Income-related health inequality in Belgium, 1994-2001

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October 2004

Abstract

In this paper, we measure income-related health inequality over time in the Belgian population. We apply the methodology of Jones and Lopez (2003) for Belgium. They develop a long-term concentration index based on weighted short-term concentration indices and some measure for health-related income mobility to measure the longitudinal effects of changes in income on health. Then, they construct an index of health-related income mobility to measure how the longitudinal outcome differs from the cross sectional ones. Further, they decompose this mobility-index through simple linear regression into the contributions of different regressors.

The empirical analysis is based on waves 3 (1994) till 10 (2001) of the Panel Survey of Belgian Households. The analysis is restricted to individuals of 16 years or older, who participated in all the waves and who filled in the questions on all the variables used in the regression. After all these omissions, the dataset contains a total of 23,152 observations, which means that there is a balanced panel of 2,894 observations per period.

For the health variable, we used the recently developed interval regression approach proposed by van Doorslaer and Jones (2003) to make our categorical self assessed health variable continuous.
The results for the cross-section concentration indices indicate that there is a pro-rich health inequality in Belgium in all periods. A closer look at the longitudinal concentration index reveals a larger inequality which means that using cross-sectional inequalities leads to an underestimation of the long-run inequality. This is because downwardly income mobile individuals tend to have below average health. From these results an index of health-related income mobility is calculated to see how much difference there is between the short run and the long run view. From the decomposition of this mobility index, we learn that the logarithm of income and age have the largest contributions.

Acknowledgements

This paper derives from the project "The dynamics of income, health and inequality", which is funded partly by the European Community. I am grateful to Diana De Graeve and Tom van Ourti for their helpful suggestions. Also the participants of the ECuity workshop in Helsinki made some useful comments on an earlier version of the paper. I also wish to thank Irina Cleemput for supplying her qaly data.

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1. Introduction

The literature on the measurement of inequality in health borrows a wide range of measures from the income inequality theory (for an overview see e.g. Wagstaff et al. 1991, Mackenbach and Kunst 1997) where, among others, the range, Atkinson's measure, Theil's entropy measure, the Lorenz curve and the Gini-coefficient are commonly used. The particular properties of each of these measures are described by Sen (1997). These are all measures of dispersion of univariate (or unconditional or marginal) distributions of health across persons: some have high health, others have low health. In that case, inequality indicates the extent of dispersion of health within the population. However, in the health literature, there are also bivariate or conditional measures. These look at differences in health across different socio-economic groups, mostly defined by income, occupation or education. For example, a conditional measure could measure if the person with higher health also has higher income (Wolfson and Rowe, 2001). Because, in our view, it is important to incorporate this socio-economic dimension, we will only look at the socio-economic inequalities in health.

Recently, the dynamics of health and their relation to socio-economic characteristics have caught the attention of researchers. Jones and Lopez (2003) develop a long-term concentration index based on weighted short-term concentration indices and some measure for health-related income mobility to measure the longitudinal effects of changes in income on health. Then, they construct an index of health-related income mobility to measure how the longitudinal outcome differs from the cross sectional ones.

Another significant contribution, which was published earlier, is from the part of Benzeval and Judge (2001). They recognise that time is a vital component in any analysis of income or poverty and health. In their study, the most important aim is to determine the causal relationship between income and health. Therefore they include initial health and average income over time. They also provide a large literature review of studies that also included the time dimension in their analysis.

2. Measuring socio-economic inequalities in health

To measure socio-economic inequalities in health, the concentration index is most widely used. Before the formula is presented, we discuss the required information and some underlying assumptions.

2.1. Measuring health

First of all, we need some measure of health. There are a variety of measures used in the literature. A distinction can be made between measures of mortality versus morbidity. In this paper, we concentrate on morbidity and therefore we will use the self-assessed health variable, as in many other recent studies (e.g. Contoyannis et al. 2003, Gravelle and Sutton 2001, van Doorslaer and Koolman 2002). Self Assessed Health (SAH) is a measure of overall health status based on the assumption that an individual can evaluate his/her own health. Although it is a simple and subjective measure that provides an ordinal ranking of the perceived health status, it has been shown that it is a valid instrument since the SAH has been found to be a good predictor of objective measures of health. For applications concerning mortality see for example Benjamins et al. 2004. Also the reliability of this measure has been studied which was found to be fair-to-good for both men and women. Only in the 75+ age group, the reliability declined (Martikainen et al, 1999).

Because it is the purpose to estimate inequalities in health, we need to transform this ordinal variable into a dichotomous or a continuous one. There exist several methods for this transformation.

The easiest way is to dichotomise the variable by setting a cut-off point between good and poor health. This method, however, is not recommended since the choice of the cut-off point is totally arbitrary and there is a loss of information which makes the results dependent on the chosen cut-off point and thus unreliable.

A second approach, developed by Wagstaff and van Doorslaer (1994) is used in several studies eg. van Doorslaer et al. 1997, De Graeve and Duchesne 1997, Wagstaff et al. 2001, van Doorslaer and Wagstaff 2002. The idea is to transform the categorical variable into a continuous one, assuming that there exists a latent, unobservable SAH variable with a standard lognormal density function. Lognormality is assumed to allow for skewness of the density function of health, because it is known that a large majority of the population report good health and only a small percentage says to be in bad or very bad health. To calculate the latent health scores per category, the surface under the standard lognormal density function needs to be split according to the sample proportions from each category. Then the latent health score is derived and accorded with the answers from the respondents. However, this method also has certain disadvantages. Most 'tricky' is the assumption of the underlying standard lognormal density function. It may be possible to find, for example, a beta-function that is also skewed, but gives different outcomes in terms of inequality. However, Gerdtham et al. (1999) prove that the standard lognormal assumption does not lead to significantly different concentration indices compared to the rating scale and the time trade-off methods. The latter two measures yield immediately a continuous measure of health, without assumptions concerning the shape of the distribution of health. However, as in our case, these are often not available in a large-scale population survey.

A third method is to estimate ordered probit regressions using the SAH categories as dependent variable and to rescale the underlying latent variable of this model to compute 'quality weights' for health between 0 and 1 (Groot 2000, van Doorslaer and Jones 2003). A fourth way to make a continuous health variable, recently developed by van Doorslaer and Jones (2003), is executing an interval regression. In this method external data are used to determine the limits for the thresholds. The advantage of the interval regression approach above the ordered probit approach is that the predicted values for the latent health variable need not to be rescaled to the interval [0,1]. van Doorslaer and Jones (2003) also carry out a comparison between ordinary least squares (OLS), ordered probit and interval regression for the transformation of the categorical health variable. From the comparison of these results with the 'benchmark' Health Utility Index (HUI) of Canada, they conclude that the interval regression outperforms the other two approaches. This method was applied by van Doorslaer and Koolman (2002) in their study to explain the differences in income-related health inequalities across European countries. As external data, they used the empirical distribution function of the HUI scores of Canada from 1994. Therefore they have to assume that this HUI also hold for all the European countries and not only for Canada, which is probably not always true.

2.2. Measuring socio-economic status

In the literature, there seems no clear-cut rule on which measure to use for socio-economic status (SES). Wagstaff and Watanabe (2002) investigate the choice of the SES-indicator in order to know whether there is a difference in the measured degree of socio-economic inequality in health. In their application to measuring socio-economic inequalities in malnutrition among under-five children in 19 countries, they compare equivalent household consumption and an asset-based wealth index as measure of SES. They conclude that, for the most part, there is not a significant difference in the estimated socio-economic inequalities in health. Further, they state that a sufficient condition for the inequalities to be similar, is that the rankings of two SES measures must be similar. Important is whether the rank differences are correlated with health or not. If they are not, the measured degree of inequality will be the same. They also provide a statistical test to see whether the difference between the concentration indices is statistically significant or not.

Mostly used as a measure of socio-economic status are income, occupation or education. In this paper, equivalent household income will be used, as in most other papers of the ECuity project.

2.3. Measuring socio-economic inequality in health

There are three minimal requirements of an inequality index in this context of socio-economic inequality in health (see Wagstaff et al. 1991, van Doorslaer et al. 1997):

1. It has to reflect the socio-economic dimension to inequalities in health
2. It has to reflect the experiences of the entire population, and not for example only those of social classes I and IV (which is what e.g. the range measures)
3. It has to be sensitive to changes in the distribution of the population across socio-economic groups

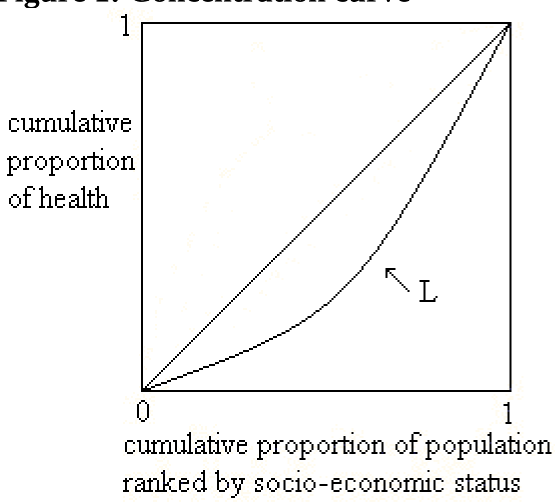
Wagstaff et al. (1991) and van Doorslaer et al. (1997) conclude that the relative index of inequality and the concentration index are the only measures satisfying these three requirements, together with their absolute counterparts (the slope index of inequality and the generalized concentration index) that are sensitive to changes in mean health status.

Moreover, it has been proven that the relative index of inequality is closely related to the concentration index (see also Kakwani et al. 1997).

The concentration index is derived from the concentration curve.

Suppose we have a continuous measure increasing in good health. Figure 1 plots the cumulative proportion of the population, ranked by socio-economic status beginning with the most disadvantaged (on the X-axis), against the cumulative proportion of health (on the Y-axis). The curve named L is the concentration curve. If this curve coincides with the diagonal, everyone, irrespective of the socio-economic status, reports the same level of health. Thus, the diagonal can be interpreted as the line of equality. If the curve lies below (above) the diagonal, the more (less) advantaged people have a better health status. The further the concentration curve L lies from the diagonal, the larger the degree of inequality.

Figure 1: Concentration curve



The concentration curve can be used to compare inequalities in different countries (see e.g. van Doorslaer et al. 1997). When the curve of country A is everywhere closer to the diagonal than that of country B, it indicates that country A has less inequality than country B. In other words, the concentration curve of A dominates that of country B. When the curves cross each other, it is not possible to say which country has more or less

inequality than the other. Then it is only possible to say something by adding additional value judgements.
The concentration index can be calculated as twice the area between the concentration curve and the diagonal, or equivalently one minus twice the area under the concentration curve. When the concentration curve coincides with the line of equality (diagonal), the concentration index is zero. An important remark here is that the value can also be zero if the inequalities favouring (disfavouring) the most disadvantaged are exactly offset by inequalities favouring (disfavouring) the least disadvantaged. This situation can happen when the concentration curve crosses the diagonal and the two areas between the diagonal and the curve before and after the cross-point are the same. The value of the concentration index will be positive if the curve lies below the diagonal, indicating an inequality favouring the better off. The reverse will also be true: a negative value appears when the curve lies above the diagonal. The minimum and maximum values are -1 and +1. These occur when all the population's health is concentrated in the hands of the least and most disadvantaged individuals respectively.

Various formulas, which are all similar, are used to calculate the concentration index (Wagstaff et al. 2003, Wagstaff 2002, Kakwani et al. 1997):

$$C = \frac{2}{N \cdot \mu} \sum_{i=1}^{N} (y_i - \mu)(R_i - \tfrac{1}{2}) = \frac{2}{N \cdot \mu} \sum_{i=1}^{N} y_i R_i - 1 = \frac{2}{\mu} \operatorname{cov}(y_i, R_i)$$

where y_i is the reported health status of individual i, μ is mean health, N is the sample size, R_i is the relative fractional rank defined as $(r_i - ½)/N$ with r_i the unconditional income rank of individual i.
These formulas can be adapted to incorporate weights (see e.g. van Doorslaer and Jones 2003, van Doorslaer and Koolman 2002).
These indices have however an implicit judgement on where the inequality matters most; there is a larger weight for the poorest persons. This can be seen if the formula is rewritten. The extended concentration index allows different weightings to be used (Wagstaff, 2002). However, this extension will lead us too far from the actual subject in this paper, so we will not deal with that in the empirical part of the paper.

This concentration index is used to calculate socio-economic health inequalities at one point in time and to compare different countries (see e.g. van Doorslaer et al. 1997). However, as Benzeval and Judge (2001) argue, time is a very important determinant in the analysis of income and health. Therefore, as we have a panel dataset at our disposal, we will work with the longitudinal concentration index. The paper of Jones and Lopez (2003) will serve as basis.

2.4. Causes of the inequality

Both the cross-section and the long-term concentration index can be decomposed in their causes without saying anything about the direction of causality.

Therefore, in both cases, a linear regression model is assumed (if one works with panel data, a time index is also needed):

$$y_i = \alpha + \sum_{k=1}^{K} \beta_k x_{ik} + \varepsilon_i$$

where, as before, y_i is the reported health status of individual i, x_{ik} are determinants of health, β_k are coefficients and ε_i is an error term.

The cross-section concentration index can then be re-written as follows:

$$CI = \sum_k \frac{\beta_k \bar{x}_k}{\mu} CI_k + \frac{GCI_\varepsilon}{\mu} \qquad where\ GCI_\varepsilon = \frac{2}{n} \sum_{i=1}^{n} \varepsilon_i R_i$$

where CI_k is the concentration index for the x_kth regressor, calculated in the same way as the health concentration index.

Thus, the concentration index can be decomposed into an explained or deterministic component and an unexplained or residual component. The first part is equal to the weighted average of the concentration indices of the k regressors. This weight can be interpreted as the health elasticity of the specific regressor. The second part reflects the inequality in health that can not be explained (Wagstaff et al. 2003, Wagstaff et al. 2001, van Doorslaer and Koolman 2002).

The decomposition of the long-term concentration index, which will be explained later in this paper, is somewhat different in the sense that the health-related income mobility index is decomposed. In that way it becomes possible to see which regressors contribute to the altering picture of short versus long term indices.

3. Previous empirical research in Belgium

In Belgium, there is no vast empirical research concerning health inequality. Lagasse et al. (1990) perform a study in southern Belgium concerning maternal and child health. Like previous studies, they confirm that there exist differences in the distribution of health between social groups: the lower socio-economic status, the higher the mortality. Morbidity shows also better results for more advantageous categories. Moreover, single-parent families and living in Charleroi seem to be more vulnerable groups. The authors further look into 'avoidable mortality' for Belgium as a whole, and here the conclusion is also that there are significant inequalities between the provinces.

van Oyen et al. (1996) research if there are differences between health status of Flemish and Walloon people. Therefore they calculate the health expectancy, an indicator which breaks down expectation of life into years of good health and years of ill-health. For this measure of health expectancy, data on perceived health/ill-health status from the Eurobarometer surveys are used (the authors dichotomized the five possible categories). This is combined with age specific rates for both mortality and morbidity. From their results it is clear that the Flemish have a longer life, moreover it seems to be healthier too. Women live longer than men at any age, in Flanders as well as in Wallonia. But, in Flanders, the ratio of healthy life expectancy to life expectancy was smaller for women than for men. The reverse is true for Wallonia. But, when the figures are compared between the two regions, Flanders has a higher healthy life expectancy for men as well as for women. A limitation of this research is that it does not look at socioeconomic dimensions.

De Graeve and Duchesne (1997) analysed health inequalities based on the individuals older than 18 years of the 1995 Panel Study on Belgian Households. Their results confirm what is already known from other studies: higher income groups are associated with better reported health. This association between income and self-assessed health seems to be statistically significant based on Kendall's Tau-b. In the same way, chronic health problems are more reported by individuals with lower incomes. Standardised[2] concentration indices have also been calculated and are found to be negative and

[2] They standardized the health variable for age and sex. In that way, they pretend as if all income groups have the same age/sex structure. As a result, the remaining inequalities are solely due to differences in socio-economic status.

significantly different from zero. This indicates that there exist significant health inequalities favouring higher income groups. Furthermore, they find that values for the concentration index are larger in Brussels than in Flanders, Wallonia or Belgium in general. The latter three do not seem to have significantly different concentration indices.
Van Ourti (2003) further refined the analyses. More specifically he examines if (1) there is a difference in using permanent or current income and (2) if inequality differs between -65 and +65 aged individuals. He concludes that there is a significant pro-rich (current) income-related ill-health in Belgium and that this inequality is significantly larger in the -65 age group compared to the +65 group. When doing the same analysis with an indicator of permanent income, the difference between the -65 and +65 age groups seems to be robust to the income concept used.

4. Data

In this study data from the Panel Study of Belgian Households (PSBH) are used. This is a national survey, based on a probability sample of Belgian private households. The same individuals are re-interviewed in successive waves and if new households are formed (e.g. marriage) the original sample members are interviewed along with all the new household members. The survey involves a household questionnaire and several individual questionnaires for all household members. Each wave leads to the following datasets:

* <u>contact page</u>: household level (composition of the household)
* <u>household questionnaire</u>: household level (e.g. home characteristics, household income, ...)
* <u>adult questionnaire</u>: individual level, individuals of 16 or older (demographics, employment, education, income, relationships, mobility, health, ...)
* <u>child questionnaire</u>: individual level, persons younger than 16 (demographics, education, leisure activities, crèche, health, …)

The collection of the data started in 1992 with 4.439 households or more than 11.000 individuals successfully interviewed. Since 1994 (the third wave) there is a cooperation with Eurostat which results in a different composition of the questionnaire as well as modification and addition of questions to satisfy the requirements of Eurostat who collects information to support European policy (De Bruyn et al., 1996). Due to this change of the survey the interpretation of some questions might change, which is likely to result in other responses. Therefore we decided not to include the first two waves in our analysis.

Thus, for the underlying research, waves 3 (1994) till 10 (2001, which is the last available wave at this moment) of the Panel Survey of Belgian Households are included. The analysis is further restricted to adults of 16 years or older, who participated in all the waves and who filled in the questions on all the variables used in the regression. After all these omissions, the dataset contains a total of 23,152 observations over the eight waves, which means that there is a balanced panel of 2,894 observations per period.

If this is compared to the case of the unbalanced panel, it is obvious that there is a large loss of information. In the unbalanced panel, there are 50,356 individuals successfully interviewed. After deleting the observations with missing values on the variables needed in de regression, we have an unbalanced panel of 48,726 observations left, which is more than double of the balanced panel. However, in these figures, the observations of an extra survey are included. If these observations are also excluded, so in that case only the sample from the beginning of the survey is retained (including children who become adults), we have an unbalanced panel of 43,448 observations. For more details of the observations in the different periods, see appendix 1.

Still, we prefer to use a balanced panel because then we are able to follow each individual in every year. Also, by removing persons with missing values for one or more variables (that will be needed in the regression) in all the periods, we obtain a dataset with complete information for all the individuals.

5. Measurement of health

As in many other recent studies, the measure of health we use is based on a self-assessed health (SAH) question. It is a very simple question asking “How is your health in general?”. The response categories are: “very good”, “good”, “reasonable”, “poor” and “very poor”.

Because a categorical variable can not be used to calculate concentration indices, our health variable is transformed using the interval regression approach as proposed by van Doorslaer and Jones (2003). In order to scale the intervals of the self-assessed health variable external data have to be used. We have to assume that there is a stable mapping from these external data to the latent health variable, in that way, the ranking of individuals is the same in both distributions.

To estimate the thresholds μ_i we first calculate the cumulative frequency of observations for each category of self-assessed health. Then we compute:

$$\mu_i = F^{-1}(G_i)$$

where $F^{-1}(.)$ is the inverse of the empirical distribution function of the external data and G_i is the cumulative frequency of observations for category i of SAH.

In their international comparison, van Doorslaer and Koolman (2002), which is as far as we know the only existing application at this moment, base on the empirical distribution function of the Canadian Health Utiltiy Index scores to scale the intervals of the SAH for all the European countries. This is because at that time there was no European alternative source available. Moreover, the relative frequencies of SAH of the Canadian sample were remarkably close to the corresponding European-wide frequencies. But, they have to assume that this HUI is appropriate for each specific country. However, it is highly doubtable that people in different cultures would respond in the same way to the health question.

For Belgium as a whole, no such data are available. However, for Flanders there has been developed a continuous health variable, based on EQ-5D questions (Cleemput, 2003). These data will be used under the assumption that this distribution can be applied for whole Belgium.

As is clear in Table 1, there are some differences in the distribution of self-assessed health between the three regions in Belgium. Flanders has more people indicating that they are in very good or good health. On the contrary, Brussels and Wallonia have more individuals with a reasonable or less good health status. But still, the percentages of Flanders are much closer to these of Belgium in general than the percentages of the Canadian sample which are 2.4% (poor), 8.6% (fair), 27.0% (good), 37.2% (very good) and 24.8% (excellent).

Table 1: The distribution of SAH by region (1994)

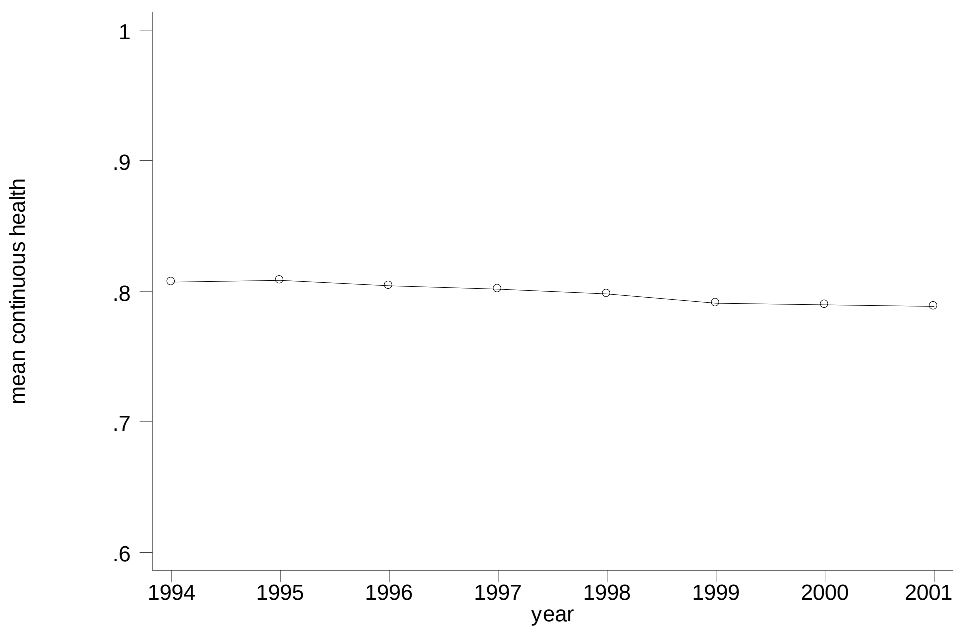
	Brussels		**Flanders**		**Wallonia**		**Belgium**	
	Percent	Cum.	Percent	Cum.	Percent	Cum.	Percent	Cum.
very bad	0.62	0.62	0.31	0.31	0.95	0.95	0.62	0.62
bad	4.05	4.67	2.22	2.52	4.51	5.45	3.42	4.04
reasonable	23.36	28.04	13.76	16.28	25.53	30.99	19.97	24.02
good	48.60	76.64	52.60	68.88	50.12	81.11	51.07	75.09
very good	23.36	100.00	31.12	100.00	18.89	100.00	24.91	100.00

The thresholds and the results of the interval regression can be found in appendix 2. Because we work with panel data, it is important to exploit the time dimension. Therefore, we first tried to execute a random effects interval regression model. This model makes use of the M-point Gauss Hermite quadrature to approximate the integral. However, a test (the quadrature check) on the applicability of this technique resulted in a rejection of this model because the number of quadrature points affect the stability of the estimated results (the relative difference between coefficients of models with another number of quadrature points is larger than 1%).

Then we performed a regression in which we allowed for clusters. This means that we assumed the observations to be independent between clusters, but they are allowed to be dependent within the cluster. As we have a panel dataset with repeated observations on individuals, we clustered by individual. The cluster-specification also implies rubust standard errors. By estimating robust standard errors, the assumption of homoskedastic disturbances (i.e. the same variance across time and individuals) is relaxed to allow for heteroskedasticity. In that way, the estimates of the regression coefficients will be more efficient (Baltagi, 1995). Because we executed the regression on the pooled dataset, time dummies are included to take into account any shocks.

From the results of this regression, the continuous health variable is predicted. In Figure 2, we present mean values per year of the resulting continuous health. In general, health is rather good as the mean value is around 0.8 in each year. However, we can see a slight decrease of the mean in succeeding years. As we work with a balanced panel, this is according to our expectations, because it is known that health decreases with age (e.g. van Doorslaer and Koolman, 2002).

Figure 2: Evolution of the continuous health measure



6. Measurement of socio-economic status

The measure of socioeconomic status used is equivalent household income. On this basis we will order our observations from the poorest to the richest individuals.

The question posed in the household questionnaire, is the following: *How much is your current total net disposable monthly income, everything included?* If the exact amount is not known, the respondents are allowed to give an estimation. Also mentioned, together with the question, is a definition of what is meant by 'net income': '*[it] means the income in the way you receive it, after tax and social contributions. If your income varies from month to month, please give an average.'* If people don't know their income, they can point a category in which their income is situated. So this income is the 'normal' income people obtain each month, thus for example a received inheritance is not included.

Because both variables (specified income and income categories) have a lot of missing values, we put them together for the analysis. The following procedure was applied for the lowest income category:

* calculate first the arithmetic mean of income where income is smaller than 20.000 Belgian francs[3]
* fill this average where the income category is 1 (the lowest category) and the specified income variable is a missing value for that observation. There are some observations where the specific income variable as well as the categorical variable is filled in. In this case we take the specific income to be the correct one.

This procedure is repeated for each category. In that way, we create a continuous variable with a lot of observations.

Next, we transform this obtained nominal income variable into real terms because there is an increasing trend due to inflation. The following formula is used to deal with the time value of money:

$$real\,income = \frac{nominal\ income}{CPI} * 100$$

[3] The reason for which the arithmetic mean is calculated and not just the middle of the income category is taken, is to minimize bias as much as possible. If for example an average which is too high (low) is taken, this will increase (decrease) the total average too. This is especially the case in the extreme classes where there are few observations.

The ratios we use are from the National Institute of Statistics, with as base year 1988. Following consumption price indices are applied:

Table 2: Consumption Price Indices

Periode	CPI
1994	118.51
1995	120.25
1996	122.73
1997	124.73
1998	125.92
1999	127.33
2000	130.57
2001	133.80

The resulting real household income is then equivalised to take account of differences in sizes and composition of families. For instance, the total net disposable income for a family with two children is not comparable to that of a single person. The equivalence scale we use is the modified OECD scale:

$$equivalent\ income = \frac{income}{1 + 0{,}5 * (householdsize - 1 - number\ of\ children) + 0{,}3 * children}$$

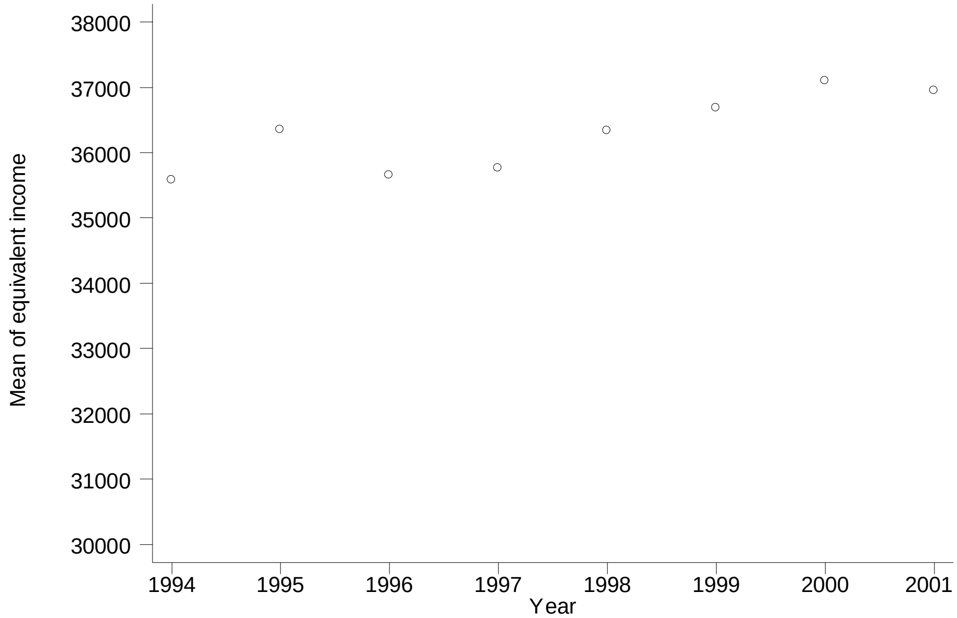
However, from the literature it is not clear yet which formula is best to rescale income. Gravelle and Sutton (2001), for example, use the following non-linear transformation:

$$equivalent\ income = \frac{income}{\sqrt{number\ of\ adults + 0{,}5 * number\ of\ children}}$$

Still others use the square root of the number of household members (e.g. Wagstaff et al. 2001, van Doorslaer and Jones 2003).

In Figure 3 we see a slight increase of the average equivalent income during the succeeding years. This means that the purchasing power is increasing.

Figure 3: Evolution of equivalent income



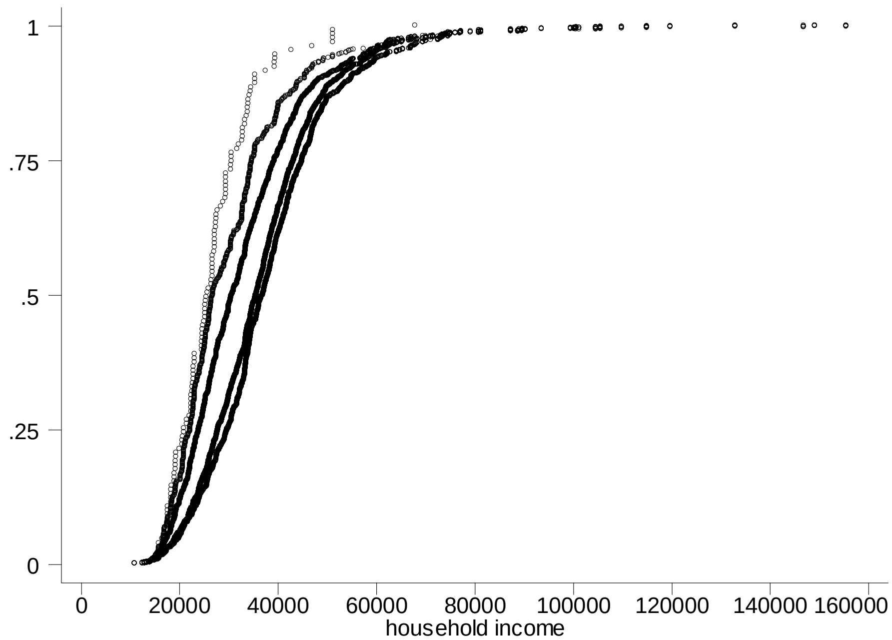
7. Description of the data

Before we turn to the analysis of socio-economic health inequality, it is important to have a look at some relationships.

In Figure 4, the cumulative distribution function of household income, pooled over all the waves, by self-assessed health status is shown. The proportion of observations below a certain household income (shown on the y-axis) is expected to be higher if health is better, as there is a positive relationship between health and income. So, the cumulative distribution functions (CDFs) for lower levels of health are expected to be above the CDFs for higher levels of health. Indeed, the figure plots stochastic dominance for the distribution of income for higher levels of SAH. This is also the case for men and women separately if the sample is split by gender.

This observed relationship between the different health levels and corresponding incomes confirms what was found earlier in the British Household Panel Survey (BHPS) by Contoyannis et al. (2003).

Figure 4: Cumulative distribution function of mean income by self assessed health



While it is important that we clearly see a linkage between health and income, it is even more important to look at the dynamics of health, which is also the focus of this paper.

In the next table, the correlations of the categorical Self Assessed Health variable across the 8 waves are given. They show the mobility of health for men and women. A correlation of one means that there is no mobility. As expected, waves closer together have higher correlations than waves further apart. So, the cells adjacent to the lead diagonal show the highest correlations. As we move from the diagonal, there is a decreasing trend. Thus, there is mobility in the health score over time. All correlations are positive, meaning that if an individual reports a health level above (below) the mean in wave X, he is likely to stay above (below) the mean in all the other waves.

Table 3: Correlation matrices of health

Men								
	1994	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
1994	1.0000							
1995	0.6359	1.0000						
1996	0.5989	0.6466	1.0000					
1997	0.5601	0.6120	0.6478	1.0000				
1998	0.5622	0.5876	0.6287	0.6535	1.0000			
1999	0.4988	0.5594	0.5802	0.5811	0.6305	1.0000		

2000	0.5200	0.5669	0.5698	0.5847	0.6570	0.6854	1.0000	
2001	0.5193	0.5653	0.5508	0.5764	0.6232	0.6597	0.7075	1.0000
Women								
	1994	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
1994	1.0000							
1995	0.6555	1.0000						
1996	0.5714	0.6615	1.0000					
1997	0.5901	0.6418	0.6342	1.0000				
1998	0.5515	0.6045	0.6114	0.6570	1.0000			
1999	0.5249	0.5754	0.5714	0.5998	0.6261	1.0000		
2000	0.5460	0.5685	0.5849	0.5730	0.6052	0.6458	1.0000	
2001	0.5515	0.5566	0.5800	0.5725	0.6170	0.6158	0.6856	1.0000

8. Measurement of inequality

We split this section in three parts. First, the conventional cross-section concentration index is described. Thereafter, we turn to the longitudinal concentration index as proposed by Jones and Lopez (2003). In the last part, the difference between both measures is shown.

8.1. Cross-sectional

For the measurement of inequality in one point of time, we use the concentration index, as is used in many other papers concerning health and health care. It is derived by ranking the population by a measure of socio-economic status (in our case: equivalent income) and then comparing the cumulative proportion of health with the cumulative proportion of the population ranked by income. We use the following (unweighted) formula:

$$C = \frac{2}{N\,\bar{y}_t}\sum_{i=1}^{N}(y_{it} - \bar{y}_t)(R_i^t - 1/2)$$

$$where:$$

$$\bar{y}_t = \frac{\sum_i y_{it}}{N}$$

N is the sample size, $\bar{y}_t$ is the mean health of the sample in period t, y_{it} is the health level of individual i in wave t and R_i is the relative fractional rank of the i^{th} individual in the distribution of incomes in period t.

8.2 Longitudinal

As it is important to have a look at the dynamics of health, Jones and Lopez (2003) present a method for the measurement of changes in health inequality and income-related health inequality over time in a population using longitudinal data. Their paper illustrates that cross-sectional concentration indices could lead to wrong conclusions when trying to explain income-related health inequality in the long run. The reason is that these indices do not take into account the possibility that people may change from income rank due to income changes (note that it is not necessary that the individual itself receives an other income).

Just as the cross-sectional concentration index can be written in terms of covariance between the health status and the relative rank of the same person, the longitudinal concentration index can also be written in this form:

$$C^T = \frac{2}{\overset{=T}{y}} \operatorname{cov}(y_i^T, R_i^T)$$

$$where\ \overset{=T}{y} = \frac{\sum_t \sum_i y_{it}}{NT} = \frac{\sum_t \bar{y}_t}{T}$$

where $\overset{=T}{y}$ is the overall average health status in T periods, y_i^T is the average health of individual i after T periods, y_{it} is the health status of individual i in period t, $\bar{y}_t$ is the within-period average health status and R_i^T is the relative rank of individual i in the distribution of average incomes after T periods.

After some substitutions, they show that the concentration index for the distribution of average health after T periods can be written as the subtraction of two terms, namely the weighted sum of the concentration indices for each of the sub-periods (term 1) minus the difference between period specific income ranks and ranks for average income over all periods and their relationship to health (term 2):

$$CI^T = \underbrace{\sum_t w_t CI^t}_{\text{term 1}} - \underbrace{\frac{2}{NT\overset{=T}{y}} \sum_i \sum_t \left(y_{it} - \bar{y}^t\right)\left(R_i^t - R_i^T\right)}_{\text{term 2}} \quad where\ w_t = \frac{\bar{y}^t}{T\overset{=T}{y}}$$

8.3 Difference between cross-sectional view and longitudinal view

To measure the degree by which the longitudinal perspective differs from the cross-sectional analysis, an index of health-related income mobility is defined. It is one minus the long-term concentration index after T periods divided by the weighted sum of the cross-sectional concentration indices:

$$M^T = 1 - \frac{CI^T}{\sum_t w_t CI^t}$$

Or, if the formulas of the concentration indices are inserted, we become the following formula:

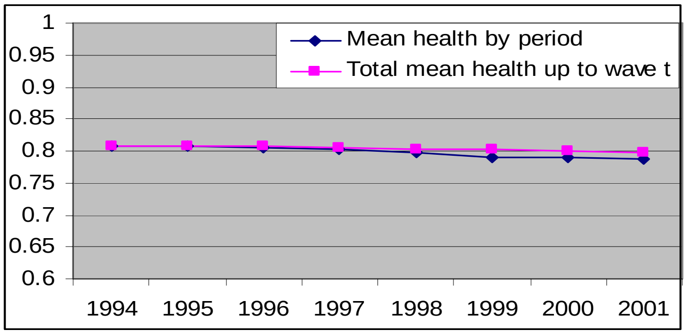
$$M^T = \frac{2}{N \sum_t \bar{y}^t CI^t} \left(\sum_i \sum_t \left(y_{it} - \bar{y}^t \right) \left(R_i^t - R_i^T \right) \right)$$

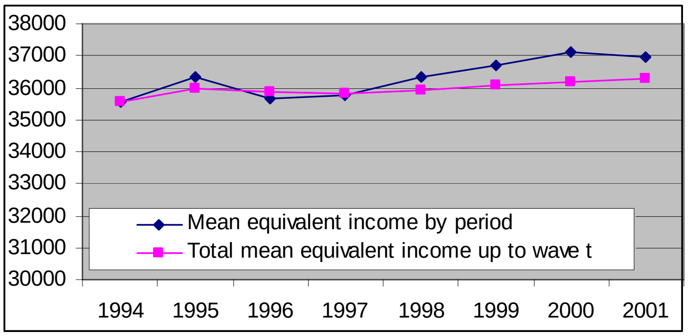
If the mobility index M^T is larger than zero, it means that the weighted average of the short run concentration indices overestimates the degree of long-run inequality (whether pro-rich or pro-poor). A value smaller than zero indicates that taking the concentration index after T periods increases inequality and thus that there is an underestimation if the weighted average of the cross-sectional concentration indices are taken. In the case of an index value of 1, there is perfect mobility so that the long-term concentration index becomes 0 after T periods. If the weighted average of cross-sectional concentration indices and the long-run index are equal to each other, the value of the health-related income mobility index will be zero.

8.4 Results

In Figure 5, the evolution of the two most important variables, health and equivalent income, is shown. There is a slight decrease of the mean health and in the meanwhile an increase of the average equivalent income.

Figure 5: Evolution of mean health and mean equivalent income





The results in Table 4 clearly show that there is pro-rich health inequality in each wave as the concentration indices are positive. A closer look to these short run concentration indices learns us that in general, there is an increase of inequality (with the exception of 1995 and 1999). The "CI total" column shows the long term concentration index. Again there is an increasing inequality towards later periods. The columns "Term 1" and "Term 2" give us some explanations on this trend.

Term 1 is the weighted average of the cross-sectional concentration indices up to the corresponding wave. Again, the same evolution can be seen: an increase of inequality with exception of the second year. So, the concentration index within a period contributes to the long-term trend. But this term 1 is smaller than the total long-term concentration index, which means that using short term indices underestimates the long term inequality. This is confirmed by term 2 which is negative in every year and thus implies that downwardly income mobile individuals tend to have below average health levels compared to upwardly income mobile individuals. The mobility index (Mt column) calculated is -0.09 which denotes that the income-related long-term health inequality increases with 9% due to this effect.

Table 4: Concentration and mobility indices

Year	CI by period	Term 1	Term 2	CI total	Mt
1994	0.0161468	0.0161468	0	0.0161468	0
1995	0.0153253	0.0157358	-0.0005159	0.0162517	-0.0327827
1996	0.0162957	0.0159219	-0.0008495	0.0167714	-0.053353
1997	0.0168828	0.016161	-0.0009977	0.0171587	-0.061735
1998	0.0177268	0.0164718	-0.0011951	0.0176669	-0.0725532
1999	0.017675	0.0166697	-0.0013203	0.0179899	-0.0792007
2000	0.0181627	0.0168802	-0.0014827	0.0183629	-0.0878392
2001	0.0190516	0.0171481	-0.001588	0.0187362	-0.0926076

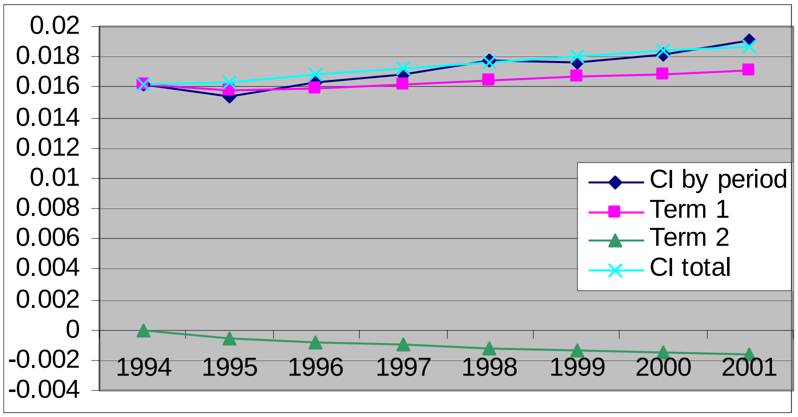
In addition to the calculations on the basis of the continuous health variable transformed using interval regression, the concentration and mobility indices were also calculated on the basis of the untransformed categorical health variable and on the basis of a transformation using the standard lognormal distribution. Compared to the results of the categorical health variable, the concentration index with the continuous variable is much smaller. However, the mobility index seems to be rather close. Using the categorical health variable, the total concentration index after 8 periods is -0.0421 and the mobility index is -10.8% (see appendix 3.1 for the full results).

Compared to the health variable with the lognormal assumption (as proposed by Wagstaff and van Doorslaer, 1994), we also see large differences in the concentration indices: it is around 6 times higher in the lognormal approach (value of 0.1243) than in the interval approach. However, again, the mobility index is remarkably close with a value of -9.25% (see appendix 3.2 for the full results).

Figure 6 shows a good visual linkage between the cross-sectional concentration index (CI by period), the weighted average of cross-sectional indices (term 1), the contribution of mobility (term 2) and the long term concentration index (CI total).

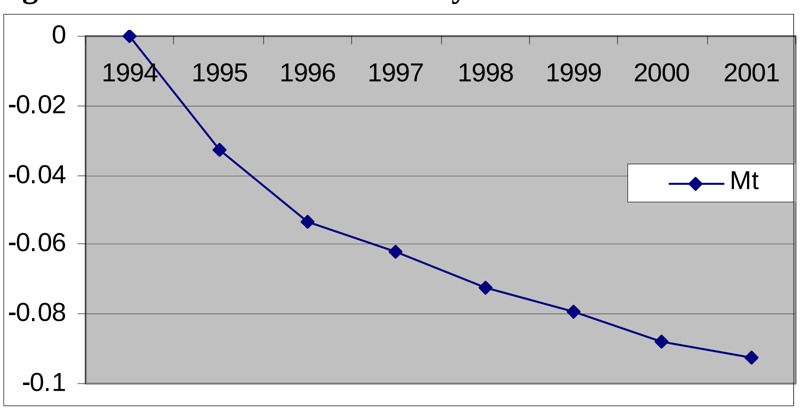
First, it is obvious that the concentration index per period has a larger variance than the long run concentration index after T periods (CI total). Second, as the weighted average of the concentration indices constantly lies closer to the zero-line than the CI total curve, taking the average of cross sectional indices leads to an underestimation of the long run income-related health inequality. It is also clear that the mobility of people in the income rank plays a increasingly larger role in the long-run inequality of health, because term 2 becomes larger in absolute values.

Figure 6: Evolution of the concentration indices



From Figure 7, it is clear that the error of underestimating long term inequality by taking averages of short-run concentration indices is becoming larger over the years.

Figure 7: Evolution of the mobility index



9. Decomposition

In this section we will decompose the index of health related income mobility. Therefore, we draw on the results of the interval regression used to predict the continuous health variable. As the linear prediction of the estimated model is calculated, our health variable can be decomposed into the sum of its contributors. The model is then as follows:

$$y_{it} = \alpha + \sum_{k=1}^{K} \beta_k x_{itk}$$

where y_{it} is the level of (predicted) health of individual i in period t, β_k are coefficients, x_{itk} is the k^{th} regressor. Indeed, there is no error term here because we estimated the model by interval regression. This means that the β_k's can be interpreted *as if* we observed the predicted health value (y*) and estimated E(y*|x)=xβ by ordinary least squares (Wooldridge, 2002).

The first order conditions imply that:

$$\overline{\overline{y}} = \hat{\alpha} + \sum_{k} \hat{\beta}_k \overline{\overline{x_k}}$$

If this is substituted in the health-related income mobility index and we define for each of the regressors an x_k- related income mobility index analogous to the health-related income mobility index, the following result shows up (for the details, the reader is referred to the paper of Jones and Lopez (2003)):

$$M^T = \sum_{k=1}^{K} \underbrace{\hat{\beta}_k \frac{\sum_t \overline{x}_k^t CI_{x_k}^t}{\sum_t \overline{y}^t CI^t}}_{\text{"elasticity"}} M_{x_k}^T$$

where $M_{x_k}^T$ is the x_k-related income mobility index after T periods defined in a similar way as the health-related income mobility index (see supra).

The term by which the mobility index of the x_kth regressor after T periods is multiplied can be interpreted as an inequality weighted elasticity. For example, suppose we have a pro-rich health inequality, then, in our case of good health-increasing health, the concentration index CI^t is positive. If a regressor x_k has a positive association with health, and thus a positive coefficient $\hat{\beta}_k$, and if at the same time the concentration index of this regressor, $CI^{t}_{x_k}$ is negative, indicating a pro-poor distribution, then the "elasticity" will be negative.

The critical reader immediately sees that we would have been able to explain 100% of the total mobility index, because there is no residual term left (contrary to the paper of Jones and Lopez who performed an OLS regression). This is indeed a disadvantage of using the interval regression method. However, this drawback does not outweigh the fact that we now have a continuous health variable without assumptions concerning the shape of the density function (contrary to the method of Wagstaff and van Doorslaer (1994) where a latent health variable with a standard lognormal density function is assumed). But, while interpreting the results, it is important to keep this in mind.

9.1 Variables

We first describe short which explanatory variables are used in the regression.

First of all, the logarithm of equivalent income is included. How this variable is constructed, was described earlier in the paper. The logarithm of average equivalent income is also included. This is just calculated as the average of equivalent income during the eight periods. So, this can be seen as a kind of permanent income of the individual. The reason to take this variable into account is that we believe that this is an important variable in the perspective of a longitudinal analysis.

Next, a dummy for sex is included (1 if the respondent is female).

To allow for a flexible relationship between health and age, a polynomial is included (age, age squared divided by 100 and age cubed divided by 10,000). In the literature, there seems no agreement on what to use best: some include age dummies for different categories of age to allow for more flexibility (e.g. van Doorslaer and Jones, 2003) others include a polynomial (e.g. Contoyannis et al., 2003). Because in the dataset, there is a continuous measure available, we decided to use a polynomial in the analysis. This makes it possible to analyse each specific age instead of age categories.

Also included is a vector of indicators of marital status (widowed, divorced, never_married; married is the excluded variable that serves as the reference category).

A vector of education is also included. Here we decided to take the observations of higher education and university together into one dummy called 'diploma' because there are only few observations, 731 and 338 respectively[4]. The other two dummy variables are secondary and no/primary education (which is the reference category).

Also the number of children under 16 is included as explanatory variable.

A dummy vector for activity status is also included. Thereby a distinction is made between employees, self-employed people (reference category) and a category of special statutes (e.g. contract for students).

To take into account possible geographical variations, a dummy vector of regional variables is included: Brussels, Wallonia and Flanders, which is the reference category.

Finally, we also included time dummies to take away shocks in certain periods (the first wave, 1994, serves as the reference category).

The description and the mean of each regressor (except for the time dummies) are presented in Table 5:

Table 5: Description of regressors

Variable	Description	Mean
logeq_income	Log of equivalent income	10.4168
logav_income	Log of equivalent average income	10.43539
Gender	1 if female, 0 if man	0.5497581
Age	Age in years	47.58673
age2	Age squared/100	25.19597
age3	Age cubed/10,000	14.59004
Widowed	1 if widowed, 0 otherwise	0.0729527
Divorced	1 if divorced, 0 otherwise	0.0905321
never_married	1 if never married, 0 otherwise	0.1585608
Secondary	1 if secondary school, 0 otherwise	0.8888649
Diploma	1 if higher education or university, 0 otherwise	0.0461731
Paidjob	1 if empoyee, 0 otherwise	0.5080339
Special	1 if special statute, 0 otherwise	0.0114029
Child	Number of children in the household	0.698039
Wallonia	1 if living in Wallonia, 0 otherwise	0.4349948
Brussels	1 if living in Brussels, 0 otherwise	0.1125173

[4] These values appeared too small to be able to calculate the concentration index (see further).

9.2 Results

As described above, we clustered by individual to take into account the panel-nature of the dataset. As a consequence we also have robust standard errors for the estimated coefficients. The full results of the regression are shown in appendix 2.

The results show that a man with a larger equivalent income (average income is significantly different from 0 while current income is not), more children and living in Flanders has a significant better level of health. The level of education seems to have no impact on the health status of individuals in our dataset.

In Table 6, the contribution of each of the regressors to the health-related income mobility index after 8 periods is presented.

"CI tot" shows the concentration index of the regressor on income after 8 periods. If this concentration index is positive, the variable has a pro-rich distribution. A negative index means a pro-poor distribution. So, for example, being divorced has a total concentration index of -0.1335. As a result, it is more concentrated among the poor. Having a diploma (higher education or university) has a long term concentration index of 0.3532 meaning that it is more concentrated among the higher incomes.

The second column presents the x_k-related income-related mobility index. A negative mobility index means that the weighted average of short run concentration indices underestimates the degree of long-run inequality (whether pro-rich or pro-poor). If this number has a positive value, it indicates the reverse. For example, the short run concentration index overestimates the pro-rich inequality of the logarithm of the (current) equivalent income, while the negative mobility index of the logarithm of average equivalent income indicates that the long-run inequality is higher.

The next column, "Elasticity(x)" contains the inequality-weighted 'elasticity' of health with respect to the regressor. Unlike as in the case of the concentration index, the sign does not immediately indicate if the dynamics of the regressor is stimulating pro-rich income-related health inequality in the long run or not. A definite example is that of the logarithm of equivalent income and the logarithm of average income: they have both a positive elasticity, but they have a different impact on the distribution of health. They both have a pro-rich distribution because of the positive concentration index. Their coefficients are positive, indicating that richer people have better health. But, the mobility indices are different. For the logarithm of equivalent income, it is positive meaning that the inequality in income is less pro-rich distributed in the long run. As a consequence, the positive 'elasticity' indicates that the dynamics of equivalent income lead to a less pro-rich income-related health inequality in the long run. The contrary is true for the logarithm of the average equivalent income. As the mobility index is negative, there is an even more pro-rich distribution of income in the long run. So, in this case, the positive elasticity means that the dynamics of the average of equivalent income leads to a more pro-rich income-related health inequality in the long run. The same reasoning can be made for the other regressors. For example, living in the southern part of Belgium (Wallonia) is pro-poor distributed, as shown by the negative concentration index. But, in the long run, there are even more Walloon people among the poor because of a negative mobility index (which indicates that cross-sectional concentration indices underestimate inequality in the long run). Moreover, the negative coefficient reveals that Walloon individuals have a significant lower health level than the respondents living in Flanders (which is the reference category). All these effects taken together lead to an even worse health among the poor, so this regressor leads to a more pro-rich income-related health inequality.

If one multiplies the mobility index and the elasticity, the result is the contribution of the regressor. If the sign of the contribution is negative, it means that the regressor stimulates a more pro-rich income-related inequality of health. The reverse is also true; a positive sign leads to a less pro-rich distributed income-related health inequality.

The last two columns show the contribution in percentages of the regressors and per vector respectively into the total index. The largest contributions come from the income and age variables.

As clarified in the theoretical part, we are able to explain 100% of the total health-related income mobility index. However, in the table we still have a very small residual term. This is because we included a vector of time dummies in the regression. These have a zero concentration and mobility index because they are constants. Thus, these regressors do not contribute in the explanation of the total mobility index. But they do have a little impact on the coefficients of the other regressors, and therefore there is a small residual term[5].

Table 6: Decomposition of the mobility index by factors

	CI tot	Mobility(x)	Elasticity(x)	Contribution(x)	%	Per vector
logeq_income	0.0190587	0.1218485	0.0481655	0.005868894	-6.337	
logav_income	0.0189791	-0.1254737	0.5773567	-0.072443081	78.226	71.888
gender	-0.0325994	-0.1279692	0.0194203	-0.0024852	2.684	2.684
age	-0.033999	-0.1270287	1.289107	-0.163753586	176.825	
age2	-0.0728007	-0.1112208	-2.423949	0.269593547	-291.114	
age3	-0.1108434	-0.1017061	1.308652	-0.133097891	143.722	29.434
widowed	-0.1650376	-0.0669437	-0.0034184	0.00022884	-0.247	
divorced	-0.1335062	0.0426978	0.0157896	0.000674181	-0.728	
never_married	0.0585067	-0.8899998	-0.0034036	0.003029203	-3.271	-4.246
secondary	-0.0096547	-0.9376209	0.0020063	-0.001881149	2.031	
diploma	0.3532126	-0.2636197	0.0043245	-0.001140023	1.231	3.262
child	0.0281937	0.0609499	0.0086609	0.000527881	-0.570	-0.570
Wallonia	-0.0182354	-0.2617101	0.0173093	-0.004530019	4.892	
Brussels	0.2045326	-0.1688796	-0.0407218	0.006877081	-7.426	-2.534
paidjob	0.1768604	-0.0013823	0.1817453	-0.000251227	0.271	
special	-0.107308	-0.1674617	-0.0010447	0.000174947	-0.189	0.082
sum				-0.092607601	100.000	
residual				1.30372E-09	-1.4078E-06	
total index				-0.0926076	100	

11. Conclusion

In this paper, we replicated the method of Jones and Lopez (2003) on Belgian data. Therefore, eight waves (from 1994 till 2001) of the Panel Study of Belgian Households were used. Unfortunately, we only have a categorical self-assessed health variable (SAH) at our disposal. But thanks to the recently developed interval regression approach (van Doorslaer and Jones, 2003) and available external data for scoring the intervals (Cleemput, 2003), we were able to transform this SAH into a continuous health variable without making assumptions about the shape of the density function, which is the case if a standard lognormal assumption is used (Wagstaff and van Doorslaer, 1994).

[5] When we used the health variable based on the standard lognormal assumption, we were able to explain around 30% of the total health-related income mobility index.

The results clearly show a pro-rich distribution of health in every year as all the concentration indices are positive, moreover, cross-section as well as long-run inequality is increasing towards later periods. In order to calculate the long-run concentration indices, taking only the weighted sum of cross-section concentration indices does not give the real picture: there is an underestimation of inequality due to the fact that downwards mobile people in the income rank tend to report a below average level of health. The percentual difference caused by this mobility is captured by the health-related income mobility index, which is 9% in absolute value in 2001. This means that the long-term income-related health inequality increases with 9% compared to taking the weighted average of the cross-sectional concentration indices. Decomposing this mobility index into its contributors reveals that the dynamics of age and income have the largest influence.

Although an other health variable and a different model are used, our main results are quite comparable with those of Jones and Lopez (2003). From the concentration indices it seems that Belgium has a larger inequality (0.018) than the UK (0.011) over the 8 periods. The health-related income mobility index in the UK is with a value of 10.21% about 1% larger than ours (9.26%). Finally, from the decomposition of this mobility index, it is clear that the largest contributions stem from the income and age vectors in both countries.

10. Future research

Although we used some new methods, there is still scope for future research. First of all, we were restricted to work with a balanced panel and we were not able to use weights. It would be nice to adapt the formulas in such a way that they can be used with unbalanced panels and weights, so that the subsample would become more representative. Moreover, in the dataset itself, some adaptions have to be made in order to have correct weights. At the moment, there are still some inconsistencies.

Further, instead of dropping observations with missings, we could have imputed missing values. In that way, our dataset would be larger. There are different imputation methods which result in different outcomes and which all have certain advantages and disadvantages. A good reference for various alternative methods can be found in Little and Rubin (1987).

As a measure of socio-economic status, we used equivalent income. However, using another measure, for example occupation or education, may lead to other results. It could therefore be interesting to extend the analyses to compare between the different measures of SES.

Finally, we did not go into the problem of the direction of causality, neither into the problem of statistical interference.

12. References

Balgati B.H. (1995), *Econometric analysis of panel data*, John Wiley & Sons, Chichester, 257 p

Benjamins M.R., R.A. Hummer, I.W. Eberstein and C.B. Nam, Self-reported health and adult mortality risk: An analysis of cause-specific mortality, *Social Science & Medicine*, Vol. 59, 2004, pp.1297-1306

Benzeval M. and K. Judge, Income and health: the time dimension, *Social Science & Medicine*, 52, 2001, pp.1371-1390

Cleemput I., Economic evaluation in renal transplantation, PhD thesis, 2003, Leuven

Contoyannis P., A.M. Jones and N. Rice, The dynamics of health in the British Household Panel Survey, August 2003, ECuity III Project, WP 3, 45 p

De Bruyn S., T. Jacobs, R. Marynissen and R. Van Dam, Methodebericht golf 3 (1994), november 1996, 75 p

De Graeve D. and I. Duchesne, Equity in health and in medical care consumption in Belgium, February 1997, 39 p

Gerdtham U.-G., M. Johannesson, L. Lundberg, D. Isacson, A note on validating Wagstaff and van Doorslaer's health measure in the analysis of inequalities in health, *Journal of health Economics*, Vol. 18, 1999, pp. 117-124

Gravelle H. and M. Sutton (2001), Income-related inequalities in self-assessed health in Britain: 1979-1995, online available: www.york.ac.uk/res/herc/docs/IneqGB.pdf , 18 p

Groot W., Adaptation and scale of reference bias in self-assessments of quality of life, *Journal of Health Economics*, Vol. 19, 2000, pp. 403-420

Jones A.M. and A. Lopez, Measurement and explanation of socioeconomic inequality in health with longitudinal data., March 2003, Working Paper of Ecuity III project

Kakwani N., A Wagstaff and E. van Doorslaer, Socioeconomic inequalities in health: Measurement, computation, and statistical inference, *Journal of Econometrics*, Vol. 77, 1997, pp. 87-103

Lagasse R., P.C. Humblet, A. Lenaerts, I. Godin and G.F.G. Moens, Health and social inequities in Belgium, *Social Science and Medicine*, Vol. 31, No. 3, 1990, pp. 237-248

Little R.J.A. and D.B. Rubin (1987), Statistical analysis with missing data, Wiley, New York, 278p

Mackenbach J.P. and A.E. Kunst, Measuring the magnitude of socio-economic inequalities in health: an overview of available measures illustrated with two examples from Europe, *Social Science and Medicine*, Vol. 44, No. 6, 1997, pp. 757-771

Martikainen P., A. Aromaa, M. Heliövaara, T. Klaukka, P. Knekt, J. Maatela, E. Lahelma, Reliability of perceived health by sex and age, *Social Science and Medicine*, Vol. 48, 1999, pp. 1117-1122

Sen A. (1997), *On economic inequality*, Clarendon Press Oxford, 260 p

van Doorslaer E., A. Wagstaff, H. Bleichrodt, S. Calonge, U.G. Gerdtham, M. Gerfin, J. Geurts, L. Gross, U. Häkkinen, R.E. Leu, O. O'Donnell, C. Propper, F. Puffer, M. Rodríguez, G. Sundberg, O. Winkelhake, Income-related inequalities in health: some international comparisons, *Journal of Health Economics*, Vol. 16, 1997, pp. 93-112

van Doorslaer E. and A. M. Jones, Inequalities in self-reported health: validation of a new approach to measurement, *Journal of Health Economics*, Vol. 22, Iss. 1, 2003, pp. 61-78

van Doorslaer E. and X. Koolman, Explaining the differences in income-related health inequalities across European countries, 2002, ECuity II Project, WP6

Van Ourti T., Socio-economic inequality in ill-health amongst the elderly. Should one use current or permanent income?, *Journal of Health Economics*, 2003, Vol. 22, pp. 219-241

van Oyen H., J. Tafforeau and M. Roelands, Regional inequities in health expectancy in Belgium, *Social Science of Medicine*, 1996, Vol. 43, No. 11, pp. 1673-1678

Wagstaff A., P. Paci and E. van Doorslaer, On the measurement of inequalities in health, *Social Science of Medicine*,1991, Vol. 33, No. 5, pp. 545-557

Wagstaff A. and E. van Doorslaer, Measuring inequalities in health in the presence of multiple-category morbidity indicators, *Health Economics*, 1994, Vol. 3, pp. 281-291

Wagstaff A., P. Paci and H. Joshi, Causes of inequality in health: who you are? Where you live? Or who your parents were?, November 2001, 20 p

Wagstaff A., Inequality Aversion, Health Inequalities and Health Achievement, January 2002

Wagstaff A. and N. Watanabe, What difference does the choice of SES make in health inequality measurement?, November 2002, 9 p, online available on: http://poverty.worldbank.org/files/13971_ses.pdf

Wagstaff A., E. van Doorslaer and N. Watanabe, On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam, *Journal of Econometrics*, 2003, Vol. 112, pp.207-233

Wolfson M. and G. Rowe, On measuring inequalities in health, *Bulletin of the World Health Organization*, 2001, Vol. 79 (6), pp.553-560

Wooldridge J.M. (2002), *Econometric analysis of cross section and panel data*, Cambridge, Mass., 752 p.

Appendix 1: Number of observations per period in unbalanced panels

Year	Total number of observations	Without extra survey	Total number of observations, dropped item-non response*	Without extra survey, dropped item-non response*
1994	6,715	6,715	6,510	6,510
1995	6,471	6,471	6,240	6,240
1996	6,182	6,182	6,004	6,004
1997	5,792	5,792	5,639	5,639
1998	7,015	5,396	6,759	5,232
1999	6,511	5,097	6,272	4,931
2000	6,060	4,794	5,880	4,668
2001	5,610	4,383	5,422	4,264
Total	50,356	44,830	48,726	43,448

* only if people did not respond on the health question and/or the question concerning their household income, they were dropped from the dataset

Appendix 2: Interval regression results

2.1 Thresholds used to execute the interval-regression

	Categorical	Lower bound	Upper bound
5	**Very bad**	0	0.13539046
4	**Bad**	0.13539046	0.53563925
3	**Reasonable**	0.53563925	0.74081465
2	**Good**	0.74081465	0.90886439
1	**Very good**	0.90886439	1

2.2 Interval regression

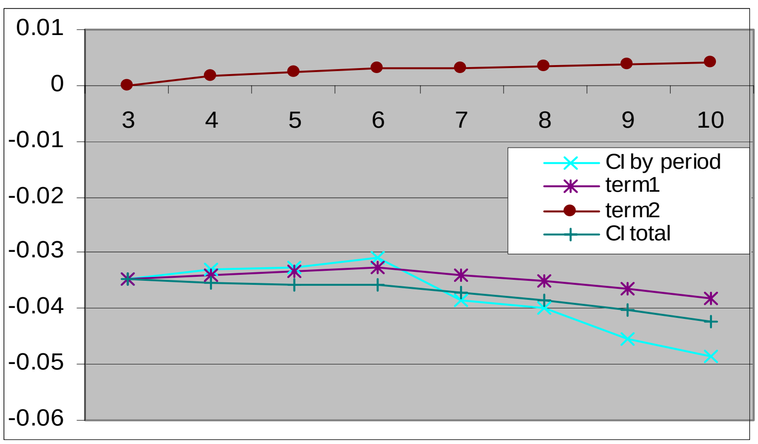
Interval regression Number of obs = 23152
Wald chi2(23) = 945.58
Log likelihood = -28162.536 Prob > chi2 = 0.0000
(standard errors adjusted for clustering on indid)

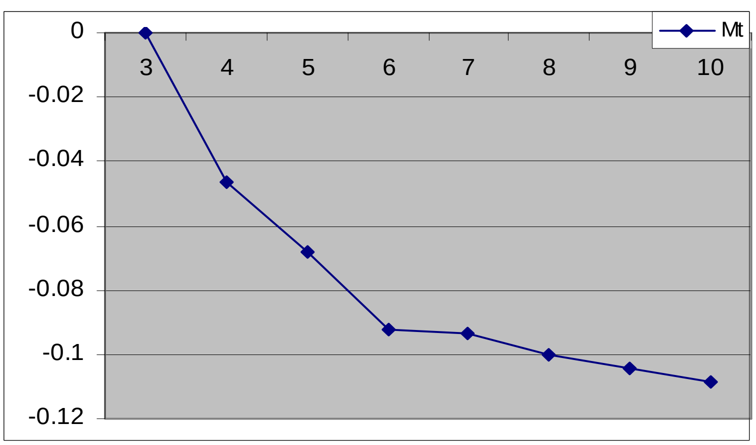
	Coef.	Rob. S.E.	z	P>|z|	[95% Conf.	Interval]
logeq_income	.002917	.0034967	0.83	0.404	-.0039364	.0097704
logav_income	.0449214	.0067516	6.65	0.000	.0316885	.0581544
gender	-.0167352	.0037771	-4.43	0.000	-.0241381	-.0093322
age	-.012295	.0030937	-3.97	0.000	-.0183586	-.0062315
age2	.0201055	.0063596	3.16	0.002	.007641	.03257
age3	-.0122062	.0040747	-3.00	0.003	-.0201924	-.00422
divorced	-.0171227	.0072729	-2.35	0.019	-.0313773	-.0028681
widowed	.0041476	.0092858	0.45	0.655	-.0140522	.0223473
never_married	-.0094941	.0062396	-1.52	0.128	-.0217235	.0027352
secondary	-.0062022	.004429	-1.40	0.161	-.014883	.0024785
diploma	.0045876	.0056527	0.81	0.417	-.0064915	.0156667
Brussels	-.0283186	.0062425	-4.54	0.000	-.0405537	-.0160836
Wallon	-.0376962	.0038527	-9.78	0.000	-.0452475	-.030145
child	.0056582	.0018962	2.98	0.003	.0019417	.0093746
paidjob	.027733	.0044115	6.29	0.000	.0190867	.0363794
special	.0136472	.0115747	1.18	0.238	-.0090389	.0363333
d_1995	.0078749	.0029641	2.66	0.008	.0020653	.0136845
d_1996	.0065017	.0030759	2.11	0.035	.000473	.0125304
d_1997	.0065356	.0031588	2.07	0.039	.0003444	.0127267
d_1998	.0048698	.0032563	1.50	0.135	-.0015125	.011252
d_1999	.0002116	.0034356	0.06	0.951	-.006522	.0069452
d_2000	.0011096	.0034158	0.32	0.745	-.0055852	.0078044
d_2001	.0024008	.0034148	0.70	0.482	-.0042922	.0090938
_cons	.5708277	.0706584	8.08	0.000	.4323398	.7093156
/sigma	.1186648	.0021449			.1144608	.1228688

Appendix 3: Results for other transformations of the health indicators

3.1 Categorical self-assessed health

Year	CI by period	term1	term2	CI total	Mt
1994	-0.034804	-0.034804	0	-0.034804	0
1995	-0.033083	-0.0339437	0.0015773	-0.035521	-0.0464686
1996	-0.0325531	-0.0334757	0.0022905	-0.0357663	-0.0684236
1997	-0.0307624	-0.03279	0.0030209	-0.0358109	-0.092129
1998	-0.0384329	-0.0339388	0.003169	-0.0371078	-0.0933724
1999	-0.0398103	-0.0349473	0.0034913	-0.0384387	-0.0999028
2000	-0.0454214	-0.0364879	0.003816	-0.040304	-0.1045832
2001	-0.0485385	-0.0380379	0.0041288	-0.0421667	-0.1085433





3.2 Continuous health with standard lognormal assumption

Year	CI by period	Term 1	Term 2	CI total	Mt
1994	-0.1080553	-0.1080553	0	-0.1080553	0
1995	-0.0999674	-0.1040695	0.0035339	-0.1076034	-0.0339571
1996	-0.0955573	-0.1012221	0.0064595	-0.1076816	-0.0638154
1997	-0.0899896	-0.0983476	0.007844	-0.1061916	-0.0797577
1998	-0.1118174	-0.1011333	0.0074143	-0.1085476	-0.0733123
1999	-0.1200417	-0.1045287	0.0085819	-0.1131106	-0.0821008
2000	-0.1348766	-0.1091762	0.0096435	-0.1188196	-0.0883293
2001	-0.1435949	-0.1137857	0.0105218	-0.1243075	-0.0924705