Measures of Health Disparity

This section reviews most of the statistics that are available to measure health disparities. The goal is to provide a brief overview of each measure, followed by the method of calculation and statistical interpretation and, often, an example of its actual or potential use for measuring disparities in cancer-related health objectives.

Note that there are methods to calculate indicators of precision (e.g., 95% confidence interval) for all of the measures reviewed here. These can be found in the source publications detailed in the references. Although issues of variability and precision are important, they are not germane to the choice of disparity measure because they ultimately derive from the precision of the underlying rates, prevalence, and proportions that are used to generate a particular disparity measure.

Measures of Total Disparity

A measure of "total disparity" in health is a summary index of health differences across a population of individuals. Generally, measures of total disparity do not account for social grouping and have been used chiefly by health economists (see, for example, 25,49). They are an important first step in understanding the scope of health variation in a population and have advantageous properties for monitoring trends, particularly for cross-country comparisons. They do not, however, inform about systematic variation in health among population subgroups, which is inherent in the *Healthy People 2010* health disparity initiatives. The measurement of health disparity as total disparity is associated most closely with and endorsed by the WHO as a component of its general framework for routinely assessing the performance of health systems in different countries. The WHO, however, is not the only advocate of measuring total disparity. Some health economists also advocate for the measurement of total health disparity (25,63,64) as the primary form of assessing health inequalities.

A number of criticisms have been levied at this kind of measure, primarily because it does not distinguish among individuals from different social groups (51,53,54,65). In addition, empirical investigations using measures of total disparity appear difficult to interpret (54,66,67). Those who endorse this measure often cite as their primary justification the weighty normative choices that must be made to measure health differences between social groups and note that the absence of such a priori choices makes disparity between individuals a more "objective" measure of health disparity. We recognize that *Healthy People 2010* specifically calls for social-group monitoring and not total variation, but we include measures of total group disparity because they are prominent in the overall framework of efforts to monitor global health disparity and because they provide an essential context for understanding the "decomposition" of health disparity measures, as described below.

Individual-Mean Differences

Individual-mean difference (*IMD*) measures of health disparity calculate the difference between the health of every individual in the population and the population average. The general formula for the class of individual/mean difference measures is given by Gakidou and colleagues (49) as:

$$IMD(\alpha,\beta) = \frac{\sum_{i=1}^{n} |y_i - \mu|^{c}}{n\mu^{\beta}} \qquad [1]$$

where an individual i's health is y_i, μ is the mean health of the population, and n is the number of individuals in the population. The parameters α and β specify, respectively, the significance attached to health differences at the ends of the distribution relative to the mean and whether the individual-mean difference is absolute or relative to the mean health of the population. For instance, large values of α emphasize greater deviations from the mean, and larger values of β emphasize relative disparity because of heavier weighting of the mean. Those familiar with basic statistics will note that, when $\alpha = 2$ and $\beta = 0$, the *IMD* simply is the variance; and when $\alpha = 2$ and $\beta = 1$, the *IMD* is the coefficient of variation (49). Similar to many other disparity measures, the *IMD* is a "dimensionless" index that is not measured in units because it always is relative to the mean in the population.

Inter-Individual Differences (IID)

The *IID* measures health differences between all individuals in the population and is consistent with the Gini coefficient but may be weighted in accordance with differential aversion to disparity (i.e., the value chosen for α). These measures are different from the *IMD* class because they compare every individual in the population with every other individual in the population, whereas the *IMD* measures disparity relative to the population average. It should be clear that different measures of disparity implicitly express different perspectives on which aspects of disparity should be emphasized in the measure. The class of inter-individual difference measures is (49):

$$IID(\alpha,\beta) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} |y_i - y_j|^{c}}{2n^2\mu^{\beta}} \qquad [2]$$

where y_i is individual i's health, y_j is individual j's health, μ is the mean health of the population, and n is the number of individuals in the population. The parameters α and β are defined as for the *IMD* above, and it is worth noting that, when $\alpha = 2$ and $\beta = 1$, the *IID* is equal to the more well-known Gini coefficient. Gakidou and King have used this disparity measure (with $\alpha = 3$ and $\beta = 1$) to compare total disparity in child survival among 50 countries (68). Weighting $\alpha = 3$ implies that the measure should be more sensitive to larger than smaller pairwise deviations between individuals and thus reflects additional concern about larger health differences between individuals. To our knowledge, there is only one study of total disparity that uses data from the United States (69).

Measures of Social-Group Disparity

The measures of total variation described above have a number of merits, including their ability to make unambiguous health disparity comparisons between populations and over time. In defining health disparity as disparity between individuals instead of between social groups, such measures avoid the difficulty of comparability of groups between populations or over time (50). This makes them particularly attractive for cross-country comparisons, in which defining comparable social groups is challenging because of differences in how social groups are classified in different countries (70).

The disparity goals of *Healthy People 2010,* however, explicitly are goals that relate to social-group differences in health. It is an open question as to whether measures of total disparity and social-group disparity are "better" or "worse" disparity measures, but the concern among health policy makers in the United States specifically is expressed in terms of social-group differences in health. Measures of total disparity therefore are insufficient for monitoring progress toward eliminating cancer-related health differences among social groups in the United States.

Pairwise Comparisons

Simple comparisons of some health indicator between two groups in a population (so-called pairwise comparisons) clearly are one of the most straightforward ways to measure progress toward eliminating disparities between groups. For example, age-adjusted incidence rates of lung cancer for black and white females in 1973 were, respectively, 23.6 and 20.4 per 100,000. By 1999, rates for both groups had increased, to 57.0 for blacks and 52.3 for whites (71). It would seem easy enough to answer the question: Did black-white disparity grow from 1973 to 1999? Unfortunately, however, the answer depends on the measure of disparity. If the disparity measure is the absolute difference between the black and white rates, then we would conclude that the black-white disparity increased from 3.2 to 4.7. If the disparity measure is the relative difference between the black and white rates (i.e., black rate ÷ white rate), however, we would conclude the opposite because the relative disparity decreased from 1.16 to 1.09. Both answers are correct. This has been a source of continuing confusion and sometimes unresolved debate in the health disparities literature (72,73) and, although most of the empirical work in health disparities has been in terms of "relative disparity," it should always be kept in mind that large relative differences can mask very small differences in absolute terms, which can be misleading with respect to the disparity's population-health impact. Conversely, there may be situations where large relative disparities may be viewed as grossly unjust, despite the fact that they reflect small absolute differences.

Absolute Disparity

The absolute disparity between two health-status indicators is the simple arithmetic difference. It is calculated as:

$$AD = r_1 - r_2 \qquad [3]$$

where r_1 and r_2 are indicators of health status in two social groups. In this case, r_2 serves as the reference population, and the *AD* is expressed in the same units as r_1 and r_2. A typical disparity measure that uses the absolute difference between two rates for an entire population is the range, where case r_1 above corresponds to the least-healthy group and r_2 to the most-healthy group.

Relative Disparity

For the same pairwise group comparison in equation [3], we also can divide r_1 into r_2 to calculate the relative disparity as:

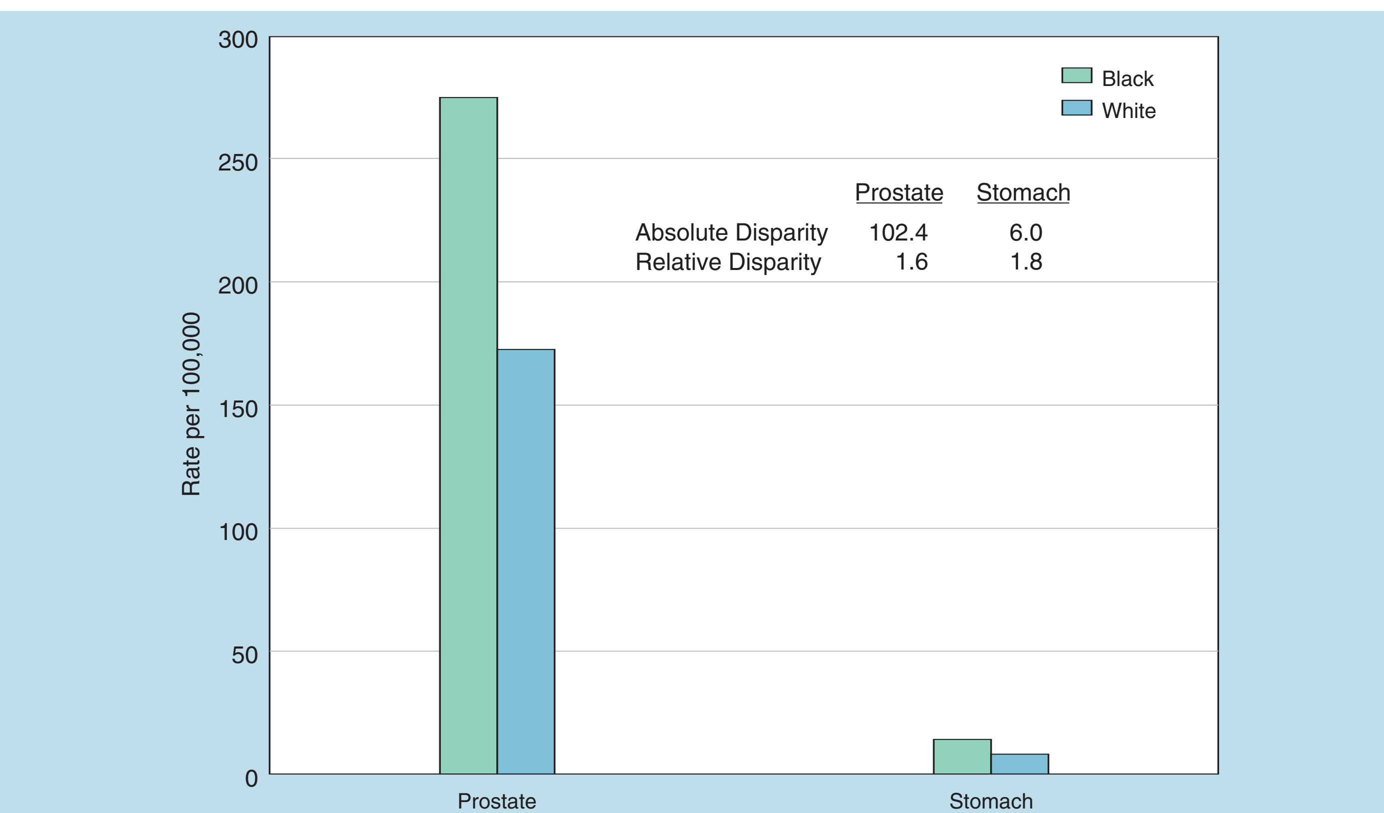
$$RD = r_1/r_2 \qquad [4]$$

where, again, r_2 is the reference population. This rate ratio can be transformed easily into a percentage difference by multiplying the ratio by 100. Figure 10 shows the absolute and relative black-white disparity for prostate and stomach cancer incidence from 1992–1999. Clearly, there is a much larger absolute disparity in prostate cancer incidence because the rates for both groups are relatively high compared to the stomach cancer rates; however, the relative disparity is larger for stomach cancer.

Regression-Based Measures

One drawback of the pairwise comparison measures of disparity is that, when a social group has more than two subgroups (as most do), information on the other groups is ignored. Normally it is desirable to use as much of the information present in the data as possible. If we

Figure 10. Absolute and Relative Black-White Disparities in Prostate and Stomach Cancer Incidence, 1992–1999



compare the “best” group to the “worst” group, we effectively ignore the information on the health status of all the groups in between, aside from knowing that they fall somewhere between the best and worst groups. One possible solution would be to calculate a series of (j–1) pairwise comparisons for j groups using one group as the reference point, or j pairwise comparisons using an external reference point. Although feasible, as the number of groups, time periods, or both increases, attempting to evaluate the disparity trend may become complicated in terms of summarizing the many pairwise comparisons. To overcome this limitation and make use of the information for all groups, one might consider calculating a summary measure of disparity. This choice, however, undoubtedly involves additional complexity and assumptions that must be traded off against the insights about disparity gleaned from the use of a summary measure (74).

Simple Linear Regression

If one is willing to assume that the relationship between social group and health status is linear (i.e., that each step up the social-group scale results in an equivalent health gain/loss), then a potential way to include information on all of the groups is to calculate a summary measure of disparity using regression. One way of writing this is:

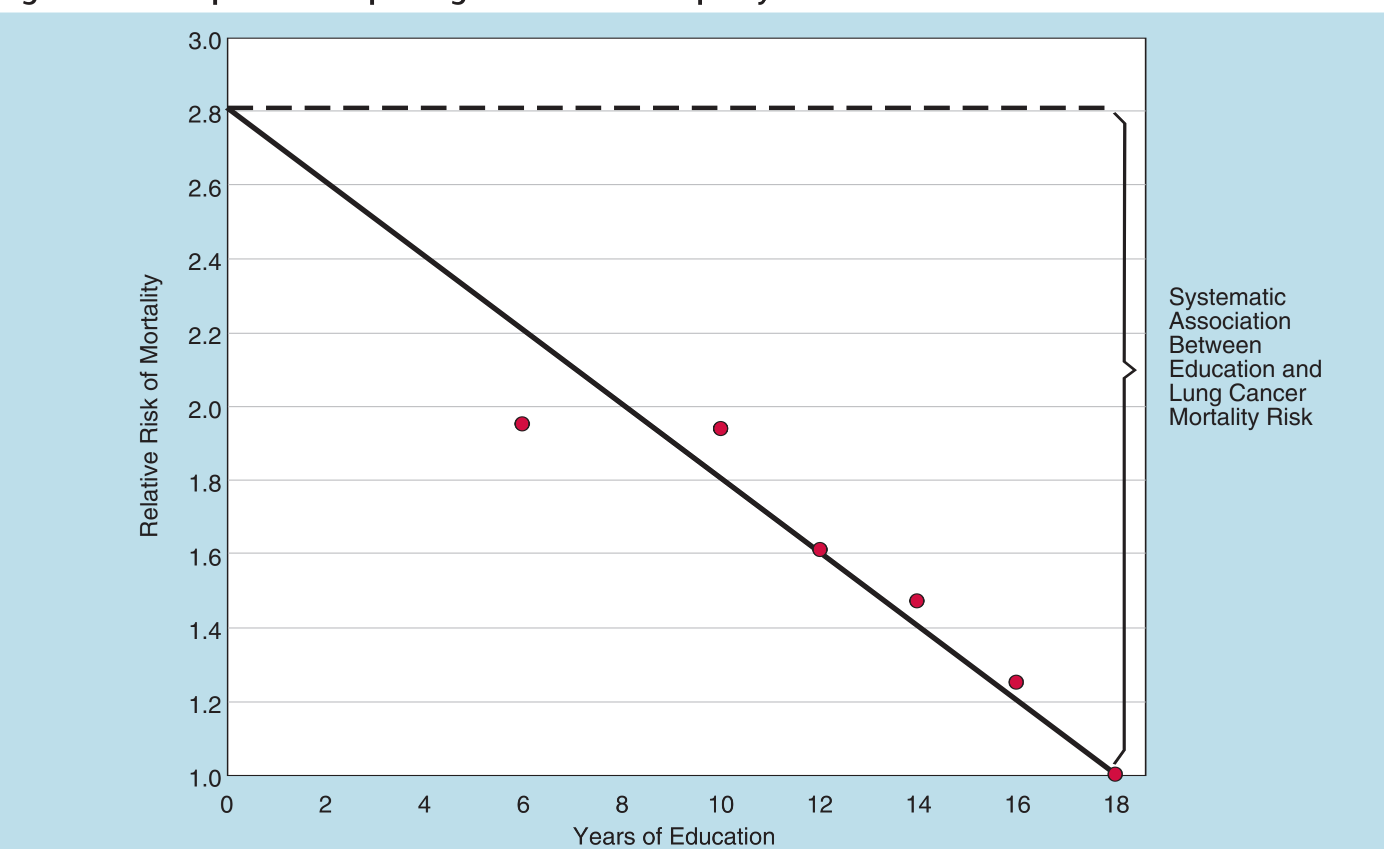
$$y_i = \beta_0 + \beta_1 X_i \qquad [5]$$

where y_i is a measure of health status for individual i, β_0 is the value of the health variable when X_i is 0 (e.g., if X_i is a continuous measure of income, then β_0 is the health status of an individual with zero income), X_i indexes social group, and β_1 is the summary measure of disparity. In general terms, β_1 is equal to the covariation of X_i and y_i expressed in terms of the variance of X_i. The specific interpretation of β_1 depends on the particular health status measure used and the specification of the model. If y_i is an untransformed health status measure—for example, BMI—then β_1 is the absolute increase in BMI associated with a one-unit change in social group and is referred to as a Regression-Based Absolute Effect or *RAE* (70). It is an absolute measure because it is expressed in the same units as the quantity of health measured in y_i. Continuous types of health outcomes, however, are relatively less common in the area of cancer-related data. More likely are noncontinuous types of health data (e.g., the presence or absence of cancer, receipt or nonreceipt of screening), where the linear relationship in equation [5] applies to some transformation of the dependent variable y_i. For transformations of the dependent variable y_i (e.g., the logarithmic or logit transformation), β_1 then becomes a relative-risk (logarithmic transformation) or odds-ratio (logit transformation) and is interpreted as the *proportional* increase in health status for a one-unit change in social group and referred to as a Regression-Based Relative Effect or *RRE* (70). Figure 11 (page 38) graphically shows a simple regression-based disparity measure, applied in this case by Steenland et al. to the risk of lung cancer among men of different education groups (grammar, some high school, high-school graduate, some college, college graduate) in the 1982–1996 Cancer Prevention Study II (36). The y-axis is the risk of mortality *relative* to those completing graduate school (whose relative risk is by definition equal to 1.0), the x-axis is the approximate number of years of education for each education group (X_i in equation [5]), and the fitted line indicates the linear decrease in relative risk—which Steenland and colleagues reported as about 10%—for each 1-year increase in the number of years of education. (It is important to note that, for ease of presentation, the plotted points in Figure 11 show only the average relative risk for each education group. The actual regression equation is performed on all 500,000 or so individuals in the CPS-II.) Relative-effect measures also may be transformed into absolute effect measures by applying them to the rates of health in the referent social group. An additional drawback to the *RAE* and *RRE* is that the assumption of linearity between health and social group may be problematic. For example, while Kunst and colleagues find linear associations between education and self-rated health (75), Manor et al. report nonlinearity between education and a number of chronic conditions (76), and Backlund and colleagues report a nonlinear association between income and mortality (77).

Slope Index of Inequality

The regression-based methods outlined above, subject to the assumptions of the model, work well for calculating a summary measure of health disparity at a single point in time. As noted above, however, over time the distribution of the population in various social groups may change

Figure 11. Example of a Simple Regression-Based Disparity Measure



Source: Adapted from Steenland et al. *Am J Epidemiol* 2002;156:11–21.

drastically, and it would be advantageous for a measure of health disparity to be sensitive to such changes. One measure that does so is the Slope Index of Inequality (*SII*). To calculate the *SII,* the social groups first are ordered from lowest to highest. The population of each social-group category covers a range in the cumulative distribution of the population and is given a score based on the midpoint of its range in the cumulative distribution in the population. For example, in the 2001 NHIS those with an income-to-poverty ratio of less than 0.5 (approximately <$9,000 for a family of four) were 3.45% of the population, and those in the next highest income group—with an income-to-poverty ratio of 0.5 to 0.74—comprised 3.02%, in which case the lowest group is assigned a score of [0 + (.0345 – 0)/2] = .0173, and the next lowest group is assigned a score of [.0345 + (.0647 – .0345)/2] = .0496.

Health status then is plotted against this midpoint socioeconomic category variable, and a regression line is fitted to the data. The *SII* thus is similar to the regression-based methods above, but differs because it uses the midpoint of the cumulative social group distribution and because it (usually) is based on grouped data and is a *weighted* index, where the weights are based on the size of the social groups. By weighting social groups by their population share, the *SII* is able to incorporate changes in the distribution of social groups over time that affect the population health burden of health disparities. Figure 12 (page 40) shows the predicted slope for the income disparity (based on income-to-poverty ratio) in current smoking for the United States in 2001. Note that, in Figure 11, the location of the data points on the *x*-axis is based on the estimated number of years of education, whereas in Figure 12, the location is based on the group's share of the population. This reflects the fact that the education groups actually comprise different proportions of the population distribution. Formally, the *SII*, which was introduced by Preston, Haines, and Pamuk (78), may be obtained via regression of the mean health variable on the mean relative rank variable:

$$\bar{y}_j = \beta_0 + \beta_1 \bar{R}_j \qquad [6]$$

where j indexes social group, $\bar{y}_i$ is the average health status, $\bar{R}_j$ is the average relative ranking of social group j, β_0 is the estimated health status of a hypothetical person at the bottom of the social group hierarchy (i.e., a person whose relative rank R_j in the social group distribution is zero), and β_1 is the difference in average health status between the hypothetical person at the bottom of the social group distribution and the hypothetical person at the top (i.e., $R_j = 0$ vs. $R_j = 1$). Because the relative rank variable is based on the cumulative proportions of the population (from 0 to 1), a "one-unit" change in relative rank is equivalent to moving from the bottom to the top of the social group distribution. Because this regression is run on grouped data (as opposed to individual data as in equation [5]), it is estimated via *weighted* least squares, with the weights equal to the population size n_j of group j (60). The coefficient β_1 in equation [6] is the *SII*, which is interpreted as the absolute difference in health status between the bottom and top of the social-group distribution. Thus, the regression equation in Figure 12 shows that the absolute difference in the prevalence of smoking across the entire distribution of income is –18.1 percentage points. The same regression also may be run on individual data (as in equation [5]), but replacing X_i with R_i, with R_i being an individual's relative rank in the social-group distribution. In this case, the data would be self-weighting and could be estimated by ordinary least squares.

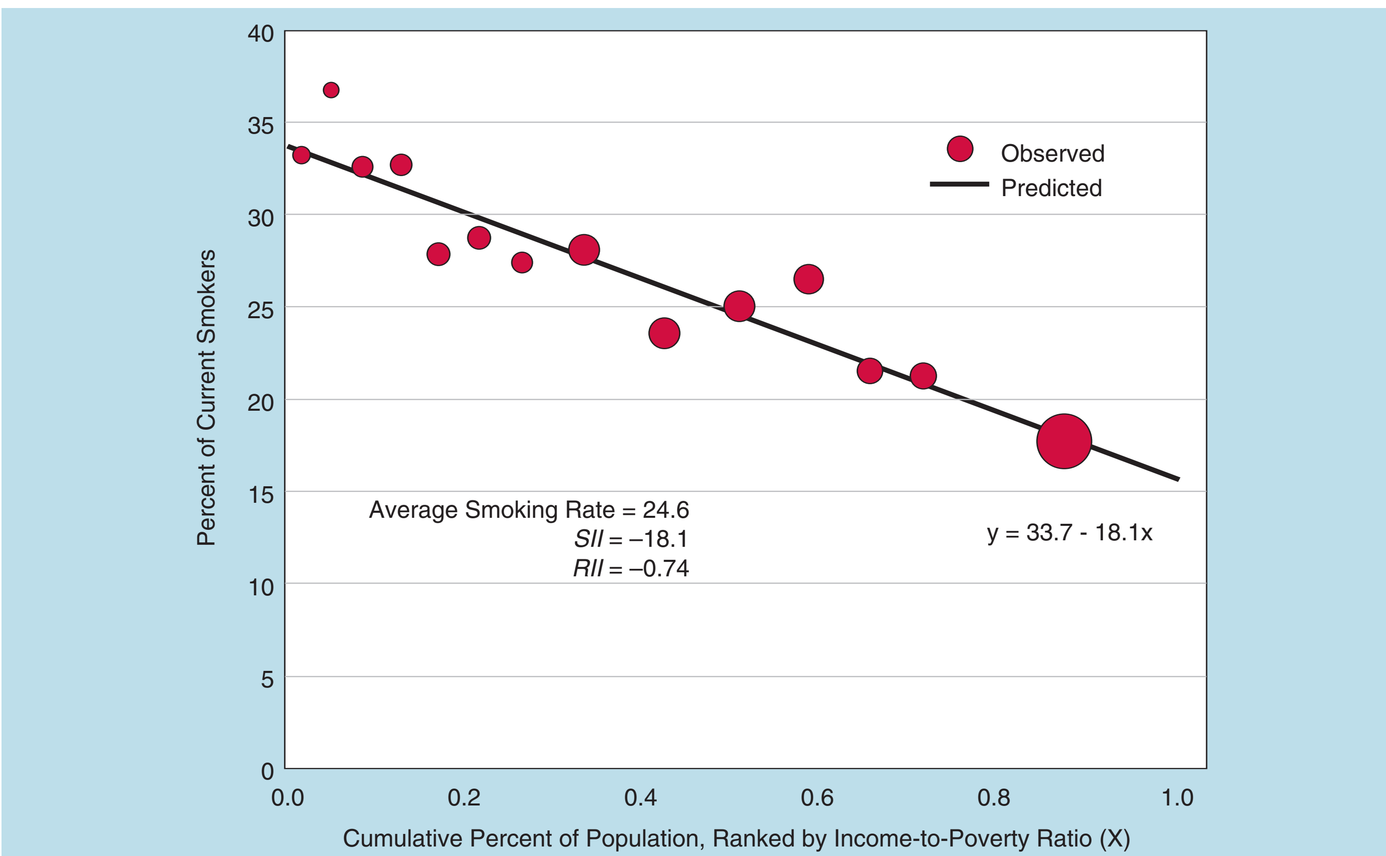
Relative Index of Inequality

The *SII* discussed above is a measure of absolute disparity. Dividing this estimated slope by the mean population health, however, provides a relative disparity measure, the Relative Index of Inequality or *RII* (79):

$$RII = SII / \mu = \beta_1 / \mu \qquad [7]$$

where μ is mean population health and the *SII* is the estimate of β_1 from equation [6]. Its interpretation is similar to the *SII*, but it now measures the proportionate (in regard to the average population level) rather than the absolute increase or decrease in health between the highest and lowest socioeconomic groups. In the income and smoking example seen in Figure 12, the *RII* is calculated as –18.1/24.6 = –0.74, indicating that a

Figure 12. Income-Based Slope Index of Inequality for Current Smoking, NHIS, 2002



move from the bottom to the top of the income distribution is associated with a 74% decline in the prevalence of smoking. Kunst and Mackenbach (70) modified this definition of the *RII* slightly by dividing the estimated health of the hypothetical person at the bottom of the social-group distribution by the estimated health of the hypothetical person at the top of the social-group distribution:

$$RII_{KM} = \frac{\beta_0}{\beta_0 + \beta_1} = \frac{\beta_0}{\beta_0 + SII} \qquad [8]$$

where β_0 and β_1 are defined as in equation [6]. From Figure 12, this is calculated as 33.7/(33.7 – 18.1) = 2.16, indicating that the rate of smoking is 2.16 times higher at the bottom of the income distribution than at the top. Thus, the Kunst-Mackenbach *RII* is more like a traditional relative risk measure in that it compares the health of the extremes of the social distribution, but it is estimated using the data on all social groups and is weighted to account for social-group sizes. As noted above, the use of the *SII* and *RII* indices (as well as the Health Concentration Index discussed below) depends on having a social-group classification scheme that is hierarchical. This seems straightforward with respect to education and income, but social-group classifications based on occupation may be somewhat more challenging because there inherently is more ambiguity in the ranking of occupations (80). In their international study of occupational mortality differences, Kunst and Mackenbach (81) note this difficulty as a possible explanation for the lack of consistency of their results with those of Wagstaff for the size of disparity in Finland versus England and Wales (60).

Population Impact Measures

Population Attributable Risk

The Population Attributable Risk (*PAR*) and its relative analogue, the *PAR%*, are longstanding epidemiologic measures of the population burden that is associated with differential health between groups. Although typically applied to groups defined by their exposure status (e.g., comparing smokers with nonsmokers), it also may be applied in the context of health differences between social groups (poor vs. nonpoor). It is a summary of differences between each social group's health and the health of the "best" group. For example, it indicates the absolute (or relative, in the case of the *PAR*%) aggregate health improvement that would be obtained if all education groups had the health of the healthiest education group. The basic formulas for *PAR* and *PAR*% as health disparity indicators (70) are:

$$PAR = r_{pop} - r_{ref} \qquad [9]$$

$$PAR\% = \frac{r_{pop} - r_{ref}}{r_{pop}} \qquad [10]$$

where r_{pop} is the rate in the total population and r_{ref} is the rate of health or disease in the reference group, typically the best-off social group. While not immediately clear from the above formula, the *PAR*% in fact is a population-weighted (by social-group size) sum of the relative risks (*RR*s) for each group (13) and also may be written as:

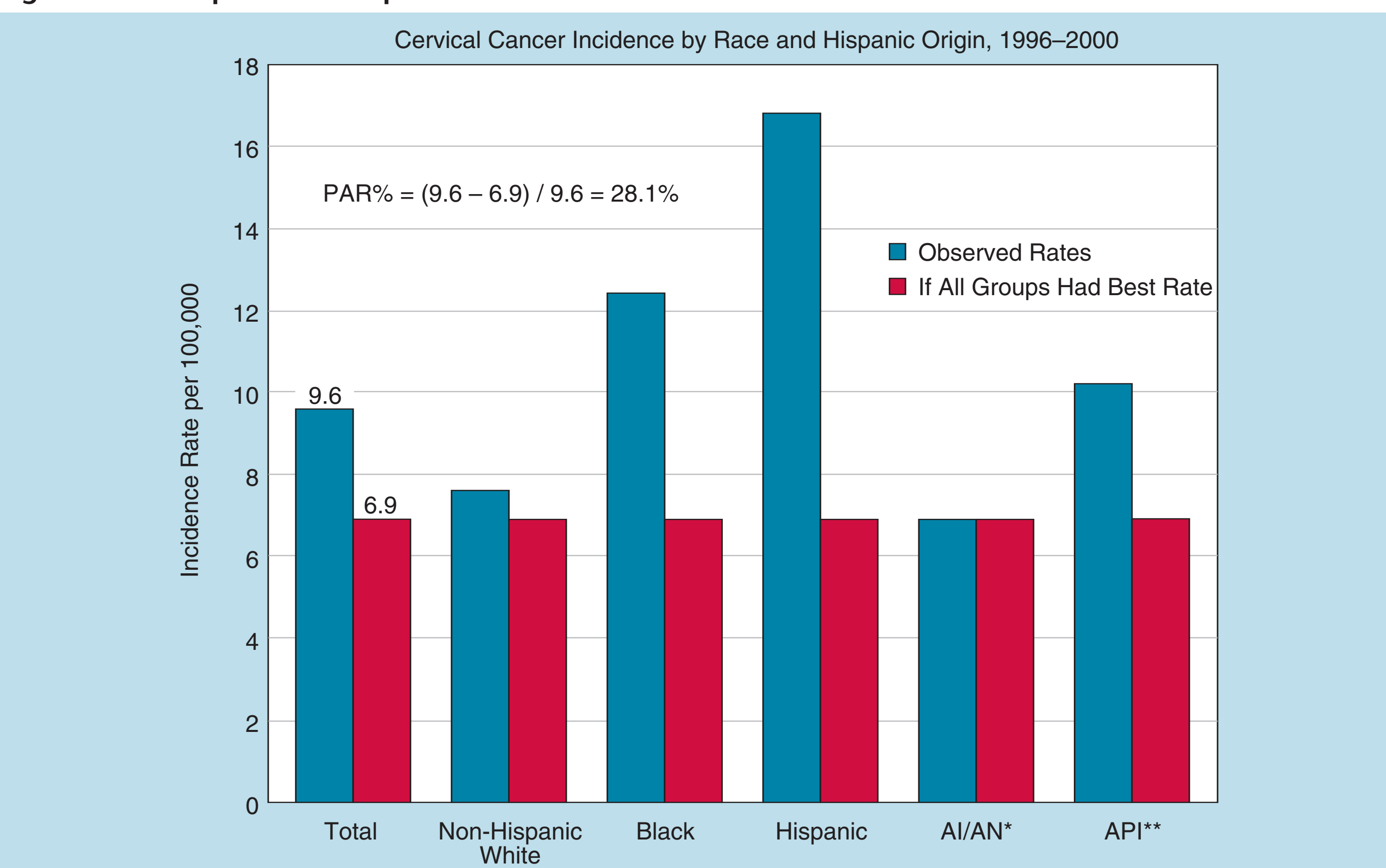
$$PAR\% = \frac{\sum p_j (RR_j - 1)}{\sum p_j (RR_j - 1) + 1} \qquad [11]$$

where p_j is the group's population share and RR_j is the relative rate of group *j* compared to the reference group. To see this, note that we could substitute r_j/r_{ref} for RR_j and r_{ref}/r_{ref} for 1 in equation [11] and multiply through by r_{ref} to get:

$$PAR\% = \frac{\sum p_j (r_j - r_{ref})}{\sum p_j (r_j - r_{ref}) + r_{ref}} \quad [12]$$

Because $\sum p_j r_j = r_{pop}$ and $\sum p_j r_{ref} = r_{ref}$, equation [12] reduces to equation [10]. The *PAR*% varies from 0 to 100 and is interpreted as the percent improvement in the health of the total population that would be achieved if all social groups had the rates of health in the best-off social group, a commonly used metric for describing the impact of health disparities. For example, Navarro argues that "the intervention that would add the most years of life to the populations of Spain or the USA (or, for that matter, any other country) would be one that would lead to all social classes having the same mortality rates as those at the top" (65, page 1701). In the example in Figure 13, the population average rate of cervical cancer would be improved by 28% if all social groups had the rate experienced by American Indians and Alaska Natives.

Figure 13. Example of the Population-Attributable Risk Percent



*American Indian/Alaska Native
**Asian/Pacific Islander
Source: SEER Cancer Statistics Review, 1975–2000.

Index of Dissimilarity

The Index of Dissimilarity (*ID*) originally was developed as a measure of residential segregation of population groups (82). For example, in the context of black-white segregation among neighborhoods within a city, the *ID* measures the proportion (using the relative version) or number (using the absolute version) of blacks (or whites) that would have to move to a different neighborhood to achieve a racial distribution in each neighborhood that was similar to that of the city as a whole. As such, the *ID* is a summary measure of the disparity between each neighborhood's racial composition and the racial composition of the city as a whole. Similarly, in the context of health disparity measurement, we can think of the *ID* as a summary measure of the disparity between, for example, each racial group's cancer rate and the cancer rate of the whole population. In this case, the *ID* would be interpreted as the number or proportion of cancer cases that would have to be redistributed across racial groups for each group's cancer rate to be the same as the rate in the whole population. The formula for the relative *ID* with respect to health is given in Wagstaff and colleagues (60) as:

$$\text{Relative } ID = \frac{1}{2}\sum_{i=1}^{J}|s_{jh} - s_{jp}| \qquad [13]$$

where j indexes social groups, s_{jh} is the jth group's share of health (e.g., share of all cancer cases), and s_{jp} is the jth group's share of the total population. According to Kunst and Mackenbach (70), equation [13] is the relative version of the *ID*. The relative *ID* compares how each social group's share of the population's health compares with its share of the total population and represents the proportion of all cases (e.g., the proportion of all cancer cases) that would have to be redistributed across social groups so that each group has the same rate as the total population. The absolute version of the ID is calculated as:

$$\text{Absolute } ID = \frac{1}{2}\sum\nolimits_{j=1}^{J}|d_j - p_j r_{pop}| \qquad [14]$$

where d_j and p_j are, respectively, the observed number of cancer cases and the population of the jth social group, r_{pop} is the cancer rate in the total population, so that $p_j r_{pop}$ is the expected number of cancer cases that would be observed if group j had the same cancer rate as the total population. One could also derive the absolute version of the *ID* by multiplying the relative *ID* by the total number of cases to determine the absolute number of cases that need to be redistributed across groups.

Table 1 on page 44 shows how one might calculate the absolute and relative *ID* for esophageal cancer incidence among working-age (ages 25–64) racial groups during 1992–2000. A comparison of columns (3) and (5) shows that the share of cancer cases is lower than the share of the SEER population for all groups except blacks, who represent 13.5% of all esophageal cancer cases but only 10.5% of the population. Similarly for the absolute *ID*, a comparison of columns (2) and (6) shows that if all groups experienced the population rate of esophageal cancer, more cases would be observed for all groups except for blacks. The relative *ID* in this case is 3.4, which means that 3.4% of the 17,186 cases of esophageal cancer need to be redistributed across racial groups to eliminate the racial disparity. In absolute terms, this means redistributing 592 cases of esophageal cancer.

Table 1. Incidence of Esophageal Cancer, Ages 25–64 by Race, 12 SEER Registries, 1992–2000

Race	Rate (1)	Cases (2)	% of Total Cases (3)	Population (4)	% of Total Population (5)	Cases if No Disparity (6)	*ID* Relative |(3) − (5)|	*ID* Absolute |(2) − (6)|
American Indian/Alaska Native	5.7	133	0.8	2,316,609	1.3	226	0.5	93
Asian/Pacific Islander	8.7	1,648	9.6	18,850,492	10.7	1,835	1.1	187
Black	12.9	2,395	13.9	18,518,113	10.5	1,803	3.5	592
White	9.5	13,010	75.5	136,864,686	77.5	13,323	1.8	313
Total	9.7	17,186	100.0	176,549,900	100.0	17,186	3.4%	592

Index of Disparity

The Index of Disparity, which we will abbreviate as ID_{isp} to distinguish it from the Index of Dissimilarity (*ID*), summarizes the difference between several group rates and a reference rate and expresses the summed differences as a proportion of the reference rate. This measure was formally introduced by Pearcy and Keppel (30) and is calculated as:

$$ID_{isp} = \left(\sum_{j=1}^{J-1} |r_j - r_{ref}| \,/\, J \right) / r_{ref} \times 100 \qquad [15]$$

where r_j indicates the measure of health status in the *j*th group, r_{ref} is the health status indicator in the reference population, and *J* is the number of groups compared. Although in principle any reference group may be chosen, the authors recommend using the best group rate as the comparison because that represents the rate desirable for all groups to achieve. In this case, it is not necessary to take the absolute value of the rate differences because they all will be positive. Other potential reference rates include the total population rate, the average of group rates, or some external target rate. A similar disparity measure was developed by Gaswirth (83), but it weights each group's deviation from the best rate by its population size, so that the disparity index (*U*) becomes:

$$U = \sum_{j=1}^{J-1} p_j \,(r_j - r_{ref}) \qquad [16]$$

where p_j is each group's population size. In this case, *U* is calculated as the weighted sum of the health difference between each group and the reference group. Similar to the Index of Disparity, above, this value also can be expressed relative to the health status of the total population, which Gaswirth defines as $G = U \div r_{pop}$. For example, Gaswirth applied this disparity measure to rates of mammography screening among non-Hispanic white, non-Hispanic black, Hispanic, and Other women ages 50–65 in the 2000 NHIS (83). The overall screening rate was 78.6%, and Figure 14 (page 45) shows that white women had the highest rates of screening (81%). The fraction of the entire population that is "underserved" (*U*, the shaded area in Figure 14) in this case is 2.04%, and if the population screening rate were increased by *G* = 2.6% and targeted to minority women, the screening disparity would have been eliminated. This measure has the additional desirable feature of intuitive graphical representation. Although not immediately clear from equation [16], however, it should be noted that, in practice, when the reference group is the group with the best rate, Gaswirth's measure *U* is equivalent to the *PAR* described above, and *G* is equivalent to the *PAR*% because their calculations are identical to the *PAR* and *PAR*%.

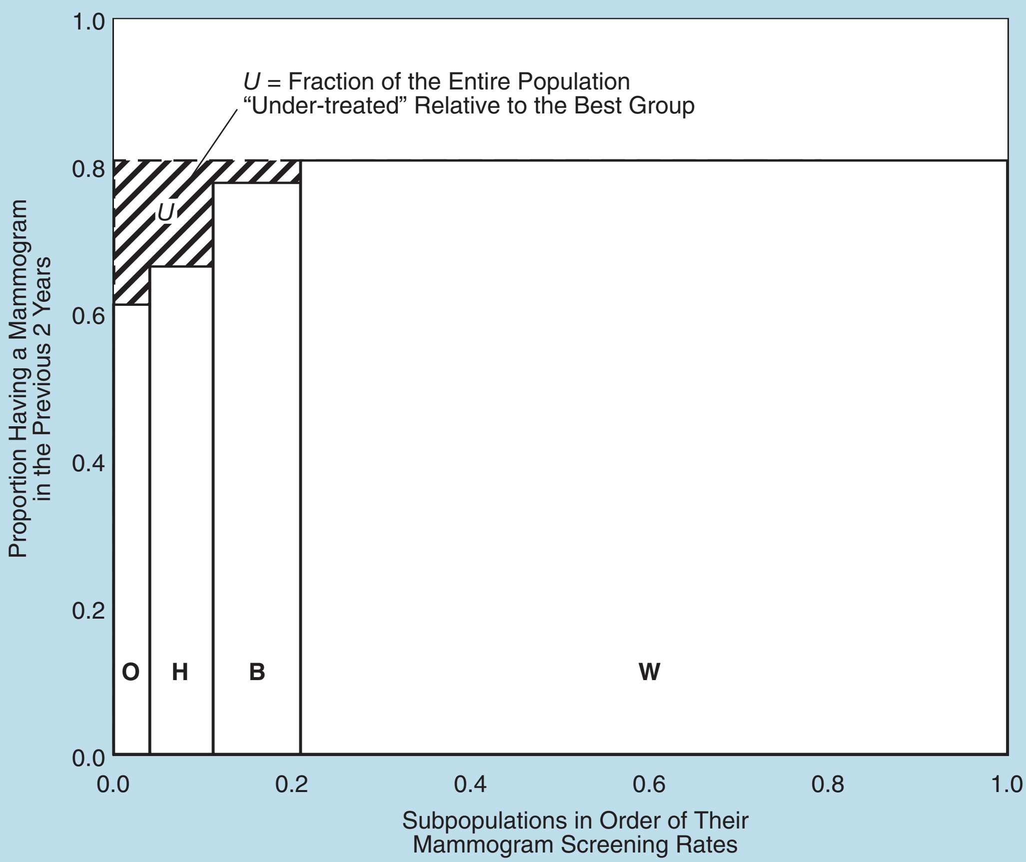
The Between-Group Variance

The variance is a commonly used statistic that summarizes all squared deviations from a population average. In the case of grouped data, this is the Between-Group Variance (*BGV*), and it is calculated according to the following formula that squares the differences in group rates from the population average and weights by their population sizes:

$$BGV = \sum_{j=1}^{J} p_j \, (y_j - \mu)^2 \qquad [17]$$

where p_j is group *j*'s population size, y_j is group *j*'s average health status, and μ is the average health status of the population. The Between-Group Variance may be a useful indicator of absolute disparity for unordered group data because it weights by population group size and is sensitive to the magnitude of larger deviations from the

Figure 14. Disparity in Mammography Screening Among Racial/Ethnic Groups, NHIS, 2000

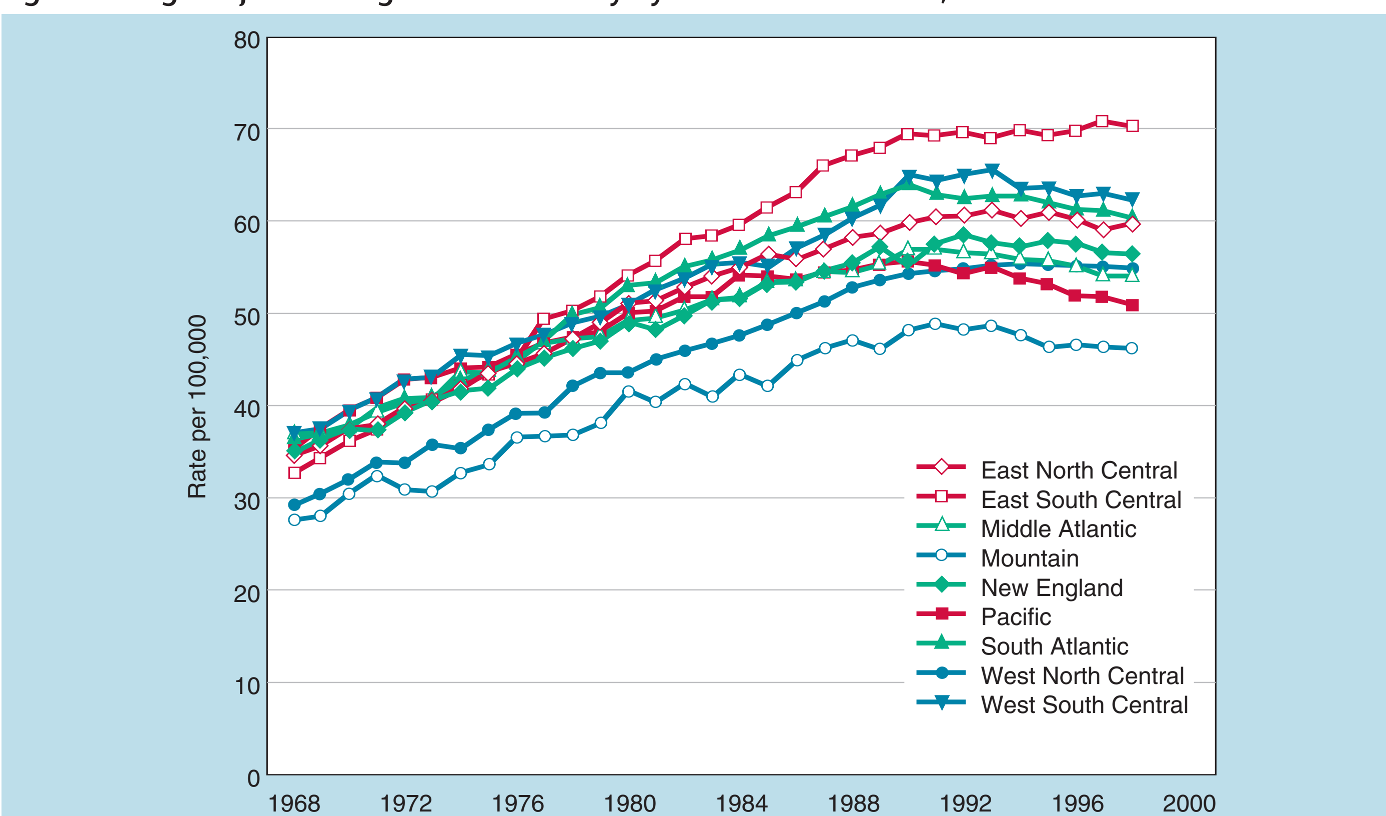


Source: Gastwirth JL. *Prev Med* (forthcoming).

population average. As an example, Figure 15 shows trends in age-adjusted lung cancer mortality among U.S. Census divisions.

The between-region variance in lung cancer mortality in 1968 was 7.1 deaths per 100,000, but in 1998 the *BGV* was 22.8 deaths per 100,000. This larger absolute disparity in regional mortality indicates divergent regional trends in lung cancer over time (see Figure 15). The use of the variance as a measure of disparity in economics sometimes is discouraged because it is not "scale invariant." In other words, it is sensitive to absolute changes, such as when everyone's income doubles over time. In this case, economists sometimes feel that it is not desirable for the disparity measure also to double, because relative inequality is maintained. Although this may be an undesirable property when dealing with income disparity, however, we believe it is not necessarily a limitation for discussing health disparity, in which we are interested in absolute disparity burdens (84). From a population health perspective, in which we may be concerned with the health care implications of increasing absolute disparity, we may care about situations in which the absolute disparity increases, and it is appropriate that the disparity indicator reflect this increased concern. In this case, then, using the variance (which squares the absolute deviations from the population average)

Figure 15. Age-Adjusted Lung Cancer Mortality by U.S. Census Division, 1968–1998



Source: NCHS. Compressed Mortality Files 1968–1998.

is consistent with a population health perspective. In the example above of changes in regional lung cancer disparity, the overall rates increase by 70%, the coefficient of variation (the variance divided by the mean) increases by 89% (indicating that relative disparity increases as well), but the variance increases by 320%. Thus, choosing this as the measure of disparity reflects our concerns with widening absolute differences among the regions.

Measures of Average Disproportionality

When describing health inequalities, public health researchers and policy makers often use what might be called the "language of disproportionality." For example, in the context of arguing for the importance of measuring health inequalities between socially meaningful population groups, Braveman and colleagues stated that "a disproportionate share of ill-health and premature mortality is borne by the socially disadvantaged" (51, page 233). Similarly, in discussing health disparity trends, the Secretary of Health and Human Services recently noted that various racial/ethnic groups in the United States "suffer an unequal burden of death and disease, despite improvements in the overall health of the general population over the past decade" (85). The terms "disproportionate share" and "unequal burden" are important descriptors because they communicate the ethical notions inherent in the collective concerns over health disparities. That is, they capture the notion that it is unfair that some groups experience more ill health than others; a just distribution of health implies that ill health should be experienced proportionately by different social groups. A more explicit example can be found in the *Guidance for the U.S. National Healthcare Disparities Report* in which, in discussing the disparity in cardiac catheterization rates between blacks and whites, LaVeist states that the "degree to which the predicted percentage of catheterization deviates from the observed percentage indicates the degree of disparity," and concludes that "African Americans received 67% of the catheterizations that they should have received, and whites received 14% more than their share" (86, page 90).

The quotations above make clear that health disparity often is equated with the concept of disproportionality. What is perhaps less clear is that, in the context of the commonly used "language of disproportionality," there usually is an implied reference group, which is the general population. In fact, in the catheterization example, LaVeist was arguing explicitly against measuring health disparity using a relative measure such as a risk ratio or odds ratio, because doing so means using a particular social group (in this case, whites) as the reference group, which necessarily assumes that the rate in the reference group is "most desirable." Thus, he argued that disparity measures that use whites as the reference group would not be able to identify their "over-utilization" of cardiac catheterization. The intuitive ethical notion expressed in the quotations above is that the amount of ill health in social group j is far greater than would be expected if ill health were evenly distributed with respect to all J social groups. An even distribution of ill health across J social groups implies that the number of individuals of social group j with condition y is proportionate to group j's share of the total population, so that the rate of ill health, Y_j, in each of the j groups is exactly the same, which would necessarily equal the rate in the total population. Thus, the proportional distribution of y among J groups implies that $Y_j = \bar{Y}$ (the mean of y) for all groups.

This is an important point because many commonly used measures of income disparity (e.g., the Gini coefficient) and residential segregation (e.g., the Index of Dissimilarity), some of which currently are employed to measure health disparities, may be expressed conveniently as measures of average disproportionality (87–89). For each social group j, we can define a health (or ill health) ratio as the ratio of measure y in the jth group to that of the mean of y for the whole population, so that $r_j = Y_j / \bar{Y}$ for each group. Note that this makes such measures relative rather than absolute disparity indicators. In this framework, measures of disparity take the general form

$$I = \sum_j p_j f(r_j) \qquad [18]$$

where p_j is group j's proportion of the total population and $f(r_j)$ is some disproportionality function of the ratio $r_j = Y_j / \bar{Y}$. It should be clear that equation [18] is a weighted disparity measure because each group's disproportionality function $f(r_j)$ is multiplied by its population share p_j. Measures of this type of disparity indicator differ because they implement different disproportionality functions. Perhaps one of the appealing features of such measures is that they provide a rather direct correspondence between the commonly used languages of health disparity in terms of "disproportionality" with the operationalization of the measurement.

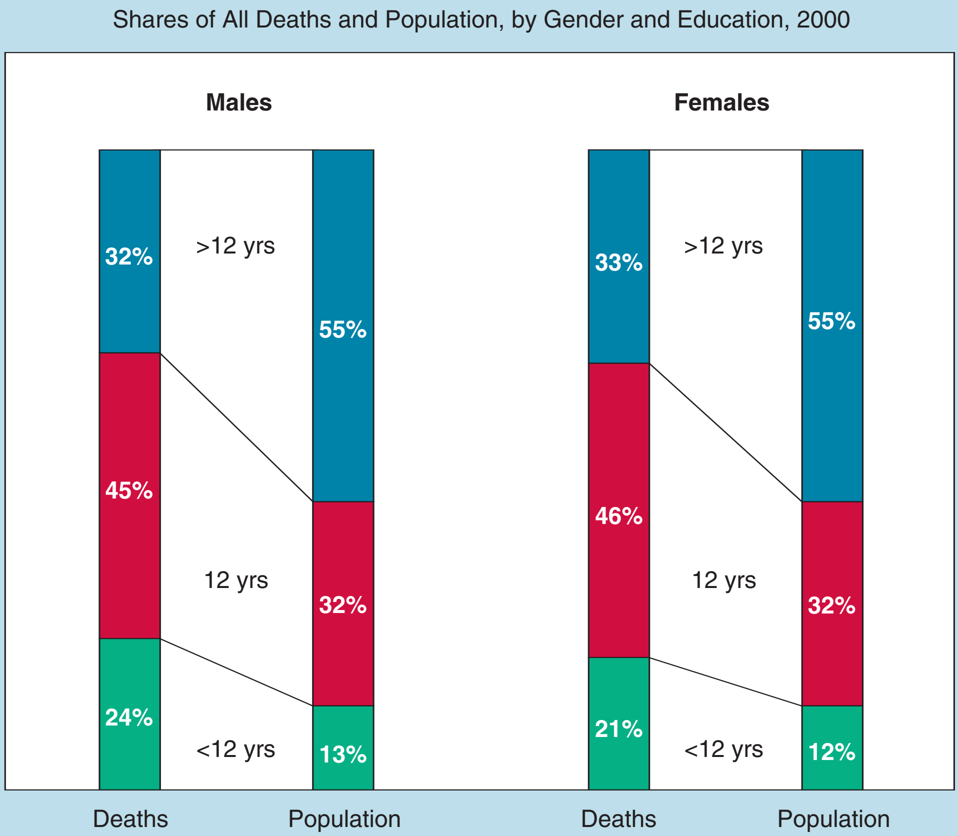
Figure 16 (page 49) depicts the concept of "disproportionality" using data on all deaths in the United States, by gender and education, for the year 2000. Among males, those with less than 12 years of education bear a disproportionate burden of all deaths, as they account for 24% of all male deaths but account for only 12% of the male population. Conversely, males with greater than 12 years of education account for 55% of the total population but only 32% of all deaths. The level of disproportionality for females with less than 12 years of education is slightly smaller.

Table 2 (page 49) shows some commonly used statistical measures and their disproportionality functions. Readers should note that the measures differ only in how they express the difference between shares of health and shares of population.

Entropy Indices

One class of disproportionality measures that often is favored by economists are measures of general entropy, developed by Henri Theil (90). The example described below is for measuring the disparity in BMI, which is a risk factor for a number of cancer sites (91,92). Theil's index gives relatively more weight to the concentration in the upper end of the health distribution and is calculated (with grouped data) by summing the product of each group's BMI share of the population's total BMI and the natural log of each

Figure 16. Example of the "Disproportionality" of Deaths and Population, by Gender and Education, 2000



Source: NCHS. Deaths: Final Data for 2000, *Natl Vit Stat Rep* 2002;50(15).

Table 2. Commonly Used Disproportionality Functions

Index Name	Disproportionality Function
Squared coefficient of variation (CV^2)	$(r_j - 1)^2$
Gini index (G)	Individual-level data: $\lvert r_i - r_j \rvert / 2$
	Grouped data: $r_j(q_j - Q_j)$, where q_j is the proportion of the total population in groups less healthy than group j, and Q_j is the proportion of the total population in groups healthier than group j (i.e., $p_j + q_j + Q_j = 1$)
Relative concentration index (RCI)	Same as for G, but groups are ranked by social group position instead of by health, so that q_j is the proportion of the total population in groups less advantaged than group j, and Q_j is the proportion of the total population in groups more advantaged than group j (i.e., $p_j + q_j + Q_j = 1$)
Theil index (T)	$r_j \ln(r_j)$
Mean logarithmic deviation (MLD)	$\ln(1/r_j) = -\ln(r_j)$
Variance of log-health ($VarLog$)	$[\ln r_j - \sum(\ln r_j)]^2$

Note: Adapted from Firebaugh, 2003 (88).

group's BMI share. For individual-level data, total disparity in BMI measured by Theil's index can be written as

$$T = \sum_{i=1}^{N} p_i r_i \ln(r_i) \qquad [19]$$

where p_i is an individual's population share (which in the case of individual data will be $1/n$, so that $\sum p_i = 1$) and r_i is the ratio of the individual's BMI to the population average BMI (i.e., $r_i = y_i / \bar{Y}$). When the population of individuals is arranged into J groups, Theil showed that equation [19] is the exact sum of two parts: between-group disparity and a weighted average of within-group disparity:

$$T = \sum_{j=1}^{J} p_j r_j \ln(r_j) + \sum_{j=1}^{J} p_j r_j T_j \qquad [20]$$

where T_j is the disparity in BMI within group j. The within-group component (the second term on the right side of equation [20] is weighted by, in this case, group j's share of the total BMI, because $p_j \times r_j = s_j$ (where s_j is the *share* of total BMI) when the denominator for r_j is the mean BMI for the total population. More importantly, the above decomposition also makes it clear that it is possible to calculate between-group disparity in BMI—the primary quantity of interest with respect to social disparities in health—in the absence of data on each individual. The only data needed are the group proportions and the ratio of the group's BMI to the population average BMI. Between-group disparity, however, may increase because total disparity is increasing (i.e., both between-group and within-group disparity are increasing simultaneously). The primary advantage of using additively decomposable inequality measures is that they allow us to determine not just whether between-group disparity is increasing, but whether the share of total disparity that is due to disparity between groups is increasing or decreasing. Although this measure has attractive qualities, the between-group/within-group decomposition requires continuous outcome data measurable in individuals, so it is not clear whether this can be applied to many relevant cancer outcomes that are based on events (e.g., incidence, mortality, or screening). Even for noncontinuous outcomes, however, entropy indices easily can be used to calculate between-group disparities in the absence of individual-level data. For example, suppose that instead of BMI we wanted to measure the between-group disparity in obesity rates. We could do this by calculating the first term on the right side of equation [20] using only the data on each group's proportion in the population (p_j) and the group's rate of obesity relative to the overall population rate (r_j)—data that are more likely to be readily available.

Measuring between-group inequality in BMI in the above manner makes clear that changes in the value of disparity over time are a function of two quantities: changing group proportions and changing social group BMI ratios. This is important— in the case of obesity, for example— because differentiating between these two components of change has different implications for obesity as a public health problem and may be the result of very different social policies. If we find that disparity is increasing but that the main reason for the observed change is that the share of the population among social groups at the tails of the BMI distribution has increased, it simply demonstrates that the inequality increase is due primarily to the movement into and out of different social groups—not to differentially increasing rates of BMI within subgroups of a social group. However, if we find that population shares have remained relatively constant over time but BMI disparity has increased because BMI ratios are increasing, this implicates differential sources of BMI change among particular groups—which may then become the target of public health intervention.

Atkinson's Measure

Atkinson's index actually is not a single index of disparity but depends on specifying the relative sensitivity of the index to different parts of the distribution. One way of writing Atkinson's index is:

$$A = 1 - \left[\sum_{j=1}^{J} p_j r_j^{1-\varepsilon}\right]^{1/[1-\varepsilon]}, \ \varepsilon > 0 \qquad [21]$$

where p_j and r_j are again, respectively, the share of population and the health ratio (relative to the total population rate), as defined above. Clearly with this index, the extent of disparity hinges on specifying the parameter ε, which indicates the degree of "aversion to disparity." Larger values of ε indicate stronger aversion to disparity, which also may be interpreted as placing increased weight on the least healthy groups. For example, if we are particularly concerned about improving the health of least-healthy individuals, we could make the measure of disparity more sensitive to changes in the bottom of the health distribution.

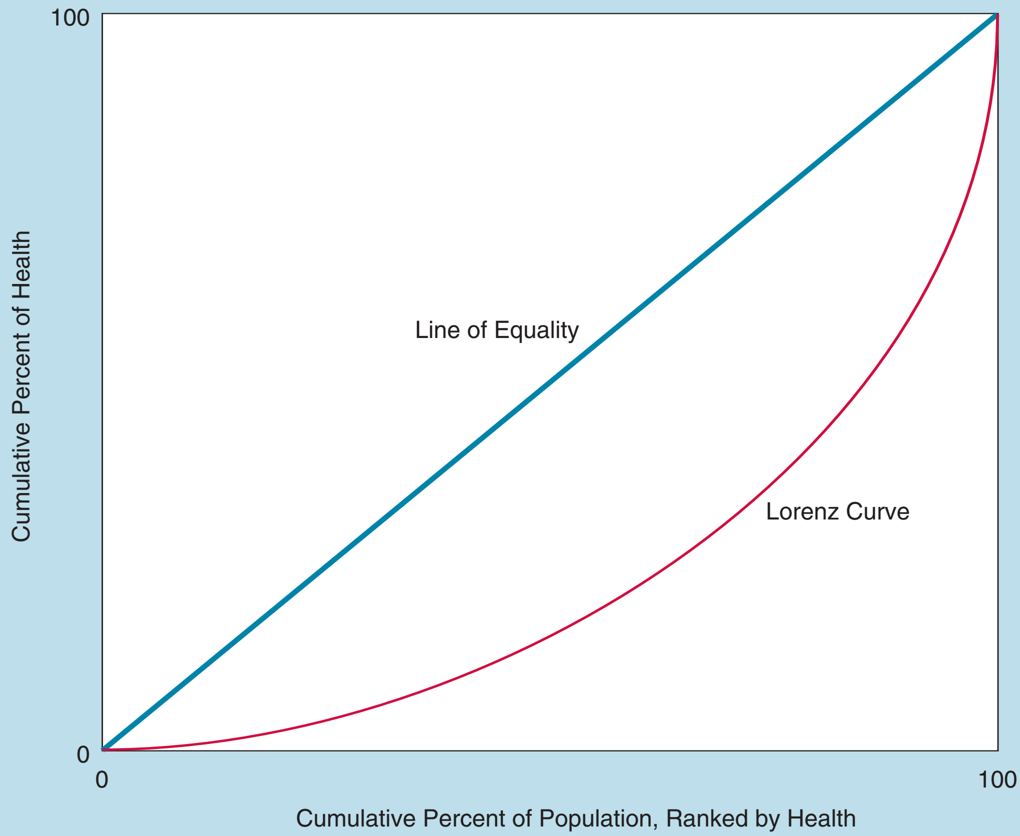
Gini Coefficient

The Gini coefficient summarizes social group differences in, for example, BMI for the entire population and can be thought of as a measure of association between each social group's share of population, ranked by the group's health and its share of health. Its formula for individual data is given above for the *IID* in equation [2], when $\alpha = 2$ and $\beta = 1$. Formally, the Gini coefficient is the ratio of the area between the line of equality in Figure 17 (page 52) and the Lorenz curve to the total area of the triangle beneath the line of equality (40). Because the Gini coefficient is a function of the disproportionality between shares of population and shares of health, one can see from Figure 17 that health disparity increases as the Lorenz curve moves further away from the line of equality (i.e., as the disproportionality between shares of population and shares of health increases).

Concentration Index

The Concentration Index (*CI*) is calculated similarly to the Gini index, but it results from a bivariate distribution of health and social-group ranking. In the same way that the Gini coefficient is derived from the Lorenz curve, the *CI* is derived from a concentration curve, where the population is ordered first by social-group status (rather than by health status, as for the Gini), and the cumulative percent of the population then is plotted against the group's share of total ill health. When the *y*-axis is the share of ill health, this results in the Relative Concentration Index (*RCI*); however, an Absolute Concentration Index (*ACI*) also may be derived by plotting the cumulative share of the population against the cumulative amount of ill health (i.e., the cumulative contribution of each subgroup to the mean level of health in the population). Figure 18 (page 53) gives a graphical representation of a relative concentration curve. Note the similarity with the Lorenz curve drawn in Figure 17 to illustrate the Gini coefficient. The two curves and

Figure 17. Representation of the Gini Coefficient of Disparity



thus the Gini coefficient and the *RCI* are calculated similarly, the only difference being the way in which social groups are ordered. In the case of the Gini coefficient, social groups are ordered by their health status (lowest to highest), regardless of their socioeconomic group ranking; for the *RCI,* social groups are ordered by their ranking in terms of, for example, years of education, regardless of their health status. It is important to note that, because the Concentration Index incorporates information on *both* health and social-group status, the concentration curve may lie either above or below the line of equality. The general formula for the Relative Concentration Index (*RCI*) for grouped data is given by Kakwani and colleagues (93) as:

$$RCI = \frac{2}{\mu}\left[\sum\nolimits_{j=1}^{J} p_j \mu_j R_j\right] - 1 \qquad [22]$$

where p_j is the group's population share, μ_j is the group's mean health, and R_j is the relative rank of the *j*th socioeconomic group, which is defined as:

$$R_j = \sum\nolimits_{j=1}^{J} p_\gamma - \frac{1}{2} p_j \qquad [23]$$

where p_γ is the cumulative share of the population up to and including group *j*, and p_j is the share of the population in group *j*. R_j essentially indicates the cumulative share of the population up to the midpoint of each group interval, similar to the categorization of the Slope and Relative Index of

Inequality above. In fact, the *RCI* has a specific mathematical relationship with the *RII* (60):

$$RCI = 2\text{var}(R)RII \quad [24]$$

where R is the relative rank variable identified in equation [23]. Thus, the *SII*/*RII* and the *ACI*/*RCI* will produce the same rank ordering of health inequality over time but will differ in scale. The absolute version of the Concentration Index (*ACI*) is calculated by multiplying the *RCI* by the mean rate of the health variable:

$$ACI = \mu RCI \quad [25]$$

where μ is the mean level of health in the population. It also is worth pointing out that, when using continuous health outcomes, the *RCI* is unbounded and takes minimum and maximum values of –1 and +1, but when using binary health outcomes, the possible values of the *RCI* are limited by the mean (e.g., the prevalence) of the distribution (94). Adam Wagstaff shows that, for a given nonzero mean of a binary variable (μ), the minimum of the *RCI* is $[\mu - 1 + (1/n)]$ and the maximum is $[1 - \mu + (1/n)]$, with n being the sample size. This of course has implications for analyses that compare the extent of socioeconomic inequality in health between areas or outcomes with very different levels of average health, and one potential strategy for facilitating comparisons is to normalize the Concentration Index by dividing it by its bound (95).

Figure 18. Representation of the Health Concentration Curve

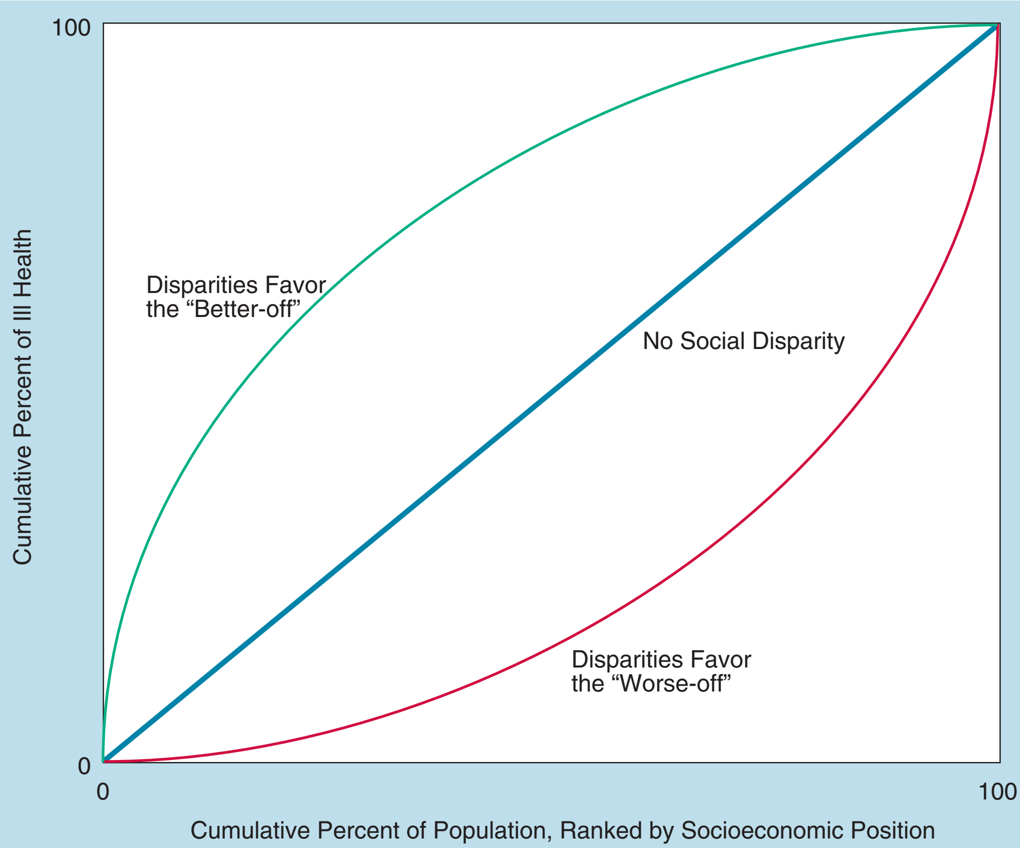


Table 3. Educational Disparity in Lung Cancer Mortality, 1999

Education	Rate per 100,000	Population Share	Midpoint (%)	*CI*
<12 years	49.8	0.128	0.064	0.408
12 years	41.0	0.327	0.292	3.913
>12 years	16.9	0.545	0.728	6.699
T otal	29.0	1.0		1 1.020
		Relative Concentration Index	→	−0.240
		Absolute Concentration Index	→	−6.959

Note: Rates are for persons aged 25–64 years and exclude the following states: Georgia, Kentucky, Rhode Island, and South Dakota. Rate data are from DATA2010…the *Healthy People 2010* Database, April 2004 edition, and SEER*Stat. Population data are from NCHS, Deaths: Final Data for 1999: Table VII.

Table 3 shows a simple example of how the *RCI* and *ACI* are calculated using equations [22] and [25] with grouped data using lung cancer mortality rates by educational attainment. One can see that lung cancer mortality rates decrease with increasing education, and the negative value of both indices shows that the disparity in lung cancer mortality favors the better educated.

One of the reasons the *ACI* and *RCI* (and, by extension, the *SII*/*RII* indices) are favored by some is that they "reflect the socioeconomic dimension to inequalities in health" (60, page 548). That is, a downward health gradient (such that health worsens with increasing social-group rank) results in a positive index, whereas an upward health gradient results in a negative index. For example, if the data in Table 3 were reversed so that lung cancer mortality rates for those with <12 years of education were 16.9 and the rates were 49.8 for those with >12 years of education, the *RCI* then would be calculated as 0.114 and the *ACI* as 4.873, indicating that lung cancer mortality actually favors the less educated. This sensitivity to the direction of the health gradient is not a property of other disproportionality measures, such as the Gini coefficient and the Index of Dissimilarity, because they do not depend on the strict ordering of social groups.

This undoubtedly is an advantage of the *RCI*, but, as with all disparity measures, it also may be seen as a disadvantage. Because of its sensitivity to socioeconomic *gradients* in health, the *RCI* may not register any disparity when health is not ranked directly by social group. Thus, when a social group ranked in the middle of a hierarchy bears a disproportionate burden of ill health, the *RCI* well may register this as zero disparity. This is not just a theoretical limitation of the *RCI*. For instance, age-adjusted rates of breast cancer deaths (per 100,000) in the United States in 1998 were 20.0 among those with less than a high-school education, 28.4 among those with a high-school education, and 22.0 among those with at least some college education (9). If the respective shares of the population in each of the education groups were approximately 38.8%, 20%, and 41.2%, the *RCI* would be virtually zero, indicating no educational mortality disparity; yet those with a high-school education will contribute roughly 40.3% of breast cancer deaths. A reasonable case could be made that a disproportionate burden of breast cancer falls on the high-school-educated (using this categorization of education), but the *RCI* would not reveal this pattern. This pattern of the worst health among those in the middle social group is not simply an artifact of breast cancer as an unusual cause of death. This pattern also is seen for colorectal and prostate cancers and melanoma as well where rates across ordered social groups are not simple gradients.

We use the breast cancer example not necessarily to suggest that the *RCI* is a poor index for measuring social-group disparities in health, but rather to emphasize that all disparity measures have advantages and disadvantages that should be considered when selecting and interpreting a disparity index; no summary disparity measure should be used as a substitute for detailed inspection of the health status indicators for each social group via tables and graphs.

Wagstaff also derived a method for incorporating a society's degree of aversion to disparity into the *RCI*, which he calls the "extended" Concentration Index (96). The aversion parameter changes the weight attached to the health of different socioeconomic groups in a manner similar to the Atkinson Index described above. The formula for this extended version of the *RCI* for grouped data is:

$$RCI(\nu) = \nu\sum_{j=1}^{J} p_j(1-R_j)^{\nu-1} - \frac{\nu}{\mu}\sum_{j=1}^{J} p_j\mu_j(1-R_j)^{\nu-1} \quad [26]$$

where ν is the "aversion parameter," and the other quantities are defined as in the *RCI* in equation [22] above. Setting $\nu = 1$ weights every group's health equally (i.e., complete indifference to inequality), and setting $\nu = 2$ gives the standard *RCI* defined above. As ν increases, the weight attached to the health of lower socioeconomic groups increases, and the weight attached to the health of higher socioeconomic groups decreases. Table 4 (page 56) shows the effect of varying the weight placed on the health of the less-educated groups for the disparity in current smoking in the state of Michigan in 1990 and 2002. The two rightmost columns are the calculated *RCI*s, with differing aversions to disparity. Setting $\nu = 2$ gives the standard *RCI* of –0.129, indicating that the disparity in current smoking favors the better educated. Increasing the weight placed on the health of the less-educated groups in 1990 results in only a marginal increase in the measure of disparity to –0.178, most likely because the rate of smoking among those with <8 years of education actually is quite low. The major effect of the differential weighting of the *RCI* can be seen in the disparity change from 1990 to 2002; in 2002, the standard *RCI*(2) was –0.19, a disparity increase of 48.5%, and the more bottom-sensitive *RCI*(4) was –0.32, indicating a much larger 81% increase in the relative education disparity in smoking. The reason the increase in disparity is so much larger for *RCI*(4) is that, although rates of smoking decreased overall and in every other education category, the estimated rate of current smoking actually increased among the least-educated group. This example shows how we can incorporate an ethical judgment (particular concern about the health status of the least educated) into a measure of health disparity.

Table 4. Example of Extended Relative and Absolute Concentration Index Applied to the Change in Educational Disparity in Current Smoking, Michigan, 1990 and 2002

Education	Population (%)	% Smokers	Midpoint (%)	*RCI* ($\nu = 2$)	*RCI* ($\nu = 4$)
1990					
<8 years	4.5	27.2	2.3	0.006	0.011
9–11 years	12.4	39.9	10.7	–0.082	–0.131
12 years	36.9	33.3	35.4	–0.068	–0.057
13–15 years	27.3	29.6	67.5	–0.003	–0.001
16+ years	18.9	13.6	90.6	0.019	0.000
Total	100.0	29.1		–0.129	–0.178
				ACI = –3.75	*ACI* = –5.16
2002					
<8 years	2.0	36.6	1.0	–0.021	–0.041
9–11 years	7.8	36.3	5.9	–0.073	–0.130
12 years	31.4	31.3	25.5	–0.137	–0.152
13–15 years	29.6	24.5	56.0	–0.003	–0.001
16+ years	29.2	12.2	85.4	0.042	0.002
Total	100.0	24.2		–0.191	–0.321
				ACI = –4.63	*ACI* = –7.77

Note: Data is for current smoking and is drawn from the 1990 and 2002 Behavioral Risk Factor Surveillance System (BRFSS).

Combining Health Disparity and Average Health

As we emphasized in the above discussion of relative and absolute health disparities, the goals of *Healthy People 2010* are couched specifically in terms of both health disparities and average levels of population health. Thus, we also may be interested in investigating potential ways to incorporate both average health and health disparity into a single summary measure. One potential measure, created by Adam Wagstaff, is called the Health Achievement Index or *HAI* (96).

The Health Achievement Index

The *HAI* in some respects is similar to the *ACI* described above, but combines disparity and average health by essentially subtracting the Absolute Concentration Index from the population's average health, creating a "disparity-discounted" level of average health. The formula for the *HAI* is (96):

$$\begin{aligned} HAI(v) &= \mu\lfloor 1 - RCI(v)\rfloor \\ &= \mu - ACI(v) \end{aligned} \qquad [27]$$

where μ is the population's average health and *RCI*(v) is the extended Relative Concentration Index defined above. Thus, applying equation [27] to the data on the average rate and educational disparity (using *RCI*[2]) in smoking in Michigan, the *HAI*(2) for Michigan in 1990 is 0.29 × (1 – [–0.129]) = 0.33, and is 0.24 × (1 – [–0.191]) = 0.29 in 2002. Clearly, if *RCI* = 0, then the *HAI* is equal to the population average rate of health, and the larger the *RCI,* the further away the *HAI* is from the population average—a kind of "disparity penalty" applied to the population average rate. In this sense, the *HAI* is not exactly a measure of health disparity but a potentially useful way of capturing both aggregative (*Healthy People 2010* Goal 1) and disparity (*Healthy People 2010* Goal 2) concerns in a single summary measure, at least with respect to ordered social groups. For example, while both relative and absolute education disparity in smoking increased in Michigan over the 12-year period (i.e., education disparity unambiguously increased, see Table 4), health achievement actually improved because almost all education groups experienced a decrease in the rate of smoking (in this case, health "achievement" increases as the population rate of smoking decreases).

Two populations (or time periods) therefore might have the same value on the Achievement Index but differ greatly on both average health and the extent of health disparity. For example, in Figure 19 (page 58) the relative concentration curves for education disparity in obesity in New York State are plotted for 1990 and 2002. Because the 2002 curve is beneath the 1990 curve for every education group, we can unambiguously declare that relative education inequality in obesity in New York decreased from 1990 to 2002. The standard *RCI*s summarizing the two curves also reflect the decrease in disparity, going from –0.284 in 1990 to –0.125 in 2002. As was mentioned at the outset, however, we do not believe that disparity is all that matters. We also are concerned with the average health of the population, and the estimated obesity rate in New York more than doubled over this period, from 9.8% in 1990 to 20.6% in 2002. Figure 20 (page 59) shows the absolute concentration curves, which clearly reflect the increase in obesity among all groups. Inspection of the education-group-specific obesity rates reveals that, in general, the education disparity in obesity declined because of increasing obesity rates, particularly among the *middle- and better*-educated groups. When we incorporate the adverse changes in overall population rates of obesity with the changes in disparity, the change in the Health Achievement Index (for which larger values are worse because the health outcome, obesity, is negative) indicates that things became worse, having increased from 0.13 in 1990 to 0.23 in 2002.

Figure 19. Relative Concentration Curves for Educational Disparity in Obesity in New York State, BRFSS, 1990 and 2002

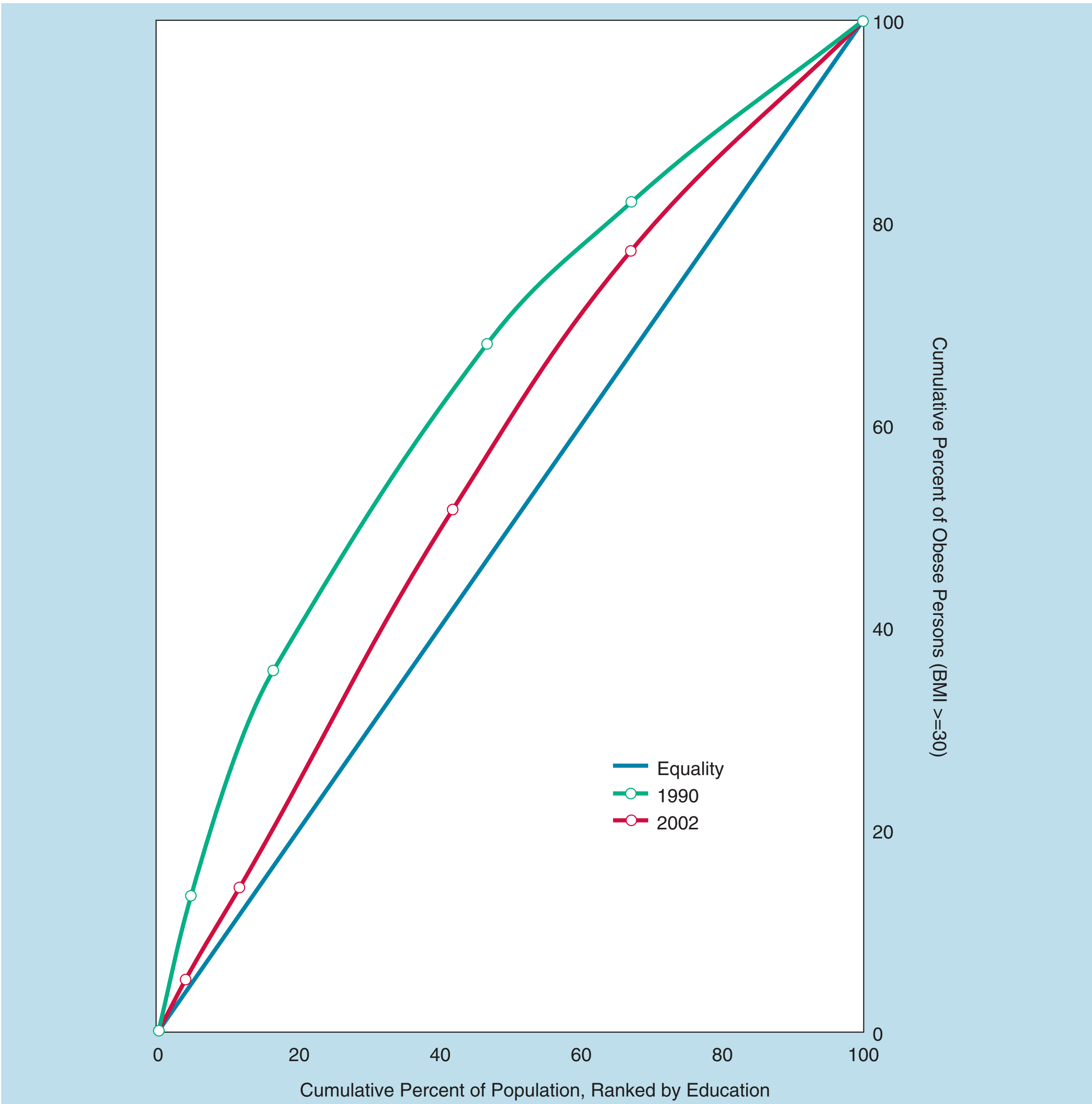


Figure 20. Absolute Concentration Curves for Educational Disparity in Obesity in New York State, BRFSS, 1990 and 2002