IEc

Review of Inequality Indicators and Distributional Analysis Methods for Environmental Justice Assessment of an Air Quality Management Plan

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1. INTRODUCTION

As part of the Socioeconomic Analysis of its 2016 Air Quality Management Plan (AQMP), the South Coast Air Quality Management District (SCAQMD) wishes to analyze the distribution of impacts of the proposed AQMP on the South Coast Air Basin (SCAB) population. Specifically, the agency wishes to analyze how a policy may differentially impact areas that have been designed as Environmental Justice (EJ) areas relative to the rest of the SCAB population using a distributional analysis of health risks before and after implementation of the AQMP. Using distributional analysis methods, the SCAQMD can examine differential impacts of its 2016 AQMP to both assess the magnitude of changes in air quality and how those changes are distributed across the affected population geographically. SCAQMD does not have access to individual-level data, so analysis of health inequality can be performed by analyzing the average health risk by spatial geographic units. The agency can also examine how individual policies may influence health risk inequalities by analyzing distributions of risk pre- and post-implementation of the policy.

A literature review of EJ definitions and screening tools was submitted in our previous report, dated April 8, 2016. In this report, we build on IEc's previous EJ analysis and recommendation to describe alternative approaches to distributional analysis that may be applied to achieve the goals described above. We analyze and review health inequality metrics literature, considering both the advantages and limitations of using these methods. We then describe key questions to help guide SCAQMD in choosing appropriate methods for utilizing inequality indicators to perform distributional analysis of health risks in the SCAB region, based on mortality or morbidity risk values separately, as calculated by the U.S. EPA's Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE). Analyzing the distribution of mortality risks focuses on a distributional impacts to adult populations, while analysis of changes in morbidity incidence such as asthma emergency department visits could allow for the evaluation of distributional impacts on the health of children in disadvantaged communities.

2. METHODS

Prior to beginning our review, IEc participated in a number of discussions with SCAQMD staff where we discussed how SCAQMD currently defines EJ areas; how SCAQMD has analyzed differential impacts on EJ areas in comparison with the rest of the population in previous studies, and what goals SCAQMD has established for an analysis of these differences in the upcoming 2016 Socioeconomic Assessment of the AQMP. We conducted a review of the literature describing inequality metrics and distributional analysis guided by the objectives SCAQMD laid out in these discussions. We began by reviewing the documents that SCAQMD specified in its statement of work, including papers by Maguire and Sheriff (2011), Post et al. (2011), Sheriff and Maguire (2013), and Harper et al. (2013). Then, we analyzed health and environmental inequality and distributional analysis literature, searching for both examples of the use of inequality indicators in health benefits analysis as well as guidance or review articles recommending inequality indicators for health benefits analysis, paying particular attention to studies focused on risks from air pollutants. Finally, we analyzed literature specifically noted by our scientific advisors, Dr. Sam Harper of McGill University and Dr. Jon Levy of Boston University. Based on this literature review, we developed a set of potential inequality indicators and criteria to serve as the basis for choosing the most appropriate indicators for SCAQMD's analysis.

3. RESULTS

In this section, we summarize the results of our literature review in three parts. We first focus on the basics of distributional analysis and inequality indicators, and then we summarize guidance that we found in the literature. Next, we present criteria and other considerations for SCAQMD to weigh before choosing inequality metrics for the agency's distributional analysis. Finally, we describe case studies that utilized these indicators and consider critiques of the use of these indicators in the health context.

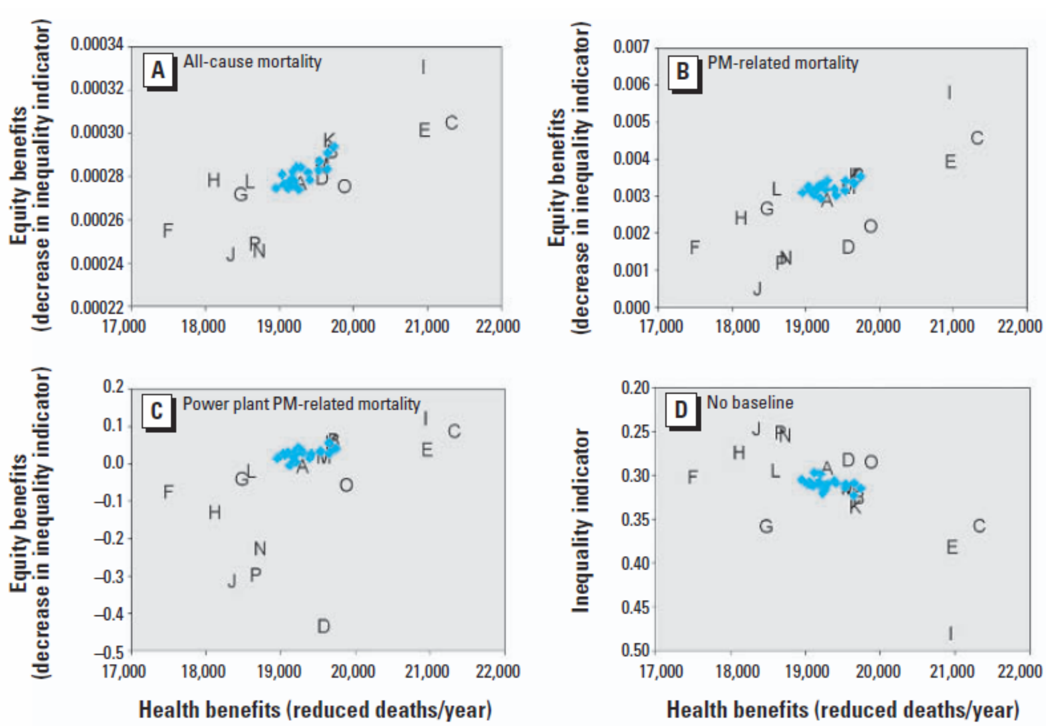
3.1 DISTRIBUTIONAL ANALYSIS

When comparing or analyzing air pollution control strategies, it is important to consider not just the magnitude but also the distribution of health benefits associated with those strategies. Distributional analysis provides a way to compare empirical distributions from different points in time for a broad assessment of health risk in populations generally, and between specific sub-populations such as EJ and non-EJ groups. Distributional analysis provides more information than an analysis comparing only the relationship between summary measures between groups. For example, it is feasible to compare health risks between EJ and non-EJ groups by comparing measures of central tendency or 95th percentiles, but these measures do not provide information about variance within groups or the shape of the distribution. Distributional analysis of health impacts can inform policy makers regarding whether or not there is a difference in health impacts between EJ and non-EJ groups at various points within the risk distribution, and whether or not these groups will benefit from an air pollution control policy differentially in ways that improve or exacerbate inequality.

Our review of the literature indicated that distributional analyses conducted thus far have focused on a single pollutant, $PM_{2.5}$ exposure, and two endpoints, PM mortality risk and asthma-related hospitalizations (Fann et al., 2011; Levy, Greco, Melly, & Mukhi, 2009; Levy, Wilson, & Zwack, 2007; Post, Belova, & Huang, 2011). For SCAQMD's distributional analysis, we recommend expanding the distributional analysis to include at least one measure of morbidity risk as well. Analyzing the distribution of mortality risk will provide information on the most extreme health endpoint. Because most air quality-related mortalities tend to impact populations which are generally older and may have pre-existing conditions, distributional analysis of mortality risk will capture this most extreme health impact on a particularly susceptible population. To capture the health impacts of air quality on different subsections of the population, morbidity risks can be analyzed. For example, including the risk of asthma exacerbation or asthma-related emergency room visits can capture major health impacts that affect a larger proportion of the younger population. Inclusion of these morbidity endpoints in the distributional analysis is contingent, however, on accessing local-level, highly-resolved baseline incidence data of an air pollution-related morbidity endpoint.

Regulatory impact analyses performed by the U.S. EPA , which focus on quantifying health and environmental benefits of policy options, have historically focused on aggregated health benefits rather than the demographic or spatial distribution of such health benefits (Levy et al., 2007). Distributional analysis allows policy makers to formally analyze air pollution control strategies given tradeoff preferences between equality and efficiency characteristics of a given policy's health impacts (Levy et al., 2009). For distributional analysis, an inequality index should be calculated for the baseline scenario and compared with the same inequality index for control scenarios to assess changes in inequality arising from different control strategies (Levy et al., 2007). The quantitative indicators utilized in distributional analysis provide information on inequality, but moving from a state of inequality to a state of equity or justice requires policy makers impose a social calculus of which inequalities are of greatest concern. As stated in Harper et al. (2013), "quantification of inequality in health or exposure to environmental hazards or benefits is necessary, but not sufficient, for determining whether or not a distribution is indeed inequitable." Policy makers must also consider potential tradeoffs between greater equality and greater improved health or welfare of the population as a whole. Exhibit 1, adapted from Levy et al. (2007), depicts tradeoffs between health benefits and equity benefits for power plant control scenarios for 4 different baseline options (all-cause mortality risk, PM-related mortality risk, power plant PM-related mortality risk, and no baseline).

EXHIBIT 1. INEQUALITY INDICATORS (LEVY ET AL., 2007)



3.2 GUIDELINES FOR USE OF INEQUALITY INDICATORS IN HEALTH BENEFITS DISTRIBUTIONAL ANALYSIS

An examination of distributional outcomes of EJ policies requires three separate analytical elements: the baseline distribution of an environmental outcome for one or more groups; the distribution of that environmental outcome under different regulatory options; and a metric to characterize how policy options change the distribution of the outcome within or between groups when compared to the baseline situation (Maguire & Sheriff, 2011). For SCAQMD's distributional analysis, the environmental outcomes being analyzed are mortality and morbidity risks associated with fine particulate matter ($PM_{2.5}$) and ozone exposure. In analyzing these mortality or morbidity risk values, the baseline distributions of mortality or morbidity risk from $PM_{2.5}$ and ozone constitute the baseline to which each air quality control strategy is compared. Mortality and morbidity risk values for both $PM_{2.5}$ and ozone exposure can be produced with BenMAP-CE, using SCAQMD's modeled air quality values for baseline and control scenarios, SCAB baseline health data, concentration-response functions, and local population characteristics.

3.2.1 NECESSARY CRITERIA

A general set of guidelines is common throughout studies attempting to create or utilize inequality indicators for health risk or EJ analysis. An indicator should be able to:

- Convert a distribution to a single index value to provide a concise and easily utilized metric to order a set of outcomes (Maguire & Sheriff, 2011; Sheriff & Maguire, 2013). This is the basic principle behind using a single indicator or index value for distributional analysis.
- Define a reference group for comparison, whether it be comparing to an average member of the population, the best-off person in a population, or to all of those who are better off (Harper et al., 2013).
- Be defined as to whether it uses relative comparisons, and thus is unaffected by proportional changes across a population (scale invariance) (Levy, Chemerynski, & Tuchmann, 2006; Maguire & Sheriff, 2011), or whether it uses absolute comparisons between groups and thus is unaffected by a uniform shift (Maguire & Sheriff, 2011).
- Clearly indicate whether the groups being considered are ordinal (e.g., defined by income) or nominal (e.g., defined by race or ethnicity)(Harper et al., 2013). In this analysis, EJ classification can be considered nominal, as it is made up of an array of factors, or can be considered ordinal, if it is presumed that those in EJ groups experience more risk than those not in EJ groups.
- Fulfill the Pigou-Dalton transfer principle (Levy et al., 2006), which states that any transfer from a better-off person to a worse-off person, should cause the indicator value to decrease, signifying a reduction in inequality. This principle prevents an indicator from displaying a reduction in inequality if the health risk of an already low-risk person decreases even further.

3.2.2 ADDITIONAL CONSIDERATIONS

The following characteristics are desirable of indicators, though not mandatory. Indicators may:

- Make an explicit value judgment that evaluates changes in one part of the distribution differently than changes in another part of the distribution (Harper et al. 2013).
- Be decomposed for evaluation of within-group and between-group inequality (Harper et al., 2013; Levy et al., 2006; Maguire & Sheriff, 2011).Subgroup decomposability allows for analysis of within-group and between-group inequality, and consideration of how they relate to one another within the construct of a particular indicator. Analyzing between-group and within-group variation provides insight on whether overall inequality within the SCAB region is driven by EJ characteristics versus other factors. For example, where between-group inequality is greater than within-group inequality, the EJ versus non-EJ division between the groups does a sufficient job of explaining this variability. Where within-group inequality is greater than between-group inequality, the EJ versus non-EJ division between the groups does not do a sufficient job of explaining this variability, as there is a greater difference in inequality within these groups than between them.

Based on these tenets and our review of relevant literature, we focus our analysis on the indicators in Exhibit 2, below.

3.3 INEQUALITY INDICATORS

The inequality indicators considered in this report have been used by economists traditionally to analyze the distribution of income or wealth (Atkinson, 1970; de la Vega & Urrutia, 2003; The World Bank, 2016). Previous studies have attempted to identify and quantify inequality and inequities in health benefits and regulatory impacts analyses using a suite of economic inequality indicators, including the Atkinson index (Post et al., 2011), Gini coefficient (Bouvier, 2014), Theil's entropy index, mean log deviation (Levy et al., 2009, 2007), and the Kolm-Pollak index (Maguire & Sheriff, 2011; Sheriff & Maguire, 2013). These indicators are summarized in Exhibit 2, adapted from Harper et al. (2013) and Levy et al. (2006). Other indicators, including concentration index, squared coefficient of variation, and variance of logarithms, which have been used in more limited contexts and not demonstrated for use in a health risk case study, are not included in this review. We also excluded Lorenz curves because they are not an index or indicator value, but rather a visualization tool for comparing outcome distributions (Sheriff & Maguire, 2013).

EXHIBIT 2. INEQUALITY INDICATORS

INEQUALITY INDICATOR	REFERENCE GROUP	ABSOLUTE OR RELATIVE INEQUALITY?	ADJUSTABLE INEQUALITY AVERSION PARAMETER?	SUBGROUP DECOMPOSABLE?	ACCOMMODATES ORDERED SOCIAL GROUPS?
Atkinson Index	Average	Relative	Yes	Yes	Yes
Gini coefficient	Average/ those better off	Relative or Absolute	No	No	No
Theil index	Average	Relative	No (ε = 1)	Yes	No
Mean log deviation	Average	Relative	No (ε = 0)	Yes	No
Kolm-Pollak index	Average	Absolute	Yes	Yes	Yes

The parameters used to define these indicators in Exhibit 2 are important for SCAQMD to consider in the context of their goals for policy analysis. In the next section, we describe different options for each parameter, and illustrate with examples how one option may impact the outcome as compared with another option. We review applications of these inequality indicators more thoroughly in section 3.5.

3.4 IMPLICATIONS OF PARAMETER CHOICES FOR POLICY ANALYSIS

The measures of inequality most appropriate for SCAQMD's analysis must reflect the aspects of health inequality that SCAQMD believes are most important to capture in its distributional analysis. There is no single "right" indicator that should be used in all cases, as these inequality indicators have attributes that are specific to the values indicated by policy makers. Deciding what aspects of health inequality are important to ensure as part of distributional analysis will affect conclusions regarding the trends and magnitude of health inequalities (Harper & Lynch, 2016). The parameter choices presented in this section are not presented in a specific order of importance, though all should be considered by SCAQMD in context of its analysis and policy goals, as each choice has implications about how to interpret the results of an analysis and may constrain the metrics available to characterize inequality.

SCAQMD should consider whether it is interested in understanding effects on total inequality which measures variation in health risk across the entire SCAB population, effects on inequality between different social groups within the SCAB population, or effects on both. It is our understanding that SCAQMD wishes to analyze inequality between different social groups, defined as EJ communities and non-EJ communities. This decision provides a framework for SCAQMD to review the options below for the attributes of alternative inequality index parameters in performing distributional analysis.

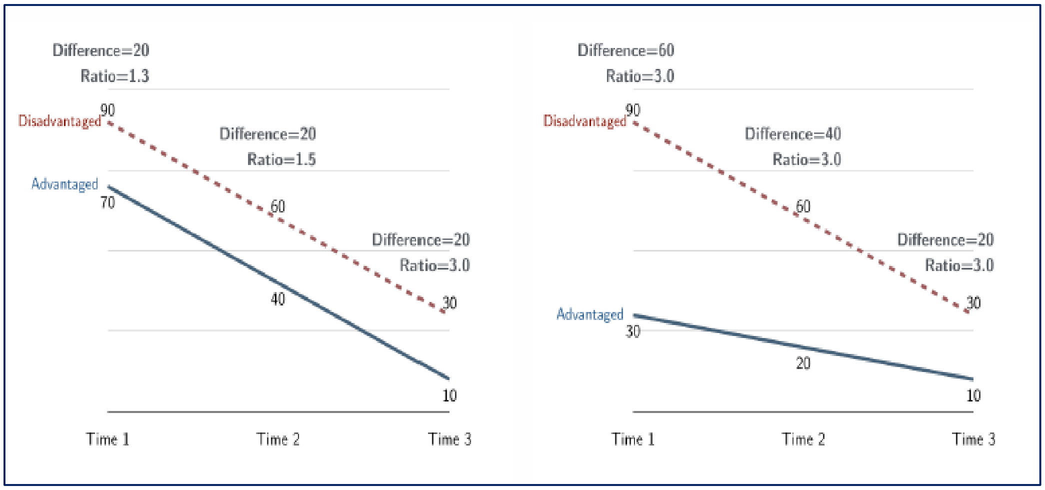
3.4.1 REFERENCE GROUP

To measure inequality, a group of interest must be compared with a reference group. It is important to clearly define the rationale for choosing a reference group, as inequality conclusions may differ depending on the reference group chosen. For example, should the health risk of those in EJ communities be compared to the average health risk in the population, or to those with the least health risk, or to those in EJ communities in a different region of the country? Many different groups can be compared – EJ communities in SCAB region with EJ communities in the Bay Area; EJ communities in the SCAB region to non-EJ communities in the SCAB region; EJ communities in the SCAB region to the national average, or to the average of California, or the average of the SCAB region. There are many possible reference group choices (Harper & Lynch, 2016). Choosing the population average health risk as a reference group provides a comparison between an EJ group and the population average, an intuitive comparison, but the population average changes over time. Choosing the healthiest group or all those better off as the reference group provides information regarding the inequality between a group and maximum health potential. Another potential reference group is a target or goal health risk, which does not change over time as the other reference groups do. Choosing a target or goal health risk value provides a stable value as a goal, but without extensive research, this health risk value may be out of the realm of possibility for a group.

3.4.2 ABSOLUTE OR RELATIVE MEASURE OF INEQUALITY

Inequality is a concept that depends on relationships between groups. An absolute comparison looks at the difference between two values, while a relative comparison looks at the ratio between two values. Absolute comparisons are translation invariant, that is, there is no absolute change if health risk values increase by a constant across a population or groups. Relative comparisons are scale invariant, as there is no relative change if health risk values double for an entire population or group. For example, in the left panel of Exhibit 3, the outcomes decrease at the same absolute rate for both groups, but because the same absolute change will be proportionally larger for a group with lower baseline levels, relative inequality will increase while absolute inequality stays the same. In the right panel of Exhibit 3, the same relative decline with different starting points will lead to decreasing absolute inequality but constant relative inequality. If we consider health risk values for two different groups, we may arrive at different conclusions about inequality depending on whether it is measured relatively or absolutely. Both of these measures are valid, but policy makers must determine which type of measure is most appropriate for their analyses.

EXHIBIT 3. DIVERGING SCENARIOS FOR ABSOLUTE AND RELATIVE INEQUALITY TRENDS (HARPER & LYNCH, 2016)



3.4.3 INEQUALITY AVERSION PARAMETER

Inclusion of an explicit inequality aversion parameter as is found in the Atkinson index and the Kolm-Pollak index allows the policy maker to use their own value judgments to determine the social acceptance of inequality in a given population. In these indices, higher values of the inequality aversion parameter indicate a society's stronger preference for equality, or aversion toward inequality. Use of an inequality aversion parameter allows policy makers to place additional weight on transfers at the bottom of the distribution when measuring inequality as a good (health) rather than a bad (health risk). However, changes in these inequality aversion parameters can be difficult to interpret, other than a broad increase or decrease in inequality aversion. Thus, inequality aversion parameters are best used in a sensitivity analysis context, unless there is a specific application in a particular policy analysis. The inequality aversion parameter (ε) ranges from 0 to infinity, and as ε increases, society exhibits greater preference for equality. In practice, for example, Fann et al. used the Atkinson index with specific inequality aversion parameters to test the robustness of their policy analysis results to the choice of ε of 0.75 and 3. They found that their multi-pollutant risk-based policy performed better at increasing equality with regard to $PM_{2.5}$-related mortality risk at both ε values than the status quo.

3.4.4 SUBGROUP DECOMPOSABLE

An inequality indicator that is subgroup decomposable allows the policy maker to assess between-group and within-group inequality, or the sources of total inequality differences across two groups. In SCAQMD's analysis, subgroups are determined by geographic unit. A geographical unit is dichotomously described as an EJ community or a non-EJ community. Subgroup decomposability is desirable, as it provides information beyond total inequality. For example, in some instances, between-group inequality may be greater than within-group inequality, providing information about the differences between the two groups and indicating similarity in risk within groups. In other instances, within-group inequality may be greater than between-group inequality, which provides the policy maker with information regarding the definition of the groups themselves, as members are not as similar in risk as was expected. A subgroup decomposable measure can incorporate risk assessment concerns like biological susceptibility with the distribution of impacts across EJ subgroups (Levy et al., 2006). However, this characteristic is not necessary in distributional analyses, as other measures provide information on total inequality across a population.

3.4.5 ORDERED SOCIAL GROUPS

Policy makers should decide whether or not it is important that an indicator allows for inclusion of groups with inherent ordering, like income or education, or no inherent ordering, like race, ethnicity, or gender. Ordinal measures allow quantification of a resulting health gradient, while nominal measures can be analyzed dichotomously only. Some inequality measures quantify health gradients and whether health risks decrease or increase with social group ordering (e.g., health gradients with income), making them inappropriate for groups without inherent order. In an instance where judgments are made about nominal groups (like EJ and non-EJ groups) for use with an ordinal-type measure of inequality, the policy maker is including an important assumption that the ranking of groups by EJ status is associated with disadvantage. Using ordinal groups in conjunction with some indicators allows quantification of health gradients that follow increasing or decreasing health status by increasing group order. For example, using an indicator designed for ordinal comparisons for an analysis of neighborhoods ordered by proportion of renter population assumes that increasing proportions of renters as opposed to owners population is directly associated with increasing disadvantage in health status. However, there may be more well-off areas with large renter populations that do not adhere to this assumption. This assumption can be appropriate in cases where individual-level data are available for those within these neighborhoods to account for outlier situations, but may be inappropriate in contexts where only group data are available (Harper et al., 2013).

3.5 USE OF INEQUALITY INDICATORS IN HEALTH BENEFITS DISTRIBUTIONAL ANALYSIS

Inequality indicators have been used in a number of studies analyzing health risk (Levy et al., 2006, 2009, 2007) and EJ (Levy et al., 2006; Post et al., 2011). Additionally, a number of authors have both assessed and proposed methods regarding how these inequality measures are best utilized in health risk or EJ analyses (Harper et al., 2013; Maguire & Sheriff, 2011; Sheriff & Maguire, 2013). Below, we briefly describe each of these indices and how they have been used in relevant literature to inform how they may be used for SCAQMD.

3.5.1 ATKINSON INDEX

The Atkinson Index was constructed to assess income inequality and is derived from a social welfare function (Atkinson, 1970). The Atkinson index ranges from 0, representing perfect equality, to 1, representing maximum inequality. The Atkinson index value is based on the true outcome rather than a ranking of outcomes, and as such it is not dependent upon a third party variable or value outside of the distribution. While it is not additively decomposable, the Atkinson index is subgroup decomposable and can be broken down into between-group and within-group components (Harper et al., 2013). The

Atkinson index can accommodate both ordered and non-ordered groups. The Atkinson index has been criticized as a health inequality indicator due to its inability to directly analyze a “bad” outcome (Maguire & Sheriff, 2011), or greater health risk, but it can be transformed to a “good” by analyzing the inverse of risk where theoretically appropriate (Harper et al., 2013). The Atkinson index is a generalized entropy indicator which utilizes an explicit parameter, ε, to allow greater sensitivity to the low end of a distribution (higher risk) over the high end in the distribution (low risk) with increasing ε (Levy et al., 2006). With inclusion of this inequality aversion parameter, the user can indicate societal concern for inequality, with higher values indicating a greater aversion to inequality.

In an analysis of the health impacts of public bus retrofits to decrease emissions in Boston, Levy et al. (2009) model the changes in emissions to determine age-adjusted mortality rates. Using the Atkinson index as their primary measure of inequality (both directly for mortality risk and for the inverse of mortality risk) between baseline and control scenarios, they find that higher mortality rates are found in lower socioeconomic status census tracts, and also that more efficient control strategies tended to do better from an inequality perspective, as well. The Gini coefficient is used to test the sensitivity of the results, as the Gini coefficient is a commonly used income inequality measure (discussed below). The results of Levy et al. (2009) are corroborated by another study using the Atkinson index to quantify inequality between national power plant emissions reductions strategies, where health benefits are maximized in concordance with spatial inequality reduction. These conclusions were robust, as the optimal policy choice did not vary with the choice of ε utilized in the Atkinson index (Levy et al., 2007). Similarly, Fann et al. (2011) utilized the Atkinson index to analyze differences in the results of different $PM_{2.5}$ reduction policies, finding that a multi-pollutant risk-based approach yielded the greatest health benefits and reduced inequality between vulnerable areas and elsewhere. Post et al. (2011) analyzed the health risks of the EPAs Heavy Duty Diesel rule for air quality for individuals living in EJ areas compared to other communities using the Atkinson index. Taking advantage of the decomposable nature of the Atkinson index, Post et al. (2011) found that inequality within racial and ethnic groups was greater than the inequality between the groups. While some of these studies looked at the distribution of risk (Levy et al., 2009, 2007) rather than EJ groups specifically (Fann et al., 2011; Post et al., 2011), all were able to analyze inequality of non-monetary (or non-income) distributions. Generally, when policy measures aim to reduce risk among EJ populations and the focus is on people who have higher environmental exposures and vulnerability attributes greater total health benefits arise in the population as a whole.

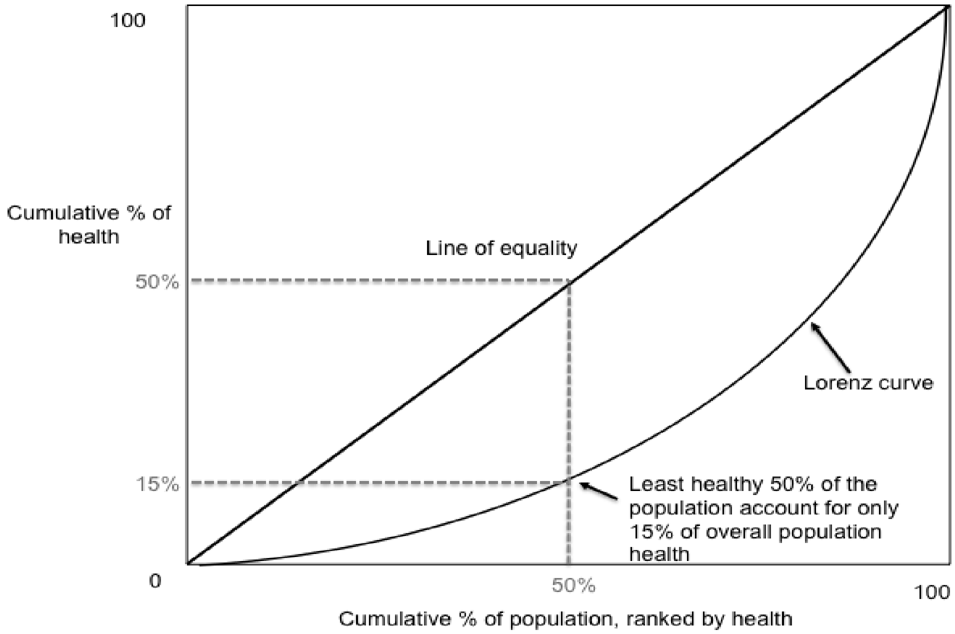
3.5.2 GINI COEFFICIENT

The Gini coefficient is a commonly used income inequality indicator, where 0 implies complete equality and 1 implies complete inequality. This index produces a value that is relative to all those better off, satisfies the Pigou-Dalton transfer principle, and does not utilize an explicit judgment parameter (Levy et al., 2006). The Gini coefficient can be derived from the Lorenz curve, which has percentiles of the population ranked by pollution exposure on the x-axis and percent of pollution exposed by percentile on the y-axis and where a 1-to-1 line indicates an equal distribution of exposure (Maguire & Sheriff, 2011). The Gini coefficient is equal to twice the area between the equality line and the Lorenz curve (Levy et al., 2006). This is depicted in Exhibit 4, below. The Gini coefficient is not subgroup decomposable in the context of health risk or EJ, as it can only be decomposed when values are ordered, and implicitly gives the most weight to the center of the distribution. While this coefficient is commonly used, transfer among the distribution is based on the ranks within the distribution rather than the difference in the outcome. Due to the use of rank differences, the Gini coefficient is impacted by third parties. For example, if there is a transfer in the distribution between two individuals, and there is a third unrelated individual between them, the transfer will have a greater impact than if there is no third individual between the two because there is a greater rank difference between the two individuals (Maguire & Sheriff, 2011).

Some have argued that the Gini coefficient can provide spurious results when comparing policy rankings, because the Gini coefficient was created to address economic inequality in amounts of a for "good," like income, not a "bad," as represented by health risk (Maguire & Sheriff, 2011). They contend that this prevents interpretation of the Gini coefficient as a relative inequality measure (Maguire & Sheriff, 2011). Their argument presupposes that an individual would be willing to trade off the level of one's health risk for greater or pure equality across health risks in the population in the same manner that economics dictates one would trade off income for greater economic equality. It also supposes that health risk could not be expressed in a manner that might make it better conform to the Gini coefficient paradigm, such as using the inverse of health risk. Other authors, such as Fann et al., (2011), Levy et al. (2007), and Levy et al. (2009), have used the Gini coefficient in addition to other metrics in their distributional analysis and found that the results were generally consistent.

The Gini coefficient is used in an analysis of toxic air emissions and income in Maine, applying the index spatially to analyze the distribution of pollution, creating an environmental Gini coefficient. Bouvier (2014) also creates an emissions-adjusted income value, deriving an index based on income and pollution. She finds that the spatial distribution of pollution is more unequal than the distribution of income, and that a fraction of the population would experience a decrease in their income when adjusting for pollution (Bouvier, 2014). This paper presents a method much different than other related studies, and should be considered based on its novelty and incorporation of important factors in an EJ analysis – pollution and income distributions. In other studies, the Gini coefficient has been used as a sensitivity analysis when using the Atkinson index (Levy et al., 2009, 2007).

EXHIBIT 4. GRAPHICAL EXAMPLE OF A LORENZ CURVE IN THE CONTEXT OF HEALTH INEQUALITY (HARPER & LYNCH, 2016)



3.5.3 THEIL'S INDEX AND MEAN LOG DEVIATION

Both Theil's index, also known as Theil's entropy index, and the mean log deviation are measures of entropy that can be used to measure inequality within and between groups. These measures allow for differential sensitivity of indices to different parts of the health distribution in the form of a constant which determines the relative sensitivity of the index. A constant value less than 1 is more sensitive to the lower end of the distribution and a value greater than 1 is more sensitive to the higher end of the distribution. The mean log deviation constant is equal to 0 and the Theil's index constant is equal to 1 (Levy et al., 2006). There are no explicit inequality aversion parameters included in either of these indices. Theil's index requires a comparison with the average and is a relative rather than absolute measure of inequality (Harper et al., 2013). Both measures are additively subgroup decomposable and fulfill the Pigou-Dalton transfer principle. Both Thiel's index and the mean log deviation measures have been used together as sensitivity analyses after utilization of the Atkinson index to determine the robustness of the results (Levy et al., 2009, 2007).

Theil's index or mean log deviation haven't been used in health risk or EJ analyses as the main inequality index to our knowledge, though they can provide important inequality information when used in tandem. Both Theil's index and mean log deviation have been used as part of sensitivity analyses in a study analyzing a tailpipe emissions control strategy (Levy et al., 2007) and in analyzing hypothetical policy control scenarios for power plants (Levy et al., 2009). In Levy et al. (2007), using the Atkinson index, Gini coefficient, mean log deviation, and Theil's index, they find that for each indicator, using policies which control risks for high-risk individuals decreased the inequality indicators, or decreased the inequality in risk. For the middle of the risk distribution, inequality increased according to the Theil index, Gini coefficient, mean log deviation, and Atkinson index at ε =0.5, though ε values greater than 0.5 indicated decreasing inequality in the distribution (Levy et al., 2007).

3.5.4 KOLM-POLLAK INDEX

The Kolm-Pollak index is a measure of absolute inequality that allows for different levels of inequality aversion (Harper & Lynch, 2016), and has similar properties to the Atkinson index. Although the Kolm-Pollak index has not been used in practice to analyze health inequalities, both Maguire and Sheriff (2011) and Sheriff and Maguire (2013) suggest consideration of this index. Both the Kolm-Pollak and Atkinson indices satisfy the Pigou-Dalton transfer principle, can accommodate ordered and non-ordered groups, are not dependent upon a third party variable or value outside of the distribution being analyzed, and both indices allow for transfer of risk from high to low-risk individuals to have a greater impact on the index value than transfer of risk from low to high-risk individuals (Sheriff & Maguire, 2013). Both are in reference to the average member of the population and are subgroup decomposable. Similar to the Atkinson index, the Kolm-Pollak index does not readily accept “bad” values to be used directly, but can be manipulated to measure the distribution of its complementary “good”. The Kolm-Pollak index provides an absolute rather than a relative measure of inequality, such that adding a value to the entire distribution does not change the index value (Maguire & Sheriff, 2011), which would change with a relative measure of inequality.

3.6 CRITERIA FOR RECOMMENDATION

To determine which inequality indicator is the best choice for distributional analysis in SCAB, we first outline criteria that should be considered.

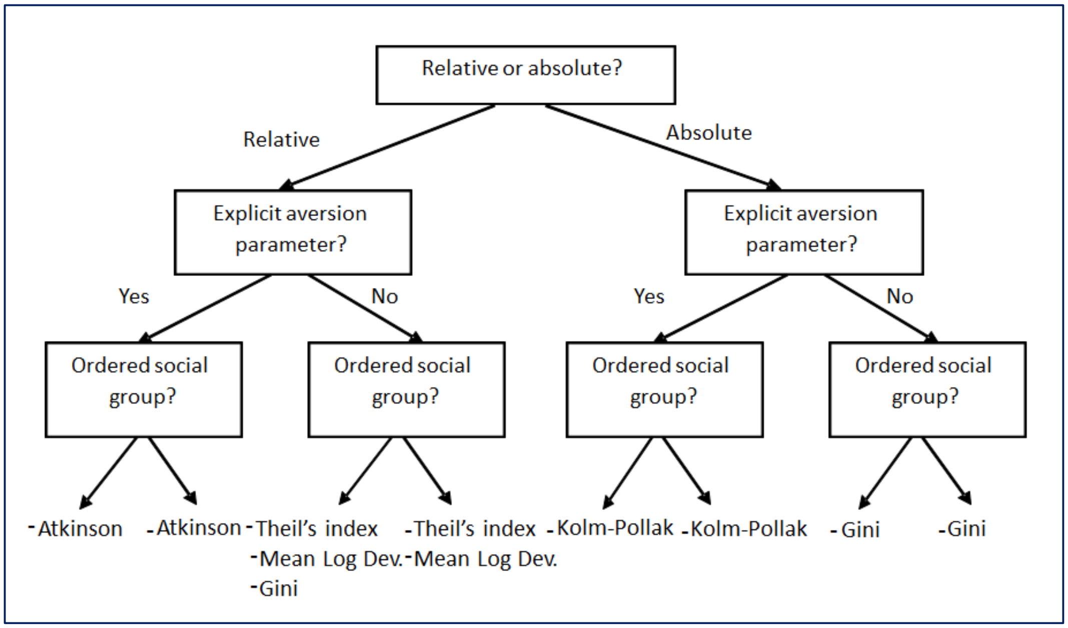
- What is the appropriate reference group or value for analysis of inequality in the SCAB region?

All indices discussed in this report have the ability to compare against the population average, or all those better-off in the case of the Gini coefficient. Indicators can generally be adapted to a chosen reference group or value.

- Should an indicator compare relative inequalities between group or absolute inequalities between groups?
- Should an indicator include an explicit inequality aversion parameter to allow SCAQMD to determine the sensitivity of the indicator to different parts of the distribution?
- Should EJ and non-EJ groups be considered as ordinal or nominal?

These three questions are portrayed in the flow chart in Exhibit 5, below.

EXHIBIT 5. INEQUALITY MEASURE SELECTION FLOW CHART



Levy et al. (2006) sought to develop recommended methods to quantify inequality within a health benefit context, performing a systematic analysis of EJ and equity measures, ultimately providing axioms for inequality indicators for health benefits analysis. Based on a set of 9 predefined axioms, Levy et al. (2006) recommends use of the Atkinson index generally to best address inequality assessment as part of health benefits analyses. Fann et al. (2011) analyzed two air quality management approaches in Detroit and their impacts on the distribution of health benefits across vulnerable and susceptible subpopulations. They applied the Atkinson index to quantify health risk inequality at baseline and for both air quality management approaches. Using the Atkinson index, they found their multipollutant risk-based approach yielded less inequality across the population than the traditional air quality management approach (Fann et al., 2011). Post et al. (2011) performed a distributional benefits analysis of U.S. EPA's Heavy Duty Diesel Rule in 2030, using modeled air quality data for 2030 as the control scenario, and analyzing the distribution among EJ subgroups. This goal is similar to that of SCAQMD, with the exception of analyzing $PM_{2.5}$ exposures rather than mortality or morbidity risk in the affected population. In this study, they used the Atkinson index to determine if there are differences in air quality due to this rule and understand the inequality between and within EJ subgroups.

Maguire and Sheriff (2011) argue against use of the Atkinson index to analyze "bad" outcomes. They argue that, similar to the problem with the Gini coefficient discussed above, input of a "bad" into the Atkinson index violates economic principles. Replacing a "bad" with its complement (e.g., parts per billion "clean" air rather than parts per billion $PM_{2.5}$) may create a very small Atkinson index value. When there is a very small change in health risk, the Atkinson index may be difficult to interpret, as a small percent change in health risk may be related to a significant valuation. They indicate that alternatively, multiplying the Kolm-Pollak index by negative one accommodates "bad" outcomes like health risk, preserving the social evaluation function ranking, similar to measuring the complementary "good" (Maguire & Sheriff, 2011). Other researchers have used the Atkinson index by applying a transformation to the health measure (e.g., using the inverse of health risk) to characterize health as a "good," ensuring the increased weight placed on the bottom of the distribution by the inequality aversion parameter is weighting the appropriate end of the distribution. Alternatively, a small range of inequality aversion parameters can be used to provide sensitivity analysis of using the Atkinson measure with health or inverse of health risk as a "good" to avoid extreme interpretations (Harper et al., 2013). Alternative policies can be analyzed based on the relationship between efficiency of reducing health risk and equity, as shown in Exhibit 1, above.

3.7 RECOMMENDATIONS

Based on conversation with SCAQMD employees to understand the values of SCAB stakeholders, IEc recommends use of both the Atkinson and Kolm-Pollak indices in understanding health risk inequality in the region. These indices were chosen based on the following factors:

- The comparison group should be the average of the health risks of the SCAB population.
- Both absolute and relative inequality should be considered. Absolute inequality can be assessed through use of the Kolm-Pollak index; relative inequality can be assessed through use of the Atkinson index.
- The index should include an adjustable inequality aversion parameter.
- The index should be subgroup decomposable.
- The index does not need to accommodate ordered social groups, as EJ is not an inherently ordered measure based on its many parameters.

Comparing the distribution of health risks with the average health risk of the SCAB population provides the most intuitive option. This allows for a dynamic comparison between the distribution of health risks across geographical population units and the average health risk of the SCAB population. Both the distribution of health risks and the average health risk will change over time such that both measures will be on the same scale. Additionally, this comparison creates what is likely to be an achievable health standard in groups whose health risks are below the average, rather than choosing a perhaps unattainable target value measure or a comparison with the most well-off population.

SCAQMD staff found merit in both an absolute measure of inequality and a relative measure of inequality. Both absolute and relative measures of inequality provide useful information to policy makers and stakeholders. An absolute measure of inequality (e.g., Kolm-Pollak index) allows for an assessment of the difference between the health risk distribution of EJ and non-EJ groups, while a relative measure of inequality (e.g., Atkinson index) allows for an assessment of the ratio between the health risk distribution of EJ and non-EJ groups.

An adjustable inequality aversion parameter is a desired quality of the chosen inequality indices, though it is not necessary. This inequality aversion parameter allows for additional sensitivity analyses to determine the robustness of conclusions across a range of societal aversion to inequality, where similar index values with changes in inequality aversion parameters indicate a result that holds regardless of the level of societal concern over inequality. Both the Atkinson and Kolm-Pollak indices include inequality aversion parameters for which values can be chosen by the user.

An indicator that is subgroup decomposable provides more information than an index that cannot be decomposed. Subgroup decomposable measures like the Atkinson and Kolm-Pollak indices provide information on within-group and between-group inequality, as well as total inequality. Not only do these measures allow for assessment of the total inequality of the population, they also allow for analysis of how EJ and non-EJ groups differ from one another in terms of health risk, as well as how the individual geographic areas within these groups differ from one another.

The indicator does not need to accommodate ordered social groups, as EJ communities are defined by a number of indicators that have been brought together based on a rank score. If these communities had been defined based on one factor alone, ordered social groups could be analyzed as a health risk gradient between the groups.

Using both the Atkinson index and the Kolm-Pollak index provides a comprehensive set of inequality measures for distributional analysis in the SCAB. Both of these measures accommodate comparison to the average population health risk, are subgroup decomposable, and include adjustable inequality aversion parameters. A key difference between these indices – the Atkinson index is a relative measure of inequality while the Kolm-Pollak index is an absolute measure of inequality -- allows these indices to account for different aspects of the distributional analysis that could not be captured by considering only relative or only absolute comparisons of health risk between EJ and non-EJ groups. By applying both of these indices, it will be possible to perform a sensitivity analysis to understand if conclusions are robust to both absolute and relative inequality considerations. Similarly, the adjustable inequality aversion parameters incorporated in both the Atkinson and Kolm-Pollak indices will allow for sensitivity analyses over a range of values for ε.

To best explain the outcome of these analyses and their resulting inequality index values to stakeholders, a comparison can be drawn between Atkinson index or Kolm-Pollak index values and stock market index values, like the NASDAQ composite or Dow Jones Industrial Average. The values associated with these financial indices do not necessarily provide information based on their magnitude alone, but in relation to the index value over time, allowing the user to judge the strength and stability of the stock market. Similarly, these inequality indices don't provide specific information on distributional risks based on their magnitude alone, but rather provide information on distributional risks through comparisons of index values between different policies. For example, looking at the total inequality, between-group inequality, and within-group inequality using either the Atkinson or Kolm-Pollak index, the user can determine how much of the total inequality is based on between-group inequality and how much of the total inequality is based on within-group inequality. For their multipollutant risk-based policy, Fann et al. (2011) found that for an Atkinson index value of 0.437, the between-group inequality was .002 and within-group inequality was 0.435, indicating that within-group inequality accounted for significantly more of the inequality in the population. The Atkinson and Kolm-Pollak indices are comprised of values between 0 and 1, where 0 or low values indicate a more equal distribution than higher values.

These recommendations are based on the state of the science in distributional analysis of health risk using inequality metrics, consideration of how EJ areas are currently defined in the SCAB, and our understanding of SCAQMD's goals for EJ analysis in the context of the socioeconomic analysis of its 2016 AQMP based on discussions with agency staff. While we feel that applying the two recommended indices would be robust approach to conducting the EJ analysis for the 2016 AQMP, if desired by SCAQMD, it would be possible and appropriate to expand the EJ analysis and consider all five inequality measures examined in this report.

4. REFERENCES

Atkinson, A. B. (1970). More on the measurement of inequality. *Journal of Economic Inequality*. http://doi.org/10.1007/s10888-007-9075-7

Bouvier, R. (2014). Distribution of income and toxic emissions in Maine, United States: Inequality in two dimensions. *Ecological Economics*, *102*, 39–47. http://doi.org/10.1016/j.ecolecon.2014.03.005

de la Vega, M. C. L., & Urrutia, A. M. (2003). A new factorial decomposition for the atkinson measure. *Economics Bulletin*, *4*(1). http://doi.org/http://www.economicsbulletin.com/

Fann, N., Roman, H. a., Fulcher, C. M., Gentile, M. a., Hubbell, B. J., Wesson, K., & Levy, J. I. (2011). Maximizing Health Benefits and Minimizing Inequality: Incorporating Local-Scale Data in the Design and Evaluation of Air Quality Policies. *Risk Analysis*, *31*(6), 908–922. http://doi.org/10.1111/j.1539-6924.2011.01629.x

Harper, S., & Lynch, J. (2016). *Health Inequalities: Measurement and Decomposition*.

Harper, S., Ruder, E., Roman, H., Geggel, A., Nweke, O., Payne-Sturges, D., & Levy, J. I. (2013). Using inequality measures to incorporate environmental justice into regulatory analyses. *International Journal of Environmental Research and Public Health*, *10*, 4039–4059. http://doi.org/10.3390/ijerph10094039

Levy, J. I., Chemerynski, S. M., & Tuchmann, J. L. (2006). Incorporating concepts of inequality and inequity into health benefits analysis. *International Journal for Equity in Health*, *5*, 2. http://doi.org/10.1186/1475-9276-5-2

Levy, J. I., Greco, S. L., Melly, S. J., & Mukhi, N. (2009). Evaluating Efficiency-Equality Tradeoffs for Mobile Source Control Strategies in an Urban Area. *Risk Analysis*, *29*(1), 34–47. http://doi.org/10.1111/j.1539-6924.2008.01119.x

Levy, J. I., Wilson, A. M., & Zwack, L. M. (2007). Quantifying the efficiency and equity implications of power plant air pollution control strategies in the United States. *Environmental Health Perspectives*, *115*(5), 743–750. http://doi.org/10.1289/ehp.9712

Maguire, K., & Sheriff, G. (2011). Comparing distributions of environmental outcomes for regulatory environmental justice analysis. *International Journal of Environmental Research and Public Health*, *8*(5), 1707–26. http://doi.org/10.3390/ijerph8051707

Post, E. S., Belova, A., & Huang, J. (2011). Distributional benefit analysis of a national air quality rule. *International Journal of Environmental Research and Public Health*, *8*(6), 1872–92. http://doi.org/10.3390/ijerph8061872

Sheriff, G., & Maguire, K. (2013). *Ranking Distributions of Environmental Outcomes Across Population Groups*.

The World Bank. (2016). GINI index (World Bank estimate) | Data | Table. Retrieved February 26, 2016, from http://data.worldbank.org/indicator/SI.POV.GINI