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The Social Distribution of Health: Estimating Quality-Adjusted Life Expectancy in England

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ABSTRACT

Objective: To model the social distribution of quality-adjusted life expectancy (QALE) in England by combining survey data on health-related quality of life with administrative data on mortality. **Methods:** Health Survey for England data sets for 2010, 2011, and 2012 were pooled (n = 35,062) and used to model health-related quality of life as a function of sex, age, and socioeconomic status (SES). Office for National Statistics mortality rates were used to construct life tables for age-sex-SES groups. These quality-of-life and length-of-life estimates were then combined to predict QALE as a function of these characteristics. Missing data were imputed, and Monte-Carlo simulation was used to estimate standard errors. Sensitivity analysis was conducted to explore alternative regression models and measures of SES. **Results:** Socioeconomic inequality in QALE at birth was estimated at 11.87 quality-adjusted life-years (QALYs), with a sex difference of 1 QALY. When the socioeconomic-sex subgroups are ranked by QALE, a differential of 10.97 QALYs is found between the most and least healthy quintile groups. This differential can be broken down into a life expectancy difference of 7.28 years and a quality-of-life adjustment of 3.69 years. **Conclusions:** The methods proposed in this article refine simple binary quality-adjustment measures such as the widely used disability-free life expectancy, providing a more accurate picture of overall health inequality in society than has hitherto been available. The predictions also lend themselves well to the task of evaluating the health inequality impact of interventions in the context of cost-effectiveness analysis.

Keywords: health inequalities, health surveys, population health, quality-adjusted life-years.

Introduction

There are various ways of summarizing a population's overall lifetime experience of health by combining information on both mortality and morbidity. Perhaps the best known metrics are disability-free life expectancy (DFLE) and healthy life expectancy (HLE), which subtract years from life expectancy (LE) using a binary indicator of ill-health or disability. Recent efforts have been made to incorporate more sophisticated measures of morbidity into health expectancy estimates. Studies by Mathers et al. [1] and Salomon et al. [2] combined injury and disability prevalence rates with a set of disability weights to estimate disability- or health-adjusted LE, thereby reflecting the severity of conditions, not just their presence. Quality-adjusted life expectancy (QALE) is another recent approach to estimating health expectancy that uses a continuous ratio scale variable to measure morbidity, thus enabling it to incorporate detailed multiattribute data on health-related quality of life (HRQOL). The rising popularity of the quality-adjusted life-year (QALY) metric through its use in health technology assessment has led to its inclusion in national health surveys, affording researchers the opportunity to estimate QALY weights for a wide range of population subgroups using large, nationally representative data sets. Implementation of the QALE metric in health inequality research, however, has been limited to regional analyses [3], despite widespread application of other health expectancy indicators to inequality measurement [4,5].

As well as health inequality measurement, estimating the social distribution of QALE can potentially play a role in addressing policy trade-offs between improving total population health and reducing unfair health inequality [6,7]. This form of "equity-efficiency trade-off" can sometimes occur, for example, if a policy intervention is cost-effective but increases health inequality or if a policy intervention reduces health inequality but is not cost-effective. Although health inequality reduction objectives are prominent in the rhetoric of public health bodies [8], routine economic evaluation of health care and public health interventions considers only cost-effectiveness. The baseline social distribution of health that is estimated in this study can potentially be used to model the distributional impacts of future interventions in distributional cost-effectiveness analysis [9], which allows equity and efficiency to be traded-off explicitly in the modeling process.

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The aim of this study is to generate predictions of QALE for age, sex, and socioeconomic groups using nationally representative survey data and mortality rates. By combining these with the associated population estimates, we then create a rank ordering of the population by QALE that reflects social inequalities in health. The merits of this endeavor are twofold. First, a QALE distribution will allow for the effects of health care and public health interventions to be modeled directly on population health using methods and metrics consistent with cost-effectiveness analysis. Second, using the QALY in population health measurement provides a more sensitive indicator of morbidity as compared with DFLE and HLE.

Methods

Our analysis has four distinct stages. First, using data in the Health Survey for England (HSE), we predict HRQOL weights as a function of age, sex, and socioeconomic status (SES), with the latter measured by the index of multiple deprivation (IMD), a small area deprivation indicator. Second, predictions of life expectancy are generated from national mortality data for age-sex-SES groups using life tables. Both stages are then combined to create a multivariate prediction of QALE for age-sex-SES groups. Last, population estimates for each group are used to create the social distribution of health.

Data and Variables

The analysis uses pooled data from the three most recent rounds of the HSE in 2010, 2011, and 2012, with a combined sample size of 35,062. The HSE is an annual series that monitors a range of health conditions and risk factors for the noninstitutionalized population. It uses a multistage stratified probability sampling design with a sampling frame of Postcode Address File that tries to ensure that every member of the population has an equal chance of being selected, details of which are covered in Boniface et al. [10].

Health status is measured using the EuroQol five-dimensional questionnaire (EQ-5D) [11], a generic instrument used in health technology assessment around the world to assess the treatment effects of interventions for a wide range of different health conditions [12,13]. The EQ-5D is a questionnaire that asks respondents to rate their own health in five dimensions: pain, mobility, anxiety/depression, self-care, and usual activities. In the original three-level EQ-5D version used in this study, subjects rate their health on each dimension using one of three possible levels: no problems, some problems, or severe problems. This generates a possible 245 health states when including the two additional states "unconscious" and "dead" ($3 \times 3 \times 3 \times 3 \times 3 + 2$). A single index figure is then given to each health state on the basis of a country-specific tariff. The standard UK value set estimated by Dolan et al. [14] was applied to our data. This analysis is restricted to adults aged 16 years and older, leaving a sample size of 25,320. This is because the EQ-5D is not responsive to the HRQOL for children younger than this age for whom there are other more appropriate instruments [15].

The SES variable used was the most recently available IMD from 2010. This is a weighted area deprivation index of 38 variables covering seven dimensions of deprivation (employment, income, education, health, crime, living environment, and housing/services) that is given to each of the 32,482 lower layer super output areas in England. In 2010, the median layer super output area population was 1551 with an interquartile range of 1429 to 1708 and 99% had fewer than 2731 residents. More information on the methods used to construct the IMD can be found in McLennan et al. [16]. The raw IMD score is not reported in the HSE; thus, the variable used in the regression analysis is the population IMD quintile group, with the first quintile group representing the most deprived and those in the fifth having the lowest deprivation. The mortality data are reported for IMD decile groups; thus, we apply the same HRQOL scores to both decile groups contained in a quintile group (i.e., quintile group 1 to decile groups 1 and 2) during the QALE prediction process outlined below.

We focus on age, sex, and SES as covariates because these are often of interest in public health campaigns and are associated with large inequalities in population health. An additional advantage of using this set of variables is that they are readily available in the data used in cost-effectiveness studies, allowing for the easy estimation of subgroup-specific costs and effects. Data on age and sex are routinely collected in any study or survey, while IMD can be ascertained from an individual's postcode.

Regression Analysis

The distribution of EQ-5D utility score is heavily skewed: the proportion of individuals reporting severe problems on any of the dimensions is rare, ranging from 0.18% for mobility to 4.29% for pain, whereas the number reporting perfect health is more than half, at 52.72%. In addition, the utility data have an upper ceiling of 1. Although these properties suggest that a linear regression model may not be appropriate, we use ordinary least squares (OLS) as our estimator for two principal reasons. First, previous studies have shown OLS to perform well in comparison with other types of estimators when used to model HRQOL, particularly when using large sample sizes such as those in the HSE [17–19]. Second, the principal diagnostic instrument for judging accurate HRQOL prediction is accurate mean EQ-5D scores for age-sex-SES groups because it is these that are used to adjust the life tables in the QALE process described below. This means that any potential imprecision of individual predicted scores caused by applying a linear model is not a cause for concern. Using OLS also has an additional benefit, in that the estimated coefficients can be directly interpreted and used to predict the EQ-5D scores (and therefore the QALE) for different populations than the one used in this study. We also perform sensitivity analysis using alternative two-part and Tobit models, as described below.

All statistical analyses are performed in Stata 12. Standard survey data analysis tools are used to incorporate the probability weights supplied in the data and to account for the fact that scores within households, the primary sampling unit, can be correlated (which may distort statistical inference by reducing the standard errors).

Another issue was missing HRQOL data, with significant item nonresponse occurring within the sample. A total of 3177 (12.6%) observations were missing a utility score, with these individuals, on average, tending to be older, male, nonwhite, and living in more deprived areas than the complete cases. A logit model regressing the probability of "missingness" on our variables of interest was used to determine whether the data are missing completely at random—that missingness is not systematic or related to individual characteristics [20]. This found that age, race, and sex (though not deprivation level) are statistically significant predictors ($P < 0.01$), correctly predicting 88% of the cases with missing values. This justified the use of predictive mean matching to impute missing values, given the non-normal distribution of utility scores. Following the recommendations of White et al. [21], the number of imputations is set at 5, while the number of values from which the EQ-5D is drawn in the predictive mean matching process is set at 3. Following imputation, predicted EQ-5D scores are generated by regressing individual utility values on age, sex, and SES group. From these we