de-mean the GL curves; their height is the difference between height of the respective GL curve at a given population percentile and the height of a hypothetical GL curve in which everyone were to receive the mean exposure (a ray from the origin to the actual GL curve at the 100th percentile). A perfectly flat curve along the horizontal axis would depict a perfectly equal distribution. The curvature represents the inequity of the distribution from this ideal, independent of overall average reductions in pollution. AL dominance occurs if a curve is somewhere below and nowhere above another. It is a partial ordering since it cannot rank distributions whose curves cross.

Analogous to the relationship between EDEs and GL curves, inequality indexes can be calculated to generate a complete ordering of distributions whose AL curves intersect. Kolm (1976) defined an absolute *income* inequality index as the mean minus the EDE. For a bad, however, the EDE is greater the mean. To ensure the index value increases as the distribution becomes less equal, we use this alternative specification:

$$I(\mathbf{x}) \equiv \Xi(\mathbf{x}) - \sum_{n=1}^{N} x_n \pi_n. \tag{4}$$

The index value indicates the maximum increase in emissions exposure the representative individual would accept to replace the actual distribution with a perfectly equal distribution. It enables analysis of whether an improvement in average emissions levels comes at the cost of increased disparity of outcomes, e.g., reducing emissions at relatively clean sources while exacerbating emission hot spots. Translatability implies that $I(\mathbf{x})$ is an index of absolute inequality. That is, the measured level of inequality is unaffected by an arbitrary common background pollution level λ: $I(\mathbf{x}) = I(\mathbf{x} + \lambda \cdot \mathbf{1})$ for any $\lambda \in \mathbb{R}^1$.

The conditions imposed on $u(\mathbf{x})$ also allow calculation of an index of inter-group inequality,

$$I_g(\mathbf{x}) \equiv \Xi(\mathbf{x}) - \sum_{d=1}^{D} \Xi_d(\mathbf{x}_d)\pi_d, \tag{5}$$

in which π_d and $\Xi_d(\mathbf{x}_d)$ are the population share and EDE pollution exposure levels corresponding to each of the D groups. It measures the pollution exposure reduction necessary to maintain the same welfare if emissions were to change from a distribution in which everyone receives the EDE of the actual distribution to an unequal distribution that allocates to each member of a demographic group the EDE of that group's actual distribution. The higher the requisite exposure reduction, the greater the inter-group inequality (for greater detail in the context of income distribution, see Blackorby et al., 1981).

Recently, several studies have used income inequality indexes to compare distributions of environmental outcomes. The inequality indexes typically used in this literature, the Atkinson index (Levy et al., 2007, 2009; Fann et al., 2011;

Clark et al., 2014), the Gini coefficient (Boyce et al., 2016), and the Generalized Entropy index (Boyce et al., 2016), are all indexes of relative inequality. For these, an equiproportional increase in pollution for all individuals does not increase inequality.

While relative indexes are convenient for comparing nominal incomes from different time periods or across countries with different currencies, they are less justified for measuring inequality of pollution exposure. It seems unsatisfactory for a distribution with individuals exposed to trivial amounts of pollution, say 0.1 tons and 0.001 tons, to be as equitable as one with exposures of 0.1 ton and 10 tons. For the index defined in Eq. (4), such proportional increases in pollution increase measured inequality (Kolm, 1976). In the next sections we provide an illustration of how to apply these concepts to evaluate the relative desirability of an emissions market versus a command and control policy from an environmental justice perspective.

II. Policy setting

Air quality regulation in the Los Angeles basin falls under the jurisdiction of the South Coast Air Quality Management District (SCAQMD). In 1989, in an attempt to reduce some of the highest smog (ozone) levels in the country, SCAQMD introduced strict NO_x emission control standards for stationary sources (NO_x is a precursor pollutant to ozone). At the federal level, an innovation in the 1990 Clean Air Act Amendments allowed local regulators to use market based mechanisms to attain ozone ambient air quality standards.

SCAQMD took advantage of these provisions to replace 40 prescriptive rules with the RECLAIM market based incentive program. Under RECLAIM, facilities were granted a limited quantity of RECLAIM trading credits (RTCs) based on historical fuel consumption and production technology characteristics. Each credit entitled the owner to emit one pound of NO_x emissions during a 12-month period. From the program's inception in 1994, SCAQMD gradually reduced the total annual supply of RTCs such that by 2003 aggregate emissions would be equivalent to the target emissions level hoped to be achieved by the command-and-control requirements that RECLAIM replaced.

The program initially included almost all facilities in the region with annual NO_x or SO_2 emissions of four tons or more (public facilities were not included). The 392 facilities initially included in RECLAIM comprised over 65 percent of stationary source NOx emissions in SCAQMD (Zerlauth and Schubert, 1999). During the California electricity crisis, power plants dramatically increased their demand for RTCs leading to a price spike and some noncompliance. RECLAIM rules were subsequently amended in 2001 to remove 14 power producing facilities from the market, instead requiring them to install pollution control devices. We exclude these electric plants from the analysis.

During the early years of the program there was an excess of RTCs, such that only after 1999 did the aggregate "cap" bind (SCAQMD, 2001). The effects of the early RTC surplus were unlikely to affect later years, however, since the credits could not be banked, i.e., they were only valid in the designated year.[4]

The primary goal of the RECLAIM program was to reduce NO_x emissions. NO_x are created when extremely high temperatures cause atmospheric oxygen and nitrogen to react with each other. Common manmade sources are fossil fuel-fired industrial boilers and internal combustion engines.

Epidemiological evidence suggests that NO_x directly affects human health via the respiratory system (U.S. EPA, 2008). NO_x emissions indirectly affect human health by contributing to the formation of ground level ozone and $PM_{2.5}$. Ozone is created by a photochemical reaction between NO_x, atmospheric volatile organic compounds and sunlight. NO_x reacts with atmospheric ammonia to create components of $PM_{2.5}$.

There is sufficient uncertainty about the direct health impact of NO_x that the U.S. Environmental Protection Agency (EPA) does not estimate these impacts

[4]Holland and Moore (2012) examine the limited potential for intertemporal trading in this market.

when quantifying the benefits of NO_x reduction. The relationship between ozone, $PM_{2.5}$, and human health is sufficiently well documented, however, that the EPA routinely monetizes national benefits from a given reduction in NO_x emissions via these indirect channels in its regulatory benefit-cost analysis (e.g., U.S. EPA, 2015).

Ideally, we would be able to trace a clear link between a unit of NO_x emissions from a particular source and an individual's health at a given location. To do so would require identifying the individual vulnerability to changes in exposure levels caused by changes in ambient NO_x concentrations arising from a marginal ton of NO_x emissions from a particular source. This vulnerability may be a function of unobservable factors such as individual health or outdoor activity (Hsiang et al., 2019). We would similarly need to estimate individual health impacts from changes in ozone and $PM_{2.5}$ concentrations corresponding to the NO_x emissions.

There is considerable uncertainty in each of these steps. Models can disagree sharply even in predicting NO_x dispersion. The Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model used by Grainger and Ruangmas (2018), for example, generates significant NO_x dispersion in areas 50 miles from a source, whereas the ICST3 model used by Lejano and Hirose (2005) shows dispersion tapering off within 3 miles. Schlenker and Walker (2016) find a similar result regressing airport impacts on monitored NO_2 levels, with marginal effects reducing substantially 3–6 miles downwind.

Moreover, the factors involved in time and place of ozone and $PM_{2.5}$ creation are extremely complex, as the process depends on sunlight, wind speed and direction, elevation, ambient temperature, and concentrations of various atmospheric chemicals. In some cases, for example, increases in NO_x can reduce ozone concentrations (Jacob, 1999). Airborne pollutants such as ozone and $PM_{2.5}$ can also travel for hundreds of miles downwind (Bergin et al., 2007). Combined with a lack of a clear dose-response function for NO_x health impacts, it is therefore difficult to estimate changes in the geographical distribution of these chemicals and their ensuing health effects arising from a change in NO_x emissions from a particular source with a reasonable degree of precision.

We take a different approach, viewing NO_x emissions as a proxy for undesirable, yet not well understood, adverse health impacts from RECLAIM facilities. We are agnostic regarding whether these impacts arise from NO_x itself, ozone, $PM_{2.5}$, or other unmeasured air toxics, such as heavy metals, that may be emitted in the combustion process that creates NO_x. We assume that a representative individual believes that these health damages increase with the tons of NO_x emitted by nearby facilities, where nearby is defined as within 3 km of her home.

We also examine sensitivity to two alternative dispersion models. Given the prevailing wind direction in most of the region (see figures in Lejano and Hirose, 2005; Schlenker and Walker, 2016; Grainger and Ruangmas, 2018), we consider a specification that places greater weight on facilities to the west; rather than assuming a facility's impacts fall evenly within a circle of 3 km radius, we model facility emissions as falling within a semicircle of 1 km radius to the west and a semicircle of 4 km radius to the east. We also consider a specification using the more sophisiticated HYSPLIT model results of Grainger and Ruangmas (2018).

III. Data

Emissions and industrial classification for NO_x emitting facilities come from the California Air Quality Resources Board (ARB). California law requires polluting facilities to report emissions to their local Air Quality Management District, and the ARB maintains a database of these reports (Fowlie et al., 2012). We use these data to calculate emissions for two periods: the 1990–1993 pre-RECLAIM period (period 1) and the 2004–2005 period in which RECLAIM was fully implemented (period 2). Only the 212 facilities reporting emissions in both periods are included in the analysis.

We use a matching algorithm similar to that employed by Fowlie et al. (2012) to calculate counterfactual estimates for what NO_x emissions would have been had

Table 1. Facility Emission Summary Statistics

Annual average tons NO_x	Baseline	Command and control	RECLAIM
Total	21,688.5	11,657.8	6,566.2
Mean	102.3	55.0	31.0
Standard Deviation	305.0	166.9	117.4
Coefficient of Variation	3.0	3.0	3.8
Minimum	0.4	0.3	0.0
Maximum	2,492.3	1,699.9	1,041.8
N	212	212	212

Notes: Baseline is 1990–1993 emissions. Command and control is counterfactual 2003–2004 emissions. RECLAIM is actual 2003–2004 emissions.
Source: Author calculations, based on data from California Air Resources Board.

facilities been regulated under command-and-control rather than RECLAIM. Our approach consists of four steps. First, for each RECLAIM facility we generate a pool of potential controls from non-RECLAIM facilities of the same industrial classification in California ozone nonattainment areas subject to command-and-control regulation. Second, from this pool we select the three nearest neighbors: those facilities whose pre-RECLAIM period emissions are closest to those of the RECLAIM facility. Third, we calculate the average percent change in emissions for these matched controls. Fourth, we apply this percent change to the RECLAIM facility's period 1 emissions to generate the period 2 counterfactual.[5]

Table 1 summarizes actual and counterfactual emissions data for the RECLAIM facilities over the two periods. Actual emissions correspond to emissions under the RECLAIM program, and counterfactual emissions correspond to the emissions that would have occurred under command and control as estimated by the matching procedure. The table shows that both policy scenarios resulted in a decline in both total emissions and the absolute dispersion of emissions relative to the baseline. The RECLAIM program had substantially lower emissions than the counterfactual. Although the standard deviation of RECLAIM emissions was lower than the counterfactual, the coefficient of variation was higher.

Block group demographic data come from the 1990 and 2000 U.S. Censuses.

[5]Our approach differs from Fowlie et al. (2012) by using percent, rather than absolute, changes to estimate counterfactual emissions. We do this to avoid negative predicted emissions for some facilities.

Table 2. South Coast Demographic Summary Statistics

	1990			2000		
		Census Block Group			Census Block Group	
Demographic Group	Total (millions)	Mean	Standard Deviation	Total (millions)	Mean	Standard Deviation
Race/Ethnicity						
Hispanic	4.4	503	633	6.2	637	671
White	6.4	725	788	5.5	574	584
Black	1.1	127	274	1.1	114	234
Other	1.3	151	260	2.1	215	299
Income						
Below poverty	1.7	198	258	2.3	241	277
1-2 × poverty	2.4	272	301	3.1	316	302
Above 2 × poverty	8.9	1,005	899	9.3	959	687
Total	13.3	1,506	1,159	14.9	1,544	958

Notes: Hispanic includes all races who report Hispanic ethnicity. All others are of non-Hispanic ethnicity.
Source: Author calculations, based on data from US Census.

The affected population analyzed here consists of all individuals living in a census block group in the SCAQMD. We divide this population along race/ethnicity and income. The Hispanic ethnicity consists of all individuals who self-report as being Hispanic, regardless of their race. The Black, White and Other race categories consist of individuals who self-report as those races, but do not report as Hispanic. Individual income is reported by the Census relative to the poverty line. We use three classifications, belonging to a household below the poverty line, between one and two times the poverty line, and more than two times the poverty line (the latter is the highest income category reported in the Census).

Table 2 reveals substantial demographic changes between the two decennial censuses. Although total population increased by about 10 percent, the white population fell and the black population remained roughly constant. The Hispanic population grew significantly, overtaking White as the largest group. All three income categories grew during this period, with the above 2 times the poverty line group growing the slowest.

To analyze the impact of neighborhood demographics on facility emissions, Fowlie et al. (2012) use the common tactic of taking the facility as the unit of analysis and calculating demographic information for surrounding areas within a given radius. That approach answers the question of how facility RECLAIM emissions can be predicted by demographics of surrounding communities. Here, we take the opposite approach, basing our analysis on individuals. This approach answers the question of how a given demographic is affected by RECLAIM. We aggregate emissions from all facilities within 3 km of the block group centroid to calculate cumulative stationary source NO_x emission exposure for each individual in a given census block group.

Appendix Figure B1 depicts kernel density functions representing the distribution of cumulative emission exposure over census block groups for each policy scenario. Cumulative emissions are the total annual average emissions from all RECLAIM facilities within 3 km of a census block group (census block groups with zero exposure from RECLAIM facilities are not included in the diagrams). Consistent with the facility-level data presented in Table 1, the figure shows a leftward shift in the distribution under both the RECLAIM and counterfactual command-and-control policies relative to the Period 1 baseline. This shift suggests that the RECLAIM emissions reductions did not come at the expense of creating pollution hotspots. To the contrary, the cumulative emissions experienced by the most exposed block groups falls from 4,000 tons under the baseline to just over 1,000 tons under RECLAIM. These diagrams do not, however, indicate how many individuals of each demographic group live in the affected block groups. Normatively ranking emissions distributions requires such individual-level information.

In the next section, we apply the methods described in Section I to actual and counterfactual NO_x distributions associated with the RECLAIM program. We begin by focusing on GL dominance, imposing as few restrictions on preferences as possible. Although this partial ordering is sufficient for answering several important policy questions, to obtain a complete ordering of pollution distribution requires more preference structure. To do so, we use Eq. (3) to calculate EDEs. Finally, recognizing the substantial differences in average emissions between policy options, we use absolute Lorenz curves and inequality indexes, effectively rescaling the counterfactual command-and-control scenario so that it achieves the same average emissions exposure as RECLAIM.

IV. Results

Here we present rankings of the emissions distributions from the three policy scenarios (baseline, counterfactual command-and-control, and RECLAIM) across four racial/ethnic groups (Black, White, Hispanic, and Other), three income groups (below poverty, 1–2 times the poverty line, and more than twice the poverty line), and the affected population as a whole, using demographic data from the 1990 and 2000 censuses. The affected population is everyone living in a SCAQMD census block whose centroid is within 3 km of a RECLAIM facility.

The analysis answers four questions relevant to environmental justice concerns with market-based environmental policy instruments. First, did any demographic group suffer a welfare loss under the RECLAIM program relative to the command- and control-alternative? Second, did the RECLAIM program favor particular demographic groups in relative terms compared with command and control? These questions consider both pollution levels and the equity of the pollution distribution. Since there are substantial differences in total pollution levels between the three scenarios, it may be the case that these differences overwhelm the distributional implications of the policies. To examine the pure distributional implications, we de-mean the distributions to conduct an absolute Lorenz curve analysis. This analysis answers the following question: Which policy would each demographic group choose if they each had the same average pollution levels?

The preceding analysis uses demographic information available at the creation of RECLAIM, the 1990 U.S. Census. Over time, geographic concentrations of demographic groups shift. Most of these changes are likely to be independent of the RECLAIM program. It is possible, however, that some population shifts may stem in part from changes in environmental quality. Improvements in air quality in some neighborhoods may have increased property and residential rental values which in turn may have attracted wealthier households and induced poorer households to leave (see, for example, Banzhaf and Walsh, 2008).

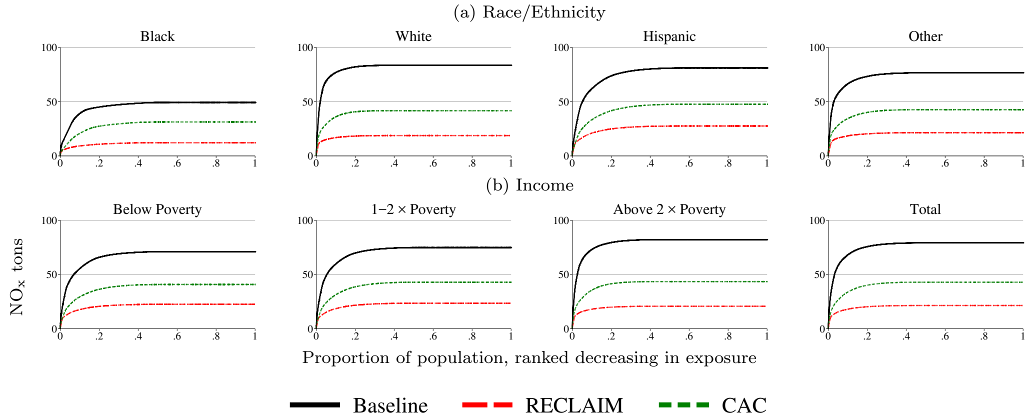
Understanding the impact of such population shifts is important for environmental justice analysis. Even if environmental programs are targeted towards poor and minority populations, it is possible that population shifts may undermine their benefits over time. To address this concern, we repeat the analysis using the 2000 census. By comparing these results to those using 1990 data we can answer the question of whether demographic shifts led to a less desirable pollution distribution for low income or minority populations.

A key advantage of the GL analysis is that it imposes few restrictions on preferences. This flexibility comes at the cost not being able to rank distributions whose GL curves cross. GL curves also do not provide information regarding the equity of distributions across demographic groups. That is, it may be of interest whether a policy treats demographic groups more or less equally. To address these issues, we impose additional structure on preferences as described in Section I, and conduct a supplementary analysis using EDEs and inequality indexes.

A. Ranking policy outcomes by generalized Lorenz curve dominance

Figure 3 addresses the question of which policy would the representative individual prefer, conditional on belonging to a given demographic group. It depicts GL curves for baseline, command-and-control, and RECLAIM NO_x exposure levels by race/ethnicity and income, holding population fixed at 1990 levels. For all demographic groups, RECLAIM GL curves dominate the counterfactual command-and-control curves which in turn dominate baseline curves. In other words, there is not evidence to support a concern that RECLAIM caused low income or minority populations to suffer relative to pollution levels they would have otherwise experienced. In this case, the GL curve ranking is equivalent to ranking distributions based on mean exposure alone (the height of the curve at

FIGURE 3. GENERALIZED LORENZ CURVE RANKING BY POLICY, 1990 CENSUS



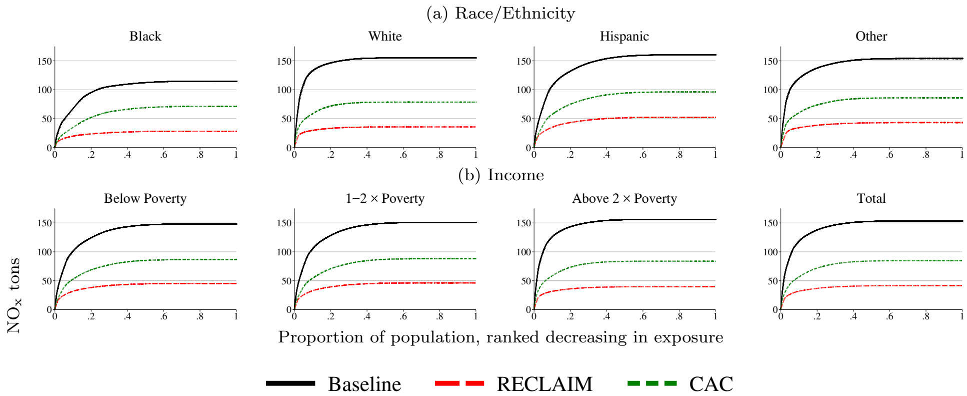
Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

the 100th percentile); any differences in intra-group inequality do not outweigh differences in average exposure.

Our main results were calculated under the assumption that the impact of NO_x emissions are evenly spread within 3 km of each facility. Due to prevailing westerly winds in the Los Angeles region, there may be concern that emissions may affect neighborhoods to the east. To address this issue we generate two alternative exposure patterns. The first assumes that emissions affect census block groups 4 km to the east but only 1 km to the west of each facility. The second uses the weighted treatment area generated by the HYSPLIT model runs used in Grainger and Ruangmas (2018). The appendix provides details on how we calculated exposure levels based on these alternate patterns.

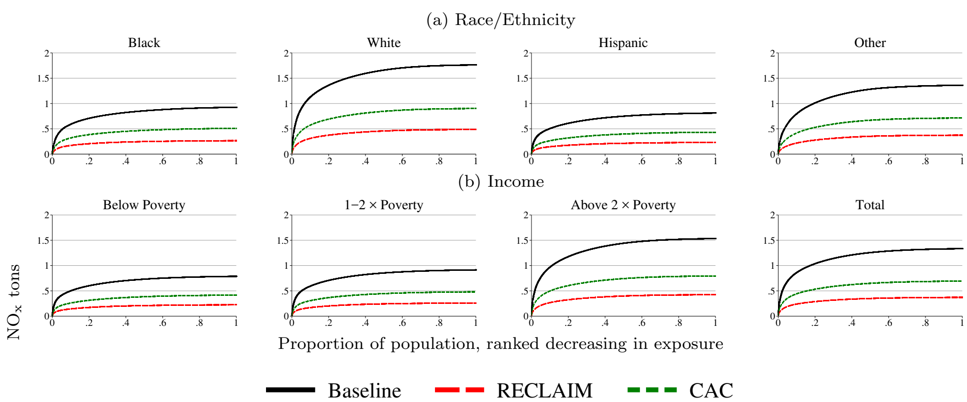
Figures 4 and 5 present the results of this sensitivity exercise. The overall relative patterns are similar, although absolute exposure levels differ. For each demographic group, RECLAIM performs better than the other two scenarios. Black consistently has the best distribution, while White and Hispanic have the worst. Only under the HYSPLIT model does Hispanic fare relatively well. The fact that overall exposures are higher under the west wind dispersion indicates

Figure 4. Generalized Lorenz Curve Ranking by Policy, 1990 Census, west wind



Notes: Distribution of RECLAIM emissions in 4 km radius to east and 1 km radius west to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are of non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and US Census.

Figure 5. Generalized Lorenz Curve Ranking by Policy, 1990 Census, HYSPLIT



Notes: Distribution of RECLAIM emissions using HYSPLIT dispersion model to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are of non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and US Census.

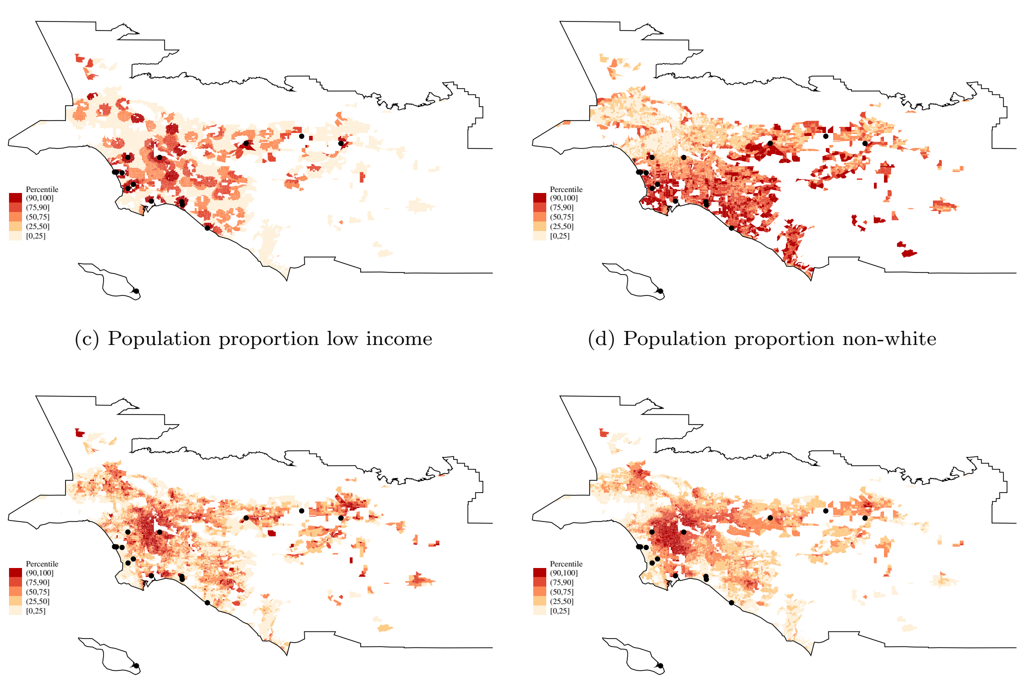
that on average more people of all demographic groups are affected to the east of facilities than in a symmetric circle. In contrast, the low exposure levels using the HYSPLIT model arise from the fact that the same emissions are spread over much greater distances, affecting areas with relatively low population density. These results suggest that adjustments for dispersion patterns are unlikely to substantially alter the environmental justice implications of RECLAIM.

The maps in figure 6 help explain why the different dispersion models do not generate qualitatively different environmental justice implications. Panels (a) and (b) depict the spatial distribution of total emissions generated by the 3 km radius and HYSPLIT dispersion models. Panels (c) and (d) respectively depict the distribution of block groups in terms of the share of population that is low income (less than 2 times the poverty line) and Hispanic or non-white. The black dots represent the 15 highest emitting RECLAIM facilities (all of which had over 300 tons average annual emissions at baseline). To focus attention on emissions that meaningfully affect the distributional rankings, we do not include the most sparsely populated block groups (below the 10th percentile in terms of population). The maps show that under both dispersion models, the most highly affected areas tend to be the predominantly white and upper income block groups along the coast. In contrast, the interior portions of Los Angeles most dominated by low income and minority residents have relatively low exposure.

Despite this pattern of overall improvement, there may be concerns that RECLAIM exacerbated a disparity between demographic groups. Figure 7 reframes the question, considering which demographic group has the preferred pollution distribution, conditional on a given policy scenario.

Consistent with Figure 6, among racial/ethnic groups Black had the most desirable distribution of NO_x outcomes at baseline, while White had the least desirable distribution. Although the Black distribution is unambiguously better than the other groups for the two policy scenarios, the relative position of White improves. For the command-and-control scenario, the White GL curve intersects the His-

FIGURE 6. SOUTH COAST NO_X EXPOSURE AND DEMOGRAPHIC COMPOSITION



(a) 3 km radius exposure (b) HYSPLIT exposure

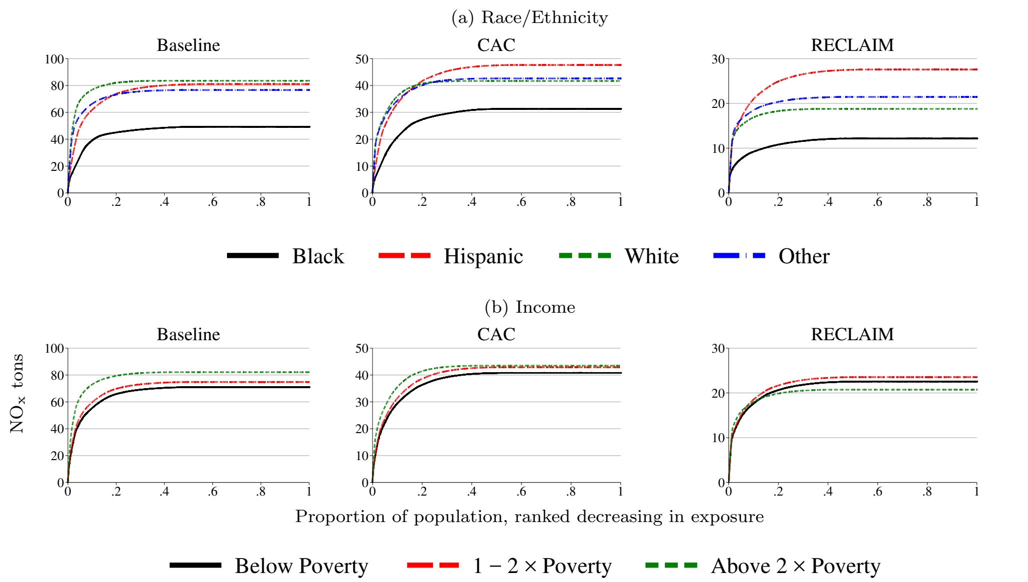
(c) Population proportion low income (d) Population proportion non-white

Notes: Panels (a) and (b) depict 1990 census block group percentiles of baseline NO_X exposure generated by the 3 km radius and HYSPLIT dispersion models. Panels (b) and (c) depict block group percentiles in terms of population proportion that is respectively low income and minority. Maps only include block groups above the 10th population percentile. Dots indicate locations of RECLAIM facilities with average annual 1990–1993 emissions exceeding 300 tons. Low income refers to individuals in households earning below 2 times the poverty line, and non-white includes all individuals of Hispanic ethnicity.

panic and Other curves, while for the RECLAIM scenario the distribution for whites is strictly preferred to these other two. Thus, although all groups are better off under RECLAIM there is room for concern that RECLAIM left White better off than say Hispanic.

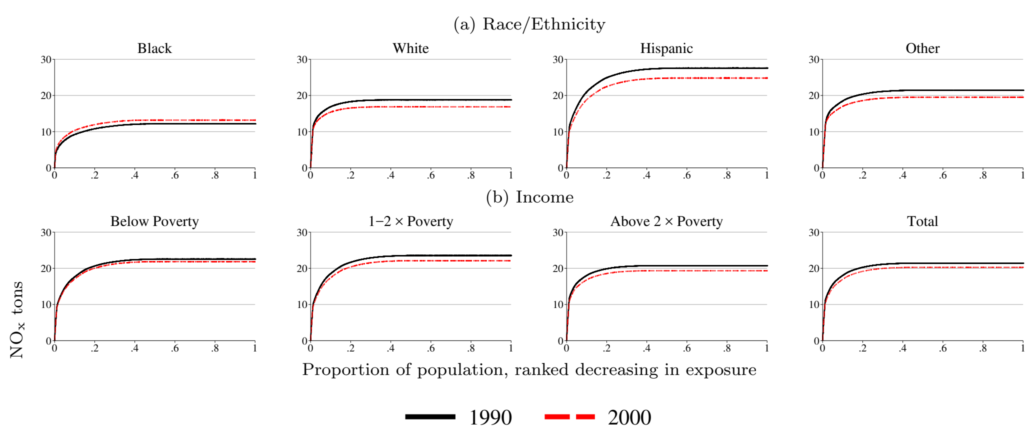
A similar story emerges with respect to income groups. Under the baseline and command-and-control scenarios, individuals below the poverty line had the most favorable distribution, whereas those whose incomes were more than twice the poverty line had the worst. Under RECLAIM, the relative position of the wealthiest appears to have improved.

Figure 7. Generalized Lorenz Curve Ranking by Demographic Group, 1990 Census



Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

Figure 8. Generalized Lorenz Curve Ranking of RECLAIM emissions by Census



Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

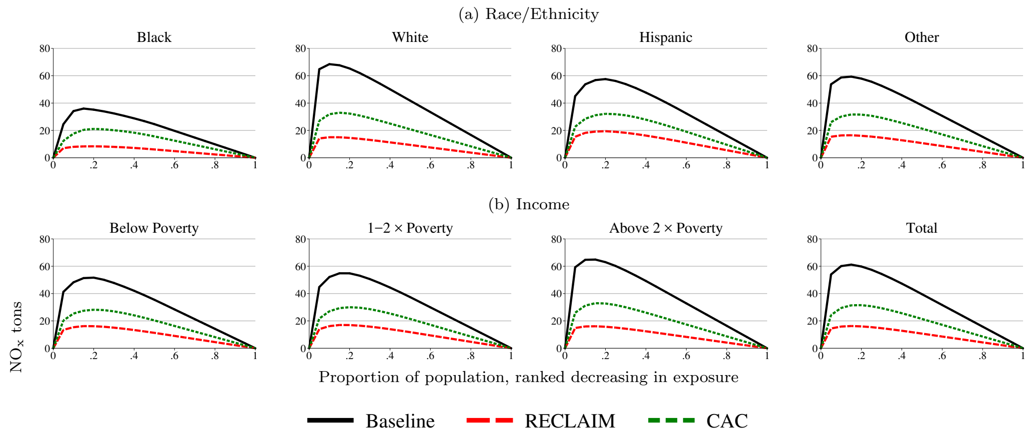
A potential drawback to using GL curves calculated from 1990 census data is that neighborhood composition may have changed over time, perhaps even due to RECLAIM itself. Improvements in air quality in some neighborhoods may have increased property and residential rental values which in turn may have attracted wealthier households and induced poorer households to leave (e.g., Banzhaf and Walsh, 2008). In such cases, GL curves in Figure 7 may overstate exposure reductions for poor communities. Such sorting would also complicate the welfare interpretation of GL curves since the rankings hold all else constant. If individuals living in areas with improved air quality were to face higher rents, their increase in utility would be lower.

Figure 8 depicts the potential impact of such demographic sorting over time. It compares RECLAIM GL curves calculated using 1990 versus 2000 census demographic information. This analysis is only suggestive at best, since we do not have a counterfactual population distribution, i.e., an estimate of 2000 demographic locations in the absence of RECLAIM. We can, however, observe how actual population shifts in 2000 affected distributions relative to what would have been predicted using 1990 demographic data. Sorting does not appear to have played a major role for most demographic groups. The notable exception is for the Black group. It is the only group for which benefits predicted by the 1990 census would have over-estimated the improvements relative to 2000. The data do not allow us to determine whether this phenomenon was due to obstacles to moving to or remaining in cleaner neighborhoods or some other cause. Interestingly, however, income does not appear to drive these results since there is no evidence of a similar shift for any income group.

B. Ranking policy outcomes by absolute Lorenz curve dominance

One reason that NO_x distributions from RECLAIM dominate those for other policy scenarios is that the overall level of emission exposure is much lower. It is unclear why RECLAIM had such a strong reduction in pollution levels since it

Figure 9. Absolute Lorenz curves ranking by policy, 1990 Census



Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Hispanic includes all who report Hispanic ethnicity. All races are non-Hispanic ethnicity.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

was intended to achieve the same reductions as the command-and control-regime, but at lower cost.

Fowlie et al. (2012) speculate that cost reductions may have provided political cover for regulators to achieve more ambitious pollution targets. Another possible explanation is that regulations are typically limited to reducing emissions on the intensive margin, e.g., emissions per unit of output. Market-based mechanisms allow sources to meet an absolute quantitative limit by changing behavior on the extensive margin as well (by reducing output). Moreover, command-and-control regulations commonly face legal constraints regarding their maximum stringency. Under the Clean Air Act, for example, existing major NO_x sources in heavily polluted ozone nonattainment areas are subject to reasonably available control technology (RACT) requirements. RACT is determined on a source-by-source basis, taking into account "technological and economic feasibility". Such constraints would not, in principle, apply to the determination of a sector-wide cap in an emissions trading program.

Regardless of the reason, it is natural to question whether focusing on GL curves obscures the larger question of the relative equity of command-and-control and market-based mechanisms behind the differences in total emissions. An alternative comparison would be between RECLAIM and a command-and-control policy with the same average exposure.

To address this question, Figure 9 presents AL curves. In terms of equity only, the RECLAIM distribution dominates both the baseline and counterfactual distributions for each demographic group and the for the population as a whole. Since the AL curves for different demographic groups intersect, it is necessary to calculate inequality indexes to make comparisons of equity implications across demographic groups as well as to rank distributions from the perspective of inter-group equity.

C. Ranking policy outcomes using equally distributed equivalents and inequality indexes

Parameter κ in Eq. (2) is a key element in calculating EDEs and inequality indexes. The choice of κ reflects a value judgement regarding the degree to which the representative individual is averse to inequality in pollution lotteries, with higher values corresponding to higher aversion. Using Eq. (2) the elasticity of marginal utility with respect to pollution is κx.

The literature provides little guidance regarding "reasonable" values of this elasticity, and such estimation is beyond the scope of this study. For income distribution, the U.S. Census Bureau uses elasticities of 0.25, 0.5, and 0.75 (e.g., Jones and Weinberg, 2000; DeNavas-Walt et al., 2012). In laboratory experiments on income inequality Amiel et al. (1999) found values in the neighborhood of 0.25. To our knowledge, Cropper et al. (2016) is the only study that estimated this elasticity for an environmental good (a hypothetical cleanup program). They found found higher values, with a mean of 0.72 and median of 2.8.

These studies assume preferences to be scale invariant, rather than translatable, meaning that inequality can be expressed with a relative, rather than absolute index. As such, the calculated elasticity, α, is constant, rather than varying with exposure as is the case for an absolute index.

To establish a correspondence between an elasticity α and a comparable vector of elasticities $\kappa\mathbf{x}$, we minimize the sum of squared differences between the absolute value of individual elasticities and the constant α:

$$\begin{aligned}\kappa(\alpha) &= -\arg\min_{\hat{\kappa}} \left\{[\hat{\kappa}\mathbf{x} - \alpha\mathbf{1}]'[\hat{\kappa}\mathbf{x} - \alpha\mathbf{1}]\right\} \\ &= -\frac{\alpha \sum_{n=1}^{N} x_n}{\sum_{n=1}^{N} x_n^2}. \end{aligned} \tag{6}$$

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 ordering remains largely unchanged.

GL curves only enable ordinal ranking of distributions in which they do not cross. Tables 3 and 4 display the mean, EDE, and inequality index values for baseline, command-and-control, and RECLAIM NO_x exposure distributions using 1990 and 2000 demographics respectively. By further restricting preferences as in Eq. (2), these tables allow cardinal welfare comparisons for all distributions.

Rankings by EDE in Panel B can only differ from those made by comparing means in Panel A for cases in which the respective GL curves cross. Under the command-and-control policy using 2000 demographics, for example, the distribution for White is less desirable than that of Hispanic despite the fact that its average exposure is lower. Looking at the inequality index values, this relative ranking is due to the fact that the the distribution for whites is less equitable (index value of 7.4 relative to 3.1 tons).

EDE values enable the determination of whether a policy generated welfare improvements for a given demographic group. They do not, however, indicate whether improvements come at the cost of increased disparity of outcomes. Such a concern is particularly relevant for emissions trading programs like RECLAIM.

Table 3. NO_X tons, 1990 census

	Baseline (a)	Command and control (b)	RECLAIM (c)	Difference (c)-(b)
Panel A. Means				
Race/Ethnicity				
Hispanic	81.0	47.6	27.6	-20.0
	(3.9)	(2.1)	(1.8)	(1.7)
White	83.5	41.7	18.8	-22.9
	(5.7)	(2.6)	(1.4)	(1.3)
Black	49.2	31.3	12.2	-19.1
	(3.1)	(1.7)	(0.9)	(1.4)
Other	76.6	42.6	21.4	-21.2
	(7.1)	(3.7)	(2.1)	(1.8)
Income				
Below poverty	71.0	40.8	22.6	-18.2
	(3.3)	(1.7)	(1.4)	(1.3)
1-2 × poverty	74.8	42.9	23.5	-19.4
	(3.5)	(1.9)	(1.4)	(1.3)
Above 2 × poverty	82.1	43.5	20.7	-22.8
	(4.7)	(2.3)	(1.3)	(1.2)
Total	**79.1**	**42.9**	**21.4**	**-21.5**
	(4.0)	**(2.0)**	**(1.2)**	**(1.1)**
Panel B. Equally distributed equivalents				
Race/Ethnicity				
Hispanic	94.3	50.9	29.6	-21.3
	(4.8)	(2.3)	(2.0)	(1.9)
White	120.7	48.9	20.9	-28.0
	(9.8)	(3.5)	(1.7)	(2.0)
Black	55.2	32.7	12.8	-19.9
	(3.6)	(1.8)	(1.0)	(1.5)
Other	104.1	48.9	23.6	-25.4
	(11.9)	(4.8)	(2.4)	(2.6)
Income				
Below poverty	84.7	44.0	24.2	-19.7
	(4.4)	(2.0)	(1.6)	(1.5)
1-2 × poverty	90.6	46.4	25.3	-21.1
	(4.9)	(2.1)	(1.6)	(1.6)
Above 2 × poverty	113.0	49.8	22.8	-27.0
	(8.0)	(3.0)	(1.5)	(1.7)
Total	**104.8**	**48.2**	**23.4**	**-24.8**
	(6.6)	**(2.5)**	**(1.4)**	**(1.5)**
Panel C. Inequality indexes				
Race/Ethnicity				
Hispanic	13.3	3.3	2.0	-1.3
	(1.0)	(0.3)	(0.3)	(0.3)
White	37.2	7.3	2.1	-5.1
	(4.4)	(1.0)	(0.3)	(0.7)
Black	6.0	1.4	0.7	-0.7
	(0.8)	(0.2)	(0.1)	(0.1)
Other	27.5	6.3	2.1	-4.2
	(5.1)	(1.1)	(0.3)	(0.8)
Between race	0.065	0.004	0.004	0.000
	(0.025)	(0.001)	(0.001)	(0.002)
Income				
Below poverty	13.7	3.2	1.7	-1.5
	(1.3)	(0.3)	(0.2)	(0.3)
1-2 × poverty	15.8	3.5	1.7	-1.8
	(1.7)	(0.4)	(0.2)	(0.3)
Above 2 × poverty	30.9	6.4	2.1	-4.2
	(3.5)	(0.8)	(0.2)	(0.6)
Between income	0.025	0.001	0.000	-0.001
	(0.012)	(0.001)	(0.000)	(0.001)
Total	**25.7**	**5.4**	**2.0**	**-3.4**
	(2.8)	**(0.6)**	**(0.2)**	**(0.5)**

Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Standard errors in parentheses calculated using a bootstrap of 1000 draws over the sample of SCAQMD census block groups. Equally distributed equivalent and inequality index calculated using $\kappa(0.50)$. Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. Below poverty indicates people below the poverty line, 1-2 × poverty indicates people between one and two times the poverty line, and Above 2 × poverty indicates people above twice the poverty line.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

Table 4. NO_X tons, 2000 Census

	Baseline (a)	Command and control (b)	RECLAIM (c)	Difference (c)-(b)
Panel A. Means				
Race/Ethnicity				
Hispanic	74.0	43.6	24.8	-18.8
	(3.1)	(1.6)	(1.3)	(1.2)
White	81.0	39.8	16.9	-23.0
	(5.5)	(2.5)	(1.4)	(1.3)
Black	56.3	35.8	13.2	-22.6
	(3.3)	(1.8)	(0.9)	(1.5)
Other	74.6	41.1	19.5	-21.6
	(7.8)	(4.0)	(2.2)	(1.9)
Income				
Below poverty	68.9	39.8	21.8	-18.0
	(3.1)	(1.6)	(1.3)	(1.1)
1-2 × poverty	70.2	41.0	22.1	-18.9
	(3.1)	(1.6)	(1.2)	(1.1)
Above 2 × poverty	78.6	41.8	19.3	-22.5
	(4.4)	(2.2)	(1.2)	(1.1)
Total	**75.4**	**41.3**	**20.3**	**-21.0**
	(3.6)	**(1.8)**	**(1.1)**	**(1.0)**
Panel B. Equally distributed equivalents				
Race/Ethnicity				
Hispanic	86.4	46.7	26.5	-20.2
	(3.9)	(1.8)	(1.4)	(1.4)
White	118.5	47.2	18.9	-28.3
	(9.5)	(3.5)	(1.6)	(2.0)
Black	65.2	37.9	14.0	-23.9
	(4.2)	(2.0)	(1.0)	(1.6)
Other	103.9	47.7	21.5	-26.1
	(13.3)	(5.2)	(2.5)	(2.8)
Income				
Below poverty	81.9	42.9	23.4	-19.5
	(4.3)	(1.8)	(1.4)	(1.3)
1-2 × poverty	85.0	44.5	23.7	-20.8
	(4.5)	(1.9)	(1.3)	(1.3)
Above 2 × poverty	108.2	48.0	21.3	-26.7
	(7.6)	(2.9)	(1.4)	(1.6)
Total	**99.2**	**46.4**	**22.1**	**-24.3**
	(6.0)	**(2.3)**	**(1.2)**	**(1.4)**
Panel C. Inequality indexes				
Race/Ethnicity				
Hispanic	12.4	3.1	1.7	-1.4
	(1.0)	(0.2)	(0.2)	(0.2)
White	37.5	7.4	2.0	-5.3
	(4.3)	(1.0)	(0.3)	(0.7)
Black	9.0	2.1	0.8	-1.3
	(1.3)	(0.3)	(0.1)	(0.2)
Other	29.2	6.6	2.0	-4.6
	(5.7)	(1.2)	(0.3)	(0.9)
Between race	0.277	0.112	0.071	-0.041
	(0.039)	(0.013)	(0.011)	(0.009)
Income				
Below poverty	13.1	3.1	1.6	-1.5
	(1.4)	(0.3)	(0.2)	(0.3)
1-2 × poverty	14.8	3.5	1.6	-1.9
	(1.6)	(0.4)	(0.2)	(0.3)
Above 2 × poverty	29.6	6.2	1.9	-4.2
	(3.3)	(0.8)	(0.2)	(0.6)
Between income	0.025	0.001	0.000	-0.001
	(0.012)	(0.001)	(0.000)	(0.001)
Total	**23.9**	**5.1**	**1.8**	**-3.3**
	(2.6)	**(0.6)**	**(0.2)**	**(0.4)**

Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Standard errors in parentheses calculated using a bootstrap of 1000 draws over the sample of SCAQMD census block groups. Equally distributed equivalent and inequality index calculated using $\kappa(0.50)$. Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. Below poverty indicates people below the poverty line, 1-2 × poverty indicates people between one and two times the poverty line, and Above 2 × poverty indicates people above twice the poverty line.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

It is possible that the dirtiest facilities may also face the least pressure to reduce emissions. It may be more costly to retrofit pollution controls onto older dirtier sources, for example. Or, perhaps communities near these sources lack the power to exert political pressure to reduce emissions.

The inequality indexes presented in Panel C of Table 3 indicate how RECLAIM impacted the disparity of outcomes. A higher index value signals a more unequal distribution, independent of the mean. These results suggest that RECLAIM's improvement in average exposure relative to command-and-control regulation displayed in Panel A did not come at the expense of increased disparity of outcomes. Index values for all demographic groups are the same or slightly lower for RECLAIM using 1990 census data.

There is little change in RECLAIM inequality index values using 2000 census data, suggesting that overall residential sorting played little role in the dispersion of outcomes within groups. Notably, however, between race inequality, as calculated by Eq. (5), increased for all scenarios from 1990 demographics to 2000 demographics.

V. Conclusion

With the implementation of cap and trade programs for carbon emissions in California and RGGI and recent ballot initiatives for carbon taxes in Washington state, market-based programs for reducing pollution have received increased attention. The flexibility of these programs relative to a regulatory command-and-control regime offers cost savings, but also raises questions about potential distributional implications.

Environmental justice advocacy groups have expressed concern that polluting facilities in low income and minority neighborhoods may respond to carbon trading programs by buying permits to increase emissions beyond what would have been allowed under a command-and-control regime. The concern is not with CO_2 per se, but with other co-pollutants that have adverse health impacts.

Southern California's RECLAIM program provides a useful test case for evaluating such concerns since it replaced command-and-control regulations with a NO_x emissions trading program. There are two key challenges to rigorously evaluating its distributional impact.

First, it is necessary to generate data for a credible counterfactual emissions scenario. It is not sufficient to compare plant emissions under RECLAIM to emissions prior to the program since many other changes affecting pollution decisions may have taken place during the intervening years. Instead, we match RECLAIM facilities with similar California facilities outside the program which continued to be subject to traditional NOx regulations. We then map actual and counterfactual emissions onto nearby census blocks whose populations are broken down into various demographic groups.

Second, it is necessary to develop an approach for ranking the alternate emissions profiles in a way that is consistent with how members of the affected populations would rank them. To do so, we postulate a hypothetical representative individual and effectively ask her to identify which emissions distribution she would prefer among the various policy scenarios and demographic groups. To ensure her choices are broadly applicable, we impose minimal restrictions on her preferences. To ensure her choices are fair, she ranks distributions from behind a veil of ignorance. When making a choice, she knows how a given distribution will affect each member of the population, but she does not know how it will affect her specifically. Instead, she will be randomly assigned a pollution exposure from the distribution chosen.

The results of this analysis are striking. Each racial/ethnic group and each income category would prefer the RECLAIM distribution over the corresponding command-and-control alternative. Moreover, there is little evidence to suggest that RECLAIM systematically favored white or high income groups over minority or low income groups. Although the pollution distribution for White under RECLAIM was preferable to that of Hispanic, for example, it was worse than that of Black. These results are robust to alternative specifications regarding spatial emissions patterns and individual preferences. Moreover, comparing demographic information from the 2000 to 1990 census suggests that migration patterns did little to alter these conclusions. Although some of the gains for Black were reduced by demographic changes, it was still better off with RECLAIM.

One reason RECLAIM performed so well was that total pollution under the program was substantially less than under the counterfactual, regardless how equitably the remaining emissions were distributed across the population. Looking forward, it would be useful to understand whether the RECLAIM distribution was more equitably distributed than the counterfactual *independently* of average pollution levels. Were RECLAIM to generate a less equitable distribution then there might be cause to require that a future market-based mechanism be more stringent than an alternative command-and-control regulation in order to compensate for its adverse distributional implications. Our approach allows us to disentangle overall pollution levels from the equity of the distribution itself. We find that the RECLAIM distribution was more equitable than the counterfactual for each demographic group, across demographic groups, and across the population as a whole.

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Appendix A: Calculating exposure using HYSPLIT weights

Our main specification assumes that the full impact of a facility's emissions is felt in census block groups with centroids within a 3 km radius of the facility. In contrast, Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) Model used by Grainger and Ruangmas (2018) assumes that wind and other meteorological and topographical factors spread the impact out out over a much larger geographic area. In this section, we describe how we use weights derived from the Grainger and Ruangmas (2018) HYSPLIT model runs to generate exposure levels in each census block group such that the aggregate amount of pollution generated is comparable to the levels generated by our main specification.

HYSPLIT models the impact of each facility's emissions on ambient NO_x concentrations on a grid of approximate 1×1 km cells using meteorological data obtained twice daily from 1990. As described in their technical appendix Grainger and Ruangmas (2018) apportion these gridded impacts to census block groups according to the area of each block group covered by each grid cell. Pollution concentrations are normalized such that they sum to 1 for each facility. The block group weight is the proportion of total emissions from facility j accruing to block group i. The authors kindly shared with us a file containing the weights for each facility-block group pair.

We use the following methodology to use these weights to allocate facility emissions across census block groups such that the total emissions generated by each facility is comparable with our main 3 km radius dispersion specification.

Let the index k denote the two dispersion models, with $k = M$ corresponding to our main specification, and $k = H$ corresponding to the HYSPLIT model. We begin by modeling exposure of individual n in block group i under dispersion model k, x^k_{in}, as the sum of scaled weighted emissions, e_j, across all facilities (indexed by j):

$$x^k_{in} = \sum_j e_j w^k_{ij} s^k_j, \text{ for } k = \{M, H\}. \tag{A1}$$

For our main specification, weights w^M_{ij} are equal to one for all census blocks with centroids within the 3 km radius and equal to zero for all others. For the HYSPLIT specification, w^H_{ij} are the weights calculated by Grainger and Ruangmas (2018). As detailed below, the scaling factors s^k_j are chosen to make the aggregate impact of each facility comparable under the two dispersion model specifications.

The total "effective" emissions within block group i, E^k_i, are defined to be the individual exposure level multiplied by the block group area a_i:

$$E^k_i = a_i \sum_j e_j w^k_{ij} s^k_j. \tag{A2}$$

The effective emissions in block group i originating from facility j are:

$$E^k_{ij} = a_i e_j w^k_{ij} s^k_j. \tag{A3}$$

The total effective emissions of facility j across all block groups is:

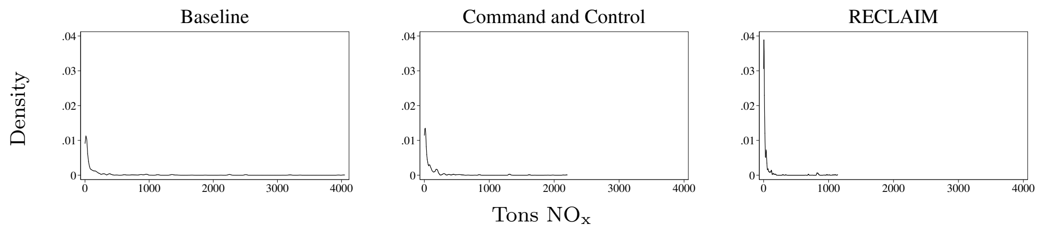
$$\tilde{E}_j^k = \sum_i a_i e_j w_{ij}^k s_j^k. \tag{A4}$$

The scaling factors s_j^M and s_j^H are chosen such that the effective emissions for facility j calculated by a given dispersion weighting scheme are equal to the effective emissions using the 3 km weights of the main specification (i.e., by definition $s_j^M = 1$):

$$s_j^k \equiv \{s : \sum_i e_j a_i w_{ij}^k s = \sum_i e_j a_i w_{ij}^M\} \text{ for } k = \{M, H\} \tag{A5}$$

$$= \frac{\sum_i a_i w_{ij}^M}{\sum_i a_i w_{ij}^k}. \tag{A6}$$

Figure B1. Distributions of cumulative NO_x emissions over census block groups



Notes: Kernel density estimates based on number of 1990 census block groups with strictly positive RECLAIM exposure. Tons NO_x indicates the total average annual emissions summed across all facilities within 3km of a census block group centroid. Baseline is 1990–1993 emissions. RECLAIM is actual 2003–2004 emissions. Command and Control is counterfactual 2003–2004 emissions based on matched facilities in California ozone nonattainment areas that did not participate in RECLAIM.
Source: Author calculations based on data from California Air Resources Board.

Table C1. Tons NO_X exposure, 1990 Census, low inequality aversion

	Baseline (a)	Command and control (b)	RECLAIM (c)	Difference (c)-(b)
Panel A. Equally distributed equivalents				
Race/Ethnicity				
Hispanic	87.0	49.2	28.5	-20.7
	(4.2)	(2.2)	(1.7)	(1.7)
White	99.0	45.0	19.8	-25.2
	(7.3)	(3.0)	(1.5)	(1.6)
Black	51.9	31.9	12.5	-19.5
	(3.4)	(1.8)	(0.9)	(1.5)
Other	88.2	45.5	22.4	-23.1
	(9.3)	(4.2)	(2.2)	(2.2)
Income				
Below poverty	77.0	42.3	23.4	-18.9
	(3.7)	(1.8)	(1.4)	(1.4)
1-2 × poverty	81.7	44.5	24.4	-20.2
	(4.1)	(2.0)	(1.4)	(1.4)
Above 2 × poverty	95.1	46.4	21.7	-24.6
	(6.0)	(2.6)	(1.4)	(1.4)
Total	**89.9**	**45.3**	**22.4**	**-23.0**
	(5.0)	**(2.2)**	**(1.3)**	**(1.3)**
Panel B. Inequality indexes				
Race/Ethnicity				
Hispanic	6.0	1.6	1.0	-0.6
	(0.4)	(0.1)	(0.1)	(0.1)
White	15.5	3.3	1.0	-2.3
	(1.7)	(0.4)	(0.1)	(0.3)
Black	2.7	0.7	0.3	-0.3
	(0.3)	(0.1)	(0.1)	(0.1)
Other	11.6	2.9	1.0	-1.9
	(2.1)	(0.5)	(0.2)	(0.4)
Between race	0.015	0.002	0.002	0.000
	(0.006)	(0.001)	(0.001)	(0.001)
Income				
Below poverty	6.0	1.5	0.8	-0.7
	(0.5)	(0.1)	(0.1)	(0.1)
1-2 × poverty	6.9	1.7	0.8	-0.8
	(0.7)	(0.2)	(0.1)	(0.1)
Above 2 × poverty	12.9	2.9	1.0	-1.9
	(1.4)	(0.3)	(0.1)	(0.3)
Between income	0.005	0.000	0.000	-0.000
	(0.003)	(0.000)	(0.000)	(0.000)
Total	**10.8**	**2.5**	**0.9**	**-1.5**
	(1.1)	**(0.3)**	**(0.1)**	**(0.2)**

Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Standard errors in parentheses calculated using a bootstrap of 1000 draws over the sample of SCAQMD census block groups. Equally distributed equivalent and inequality index calculated using $\kappa(0.25)$. Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. Below poverty indicates people below the poverty line, 1-2 × poverty indicates people between one and two times the poverty line, and Above 2 × poverty indicates people above twice the poverty line.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.

Table C2. Tons NO_x exposure, 1990 Census, high inequality aversion

	Baseline (a)	Command and control (b)	RECLAIM (c)	Difference (c)-(b)
Panel A. Equally distributed equivalents				
Race/Ethnicity				
Hispanic	103.5	52.8	30.7	-22.1
	(5.4)	(2.4)	(2.1)	(1.9)
White	151.9	53.8	22.1	-31.7
	(13.5)	(4.1)	(1.8)	(2.5)
Black	59.5	33.5	13.2	-20.3
	(4.2)	(1.9)	(1.1)	(1.6)
Other	126.0	53.0	24.8	-28.2
	(16.3)	(5.6)	(2.6)	(3.1)
Income				
Below poverty	94.9	45.9	25.2	-20.7
	(5.4)	(2.1)	(1.7)	(1.6)
1-2 × poverty	102.4	48.6	26.3	-22.3
	(6.2)	(2.3)	(1.7)	(1.7)
Above 2 × poverty	138.3	54.0	24.1	-29.9
	(10.9)	(3.4)	(1.6)	(2.1)
Total	**125.6**	**51.7**	**24.5**	**-27.2**
	(9.0)	**(2.9)**	**(1.5)**	**(1.8)**
Panel B. Inequality indexes				
Race/Ethnicity				
Hispanic	22.4	5.2	3.1	-2.1
	(1.8)	(0.4)	(0.4)	(0.4)
White	68.4	12.1	3.4	-8.8
	(8.1)	(1.6)	(0.4)	(1.2)
Black	10.3	2.2	1.1	-1.2
	(1.6)	(0.3)	(0.2)	(0.2)
Other	49.4	10.3	3.3	-7.0
	(9.4)	(1.9)	(0.5)	(1.4)
Between race	0.231	0.008	0.007	-0.001
	(0.085)	(0.003)	(0.002)	(0.004)
Income				
Below poverty	23.8	5.1	2.6	-2.5
	(2.5)	(0.5)	(0.3)	(0.4)
1-2 × poverty	27.5	5.7	2.8	-2.9
	(3.1)	(0.6)	(0.3)	(0.5)
Above 2 × poverty	56.2	10.5	3.3	-7.2
	(6.5)	(1.3)	(0.3)	(1.0)
Between income	0.091	0.003	0.000	-0.003
	(0.035)	(0.002)	(0.000)	(0.002)
Total	**46.5**	**8.8**	**3.1**	**-5.7**
	(5.3)	**(1.0)**	**(0.3)**	**(0.8)**

Notes: Distribution of RECLAIM 3 km radius emissions to individuals in the SCAQMD. Standard errors in parentheses calculated using a bootstrap of 1000 draws over the sample of SCAQMD census block groups. Equally distributed equivalent and inequality index calculated using $\kappa(0.75)$. Hispanic includes people of all races who claim Hispanic ethnicity. All races are non-Hispanic. Below poverty indicates people below the poverty line, 1-2 × poverty indicates people between one and two times the poverty line, and Above 2 × poverty indicates people above twice the poverty line.
Source: Author calculations, based on data from California Air Resources Board and U.S. Census.