Inequalities in self-assessed health in the Health Survey of England

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Abstract

Objective: To determine the level of health inequalities and decompose the factors that are associated with them, using different approaches based on the analysis of self-assessed health of individuals, and to assess the suitability of these methods.

Methods: Data from the Health Survey of England 1996 are used. Ordinary least squares, interval regression and ordered probit models are used to establish the relationship between measures of inequality based on self-assessed health and on the EQ-5D index of health related quality of life. Decomposition analysis explores the factors that are associated with health inequality.

Results: The interval regression approach provides the best match between results based on self-assessed health and those based on the EQ-5D index.

Conclusions: Comparison of the results of the regression models shows that the interval regression can best explain inequality in EQ-5D, the model accounted for 43.9%. (155 Words)

Keywords: Equity, inequality, EQ-5D, self-assessed health

Full word count: 4,624

1. Introduction

Equity has been a broad topic of debate in the health sector. In the United Kingdom, discussions about this issue can be traced back to the 19th century (Benzeval et al, 1995). The appearance of health inequalities has been associated with socio-economic differences among groups in society as well as among individuals within those groups (see e.g., Black et al., 1995, Marmot and Wilkinson, 1999). Since reducing inequalities in health is an explicit objective of health policy, its measurement is essential for the design and evaluation of health policies. Government agencies and researchers have developed methodologies aimed to accomplish this measurement.

On account of this concern, health economists have proposed methodologies to measure inequality (Wagstaff and van Doorslaer (2000)). These methods have taken advantage of the development of new econometric techniques and the improvement in computational resources. Despite the methodological progress achieved, the quality and reliability of the analysis not only lies on the methods but also on the availability of data. The majority of the methodologies available for inequality analysis require information of health status at the individual level on a cardinal scale; however, this is not always available. Most general population surveys only include information of self-assessed health, where individuals classify their own health into a limited number of categories. Although information about self-assessed health is widely available, its use to assess health inequalities presents some methodological problems due to its categorical and ordinal nature. However, finding a relationship between this categorical variable and a cardinal measure of health-related quality of life (HRQoL) would allow us to analyse health inequalities from self-assessed health information. In order to achieve this, we have used information from the Health Survey of England (HSE) of 1996 and applied the methods proposed by van Doorslaer and Jones (2003) to examine the validity of their approach. This exploits the fact that the 1996 HSE includes information on self-assessed health and an index of HRQoL, based on the EuroQol instrument.

We apply the interval regression model, proposed by van Doorslaer and Jones (2003), assuming the existence of a direct association between the empirical distribution of the self-assessed variable and the distribution of the HRQoL index that allows us to fix cut-points for the boundaries of the categorical variable. The estimates provided by the regression are used to estimate health inequality. For comparison, we also use an ordered probit model for self-assessed health and the results are re-scaled to provide a measure of HRQoL. Finally, we compare the results of both approaches to an ordinary least squares regression on the actual HRQoL index and compare the results.

Due to the lack of information on incomes of the respondents in the HSE, the analysis of health inequality is based on the Gini coefficient for total health inequality instead of the concentration index for income-related health inequality. However the two concepts are directly related to each other, with income-related inequality being a fixed proportion of total inequality (see van Doorslear and Jones (2003) for details).

2. Methods

2.1. Measuring health status

We assume that an individual's health status is associated with a set of variables related to that individual. While some of these variables are inherited and difficult to change, others are imposed by socio-economic conditions and thus feasible to modify through policy. The set of variables is denoted by x_i where i refers to the i^{th} individual. It is possible to specify a regression model for the health status of an individual (y_i):

$$y_i = \beta \cdot x_i + \varepsilon_i \qquad (1)$$

where ε_i is an error term. However, in order to estimate a model like the one shown in (1), besides information about the socio-economic characteristics, it is necessary to know the health status of each individual. In reality, survey data often provides information about how individuals assess their own health status according to two or more categories; e.g. "poor", "fair", "good", "very good", "excellent". This evaluation is called *Self-assessed Health*, (from now on SAH) and it is clear that these categories are ranked or ordered, e.g. a "poor" health status is worse than a "fair" one and so on. As SAH is a categorical variable it is necessary to apply an ordered probit or an interval regression model, which will be described below.

2.2. Measurement of health using EuroQol

The measure of HRQoL collected in the Health Survey of England is based on the EuroQol instrument (EQ-5D). This is one of the methodologies currently available to measure health status of individuals. It was developed in 1987 as an initiative to create a standard methodology to describe and value health on a cardinal scale (Brooks, 1996). The instrument is based on the responses to a questionnaire. First respondents rate their health status in five dimensions: mobility, self care, usual activities, pain/discomfort, anxiety/depression. Each dimension is divided in three levels or categories; as a result, the health status is defined by the combination of the answers to each of the five dimensions. This combination of answers can deliver 243 possible health states. Then respondents rate their health in a 0-100 scale, as well as their judgment of 13 different health states.

In order to obtain a cardinal scale, scores are applied to the information on the five dimensions transforming them into a single utility index (Badia et al., 1999). That is to say, from the 243 categorical outcomes, a continuous index is computed. There are a variety of scores available, derived from different population surveys, reflecting the preferences and values assigned by those populations to different health states. These include the York formula and the European VAS value set (Szende, 2002). Since different populations, according to their backgrounds, can have different valuations of health, the indices obtained can differ with the score values applied. Thus it is important to choose scores that are related to the population of interest.

2.2.1. Ordered probit models

The ordered probit model assumes that individuals will report SAH in accordance with their true health status, as modelled in equation (1). As there are only a limited number of SAH categories to choose from, say $j=1, 2, 3, \ldots m$, individuals will report the first category, e.g. "poor", if their health status is below a cut-point value μ_1; or else they will report the next category of SAH ("fair") if their health status is above μ_1 but below a second cut-point value μ_2, and so on. When the SAH outcome is denoted as y_i, the model can be stated as:

$$y_i = j \text{ if } \mu_{j-1} < y_i^* \leq \mu_j \text{, for j=1, 2, 3, … m} \quad (2)$$

The variable y_i^* is said to be latent and can be decomposed in observable and unobservable components. The observable component in this case is based on the vector of socio-economic variables $\boldsymbol{x_i}$ as defined above, while the unobserved component ε_i is considered random (Train, 2002), normally distributed with zero mean and variance equal to 1, that is:

$$y_i^* = \beta \cdot x_i + \varepsilon_i, \qquad \varepsilon_i \sim \mathrm{N}(0,1) \quad (3)$$

Estimates of β and the cut-points μ_j can be obtained by maximum likelihood estimation. The predicted value of the latent variable y_i^* can be considered as a measure of health status of the i[th] individual which, once re-scaled to the interval [0,1], can be used as an utility proxy (van Doorslaer, and Jones, 2003).

2.2.2. Interval regression

This model, also known as grouped regression, is a variant of the ordered probit model that applies when the cut-point values are known. Having this extra information allows more efficient estimation of β and identifies the variance of the error term and, hence, the scale of y_i^* (van Doorslaer and Jones, 2003). In the case of SAH, the cut-point values can be calculated if there is external information available about the health status of individuals. In the present case, the HSE data includes EuroQoL tariffs, which can be used to scale the health status index (HSI from now on).

This approach is valid if there is a direct mapping from HSI to SAH, such that the ranking of individuals by HSI is the same as the ranking by SAH. Assuming the existence of this direct relationship between both distributions, then we can estimate the values of μ_j using a nonparametric approach. This task can be done by finding the quantiles of the empirical distribution function for the HSI that match the cumulative frequencies of the observations for each category of the SAH (van Doorslaer and Jones, 2003).

2.3. Measuring inequality

It is possible to measure inequality by using the Gini coefficient for health, as described by Wagstaff et al (1991). Under this approach, if we have information about a variable *'y',* denoting health of individuals, by plotting the cumulative proportion of *'y'* against the cumulative proportion of the individuals ranked by their health, we obtain a health Lorenz curve, *L,* whose shape give us a measure of the level of health inequality. A society with no inequalities in health would have a curve *L* lying exactly on a diagonal *D*, that corresponds to perfect equality. So the farther *L* is from *D*, the greater the level of inequality. The Gini coefficient (G) measure of the level of inequality is given by twice the size of the area between the Lorenz curve and the diagonal. With weighted data, the Gini coefficient can be computed using the formula given in Kakwani et al (1994) modified by van Doorslaer and Jones (2003). Although the formulas refer to the concentration index, we will apply them to compute the Gini coefficient.

2.4. Decomposition of inequality

Wagstaff, van Doorslaer and Watanabe (2003) advocate a method for decomposing Gini coefficients and concentration indices using a linear regression model for health. Because of the relation between y_i and $x_{ki,}$ as described in (1), the Gini coefficient can be decomposed in the following way,

$$G = \sum \left(\frac{\beta_k \cdot \bar{x}_k}{\bar{y}} \right) \cdot C_k + \frac{GC_\varepsilon}{\bar{y}} \qquad (4)$$

where $\bar{y}$ is the mean of y, $\bar{x}_k$ is the mean of x_k, C_k is the concentration index for each x_k based on the health rank, and $GC\varepsilon$ is the generalized concentration index for ε_i. From equation (4) it can be seen that the Gini coefficient is composed of two elements. The first element is equal to a weighted sum of the concentration indices of the k regressors; the weights in this case are the elasticity of y with respect to x_k. The second element of equation (4) arises from the residual term in (1).

3. Data and variable definitions

This study uses the Health Survey of England of 1996 (HSE). The HSE is a series of surveys conducted on behalf of the Department of Health of the United Kingdom, designed to keep track of the overall health of the country's population. The survey is executed every year in order to achieve a continuous monitoring of the current state and trends of health. The 1996 survey contains information on 20,388 individuals, including 4,404 under 18 years old. It was designed to collect data from persons living in private residential accommodation in England.

Although the HSE includes information about children and young persons, due to the design of the survey not all the information was collected for all the respondents, so for this study only data from individuals aged 18 years old or more are used. After excluding incomplete records, the sample selected for the analysis consisted of 15,414 individuals. For each individual, the survey collected information about socio-economic conditions and a measurement of health status obtained through the EuroQol methodology (HSI). The survey also incorporates a self-assessed dimension of health, consisting of five categories (SAH).

As described in the Methods section, the analysis is based on two measures of health. One is the SAH of each individual. During the survey respondents were asked, *"In general, would you say your health is?"*, with responses *Excellent, Very good, Good, Fair* and *Poor*. For the purpose of this study, categories "*Excellent*" and *"Very good"* were combined in one category (the reasons for this will become apparent below when we discuss the mapping from SAH to EQ-5D scores). Table 1 shows the distribution of responses.

Table 1 here

The second measure of health status in the survey is the EuroQol tariff (HSI), as described in the previous section. Initially this variable contained 252 observations (1.6%) with negative values, these were reassigned a value of 0 to facilitate the subsequent analysis; it was considered that the change would not have an important effect on the final results. The distribution of HSI is highly skewed towards the right, i.e. the upper values. This is can be seen in Table 2.

Table 2 here

3. Results

3.1. Distribution of Self-assessed Health and the Health Status Index

The distribution of HSI related to the SAH of individuals is shown in Table 3. From the table we can see that a relatively small fraction of the sample (4.1%) reported their health as "poor". This is despite the fact that, in this category, there are individuals with a HSI of 1.000, i.e. perfect health status. It is also noticeable that in all the SAH categories we can find individuals with the lowest HSI (0.000), even among those reporting their health as "very good" and "excellent". However, if we look at the mean of HSI we can observe that it increases for each category and the standard deviation decreases at the same time.

Table 3 here

According to the methodology proposed, using the assumed mapping between the HSI and the SAH, the quantiles corresponding to each SAH category were matched with the values of the HSI distribution. This process resulted in the values used in the interval regression model; see Table 4. It is important to note how the distribution becomes flat relatively fast, this is because more than half of the individuals have a HSI of 1; actually, the median of the sample is 1.000. Such characteristic results in the "good" and "very good/excellent" upper bounds having the same value (1.000), therefore the lower bound for the latter is also 1.000.

Table 4 here

3.2. Regressions Results

As explained in the methods section, regression models are used to study the mapping of the SAH latent variable linked to the HSI. In order to examine the functioning of the regression models chosen, comparisons must be made between the estimates of the models and the actual HSI.

The variables selected from the survey to measure socio-economic status for each individual are the following: age, gender, civil status, ethnic group, highest academic qualifications, social class, type of ownership/renting of the house they live in, type of location where they live, divided in two categories: rural or urban, NHS region. These are all measured as binary variables, defining the reference individual as a white woman living, in an urban area of the Northern and Yorkshire Region of the NHS, who owns her house, is married or cohabitating, from the social class III-skilled non-manual, whose highest academic qualification is an A-level, is currently employed and aged between 36 and 44 years old.

Table 5 presents descriptive statistics for the actual HSI, along with predictions based on OLS applied to the actual HSI (OLS), interval regression for SAH with cut-points based on the quantiles of HSI (IR), and an ordered probit model of SAH. The latent variable in the ordered probit model can take values in the range of minus infinity to plus infinity; following van Doorslaer and Jones (2003), the predictions of the OP were re-scaled: to the [0,1] range (OP-I) and to the range of the minimum and maximum OLS predictions (OP-II).

Table 5 here

From the mean figures in the table above we can observe that the predictions for OLS and IR are close to the actual HSI, as well as the OP-II. It is also noticeable that the results of the predictions show smaller standard deviations than the actual HSI, this is due to the nature of a prediction itself. On the other hand, the OP-I re-scaling of the ordered probit predictions is far from the actual HSI and does not seem a reasonable method to apply; at least for the HSE data. Overall, it appears that IR provides the best performance when the results are compared to OLS.

Another approach to assess the results is to compare the Gini coefficient of each of model to that of the actual HIS. This is shown in Table 6, where the minus sign in columns 3, 4, 5 and 6 denotes an underestimation with respect to the actual HSI and the predicted health values of OLS, in that order. We notice that the predictions of the Gini coefficient of HSI for OLS, IR, and OP-II underestimate the inequality level in health, while OP-I overestimates it. The under and overestimations of inequality appear to be quite large for all the models used. Furthermore, we can say that those models showing underestimation compared to the actual coefficient, are able to explain the actual inequality in that percentage presented in column 4 of Table 6, e.g. the OLS estimates can explain only 39.8% of the actual inequality in health; the difference should be attributed to other factors (variables) not included in the regression model that also determine the level of health of each individual, hence contained in the residuals of the OLS and not explained by the model. Note that the computation of the Gini coefficients in Table 6 for each model is based on their predicted values. Undertaking the same type of comparison, but instead using the OLS results as the benchmark, we see that the OP-II result is closest, followed by the IR; in both cases there is a slight overestimation. The estimation of the Gini coefficient for OP-I is very inappropriate, overestimating by more than 300%.

Table 6 here

3.3. Decomposition of health inequality

The contribution of each regressor was calculated according to the method in equation (4) to analyse the composition of the Gini coefficient of a health distribution (see Table 7). In order to make it clear how each variable affects the inequality in health, the contribution is presented in percentage terms, i.e. the extent of the influence of each variable on health inequality, measured by the Gini coefficient. It is important to pay attention not only to the magnitude but also to the sign of those figures, some variables have a positive contribution to the degree of inequality while others are negative. Only OLS, IR and OP-II models are used in this part of the analysis.

A negative sign of the Gini coefficients for the regressors means a disadvantage for those individuals having that particular characteristic (see second column in Table 7). So, those living in the North West, Trent and West Midlands NHS regions are worse-off in terms of health in contrast with the other regions, it is also important to bear in mind that a "reference individual" was defined above, so the figures are of particular interest for comparisons to that individual. We can also see that widowed and divorced or separated individuals are relatively more disadvantaged. It is worth noticing that, consistent with findings from other studies, persons with the lowest education, minority ethnic groups, the elderly and those who do not own their house show disadvantages as well as. The Gini coefficient of the age category becomes more negative with ages above 54 years old, i.e. there is an age related gradient in inequality for the elderly; however, it is interesting to note that the largest positive Gini coefficient associated with health is in the category of 18-26 years old, that is, the youngest individuals in the sample.

Further analysis of the results shown in Table 7 reveals that the major negative role in health inequality is given by the age of individuals. Moreover, all the models provide the same order for the five major negative contributors to health inequality; besides the age of more than 72 years, in sequence they are: no reported qualification (presumably no qualification at all), 63-71 years old, not owning the house where they live and 54-62 years.

As equations (1) and (4) indicate, when a linear relationship with health is established (through a model), the Gini coefficient has an unexplained component that is associated to the residuals of the equation, i.e. the contributions shown in Table 7 can not explain all of the Gini coefficient. We can deduce this from Table 7, for instance the IR model can only explain 43.9% of the Gini coefficient.

4. Conclusions

We have applied three econometric models to explore the relationship between SAH and HSI and compared the performance of each one. The models used were: ordinary least squares, interval regression and ordered probit, the latter re-scaled to improve comparability. Results from the regression models show that the average predictions of the models were close to the mean of the actual HSI but were not able to reproduce the full variability of the HSI, particularly for the lower end of the distribution.

Nevertheless, the main aim of the modelling is to analyse inequalities. The Gini coefficient is used as an indicator of health inequality. Most of the models underestimate the Gini coefficient; the interval regression estimations showed the closest measurement of the actual inequality, accounting for 43.9% of the actual Gini coefficient. The Gini coefficient of the actual HSI of the sample is 0.123. The results of the decomposition analysis show disadvantages for individuals with low education, from minority ethnic groups and the elderly; all the models identified that persons with 54 or more years old were in a worse situation than younger individuals.

Finally, we did not include income data because it was not available in the survey. Several studies have found a strong relationship between income, income inequality and health inequality. The small magnitude of the contributions of the explanatory variables used in the regression models could be caused by the absence of income information in the analysis.

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Table 1: *Self-assessed health of respondents*

SAH category	Frequency	Percentage
Poor	636	4.1 %
Fair	2,601	16.9 %
Good	5,271	34.2 %
Very good/Excellent	6,906	44.8 %
Total	**15,414**	**100.0 %**

Table 2: *Distribution of HSI*

HIS	Frequency	Percentage
0.0 – 0.2	647	4.2 %
0.2 – 0.4	249	1.6 %
0.4 – 0.6	386	2.5 %
0.6 – 0.8	4,589	29.8 %
0.8 – 1.0	9,543	61.9 %
Total	**15,414**	**100.0 %**

Table 3: *Distribution of HSI by category of SAH*

Self-assessed health category	Frequency	Sample percentage	Mean HSI	Standard deviation	Minimum HSI	Maximum HSI	Percentile of HSI
Poor	636	4.1	0.347	0.309	0.000	1.000	0.195
Fair	2,601	16.9	0.685	0.259	0.000	1.000	0.725
Good	5,271	34.2	0.866	0.160	0.000	1.000	1.000
V.good/Excellent	4,842	31.4	0.925	0.132	0.000	1.000	1.000
Total	15,414	100.0	0.845	0.222	0.000	1.000	

Table 4: *Upper bounds of HSI corresponding to the SAH distribution*

Self-assessed health category	Frequency	Cumulative frequency	Lower bound of HSI	Upper bound of HSI
Poor	0.041	0.041	0.000	0.195
Fair	0.169	0.210	0.195	0.725
Good	0.342	0.552	0.725	1.000
Very good/Excellent	0.314	1.000	1.000	1.000

Table 5: *Descriptive statistics for actual and predicted values*

Estimation	**Mean**	**Standard Deviation**	**Minimum**	**Median**	**Maximum**
Actual HIS	0.845	0.222	0.000	1.000	1.000
OLS	0.845	0.072	0.634	0.855	1.002
IR	0.848	0.080	0.618	0.856	1.019
OP-I	0.525	0.198	0.000	0.535	1.000
OP-II	0.828	0.073	0.634	0.831	1.002

Table 6: *Gini coefficients for estimates of HSI*

Model	**Gini (*) coefficient**	**Difference to HSI**	**Percentage of HSI**	**Difference to OLS-I**	**Percentage of OLS-I**
Actual HSI	0.123	-	-	-	-
OLS	0.049	-0.074	-39.8 %	-	-
IR	0.054	-0.069	-43.9 %	0.005	110.2 %
OP-I	0.215	0.092	174.8 %	0.166	438.8 %
OP-II	0.050	-0.073	-40.7 %	0.001	102.0 %

(*): Based on actual HSI for actual health and predicted values for each model

Table 7: Decomposition of Gini coefficients, calculations based on predictions of each model

	Actual health	IR	OLS	OP-II
Gini	0.1231	0.0538	0.0486	0.0502
Variable	Gini	%	%	%
NHS North West	-0.01442	0.001%	0.013%	-0.010%
NHS Trent	-0.04648	-0.002%	0.028%	-0.001%
NHS West Midlands	-0.01721	-0.008%	0.000%	-0.043%
NHS Anglia & Oxford	0.04144	0.055%	0.052%	0.173%
NHS North Thames	0.00599	0.026%	0.001%	0.091%
NHS South Thames	0.02192	0.048%	0.011%	0.200%
NHS South West	0.01752	0.047%	0.021%	0.232%
Male	0.03821	-0.002%	0.109%	0.138%
Single	0.09577	-0.064%	-0.068%	-0.287%
Widowed	-0.02451	-0.003%	0.004%	-0.028%
Divorces/separated	-0.01006	0.008%	0.014%	0.030%
Professional	0.10799	0.087%	0.033%	0.915%
Managerial/technical	0.06281	0.11%	0.06%	1.46%
Skilled manual	-0.03585	0.17%	0.07%	0.93%
Semi-skilled manual	-0.07749	0.07%	0.05%	0.33%
Unskilled manual	-0.10245	0.09%	0.00%	0.56%
Other (students, armed forces etc)	0.00600	0.01%	0.00%	0.11%
Urban	0.03147	0.12%	0.07%	0.78%
School certificate	-0.14458	0.00%	0.01%	0.03%
Vocational qualification	0.00000	0.00%	0.00%	0.00%
GCSE/O Level	0.10376	-0.07%	-0.13%	-0.73%
Teaching/nursing qualification	0.08166	-0.03%	-0.10%	-0.56%
Degree	0.15728	0.17%	0.06%	1.67%
No reported qualification	-0.15926	1.62%	1.21%	9.82%
Black Afro-Caribbean	0.00648	0.01%	0.00%	0.08%
Bangladeshi, Indian, Pakistani	0.00786	0.04%	0.00%	0.31%
Other Asian	0.05251	0.00%	0.00%	0.00%
Other ethnic group	-0.03318	0.01%	0.01%	0.06%
Renting	-0.08540	0.97%	0.56%	4.73%
Age 18-26	0.15946	0.13%	0.34%	0.25%
Age 27-35	0.15723	0.16%	0.31%	0.99%
Age 45-53	0.00676	-0.04%	0.00%	-0.23%
Age 54-62	-0.10367	0.42%	0.50%	2.12%
Age 63-71	-0.15882	0.61%	0.62%	3.31%
Age 72+	-0.29042	1.45%	1.65%	7.42%