5

Health Outcome #3: Adult Health

Child mortality and nutrition status, considered in chapters 3 and 4, respectively, are important indicators of population health. But they provide only a partial picture of the level and distribution of health in a population. Survival is a rather crude indicator of health that ignores all aspects of health-related quality of life. Anthropometrics do indicate quality of life but only in a very partial manner. They are not sensitive to many health problems and are of relatively limited use as indicators of adult health status. To examine inequalities in general health in a population, a measure of health is required that is sensitive to a wide range of health problems and is informative about the health of adults. The literature on health status or health-related quality of life measurement is vast (see, e.g., Patrick and Chiang [2000]). In this chapter, we restrict attention to the measurement of self-reported adult health in the context of general population health inequalities.

Although health is intrinsically a multidimensional concept, for many purposes the interest is in an overall measure that collapses the separate dimensions into one construct. Several index-scoring algorithms have been developed for a number of generic health profiles, such as the SF-36 (Brazier et al. 1998), the Euroqol-5D (Busschbach et al. 1999), the McMaster health utility index (HUI) (Feeny et al. 2002), and more recently, the index fielded in the World Health Organization (WHO) World Health Surveys (Salomon et al. 2002). Such aggregated measures are preferable to others that either treat health as unidimensional or restrict attention to a single dimension, but their availability is usually restricted to health interview surveys, which have very limited information on living standards and so are often not suitable for the analysis of socioeconomic inequalities in health.

Besides the distinction between self-perceived and observed health indicators introduced in chapter 2, the types of indicators typically available for health equity analysis can be categorized under the headings medical, functional, and subjective (Wagstaff et al. 1991). Self-perceived indicators could fall into all three categories; observed indicators are either medical or functional. Medical indicators measure health as defined in relation to deviation from medical norms, such as the presence of certain diseases, conditions, or handicaps. Examples are lists on which the respondent indicates the presence of chronic or acute conditions, possibly diagnosed by a physician. There may be an indication of the duration of the condition. Functional indicators define health in relation to a lack of ability to perform "normal" tasks or roles. Examples include lists of impaired activities of daily living (ADL) or the number of days in a certain period that activities were restricted. According to a subjective model, health is defined in relation to the individual's

overall perception of his or her health or the changes therein, possibly relative to that of other people of a similar age. Typical examples here include the question, "How do you rate your health in general—excellent, good, fair, or poor?" or a question asking whether respondents feel that their health has improved or deteriorated during the past year. It is advisable to use these various measures alongside one another to obtain a better picture of the distribution of health in a population.

In the next section of this chapter, we illustrate the use of different types of adult health indicators—medical, functional, and subjective—to describe the distribution of health in relation to socioeconomic status (SES). One may wish to examine the distribution of health in relation to SES conditional on third factors, such as age and sex, which are correlated with both health and SES. In the third section, we demonstrate how to standardize health distributions for differences in demographic composition of SES groups and so provide a more refined description of socioeconomic inequality in health. The final section considers the extent to which the measurement of health inequality is biased by socioeconomic differences in the reporting of health.

Describing health inequalities with categorical data

Some health survey questions demand simple yes or no responses. From these, samples can be divided into fractions of ill and not ill and inequalities in illness rates analyzed. But many questions have ordered response categories, for instance, self-assessed health (SAH) is (i) very good, (ii) good, (iii) fair, (iv) poor, or (v) very poor. Such answers cannot simply be scored as for example, 1,2,3,4,5 because the true scale will not be equidistant between categories. Several methods of scaling SAH for the purpose of inequality measurement have been tried:

a. Dichotomize the multiple-category responses and measure health as the percentage of individuals with that characteristic, that is, those who report their health to be "less than good." This practice avoids the imposition of some scale that is assumed to indicate how much more health is enjoyed in one category compared with another for any one individual. But it obviously results in a loss of information and requires the introduction of an arbitrary cutoff point (Wagstaff and van Doorslaer 1994). If the threshold at which "less than good health" is reported varies across cultures and/or population subgroups, then the dichotomous indicator will not indicate variation in prevalence of a given level of health across countries and/or socioeconomic groups (c.f. Salomon et al 2004).

b. Use a scoring algorithm to construct a scale that has been validated in another context (e.g., Hays et al. 1998). One example is the indicator of functional limitations or ADL index as proposed by the RAND-MOS researchers (Hays et al. 1998). It is defined simply as the sum of all activities scored as 0 if "unable to do," 50 if "able with difficulty," and 100 if "able without any difficulty." This sum ranges between 0 and k*100, where k is the number of activities, but can be rescaled to (0,1) using ADL index = (max-sum)/(max-min), where max and min are the sample maximum and minimum sums, respectively. Direct use of generic index scores (such as the HUI, the SF-36, or the WHO index) is also based on the use of a "scoring" algorithm derived from a (multi-attribute utility) valuation exercise (Brazier et al. 1998; Feeny

et al. 2002; Salomon et al. 2002). The relative weights of the various health dimensions and items are then derived from (possibly other) respondents' answers to health (utility) valuation questions. One option is to attribute to each SAH category the mean, or median, scores of the index value (e.g., mean SF-36 score) calculated for the same SAH categories from some other data source in which both types of health measures are available.

c. If no other information on the distribution of health across response categories is available, one can proceed by arbitrarily assuming a functional form for the distribution. The aim is to exploit the full range of categories in the SAH question without imposing the unrealistic assumption of equal distances between categories. One proposed (but arbitrary) procedure is to assume that the observed frequency distribution across the SAH categories is generated by a latent health variable following a standard lognormal distribution (Wagstaff and van Doorslaer 1994). Then, the inverse of the cumulative lognormal distribution gives the cut points corresponding to the observed frequency distribution. Category scores can then be obtained as the expected values within each of the intervals defined by the cut points.

d. An alternative to method c is to generate predictions of an underlying latent variable using an ordered probit/logit or an interval regression model (see chapter 11) and to rescale these predictions to a 0-1 interval using index = (max-sum)/(max-min). If (external) information on the actual distribution of a continuous health measure is available (e.g., from another survey), then this can be used to scale the responses (van Doorslaer and Jones 2003). This has the same aim as method c but estimates the expected values of a latent health index given SAH responses and covariates and an assumed distribution of the error term (normal or logistic). A problem with that approach is that the measures then become highly dependent on the variables included in the prediction equation.

Allison and Foster (2004) introduce a method of obtaining a partial inequality ordering of SAH distributions that is invariant to the scaling of SAH. This is a significant advance in the literature, but it does have two limitations. First, the inequality of two SAH distributions can be compared only when their median categories coincide. Second, the method allows comparison of total inequality in SAH and not in socioeconomic-related inequality in SAH.

Table 5.1 shows the distributions of adult health across quintiles of equivalent expenditure in Jamaica derived from the 1989 Survey of Living Conditions (SLC) for 12 different indicators. All of the medical model indicators are dichotomous except the number of illness days. Two of the functional model indicators are dichotomous, the third is a count (number of restricted-activity days), and the fourth is the ADL index transformed to a (0,1) scale as described in procedure b above. The subjective indicator is SAH with five response categories. From that, two dichotomous indicators of less than good health and poor health are created. A third indicator (SAH index [lognormal]) is constructed following procedure c above, assuming a lognormal distribution for latent health. The final indicator (SAH index [HUI]) is derived by assigning the mean SAH-category-specific McMaster HUI values estimated from Canadian data to the corresponding SAH categories in the Jamaican SLC. While avoiding the assumption of lognormality, this involves imposing the obviously strong assumption that within SAH categories, health is on average equal in Jamaica and Canada.

Table 5.1 *Indicators of Adult Health, Jamaica, 1989*
Population and Household Expenditure Quintile Means

		Household expenditure quintiles				
	Total	Poorest	2	3	4	Richest
Medical model: 4-week illness						
Any illness or injury?	0.144	0.163	0.135	0.141	0.143	0.140
Number of illness days	1.675	2.279	1.643	1.715	1.550	1.218
Any acute illness (<4 weeks)	0.088	0.080	0.085	0.087	0.094	0.093
Any chronic illness (>4 weeks)	0.055	0.083	0.049	0.055	0.047	0.044
Functional model: activity limitations						
Any major limitation	0.147	0.203	0.169	0.153	0.101	0.115
Any minor limitation	0.260	0.334	0.314	0.255	0.199	0.205
Num. of restricted activity days	0.825	1.307	0.818	0.807	0.752	0.461
ADL index	0.898	0.852	0.885	0.899	0.930	0.924
Subjective model: self-perceived						
Less than good SAH	0.170	0.238	0.193	0.169	0.134	0.120
Poor SAH	0.058	0.097	0.066	0.061	0.035	0.034
SAH index (lognormal)[a]	1.576	1.948	1.621	1.594	1.404	1.331
SAH index (HUI)[b]	0.877	0.856	0.874	0.876	0.887	0.891

Note: a. Larger values indicate worse health.
        b. Larger values indicate better health.
Source: Authors.

All indicators show health to be lower among poorer quintiles, but relative differences in health between the richest and poorest quintiles vary across the indicators.

Demographic standardization of the health distribution

In the analysis of health inequality, the basic aim of standardization is to describe the distribution of health by SES conditional on other factors, such as age and sex. This will be referred to as the age-sex standardized health distribution. It is interesting only in the case in which two conditions are satisfied: (i) the standardizing variables are correlated with SES and (ii) they are correlated with health. It is important to realize that the purpose is not to build a causal, or structural, model of health determination. The analysis remains descriptive, but we simply seek a more refined description of the relationship between health and SES.

There are two fundamentally different ways of standardizing, direct and indirect. Direct standardization provides the distribution of health across SES groups that would be observed if all groups had the same age structure, for example, but had group-specific intercepts and age effects. Indirect standardization, however, "corrects" the actual distribution by comparing it with the distribution that would be observed if all individuals had their own age but the same mean age effect as the entire population.

Both methods of standardization can be implemented through regression analysis. In each case, one can standardize for either the full or the partial correlations

of the variable of interest with the standardizing variables. In the former case, only the standardizing, or confounding, variables are included in the regression analysis. In the latter case, nonconfounding variables are also included, not to standardize on these variables but to estimate the correlation of the confounding variables with health conditional on these additional variables. For example, take the case in which age is correlated with education and both are correlated with both health and income. If one includes only age in a health regression, then the estimated coefficient on age will reflect the joint correlations with education and, inadvertently, one would be standardizing for education, in addition to age, differences by income. One may avoid this, if so desired, by estimating the age correlation conditional on education.

Indirect standardization

The most natural way to standardize is by the indirect method, which proceeds by estimating a health regression such as the following:

$$(5.1) \qquad y_i = \alpha + \sum_j \beta_j x_{ji} + \sum_k \gamma_k z_{ki} + \varepsilon_i,$$

where y_i is some indicator of health; i denotes the individual; and α, β, and γ are parameter vectors. The x_j are confounding variables for which we want to standardize (e.g., age and sex), and the z_k are nonconfounding variables for which we do *not* want to standardize but to control for in order to estimate partial correlations with the confounding variables. In the instance that we want to standardize for the full correlations with the confounding variables, the z_k variables are left out of the regression. Ordinary least squares (OLS) parameter estimates ($\hat{\alpha}$, $\hat{\beta}_j$, $\hat{\gamma}_k$), individual values of the confounding variables (x_{ji}), and sample means of the nonconfounding variables ($\bar{z}_k$) are then used to obtain the predicted, or "x-expected," values of the health indicator $\hat{y}_i^X$:

$$(5.2) \qquad \hat{y}_i^X = \hat{\alpha} + \sum_j \hat{\beta}_j x_{ji} + \sum_k \hat{\gamma}_k \bar{z}_k.$$

Estimates of indirectly standardized health, $\hat{y}_i^{IS}$, are then given by the difference between actual and x-expected health, plus the overall sample mean ($\bar{y}$),

$$(5.3) \qquad \hat{y}_i^{IS} = y_i - \hat{y}_i^X + \bar{y}.$$

The distribution of $\hat{y}_i^{IS}$ (e.g., across income) can be interpreted as the distribution of health that would be expected to be observed, irrespective of differences in the distribution of the x's across income. A standardized distribution of health across quintiles could be generated, for instance, by averaging $\hat{y}_i^{IS}$ within quintiles.

Direct standardization

The regression-based variant of direct standardization proceeds by estimating, for each SES group g, an equation such as the following:

$$(5.4) \qquad y_i = \alpha_g + \sum_j \beta_{jg} x_{ji} + \sum_k \gamma_{kg} z_{ki} + \varepsilon_i,$$

which is a group-specific version of equation 5.1. OLS estimates of the group-specific parameters ($\hat{\alpha}_g, \hat{\beta}_{jg}, \hat{\gamma}_{kg}$), sample means of the confounding variables ($\bar{x}_j$), and group-specific means of the nonconfounding variables ($\bar{z}_{kg}$) are then used to generate directly standardized estimates of the health variable $\hat{y}_i^{DS}$ as follows:

$$(5.5) \qquad \hat{y}_i^{DS} = \hat{y}_g^{DS} = \hat{\alpha}_g + \sum_j \hat{\beta}_{jg}\bar{x}_j + \sum_k \hat{\gamma}_k\bar{z}_{kg}.$$

Note that this method immediately gives the standardized health distribution across groups because there is no intragroup variation in the standardized values.

For grouped data, both the direct and indirect methods answer the question, "What would the health distribution across groups be if there were no correlation between health and demographics?" But their means of controlling for this correlation is different. The direct method uses the demographic distribution of the population as a whole (the $\bar{x}_j$), but the behavior of the groups (as embodied in the $\hat{\beta}_{jg}$'s and $\hat{\gamma}_{kg}$'s). The indirect method employs the group-specific demographic characteristics (the $\bar{x}_{jg}$), but the populationwide demographic effects (in $\hat{\beta}_j$ and $\hat{\gamma}_k$). The advantage of the indirect method, however, is that it does not require any grouping and is equally feasible at the individual level. The results of the two methods will differ to the extent that there is heterogeneity in the coefficients of *x* variables across groups because the indirect methods impose homogeneity and the difference will depend on the grouping used in the direct method.

Example—age-sex standardization of an SAH distribution, Jamaica 1989

Table 5.2 shows household expenditure quintile means of SAH in Jamaica with categories coded according to mean HUI values for corresponding SAH categories from Canadian data. Results are presented for nonstandardized means and for means standardized for age and sex by both direct and indirect methods. For each method, results are given with and without control for household expenditure when estimating the age/sex effects on SAH. In the former case, household expenditure is being treated as a *z* variable in equations 5.1 and 5.4. Without doing this, the age-sex effects will pick up the omitted expenditure effects and there is a danger that standardization will not only correct for differences in demographic composition but will also remove part of the "effect" of household expenditure on

Table 5.2 Direct and Indirect Standardized Distributions of Self-Assessed Health Household Expenditure Quintile Means of SAH Index (HUI)

| | | Standardized | | | |
| | | Indirect | | Direct | |
Quintiles	Observed	Excl. expenditure	Incl. expenditure	Excl. expenditure	Incl. expenditure
Poorest	0.8564	0.8683	0.8682	0.8669	0.8668
2	0.8742	0.8739	0.8738	0.8777	0.8777
3	0.8763	0.8772	0.8772	0.8756	0.8756
4	0.8870	0.8804	0.8805	0.8816	0.8816
Richest	0.8913	0.8859	0.8860	0.8862	0.8862

Source: Authors.

SAH. In fact, the four standardized distributions are very similar in this example, suggesting that there is little heterogeneity in the age-sex effects across quintiles and that omitting expenditure from the SAH regressions does not bias these effects. However, standardization, by whichever method, does reduce the measured rich-poor disparities in SAH.

Computation for demographic standardization

Computation of standardized quintile means such as those in table 5.2 is straight-forward in a package such as Stata. Demographics can be represented by age-sex specific dummies. In the example above, we use five age groups (18–34, 35–44, 45–64, 65–74, 75+) for each gender to give 10 dummies (`fage1`, `fage2`, etc.). Label the health variable y; in the example it is SAH index (HUI). For illustration, (log of) household expenditure (`lnhhexp`) will be included in the standardizing regression as a control (*z*) variable along with years of education (`education`) and a dummy for employment (`works`).[1] Let there be a sample weight variable, `weight`.[2]

INDIRECT STANDARDIZATION   First, estimate equation 5.1.

```
global xvar "mage2 mage3 mage4 mage5 fage1 fage2 fage3 fage4
fage5"
global zvar "lnhhexp education works"
regress y $xvar $zvar [pw=weight]
```

If control (*z*) variables were not included in the regression, then predicted values (equation 5.2) would be obtained immediately using,

```
predict yhat
```

When control variables are included, as above, they must be set to their mean values before predictions are obtained. This can be done by using loops, as follows:

```
foreach z of global zvar {
      quietly sum `z' [aw=weight]
      gen `z'_mean = r(mean)
      gen `z'_copy = `z'
      replace `z' = `z'_mean
}
predict yhat
foreach z of global zvar {
      replace `z' = `z'_copy
      drop `z'_copy `z'_mean
}
```

Standardized values (equation 5.3) are then computed by the following:

```
qui sum y [aw=weight]
gen yis = y-yhat + r(mean)
```

---

[1]In the Jamaican example, `lnhhexp` was the only *z* variable. We include others here to make the computation more generally applicable.

[2]The Jamaican sample was self-weighting, but we illustrate a more general case with weights.

DIRECT STANDARDIZATION   Direct standardization requires group-specific estimates of the regression coefficients. We illustrate the procedure when groups are defined as expenditure (hhexp) quintiles. Compute a categorical variable identifying quintiles, as follows:

```
xtile quintile=hhexp [pw=weight], nq(5)
```

Use a loop to obtain estimates of population means of the standardizing variables to be used in the prediction equation (equation 5.5):

```
foreach x of global xvar {
        qui sum `x' [aw=weight]
        gen `x'_mean = r(mean)
        gen `x'_copy = `x'
}
```

Now loop through each quintile group, running a regression for each one and obtaining predicted values with standardizing variables at population means and control variables at group means, as in equation 5.5:

```
gen yds=.
forvalues i=1/5 {
    qui regr y $xvar $zvar [pw=weight] if quintile==`i'
    foreach x of global xvar {
        replace `x' = `x'_mean
    }
    foreach z of global zvar {
        qui sum `z' [aw=weight] if quintile==`i'
        gen `z'_mean = r(mean)
        gen `z'_copy = `z'
        replace `z' = `z'_mean
    }
    predict yds`i' if e(sample)
    replace yds=yds`i' if quintile==`i'
    foreach z of global zvar {
        replace `z'=`z'_copy
        drop `z'_mean `z'_copy
    }
    foreach x of global xvar {
        replace `x'=`x'_copy
    }
}
```

The predicted variable, yds, is the directly standardized mean health for each quintile. The quintile means of nonstandardized and indirectly and directly standardized health can be compared using the following:

```
tabstat y yis yds [aw=weight], by(quintile)
```

Conclusion

Most of the health indicators obtained from surveys are self-reported. Besides being convenient, these indicators have been demonstrated to be effective in capturing health variation in a population. Self-assessed health, in particular, has been shown to predict mortality even conditional on detailed physiological measures of health (Idler and Benyamini 1997; van Doorslaer and Gerdtham 2003). Inevitably, however, there is heterogeneity in the reporting of health. Perceptions of health depend on expectations about health. If these expectations differ systematically across the population, comparison across subgroups becomes problematic. If, for instance, the poor systematically understate their true health, then the self-reported measures will not reflect the full extent of health inequalities.

Differences in health disparities derived from self-reported and more objective indicators are suggestive of systematic variation in reporting behavior. In Australia, Aboriginals tend to report better health despite being seriously disadvantaged according to more objective health indicators, such as mortality (Mathers and Douglas 1998). In India, the state of Kerala consistently shows the highest rates of reported morbidity, despite having the lowest rates of infant and child mortality (Murray 1996). Wagstaff (2002) notes that income-related inequalities in objective indicators of ill health, such as malnutrition and mortality, tend to be higher than those in subjective health. Moreover, the use of subjective health measures has led to some improbable health gradients in developing countries, with the rich reporting worse health than the poor (Baker and Van der Gaag 1993), which seems quite inconsistent with substantial pro-rich inequality in infant and child mortality rate and in anthropometric indicators (Gwatkin et al. 2003).

Formal testing has found evidence of reporting differences across age-sex groups but not across socioeconomic groups in Sweden and Canada (Lindeboom and van Doorslaer 2004; van Doorslaer and Gerdtham 2003). Milcent and Etile (2006) find some evidence of reporting differences by income in the middle categories of SAH and suggest that bias in the measurement of health inequality can be minimized by dichotomizing SAH into an indicator of poor health. This evidence is encouraging for the measurement of health inequality in developed countries, but one may worry that the bias is greater in developing countries where differences in the conception of illness by education and income levels may be greater. A promising solution to the reporting heterogeneity problem is to identify reporting differences from evaluations of given health states represented by hypothetical case vignettes and then to purge these reporting differences from individuals' evaluations of their own health (Salomon et al. 2004; Tandon et al. 2003). Case vignettes have been collected in the WHO World Health Surveys. Bago d'Uva et al. (2006) use vignettes to test for reporting heterogeneity by demographic and socioeconomic factors in data from China, India, and Indonesia. They find that reporting differences by sociodemographic groups are significant, but that, in general, the size of the reporting bias in measures of health disparities is not large.[3]

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[3]Reporting bias is likely to be larger in response to questions about illness in the past four weeks, a common question in the World Bank Living Standards Measurement Surveys. The answer to that question may be influenced by conceptions of illness, access to health care, and work activity (Makinen et al. 2000).

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