Can economics contribute to an understanding of socioeconomic inequality in health?

Andrew M Jones[1] and Nigel Rice[2]

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Abstract

Health economics has been at the forefront of developing analytic tools for the measurement and explanation of socioeconomic inequalities in health. These methods have traditionally been applied only to cross sectional information. However, there is evidence that inequalities persist over time in spite of policies aimed at promoting equal access and combating social exclusion. It is therefore clear that attention must be paid to the dynamics of health and their relation to socio-economic characteristics, as revealed by longitudinal survey data. This paper provides an overview of methods for the analysis of health inequalities and health mobility when such longitudinal data are available. The underlying question is: what explains the differences in the degree to which health and health care utilisation are unequally distributed by income? Only by developing a proper understanding of the causal mechanisms generating these inequalities will it be possible to develop effective policies. New data sets and advanced econometric techniques offer the prospect of major advances to this end.

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[1]Corresponding author: Department of Economics and Related Studies, University of York, Heslington, York, YO10 5DD, United Kingdom: Tel: +44-1904-433790; Fax: +44-1904-433759; Email: amj1@york.ac.uk
[2]Centre for Health Economics, University of York, United Kingdom

1 Introduction

Over the last twenty years the UK has enjoyed increased prosperity, but despite this there remain striking inequalities in health across geographical areas and between socio-economic groups within society and evidence suggests that such inequalities are widening. Concern over the level of health inequalities prompted the present Government's commission of Sir Donald Acheson's *Independent Inquiry into Inequalities in Health* (Acheson, 1998) shortly after taking-up office. This provided the basic evidence about the scale and nature of health inequalities and formed the foundation of subsequent policy initiatives aimed at their amelioration. Targeting groups most at risk in an attempt to tackle such inequalities has been stated as a top priority of the Government (see for example, Department of Health, 2002).

The *NHS Plan* (Department of Health, 2000) has emphasised the commitment to reduce inequalities in health by providing extra funding for the NHS. Additional resources are being directed to areas of greatest need through improved resource allocation mechanisms and monies ring-fenced specifically for the reduction of health inequalities. Linked to these are national targets for 2010 to reduce the gap in infant mortality across social class groups and raise life expectancy in the most disadvantaged areas faster than elsewhere. Moreover, *Tackling Health Inequalities: A Programme for Action* (Department for Health, 2003) states the need to improve the health of the poorest 30-40% of the population if significant reductions in health inequalities are to be achieved. Further efforts to tackle inequalities in health have been taken, in part, through policy initiatives such as increasing the minimum wage, welfare and benefit reforms, transport and housing improvements, Sure Start and Neighbourhood Renewal Schemes. These policies indicate a commitment on behalf of the Government to a cross-departmental perspective to reducing health inequalities. Indeed, the recent review *Tackling Health Inequalities: Summary of the 2002 Cross-Cutting Review* (Department of Health, 2002) places health inequalities at the heart of every key public service and recognises the need for concerted action across Government and with other sectors.

Further concern over the level of inequalities in health have been expressed in the "*Wanless Report:" Securing our Future Health: Taking a Long-Term view* (Wanless, 2002). In his review of future health care resource requirements Wanless identifies,

among other needs, a better understanding of the role of income and other socio-economic inequalities in explaining observed differences in health outcomes and the subsequent use of health care. It is noted that health inequalities affect resource requirements for health and social care but knowledge of how socio-economic need and health need are related is incomplete.

A great deal of academic research effort has focused on measuring and identifying the nature of inequalities in health and speculated on the form policy initiatives may take to help reduce such inequalities. In particular, the disciplines of public health and epidemiology have contributed greatly to this end. The aim of this paper is to highlight the distinct contributions made by economists to the measurement and explanation of socioeconomic inequalities in health and to point towards areas of potential future research that will help elucidate further the nature and composition of health inequalities. We will concentrate on the central role that income plays both as an instrument in the measurement of health inequalities and as a determinant of health and inequality in health. Further, the advantages of and scope for adopting a longitudinal perspective to investigate health inequalities will be discussed.

In particular the paper will concentrate on the long running *ECuity Project*, which has pioneered the use of economic tools to measure inequality and inequity in the financing and delivery of health care and in the distribution of health within the population. The ECuity project has recently entered a new phase: "ECuity III". This involves an international network of researchers coordinated by Erasmus and York universities. The objectives of ECuity III are:

- to investigate the causal effect of socioeconomic status, in particular income, on individuals health,
- to analyse the dynamics of individual health exploiting the availability of longitudinal data,
- but also to analyse the reverse effect of health on income disentangling the impact of health on labour market outcomes such as unemployment and retirement.
- the fourth objective is to explore the effect of socioeconomic status in particular income, on the use of health care, again exploiting the availability of longitudinal data.

- and finally, empirical analysis of all four of these objectives will be motivated by estimating the impact of specific health and fiscal policy interventions on the degree of socioeconomic or income related inequalities in health and in access to health care.

The methodology of the ECuity III Project will be built around the analysis of longitudinal data, both the European Community Household Panel (ECHP) and other national datasets such as the British Household Panel Survey (BHPS). This will entail panel data econometric analysis of the impact of income on health, the dynamics of health, the impact of health on earnings and labour market outcomes such as early retirement, and on the utilisation of health care. Results from these econometric analyses will form the basis for the measurement and explanation of socioeconomic inequalities. The aim of this paper is to review recent innovations in these methods.

2 Measurement of income related inequality

2.1 Concentration and Gini indices

In order to measure socioeconomic or income-related inequality in health, economists have borrowed tools from the income inequality literature. Foremost among these is the health concentration index, which provides a measure of relative income-related health inequality (Wagstaff, Van Doorslaer and Paci, 1989). The health concentration index is derived from the health concentration curve; this is illustrated in Figure 1. The sample of interest is ranked by socioeconomic status, so for example if income is used as the relevant ranking variable the horizontal axis begins with the poorest individual in society and progresses through the income distribution up to the very richest individual in society. This relative income rank is then plotted against the cumulative proportion of health on the vertical axis. This assumes that a cardinal measure of health is available, that can be compared and aggregated across individuals. The solid black line shows the line of perfect equality, in which case shares of population health are proportional to income, such that the poorest 20% of individuals receive 20% of the available health in the population and so on. In reality there is likely to be pro-rich inequality in the distribution of health, this is illustrated by the red line on the figure - the concentration curve. In the example shown the poorest 20% of income earners receive less than 20% of the health available, in other

words less than their fair share. So the fact that the concentration curve lies below the line of perfect equality indicates that there is pro-rich inequality in health. The size of this inequality can be summarised by the health concentration index, which is given by twice the lens shaped area between the concentration curve and the 45-degree line.

There are various ways of expressing the concentration index (C) algebraically. The one that is most convenient for our purposes is,

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

This shows that the value of the concentration index is equal to the covariance between individual health (y) and the individual's relative rank (R), scaled by the mean of health in the population (μ). Then the whole expression is multiplied by 2, to ensure the concentration index lies between -1 and +1. Writing the concentration index in this way emphasises that it is an indicator of the degree of association between an individual's level of health and their relative position in the income distribution, and hence provides our measure of socioeconomic inequality in health.

Socioeconomic inequality in health is cited widely as a concern for health policy makers, however it may not be the whole story. Recent work at the World Health Organisation through their Evidence for Health Policy programme has argued that policy makers should also be concerned about other sources on inequality, and that measurement should focus on total health inequality. Using the concentration index as the basic approach to measurement provides one way of moving between socioeconomic and total health inequality. As long as a cardinal measure of health is available such as a health utility index or EQ-5D scores, which provides sufficient inter-individual variation, then they can be used to look at total or pure health inequality. This allows for broader analysis based on health Lorenz curves and inequality can be measured using the Gini coefficient of health inequality, G (Le Grand, 1989 and Wagstaff, Paci and van Doorslaer, 1991). The attraction of this approach is that there is a direct relationship between the concentration index and the Gini coefficient for health, this is given by $C = \{\rho(y,R)/\rho(y,R')\}G$. This shows that the concentration index C is proportional to the Gini coefficient G, where the factor of proportionality is given by the ratio between the correlation coefficient for health and

income rank (R) and the correlation coefficient between health and health rank (R'). This means that it is easy to move between the two measures of socioeconomic and pure health inequality.

The proceeding analysis has been on the assumption that a cardinal measure of health is available. This is straightforward for indicators of illness such as the presence of chronic conditions as the concentration index or Gini coefficient can be based on the head-count of the number of individuals experiencing the illness. It is more difficult when health is measured using self-reported subjective scales. Self-assessed health (SAH) is widely available in many general population surveys and has been used extensively in the ECuity project. The problem with this measure is that respondents are asked to describe their health in ordered categories and the variable is inherently ordinal rather than cardinal. In the past researchers have dealt with ordinal measures of health either by dichotomizing the variable so that individuals are described as either healthy or non-healthy, or by imposing some sort of scaling assumption. The problem with the former is that information is lost and not all of the health variation contained in the original SAH variable is used. Evidence shows that comparisons of inequality over time or across populations may be sensitive because the results differ depending on the choice of the cut-point between healthy and non-healthy. A variety of methods have been used to rescale the ordinal measure of health into a cardinal measure. Early work in the ECuity project imposed a lognormal distribution on self-assessed health. More recently external information such as, the average level of health utility within categories of self-assessed health have been used in the rescaling. A third approach is to adopt an appropriate econometric specification such as the ordered probit model and use the predictions from this model as a scaled measure of individual health.

Van Doorslaer and Jones (2003) suggest an approach that combines the use of external information with the ordered probit model. This relies on having a dataset that includes both self-assessed health and a cardinal index of health: in there case the Canadian National Population Health Survey (NPHS), which includes SAH and the McMaster health utility index. Figure 2 illustrates the approach. The solid line represents the empirical distribution function of individual HUI scores. This is used to construct a mapping from HUI to SAH. On the assumption that there is a systematic relationship between the two measures of health such that those at the bottom of the distribution of self assessed health will also be those at the bottom of the distribution

of health utility, it is possible to scale the cut-points for categories of self-assessed health using health utility values. For example, 2.4% of the Canadian sample reports poor health. Applying this number to the empirical distribution of HUI shows that 2.4% of the sample has health utility scores less than 0.428. Similarly, 11% of the sample report either poor or fair health and the corresponding HUI score is 0.756. So, these percentiles of the distribution of HUI can be used to scale the cut-points between the different categories of self-assessed health. These cut-points can then be incorporated into the ordered probit model and self-assessed health can be estimated as an interval regression, where the values of the cut-points are treated as known. The attraction of this approach is that predictions from the interval regression model are on the same scale as health utility.

The validity of this approach as a way of rescaling self-assessed health in the measurement of socioeconomic inequality in health is assessed in Figure 3. The solid black line shows the concentration curve measured as deviations from the 45 degree line for the actual measure of health utility. This is tracked closely by both the predictions from OLS applied to actual HUI but also the predictions from the interval regression model. Predictions from the ordered probit model or from a measure of self-assessed health rescaled using the mean HUI scores within category of self-assessed health, do not perform well. Those based on category means under-estimate the concentration index while those based on the ordered probit model over-estimate the concentration index.

Figure 4, taken from Van Doorslaer and Koolman (2002), illustrates an international comparison of concentration indices for socioeconomic inequality in health based on the Europanel (ECHP) data. These are calculated using the interval regression method of scaling self-assessed health. The horizontal axis shows the level of income inequality measured by the Gini coefficient for log income, while the vertical axis shows health inequality measured by the concentration index. The Netherlands and Germany have the lowest levels of socioeconomic inequality in health, while Portugal stands out as having both the highest levels of income inequality and of socioeconomic inequality in health. These numbers summarize international differences in the overall level of socioeconomic inequality in health as measured by the association between health and income rank. The story can be taken further by decomposing the concentration index into its component parts.

2.2. Decomposing inequality indices

Like the Gini coefficient of income inequality, the concentration index has the attraction that it can be decomposed by factors (Rao, 1969, Kakwani, 1980). For example this property has been used in the past to decompose the concentration index for health care financing into different sources of health care payments such as taxation, social insurance contributions, user charges etc. A recent paper by Wagstaff, van Doorslaer and Watanbe (2003) exploits the result that if a reduced form demand for health equation is additively separable,

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i ,$$

then, because the concentration index is additively decomposable, which stems from the fact that the covariance of a linear combination is equal to the linear combination of covariances, the overall concentration index for health can be written as follows,

$$C = \sum_k (\beta_k \bar{x}_k / \mu) C_k + GC_\varepsilon / \mu = C_{\hat{y}} + GC_\varepsilon / \mu$$

This has the convenient form that C can be split into two parts, the first term can be thought of as the explained component $(C_{\hat{y}})$ and the second term as the unexplained component. Within the explained component there is a contribution for each of the regressors (X) and this is made up of the product of two terms. The first term is the elasticity of health with respect to that variable, for example the income elasticity of health, and the second term is the concentration index of that variable, for example in the case of income this would be the Gini coefficient.

Figure 5 shows the decomposition of concentration indices based of the 1996 ECHP, and is taken from van Doorslaer and Koolman (2002). The length of the horizontal bars indicates the overall size of the concentration index for each country, and the coloured blocks show the contribution of different groups of variables. One notable feature is that although income itself makes a sizeable contribution in most countries, it is only part of the story. Other sources of income related inequality in health include variables such as activity status, in fact it is striking that in Denmark activity

status explains the bulk of the association between health and income rank, with a negligible contribution from income itself.

A recent paper by Jones and Lopez Nicolas (2002) shows that the decomposition proposed by Wagstaff, van Doorslaer and Watanabe (2003), can be taken a stage further and that the unexplained component given by the generalised concentration index of the residual from the regression equation can be further decomposed. This applies when there is heterogeneity in individual responses to the impact of the regressors on individual health.

2.3 Standardised concentration indices

The concentration index measures income-related inequality in health. This is not the same thing as inequity in health. For example, variations in health that are attributable to age and gender may be seen as unavoidable and hence legitimate sources of inequality. The same argument applies to measures of inequality in the use of health care (see e.g., van Doorslaer, Koolman and Jones, 2003). Usually, the horizontal version of the egalitarian principle is interpreted to require that people in equal need of care are treated equally, irrespective of characteristics such as income, place of residence, race, etc. While the concentration index of medical care use (C_M) measures the degree of inequality in the use of medical care by income, it does not yet measure the degree of inequity. For any inequality to be interpretable as inequity, legitimate or need-determined inequality has to be taken into account.

There are two broad ways of standardising distributions for need differences: the direct and the indirect method. The direct method proceeds by computing a concentration index for medical care use that would emerge if each individual had the same need characteristics as the population as a whole. Wagstaff *et al.* (1991) have used this procedure to compute what they call HI_{WVP} indices, which are essentially directly standardised concentration indices. More recently, Wagstaff and Van Doorslaer (2000) have advocated the technique of indirect standardisation for the measurement of so-called HI_{WV} indices on the grounds that it is computationally easier and does not rely on grouped data. A measure of the need for medical care is obtained for each individual as the predicted use of a regression on need indicators. This means that in order to statistically equalize need for the groups or individuals to be compared, one is

effectively using the average relationship between need and treatment for the population as a whole as the vertical equity norm and horizontal inequity is measured by systematic deviations from this norm by income level.

Wagstaff and van Doorslaer (2000) proposed to measure *HI* by the difference between the inequality in actual and needed use of medical care:

$$HI_{WV} = C_M - C_N$$

where C_M and C_N denote the concentration index corresponding to actual and needed use of medical care, respectively. C_N is computed using predicted values $\hat{y}_i$, which can be estimated for each individual i as the expected amount of medical care he or she would have received if he or she had been treated at the average level of treatment received by others with the same need characteristics.. Typically, these are obtained from regressing actual y_i on a set of need indicators like health status and morbidity measures and demographics. The average relationship between need indicators and utilization, as embodied in the regression coefficients, is the implied norm for assessing equity in the health care system.

The issue of the role of explanatory models in the measurement of inequity deserves some further attention. Recently, some authors have drawn attention to the potential biases involved in these standardisation procedures. First, the problem of determining which systematic variations in medical care use by income are "needed" and therefore, in a sense, justifiable, and which are not, bears some resemblance to the problem of determining legitimate compensation in the risk adjustment literature. Schokkaert and Van de Voorde (2000) have argued that while there is a difference between the positive exercise of *explaining* medical care expenditure (or use) and the normative issue of justifying medical expenditure (or use) differences, the results of the former exercise have relevance for the second. Drawing on the theory of fair compensation, they show that failure to include 'responsibility variables' (which *do not* need to be compensated for in the capitation formula) in the equation used for estimating the effect of 'compensation variables' (which *do* need to be compensated for) may give rise to omitted variable bias in the determination of the 'appropriate' capitations (or fair compensations). Their proposed remedy to this problem is to include the 'omitted variables' in the estimation equation but to 'neutralize' their impact by setting these

variables equal to their means in the need-prediction equation. A similar argument to Schokkaert and Van de Voorde was made and taken further by Gravelle (2003) in the context of the measurement of income-related inequality of health or health care. He uses an 'augmented partial concentration index' which is defined as the (directly) standardised concentration index, but controlling for income and other non-standardising variables in the process. This can be obtained from the regression-based decomposition of the concentration index.

One important problem with measuring horizontal inequity and applying the decomposition analysis is that the dependent variable in health care demand models is typically modelled as a nonlinear function of the regressors . In van Doorslaer, Koolman, and Jones (2003) the empirical models of health care use are based on logistic and truncated and generalized negative binomial regression models, which are intrinsically nonlinear. A complication compared to the linear case is that the HI index for the nonlinear model is contingent on the values used for the non-need variables and therefore their effect is not completely neutralised.

Further so long as the model for y is linear then the Schokkaert and Van de Voorde (2000) approach of estimating the linear regression and then neutralizing the non-need variables by setting them equal to their mean (or, in fact, any constant value) and the decomposition approach lead to the same measure of horizontal inequity (van Doorslaer, Koolman and Jones, 2003). This does not hold for a nonlinear model, as the linear decomposition does not apply. However it is possible to approximate the decomposition analysis. To do this, van Doorslaer, Koolman and Jones (2003) opted to use a linearised 'partial effects' representation for the decomposition. This has the advantage of being a linear additive model of actual utilisation, but is only an approximation.

2.4 Measurement of inequality and mobility with panel data

Up to now we have focused on methods for the measurement and explanation of socioeconomic inequalities in health that have been designed for use with cross sectional data. Jones and Lopez Nicolas (2003) explore what more can be gained by using panel data. Again it is possible to borrow from the income inequality literature.

Work on income mobility has focused on comparing the distribution of income using two perspectives, first of all a cross sectional or short-run perspective and secondly a long-run perspective where income is aggregated over a series of period, for example over ten years. If an individual's income rank differs between the short-run and the long-run there is evidence of income mobility. One way of measuring this phenomenon is through the index of income mobility proposed by Shorrocks in 1978. The aim of the paper by Jones and Lopez Nicolas (2003) is to apply the same principles to income-related health inequality. They show that the long-run concentration index can be written as the sum of a weighted average of short-run concentration indices plus a term that captures the covariance between the fluctuations in health over time and fluctuations in income rank over time. This differs from income inequality in that income-related health inequality can be either greater or smaller in the long run than the short run but, once again, these changes can be measured through an index of health-related income mobility which is based on the familiar tools of the concentration index. The paper shows that this mobility index can be decomposed using the contribution of different factors through a regression model for health and this is illustrated using the GHQ measure of subjective well-being from the first nine waves of the British Household Panel Survey (BHPS).

Figure 6 illustrates the long-run concentration index with data on individuals GHQ scores from the first nine waves of the British Household Panel Survey (BHPS). The pink line shows the weighted average of cross sectional concentration indices, as time progresses this deviates from the purple line which gives the long run concentration index. The size of the deviation is given by the turquoise line the second term in the decomposition analysis. In Figure 7 this deviation is summarised by the health related income mobility index, which shows that by the ninth wave the short run measure under-estimates long run inequality by around 10%.

3. Panel data econometric analysis of health

The previous section has summarised recent innovations in the measurement and explanation of socioeconomic inequalities in health and is concluded by showing the scope for using longitudinal data to learn more about the dynamics of health inequalities. This section turns to the estimation of regression models for health that also exploit the longitudinal dimension of panel data.

3.1. Empirical evidence on mobility in health

Empirical research into the extent and nature of inequalities in health have, to date, tended to rely on cross-sectional observations of the level of observed health within socio-economic groups of interest. Cross-sectional information can, at best, provide a snap-shot of the overall distribution of health at any particular point in time with respect to factors of interest such as income, employment status or social class. What they cannot provide is evidence on the intertemporal experience of health problems and how this may vary across different socio-economic groups.

Section 2.3. describes methods to measure intertemporal mobility in income-related health inequalities based on the index of income mobility proposed by Shorrocks (1978). An empirical study aimed at incorporating a time dimension into the analysis of health inequalities is provided by Hauck and Rice (2003). The paper is concerned with the extent to which individuals move over time within the overall distribution of mental health. Mobility is then compared across socio-economic groups. Interest focuses on both the level of observed mental ill-health and how mobile over time individuals are within their respective health distributions. Data from eleven waves of the British Household Panel Survey (BHPS) are used.

The measure of mental health is based on the 12-item version of the General Health Questionnaire (GHQ). The GHQ is a self-administered screening test aimed at detecting psychiatric disorders that require clinical attention among respondents in community settings and non-psychiatric clinical settings. A Likert scale is used to form an overall score for each respondent based on summing across the item specific responses. This provides a variable ranging from 0 (least problems) to 36 (most problems).

A simple description of mobility is presented for men and women in Table 1. The correlations in GHQ scores across the eleven waves of data show a clear pattern. As expected, waves closer together have, in general, higher correlations than waves further apart. The highest correlations occur in the cells adjacent to the lead diagonal. These correlations then show a tendency to decrease as one moves further away from the lead diagonal until a degree of levelling out occurs. The off-diagonal correlations vary between 0.315 and 0.556 for men and 0.302 and 0.525 for women. The

correlations show that although health outcomes are more similar the closer the reporting period, their absolute size suggest that there exists considerable mobility in GHQ scores over time. For example, all correlations off the lead diagonal are much smaller than one (one indicating an absence of mobility) and less than one fifth are over 0.5. However the non-zero correlation at the extremes suggests that this mobility operates around some underlying persistence in individual health trajectories.

More formal approaches to estimating the extent of mobility are achieved using two comparative measures. The first partitions unobserved variability in health status from an error components model into transitory and permanent components and uses the proportion of total variability attributed to the permanent component as a measure of mobility. The following model is specified:

$$h_{it} = X'_{it}\beta + Z'_i\gamma + \alpha_i + \varepsilon_{it},\ i = 1,2,\ldots,N;\ t = 1,2,\ldots T_i$$

where h_{it} is the GHQ score for the *i-th* individual at time *t*. X_{it} represents a vector of time-varying explanatory variables and Z_i a vector of time-invariant explanatory variables, assumed to influence h_{it} but to be uncorrelated with the error term, $\alpha_i + \varepsilon_{it}$. The total error is composed of α_i, an individual specific and time-invariant error and ε_{it}, the usual idiosyncratic error component. β and γ are conformably dimensioned vectors of parameters to be estimated. To allow for potential correlation between α_i and the set of time-varying regressors, X_{it} the individual effect is parameterised to obtain a correlated random effects model (Mundlak (1978), Chamberlain (1984)). The first estimate of mobility is based on the intra-unit correlation coefficient, ρ:

$$\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2}$$

This coefficient represents the conditional correlation of GHQ scores across periods of observation. Should ρ be large then individuals are said to experience relatively high persistence (low mobility) in health outcomes. Conversely, if the majority of unexplained variability is attributable to σ_ε^2 then individuals experience relatively high

random fluctuations resulting in high mobility and low persistence in health outcomes. Estimates of ρ are calculated by maximum likelihood.

A second measure of mobility is based on the estimated coefficient on lagged health status from a dynamic regression model. Here the set of regressors is augmented to include the previous period's GHQ score in order to estimate the impact of previous health on current health. The general form of this dynamic model can be written as:

$$h_{it} = \lambda h_{it-1} + X'_{it}\beta + Z'_i\gamma + \nu_{it}, \qquad i = 1,2,\ldots,N; t = 1,2,\ldots T_i$$

where h_{it}, X_{it}, Z_i, are defined as before.

The model is estimated by OLS (see, Jarvis and Jenkins (1998) for an application to income mobility). A coefficient close to zero provides evidence of high mobility since current health is not a function of previous period's health (conditional on X_{it}, and Z_i). Accordingly, health outcomes fluctuate in a non-deterministic and random manner over time. Should the estimate of λ be positive and large, individuals are characterised by relatively low health mobility. A negative coefficient would indicate cyclical fluctuations in health outcomes over time.

Table 2 presents estimates of mobility for men and women. Gradients across the categories of the socio-economic groups are clearly apparent. Greater mobility is observed for ethnic groups other than white, for individuals with greater educational qualifications, for higher income groups, for younger individuals and for healthier individuals. Estimates derived from the lagged health variable estimated via OLS are larger than the mobility estimate derived from the proportion of variance attributable to the unobserved individual effect in the variance components model. In general, mobility estimates for women are smaller than those for men but these differences are often negligible. The differences in estimates within the different socio-economic groups are quite striking. For example, for men the increase in the estimated coefficient, $\hat{\rho}$, as one moves from degree or higher degree (DEGHDEG) to no qualifications (NOQUAL) is 50%. The corresponding increase for the OLS coefficient, $\hat{\lambda}$, is 33%. For women these differences are greater still at 78% and 56% respectively. Increases are even more pronounced across age quintiles. The

differences in estimates as one moves from the 1st (youngest) to the 5th (oldest) age quintile are greater still (men: 51% for $\hat{\rho}$ and 68% for $\hat{\lambda}$; women: 106% and 78% respectively). The results for educational attainment and income quintile are displayed graphically for men in Figures 8 and 9.

Estimates of mobility vary across social class groups with some indication of a gradient. For both men and women the lowest estimates, corresponding to greatest mobility, are observed for professional, managerial and technical and skilled non-manual workers. The highest coefficients (least mobility) are observed for the retired and other social class group.

To summarise these findings, Hauck and Rice (2003) find evidence of substantial mobility in mental health. This is apparent for both men and women. Further, they find evidence of systematic differences in mobility across socio-economic groups. In general individuals from an ethnic origin other than white experience worse mental health outcomes (although these effects are not statistically significant) but greater mobility over time compared to white ethnic groups. Individuals from lower income groups are associated with greater mental ill-health but are also associated with greater persistence over time compared to individuals from higher income groups. Cross-sectional analyses find that mental health problems are concentrated among groups with low educational status (for example, Henderson, 1998, Goldberg, 1999). The results concur with this but also imply that mental health problems among low education groups are aggravated by the fact that they tend to be of a more permanent nature. Mental health deteriorates with age and becomes more permanent in nature. The unemployed, and individuals categorised as other social class report worse GHQ scores than the baseline of skilled non-manual workers. Further women occupied with family care report greater levels of mental ill-health compared to the baseline group. However, the retired and other social class group experience greatest permanence in outcomes over time.

3.2. The socioeconomic determinants of health

A recent paper by Contoyannis, Jones and Rice (2004) explores the dynamics of self-assessed health in the British Household Panel Study (BHPS). The variable of interest is an ordered measure of self-assessed health and the BHPS reveals evidence of

considerable persistence in individual's health status. This is illustrated by Figure 10, which shows the distribution of self-assessed health at wave 2 split according to reported categories of self-assessed health at wave 1. So for example, it is clear that Men who report excellent health at wave 1 are most likely to report excellent health again at wave 2. If they change health status they are most likely to report good health, those who report good health at wave 1 are most likely to report good health at wave 2 and if they change it is most likely to be to excellent health or fair health and the same pattern applies to all categories of self-assessed health. Two possible sources of this persistence are unobservable heterogeneity, inherent individual differences in health that remain constant throughout the survey, and state dependence such that an individuals previous experience of health influences their current health outcomes.

The BHPS data also reveal clear socioeconomic gradients in self-assessed health; Figure 11, which shows the empirical distribution function for household income averaged across the eight waves of the panel, illustrates these. These distributions have been split according to individual's level categories of self-assessed health. This reveals a clear pattern with the distribution of income for those reporting very poor health lying to the left of the distribution for those reporting poor health and so on, so that the figure illustrates the phenomenon of health related income inequality.

Econometric analysis of health based on longitudinal data needs to take account of the fact that the sample changes over time and in particular the results of the analysis may be influenced by attrition bias. Patterns of attrition in the BHPS data are illustrated in Table 3; this shows how the number of individuals among both men and women in the sample used by Contoyannis, Jones and Rice evolves over the eight waves of the panel. The survival rate shows how the number of respondents declines so that by the 8th wave only 64% of the original sample of men and 69% of the original sample of women are included. The number of dropouts from the sample can be summarised by the attrition rate, this gives the number of individuals who drop out between two waves as a percentage of the number of respondent at the start of the period. This shows that the attrition rate is highest between waves 1 and 2 and 2 and 3 and then declines over time. So the overall attrition rate for men is 13% between waves 1 and 2 and for women it is 12%. What is striking about table 3 is the evidence of health-related attrition; the final five columns show the attrition rates for those in different categories of self assessed health at the previous wave. Attrition rates are noticeably

higher among those whose report very poor health at the previous wave, providing evidence of health related attrition, which may be a source of attrition bias in econometric models of health.

Contoyannis, Jones and Rice (2003) develop an econometric model for self-assessed health. In the BHPS SAH is an ordered categorical variable based on the question "Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been excellent/good/fair/poor/very poor?" As this is measured at each wave of the panel there are repeated measurements (t = 1….T) for a sample of individuals (i = 1…n). This is modelled using a latent variable specification

$$h^*_{it} = \beta' x_{it} + \gamma h_{it-1} + \alpha_i + \varepsilon_{it} \quad (i=1,\ldots,N;\ t=2,\ldots T_i)$$

Which can be estimated using pooled ordered probits (with robust inference) and random effects ordered probit models. X includes measures of socioeconomic status such as income and education. The presence of h_{t-1} is designed to capture state dependence, the influence of previous health history on current health. The error term is split into two components, the first captures time invariant individual heterogeneity, the second is the usual time varying idiosyncratic component . In this kind of application it is quite likely that the unobserved individual effect, which encompasses omitted variables that are not included in the survey, is likely to be correlated with the other regressors, such as education and income. Also, it is well known that in dynamic specifications the individual effect will be correlated with the lagged dependent variable, this gives rise to what is known as the initial conditions problem, that an individual's health at the start of the panel is not randomly distributed and will reflect the individual's previous experience and be influenced by the unobservable individual heterogeneity. To deal with the initial conditions an attractively simple approach suggested by Wooldridge (2002b) is used. This involves parameterising the distribution of the individual effects as a linear function of initial health at the first wave of the panel and of the time means of the regressors, and assuming that it has a conditional normal distribution. As long as the correlation between the individual effect and initial health and the regressors is captured by this equation it will control for the problem of correlationed effects. Its ease of implementation stems from the fact that α_i can be substituted back into the previous equation and the model can

then be estimated as a pooled ordered probit or a random effects ordered probit using standard software to retrieve the parameters of interest.

Inverse probablity weights are used to attempt to control for attrition (Wooldridge,2002c). This works by estimating separate probit equations or whether an individual responds or does not respond at each of the waves of the panel from 2 to 8. Then the inverse of the predicted probabilities of response from these models are used to weight the contributions to the log likelihood function in the pooled probit models for health. The rationale for this approach is that a type of individual who has a low probability of responding represents more individuals in the original sample and therefore should be given a higher weight. There are two variants on this approach, the first uses only information from the initial period including initial health and socioeconomic characteristics, and the second uses information on the previous period including previous health, but this requires monotone attrition such that, once somebody has dropped out of the sample they remain out of the sample. In both cases inverse probability rates will correct attrition as long as an ignorability assumption holds. This assumes that non-response is ignorable conditional on the variables that are included in the probit models for non-response. If this assumption holds then inverse probability estimates give consistent estimates with conservative inference, such that standard errors are over-estimated.

Table 4 shows the average partial effects of selected variables on the probability of an individual reporting excellent health; these are given for pooled probit models with and without inverse probability weights and estimated on balanced and unbalanced samples and also for random effect specifications of the ordered probit models on balanced and unbalanced samples. The results show that state dependence is important the estimated effects of lagged health status are large and highly statistically significant, what's more a clear gradient is observed in the coefficients as they move from very poor to excellent previous health. So state dependence is one source of the observed persistence in self-assessed health in the BHPS. Another source is individual heterogeneity, the intra-class correlation coefficient (ICC) shows the proportion of the overall variance of the error term which is attributable to the individual effect. Approximately 32% of the latent error variance is accounted for by individual heterogeneity for both men and women.

There is little difference between the results and for estimates of the pooled model with and without inverse probability weights. This suggests that while there is evidence of health-related attrition in the data, the average partial effects of socioeconomic variables and of lagged health status are not influenced by sample attrition. However, this does rely on the ignorability assumption built into the inverse probability weight approach and deserves further analysis.

Results for the income variables show that the effects of mean income are larger than those of current income and the effects of mean income are statistically significant while those from current income are not. This deserves further investigation. The effect of mean income could be a genuine influence of permanent financial status on health or it could reflect the correlation between the unobserved individual effect and current income. For men educational qualifications are positively associated with better health but we don't observe a clear gradient across individual qualifications. For women, educational qualifications are more significant and a clear gradient is observed.

To summarise these findings, there is clear evidence of health related attrition in the BHPS data but it does not appear to distort estimates of our models for self-assessed health; there is evidence of persistence in self-assessed health, this is explained in part by state dependence which is stronger amongst men than women, and by individual heterogeneity, with around 30-35% of the unexplained variation accounted for by individual heterogeneity. There is evidence of a socioeconomic gradient by education and income with the long-run effect of income greater than the short-run effect

3.3. The role of income as a determinant of health

The analysis reported above specifies the log of the level of income as a key determinant of individual health. However, recent literature on the role of socio-economic status in explaining differences in health have made the distinction between the impact of an individual's absolute level of income and their relative standing in the distribution of income. This distinction has been termed the "absolute" income hypothesis versus the "relative" income hypothesis. The former suggests that higher individual incomes lead to better health outcomes, the latter suggests that levels of

income inequality and where one lies within the distribution of income has the greater impact on health outcomes (see, for example, Wilkinson, 1996).

Estimating the relationship between income and health is important to inform the debate on health inequalities. If the absolute income hypothesis is dominant then policies aimed at income growth will be sufficient to reduce health inequalities, provided that the relationship between health and income is non-linear such that increases in income lead to increases in health but at a decreasing rate. The relative income hypothesis leads to quite different policy recommendations; under such circumstances reductions in health inequalities would require redistributive income policies.

The majority of empirical evidence in support of the relative income hypothesis has been derived from aggregate studies of country or area level data. These studies have been criticised for their reliance on aggregate data (Wagstaff and van Doorslear, 2000). Indeed, Gravelle (1999) shows how (misleading) evidence in favour of the relative income hypothesis can be obtained from aggregate data when, in reality a relationship between health and income inequality does not exist. More recently research has attempted to disentangle the two hypotheses using individual level data but has met with limited success. This, in part, is due to inconclusive evidence on the reference group with which individuals judge their position in the income distribution. For example, Wildman and Jones (2003) use the UK population as the relevant group whilst Lindley and Lorgelly (2002) use the income distribution within UK geographical regions. Neither study finds convincing evidence in support of the relative income hypothesis. Further research in this area would benefit from information concerning the income distribution measured at a more local level than hitherto has been possible.

4. Conclusions

The continuing concern over the level of inequalities in health has ensured that efforts to alleviate them have remained high on the policy agenda. Health economics has been at the forefront of developing analytic tools for the measurement and explanation of health inequalities and is well placed to continue to play a pivotal role in this important area. Methodological extensions to health of the literature on income

inequality together with the availability of high quality longitudinal survey data has extended the capacity of health economists to inquire into the nature and determinants of health inequalities. The availability of the ECHP has made detailed cross-country comparative analysis of health inequalities more amenable to empirical research providing additional evidence on the extent of inequalities and how they are systematically related to socio-economic factors in different health care systems.

An area that is under-researched and that would benefit greatly from the input of health economists is the evaluation of policy initiatives aimed at the reduction of inequalities in health. The proper evaluation of such initiatives is crucial if interventions are to be judged on the effectiveness (and cost-effectiveness) of their impact on the distribution of health. Economists have long been interested in the evaluation of social programmes and to this end have developed a comprehensive toolkit of techniques upon which to draw (for example, see Blundell and Costa-Dias, 2000). A combination of factors such as the non-experimental setting, identification of relevant risk groups, lags between intervention and outcome, and clear identification of the policy instrument all pose challenging issues for the successful evaluation of policies aimed at the reduction in health inequalities.

References

Acheson, D. (1998) *Independent Inquiry into Inequalities in Health*. HMSO: London.

Arellano, M., Bond, S. (1991) Some tests of specifications for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*; 58: 277 – 297.

Blundell, R., Costa-Dias, M. (2000) Evaluation methods for non-experimental data. *Fiscal Studies;* vol 21, no. 4: 427-468.

Chamberlain, G. (1984). Panel data, Chapter 22 in Z. Giliches and M. Intrilligator,, eds., *Handbook of Econometrics*, North-Holland, Amsterdam: 1247 - 1318.

Contoyannis, P., Jones, A.M., Rice, N. (2004) The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics*, forthcoming.

Department of Health (2000). The NHS Plan: A plan for investment, a plan for reform. The Stationary Office, London.

Department of Health (2002). Tackling Health Inequalities: Summary of the 2002 Cross-Cutting Review. Department of Health, London.

Department of Health (2003). Tackling Health Inequalities: A Programme for Action. Department of Health, London.

Goldberg, D. (1999). *Mental Health*. Policy Press, Bristol.

Gravelle, H. (1999) How much of the relation between population mortality and unequal distribution of income is a statistical artefact? *British Medical Journal*, 316: 382-85.

Gravelle, H. (2003) Measuring income related inequality in health: standardization and the partial concentration index. *Health Economics*; 12: 803-819.

Hauck, K., Rice, N. (2003*) A longitudinal analysis of mental health mobility in Britain*. Ecuity III WP#9.

Hausman, J. (1978). Specification tests in econometrics, *Econometrica*; 46: 1251-1271.

Henderson, C.E.A. (1998). Inequalities in mental health. *British Journal of Psychiatry*; 173: 105-109.

Jarvis, S., Jenkins, S. (1998) How much income mobility is there in Britain? *The Economic Journal*; 108: 428-443.

Jones, A.M., López-Nicolás, A. (2002) "The importance of individual heterogeneity in the decomposition of measures of socioeconomic inequality in health: an approach based on quantile regression", ECuity II Project, Working Paper #10.

Jones, A.M., Lopez Nicolas, A. (2003) Measurement and explanation of socioeconomic inequality in health with longitudinal data. Ecuity III WP#1.

Kakwani, N.C., (1980). *Income Inequality and Poverty. Methods of Estimation and Policy Implications.* Oxford University Press, Oxford.

Le Grand, J., (1989). An international comparison of ages-at-death. in J. Fox (ed.) *Health inequalities in European countries.* Gower, Aldershot.

Lindley, J. and Lorgelly, P.K. (2002) *The relative income hypothesis: does it exist over time?* Evidence from the BHPS. Presented to the Health Economists' Study Group, Winter 2003, Leeds.

Mundlak, Y. (1978). On the pooling of time series and cross-sectional data. *Econometrica*; 48: 69-85.

Rao, V. (1969). Two decompositions of the concentration ratio. *Journal of the Royal Statistical Society, Series A*; 132: 418-425.

Shorrocks, A. (1978) Income inequality and income mobility. *Journal of Economic Theory*; 19: 376-93.

Schokkaert, E., van de Voorde, C. (2000). *Risk selection and the specification of the risk adjustment formula*. Centre for Economic Studies Discussion Paper, 2000/011, University of Leuven, Leuven,

van Doorslaer, E. and Koolman, X. (2002). Explaining the differences in income-related health inequalities across European countries. ECuity II Project Working Paper #6

van Doorslaer, E., Koolman, X. Jones, A.M. (2003) "Explaining income-related inequalities in doctor utilisation in Europe", ECuity II Project, WP#5.

van Doorslaer, E.,Jones, A. M. (2003). Inequalities in self-reported health: validation of a new approach to measurement. *Journal of Health Economics,* 22(1): 61-87.

Verbeek, M., Nijman, T.E. (1992). Testing for selectivity bias in panel data models. *International Economic Review,* 33: 681-703.

Wagstaff, A., van Doorslaer, E., Paci, P., 1989. Equity in the finance and delivery of health care: some tentative cross-country comparisons. *Oxford Review of Economic Policy* 5, 89-112.

Wagstaff, A., Van Doorslaer, E., Paci, P. (1991). On the measurement of horizontal inequity in the delivery of health care. *Journal of Health Economics*, **10**(2): 169-205.

Wagstaff, A., van Doorslaer, E. (2000). Measuring and testing for inequity in the delivery of health care. *Journal of Human Resources*, **35**(4): 716-733.

Wagstaff, A., Paci, P., van Doorslaer, E., (1991). On the measurement of inequalities in health. *Social Science and Medicine* 33, 545-557.

Wagstaff, A.,van Doorslear, E. (2000) Income inequality and health: what does the literature tell us? *Annual Review of Public Health*, 21: 543-567.

Wagstaff, A, van Doorslaer, E., Watanabe, N., (2003). On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam, *Journal of Econometrics*, 112: 207-223.

Wanless, D. (2002). Securing our future health: taking a long-term view. Final Report. HM Treasury, London.

Wildman, J., 2002. Income related inequalities in mental health in Great Britain: analysing the causes of health inequality over time. *Journal of Health Economics* 22, 295-312.

Wildman, J., Jones, A.M. (2002) *Is it absolute or relative deprivation that leads to poor psychological well being? A test based on individual-level longitudinal data*. Ecuity III WP#4.

Wilkinson, R. (1996) *Unhealthy Societies: The Afflictions of Inequality*. London, Routledge.

Wooldridge, J. (2002a) *Econometric analysis of cross section and panel data*. MIT Press, London.

Wooldridge, J. (2002b). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *CEMMAP Working Paper CWP18/02,* Centre for Microdata Methods and Practice, IFS and UCL.

Wooldridge, J. (2002c). Inverse probability weighted M-estimators for sample stratification, attrition and stratification. *Portuguese Economic Journal,* 1: 117-139.

Table 1: Correlation Matrices
(Source: Hauck and Rice (2003))

a) Men

Wave	1	2	3	4	5	6	7	8	9	10	11
1	1.00										
2	.489	1.00									
3	.422	.531	1.00								
4	.388	.451	.524	1.00							
5	.383	.454	.484	.526	1.00						
6	.338	.393	.414	.471	.556	1.00					
7	.316	.348	.383	.455	.451	.532	1.00				
8	.328	.374	.385	.421	.436	.467	.525	1.00			
9	.315	.361	.373	.406	.392	.442	.465	.536	1.00		
10	.353	.359	.391	.404	.388	.409	.433	.455	.544	1.00	
11	.355	.351	.363	.401	.386	.392	.395	.441	.477	.538	1.00

b) *Women*

Wave	1	2	3	4	5	6	7	8	9	10	11
1	1.00										
2	.484	1.00									
3	.444	.506	1.00								
4	.395	.438	.516	1.00							
5	.363	.386	.408	.502	1.00						
6	.357	.370	.387	.435	.470	1.00					
7	.332	.311	.322	.368	.435	.456	1.00				
8	.322	.302	.348	.393	.402	.444	.525	1.00			
9	.327	.328	.352	.352	.391	.411	.448	.504	1.00		
10	.331	.309	.354	.331	.334	.370	.387	.463	.521	1.00	
11	.324	.325	.315	.323	.329	.347	.355	.422	.464	.518	1.00

Table2: Mental health mobility across socio-economic groups
(Source: Hauck and Rice (2003))

	MEN		WOMEN	
	MLE	OLS	MLE	OLS
	$\hat{\rho}$	$\hat{\lambda}$	$\hat{\rho}$	$\hat{\lambda}$
ALL DATA:	.414 (.007)	.510 (.005)	.385 (.006)	.487 (.005)
ETHNICITY:				
WHITE	.417 (.007)	.511 (.005)	.385 (.006)	.488 (.005)
OTHETH	.300 (.035)	.422 (.030)	.338 (.035)	.431 (.029)
EDUCATION:				
DEGHDEG	.318 (.018)	.420 (.015)	.262 (.018)	.362 (.016)
HNDALEV	.379 (.013)	.483 (.010)	.314 (.014)	.425 (.011)
OCSE	.409 (.013)	.498 (.010)	.341 (.011)	.447 (.009)
NOQUAL	.469 (.012)	.557 (.009)	.466 (.010)	.564 (.007)
INCOME:				
1st Quintile	.477 (.015)	.567 (.011)	.436 (.014)	.519 (.011)
2nd Quintile	.435 (.015)	.539 (.011)	.400 (.014)	.508 (.010)
3rd Quintile	.386 (.016)	.453 (.012)	.397 (.014)	.494 (.010)
4th Quintile	.367 (.015)	.472 (.012)	.327 (.013)	.439 (.011)
5th Quintile	.329 (.015)	.451 (.012)	.295 (.013)	.417 (.011)
AGE:				
1st Quintile	.285 (.014)	.385 (.012)	.266 (.012)	.353 (.011)
2nd Quintile	.354 (.015)	.456 (.012)	.316 (.014)	.425 (.011)
3rd Quintile	.399 (.015)	.494 (.012)	.349 (.014)	.469 (.011)
4th Quintile	.432 (.016)	.537 (.011)	.463 (.014)	.567 (.010)
5th Quintile	.586 (.014)	.649 (.010)	.550 (.013)	.629 (.010)
SOCIAL CLASS:				
PROF	.315 (.027)	.415 (.022)	.212 (.045)	.267 (.046)
MANTECH	.323 (.014)	.431 (.011)	.318 (.014)	.447 (.011)
SKNONM	.303 (.023)	.449 (.020)	.287 (.013)	.373 (.011)
SKMANAR	.376 (.014)	.464 (.011)	.375 (.030)	.450 (.023)
UNPSKL	.369 (.020)	.497 (.016)	.374 (.019)	.482 (.014)
UNEMP	.396 (.038)	.457 (.031)	.177 (.056)	.160 (.065)
FAMCARE	-	-	.398 (.105)	-.497
RETIRED	.585 (.014)	.651 (.010)	.522 (.012)	(.012)
SCOTHER	.482 (.029)	.605 (.020)	.425 (.037)	.629 (.009)
HEALTH:				.535 (.026)
HEALTHY	.128 (.006)	.236 (.007)	.134 (.006)	
UNHEALTHY	.208 (.009)	.348 (.009)	.160 (.007)	.245 (.007)
				.305 (.008)

Notes:
1. Individuals are classified as being healthy if their mean GHQ score was lower than the sample mean GHQ score. Individuals are classified as being unhealthy if their mean GHQ score was higher than the sample mean GHQ score.
2. Too few observations for FAMCARE to provide reliable estimates for men.

Table 3: Sample size, drop outs and attrition rates by wave
(Source: Contoyannis, Jones and Rice (2003))

a) All data

		FULL SAMPLE			EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. individuals	Survival rate	Drop outs	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	10256								
2	8957	87.33%	1299	12.67%	11.54%	12.57%	13.01%	13.73%	23.74%
3	8162	79.58%	795	8.88%	8.08%	8.13%	9.65%	12.62%	19.46%
4	7825	76.30%	337	4.13%	6.67%	6.54%	6.73%	10.35%	14.74%
5	7430	72.45%	395	5.05%	6.21%	6.18%	7.87%	9.11%	16.34%
6	7238	70.57%	192	2.58%	3.11%	3.24%	5.06%	10.47%	18.83%
7	7102	69.25%	136	1.88%	3.15%	3.85%	4.79%	8.83%	8.75%
8	6839	66.68%	263	3.70%	3.43%	3.82%	5.30%	5.88%	17.01%

b) Men

		FULL SAMPLE			EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. individuals	Survival rate	Drop outs	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	4832								
2	4180	86.51%	652	13.49%	12.17%	13.45%	14.23%	14.63%	26.88%
3	3752	77.65%	428	10.24%	8.92%	9.51%	11.49%	14.58%	24.00%
4	3593	74.36%	159	4.24%	6.65%	7.40%	7.29%	8.52%	14.52%
5	3392	70.20%	201	5.59%	5.40%	7.42%	9.61%	9.72%	22.95%
6	3308	68.46%	84	2.48%	3.56%	3.05%	4.80%	12.16%	25.40%
7	3249	67.24%	59	1.78%	3.27%	4.46%	4.62%	9.65%	11.48%
8	3105	64.26%	144	4.43%	4.06%	4.43%	6.36%	7.00%	22.89%

c) Women

		FULL SAMPLE			EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. individuals	Survival rate	Drop outs	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	5424								
2	4777	88.07%	647	11.93%	10.83%	11.81%	12.06%	13.16%	21.43%
3	4410	81.31%	367	7.68%	7.19%	6.94%	8.21%	11.33%	16.36%
4	4232	78.02%	178	4.04%	6.69%	5.82%	6.32%	11.53%	14.89%
5	4038	74.45%	194	4.58%	7.12%	5.15%	6.67%	8.61%	11.96%
6	3930	72.46%	108	2.67%	2.63%	3.40%	5.24%	9.27%	14.29%
7	3853	71.04%	77	1.96%	3.02%	3.34%	4.91%	8.26%	7.07%
8	3734	68.84%	119	3.09%	2.74%	3.32%	4.53%	5.16%	12.61%

Table 4: Average partial effects on probability of reporting excellent health for selected variables
(Source: Contoyannis, Jones and Rice (2003))

a) Men

	(1) Pooled model, balanced sample	(2) Pooled model, unbalanced sample	(3) Pooled model, IPW-1	(4) Pooled model, IPW-2	(5) Random effects, balanced sample	(6) Random effects, unbalanced sample
Ln(INCOME)	.009 (.004)	.009 (.004)	.009 (.004)	.011 (.005)	.013 (.006)	.012 (.005)
Mean Ln(INCOME)	.049 (.024)	.043 (.022)	.042 (.021)	.045 (.022)	.066 (.028)	.056 (.025)
DEGREE	.010 (.005)	.017 (.009)	.018 (.009)	.018 (.009)	.015 (.006)	.027 (.012)
HND/A	.019 (.009)	.021 (.011)	.021 (.010)	.022 (.011)	.028 (.011)	.030 (.013)
O/CSE	.016 (.008)	.020 (.010)	.020 (.010)	.020 (.010)	.024 (.010)	.028 (.012)
SAHEX(t-1)	.234 (.087)	.231 (.090)	.231 (.090)	.230 (.089)	.082 (.031)	.085 (.035)
SAHFAIR(t-1)	-.170 (.085)	-.163 (.084)	-.162 (.084)	-.162 (.083)	-.080 (.034)	-.077 (.036)
SAHPOOR(t-1)	-.242 (.167)	-.233 (.163)	-.232 (.162)	-.232 (.162)	-.151 (.077)	-.145 (.078)
SAHVPOOR(t-1)	-.260 (.198)	-.253 (.197)	-.255 (.199)	-.255 (.200)	-.184 (.104)	-.179 (.106)

b) Women

	(1) Pooled model, balanced sample	(2) Pooled model, unbalanced sample	(3) Pooled model, IPW-1	(4) Pooled model, IPW-2	(5) Random effects, balanced sample	(6) Random effects, unbalanced sample
Ln(INCOME)	.006(.004)	.007 (.004)	.005 (.003)	.004 (.002)	.006 (.003)	.008 (.004)
Mean Ln(INCOME)	.028 (.016)	.025 (.015)	.029 (.017)	.030 (.017)	.039 (.020)	.033 (.018)
DEGREE	.037 (.020)	.034 (.019)	.036 (.020)	.039 (.022)	.049 (.024)	.044 (.022)
HND/A	.019 (.011)	.022 (.013)	.023 (.013)	.022 (.013)	.027 (.014)	.030 (.015)
O/CSE	.026 (.015)	.023 (.013)	.024 (.014)	.025 (.015)	.035 (.018)	.029 (.015)
SAHEX(t-1)	.220 (.095)	.206 (.092)	.205 (.091)	.208 (.092)	.082 (.038)	.074 (.035)
SAHFAIR(t-1)	-.132 (.078)	-.128 (.076)	-.127 (.075)	-.127 (.074)	-.064 (.034)	-.061 (.033)
SAHPOOR(t-1)	-.185 (.144)	-.182 (.142)	-.183 (.142)	-.183 (.142)	-.121 (.073)	-.118 (.072)
SAHVPOOR(t-1)	-.201 (.175)	-.198 (.173)	-.199 (.173)	-.199 (.173)	-.144 (.095)	-.144 (.097)

Figure1: The concentration curve

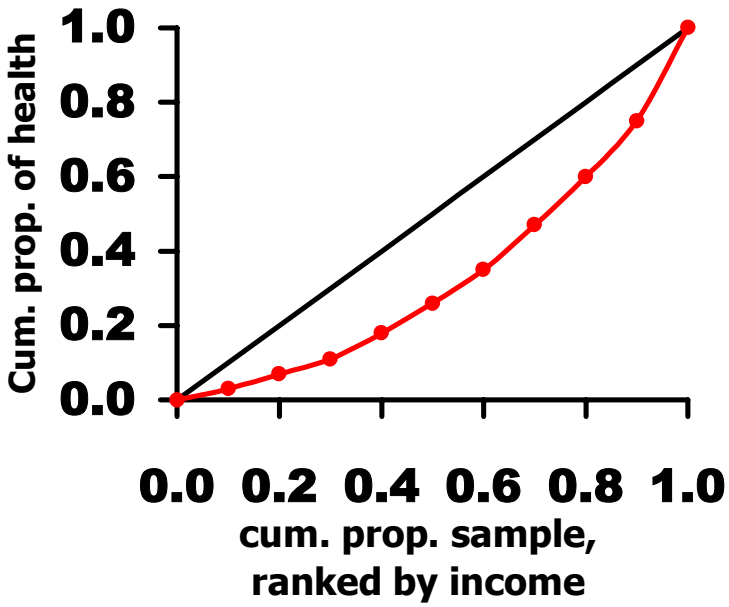


Figure 2. HUI interval boundaries of SAH levels derived from the empirical cumulative distribution for the Canadian NPHS 1994 sample. (Source: van Doorslaer and Jones (2003))

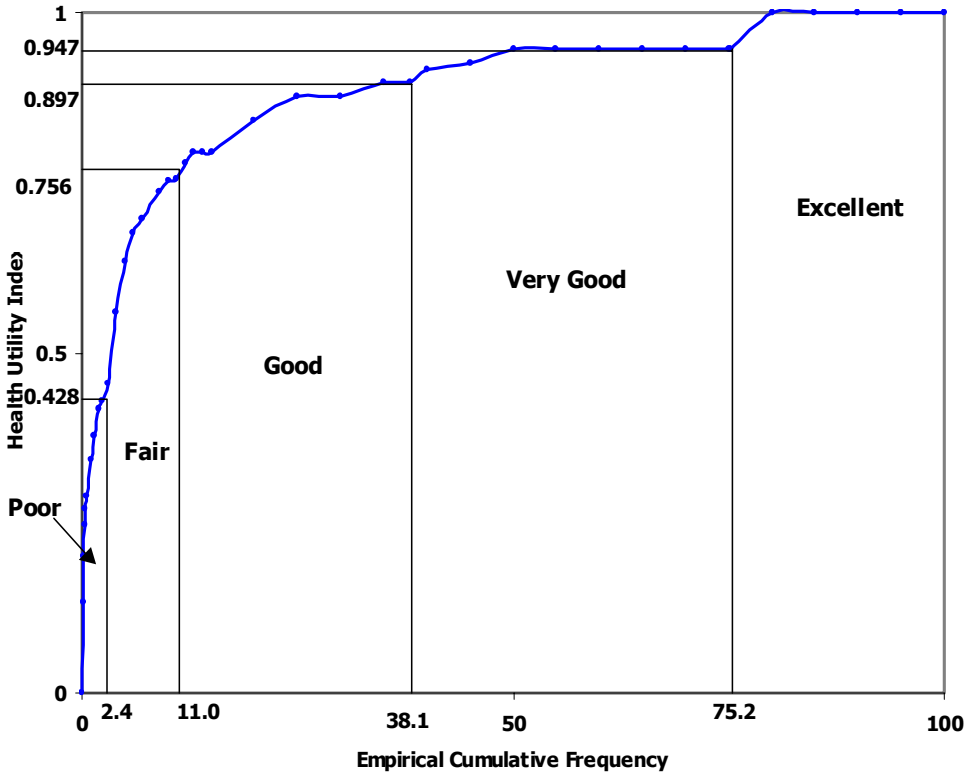


Figure 3: Health concentration curves
(Source: van Doorslaer and Jones (2003))

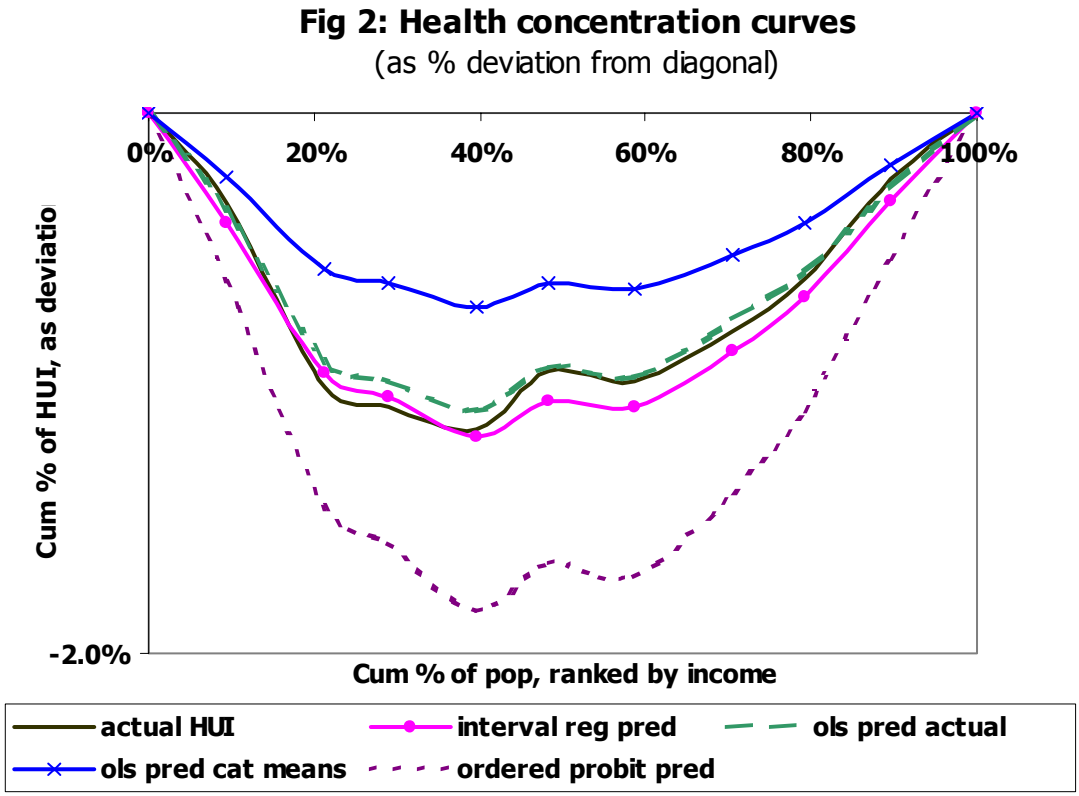


Figure 4: Income and health inequality in Europe
(Source: van Doorslaer and Koolman (2002))

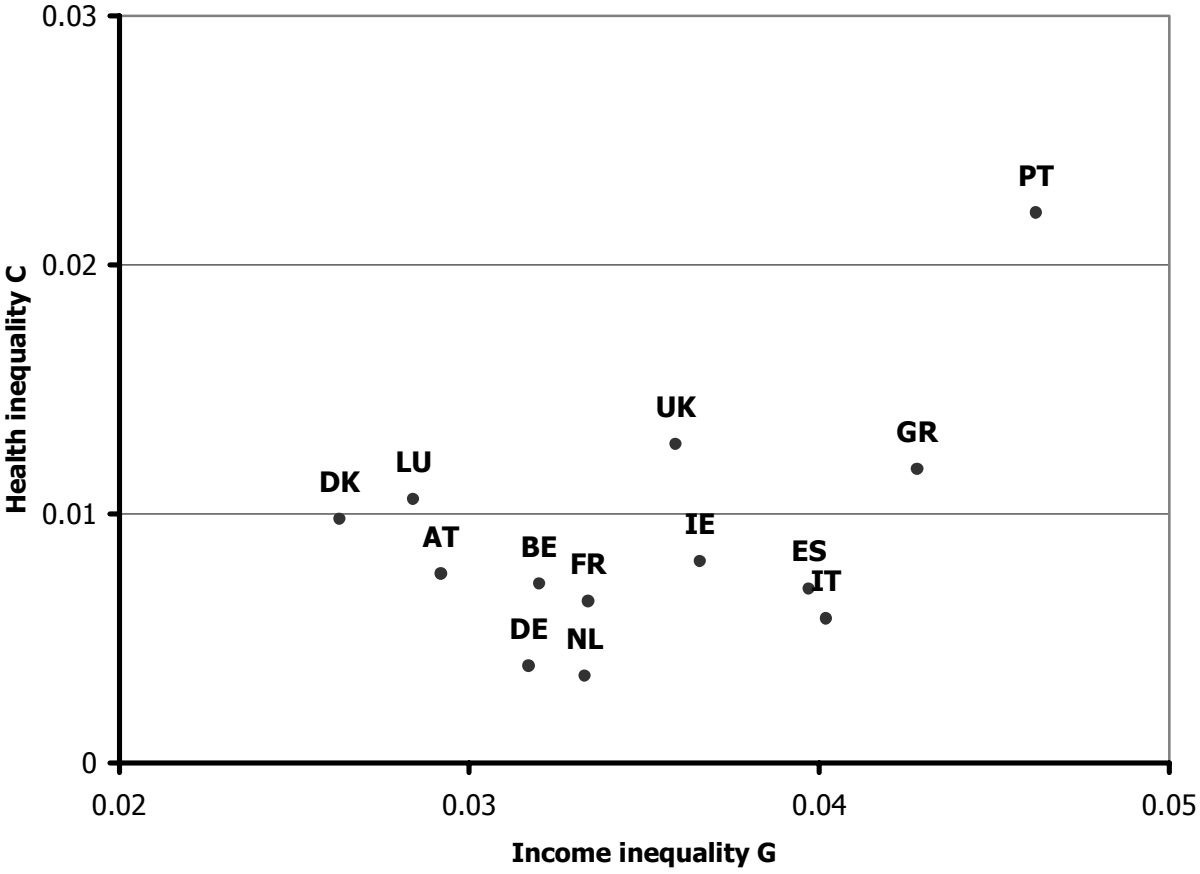


Figure 5: Decomposition of socioeconomic inequality in health in Europe (Source: van Doorslaer and Koolman (2002))

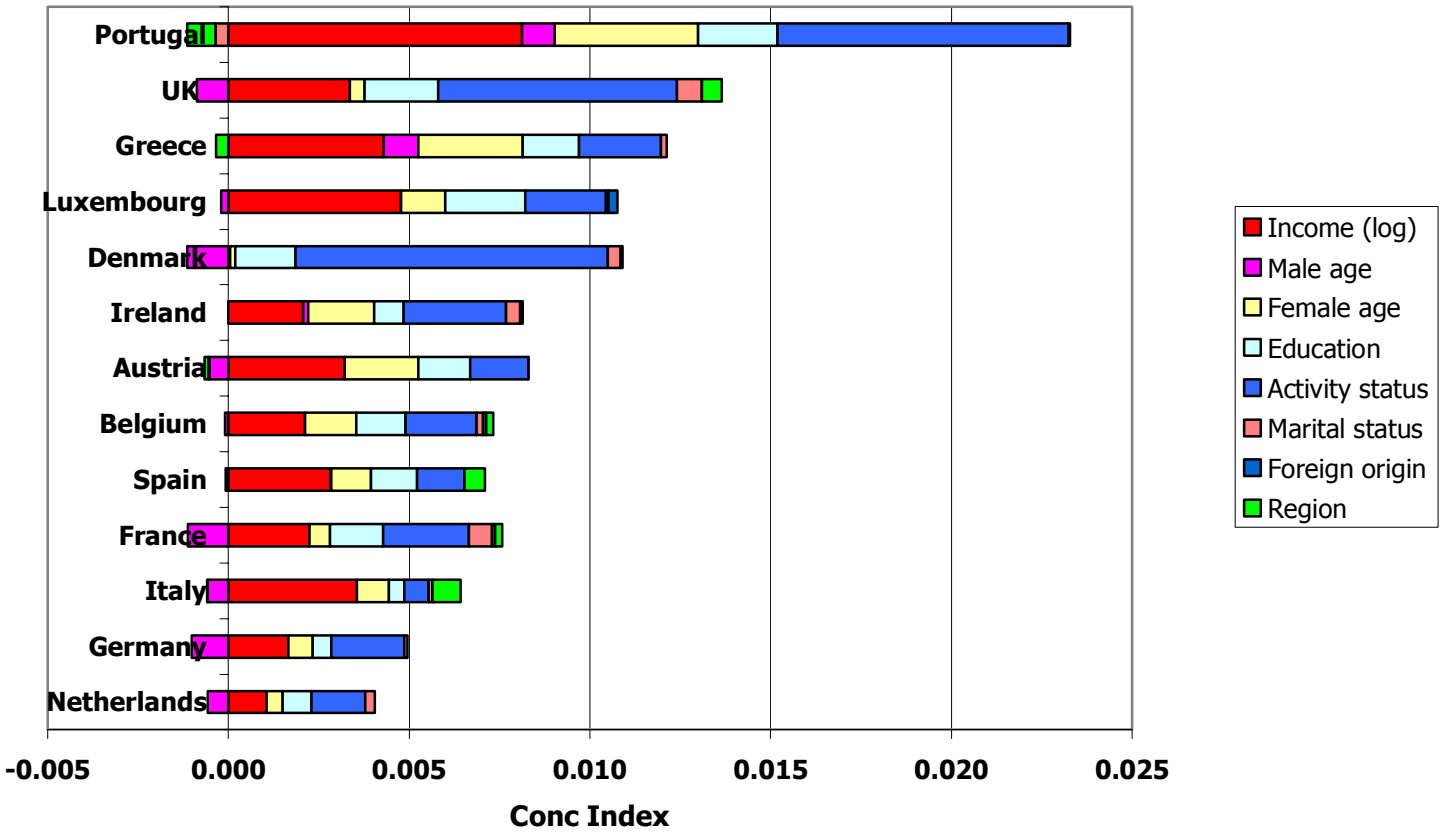


Figure 6: Income related health inequality in the BHPS, 1991-1999
(Source: Jones and Lopez Nicolas (2003))

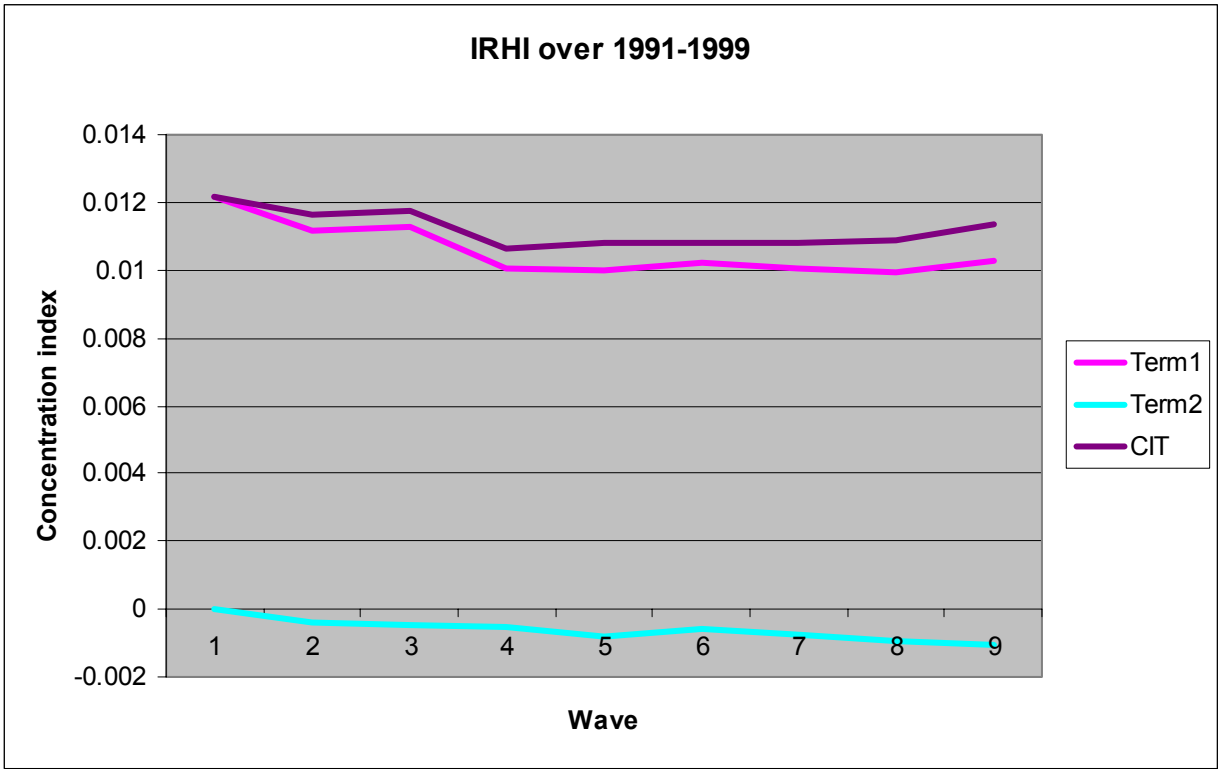


Figure. 7: Health-related income mobility in the BHPS, 1991-1999
(Source: Jones and Lopez Nicolas (2003))

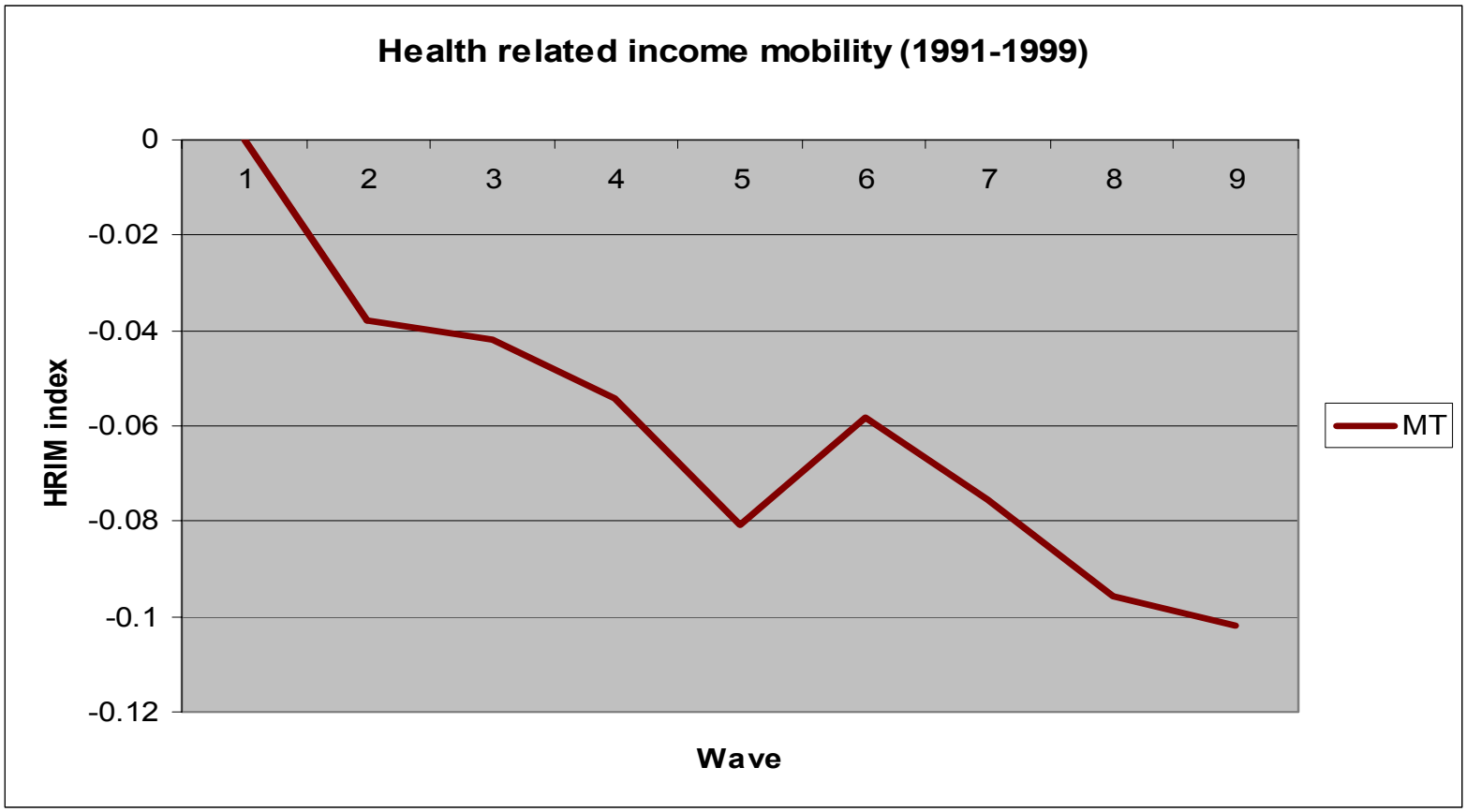
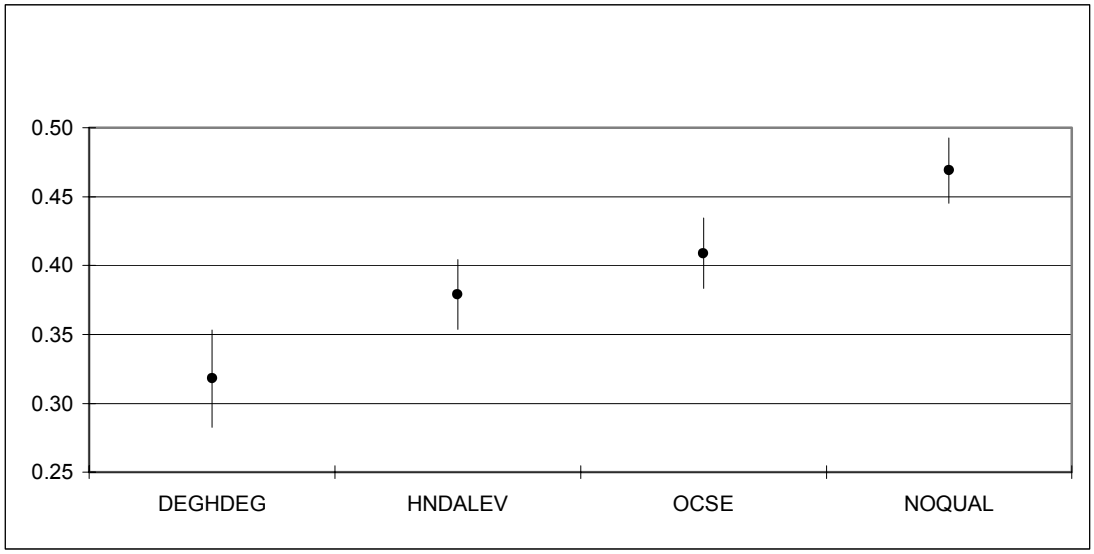
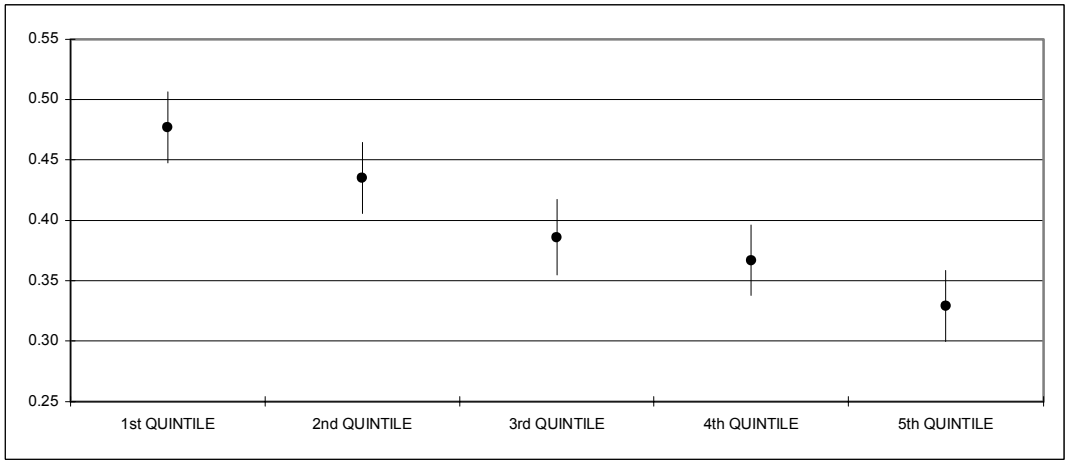


Figure 8: MLE estimates of mobility (ρ)
(Source: Hauck and Rice (2003))

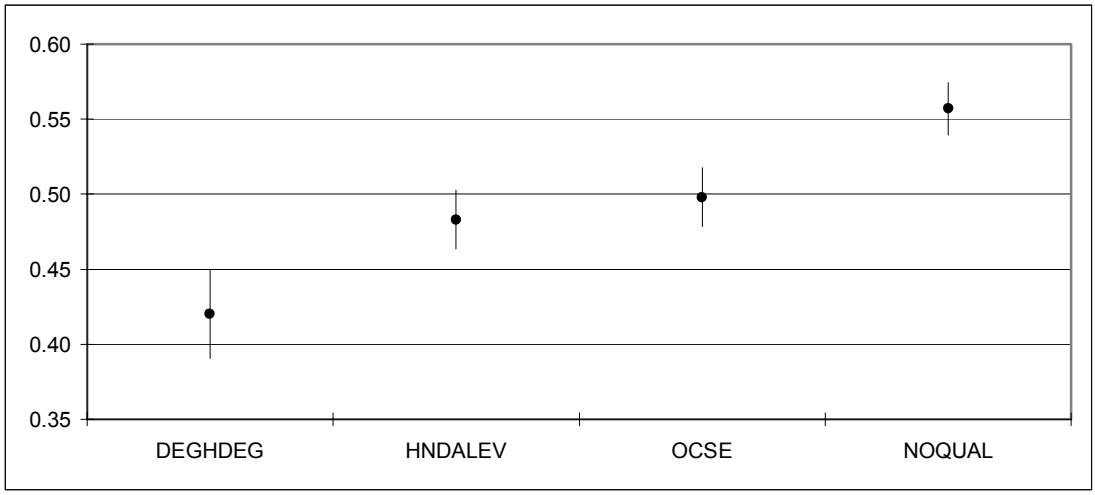


Educational attainment

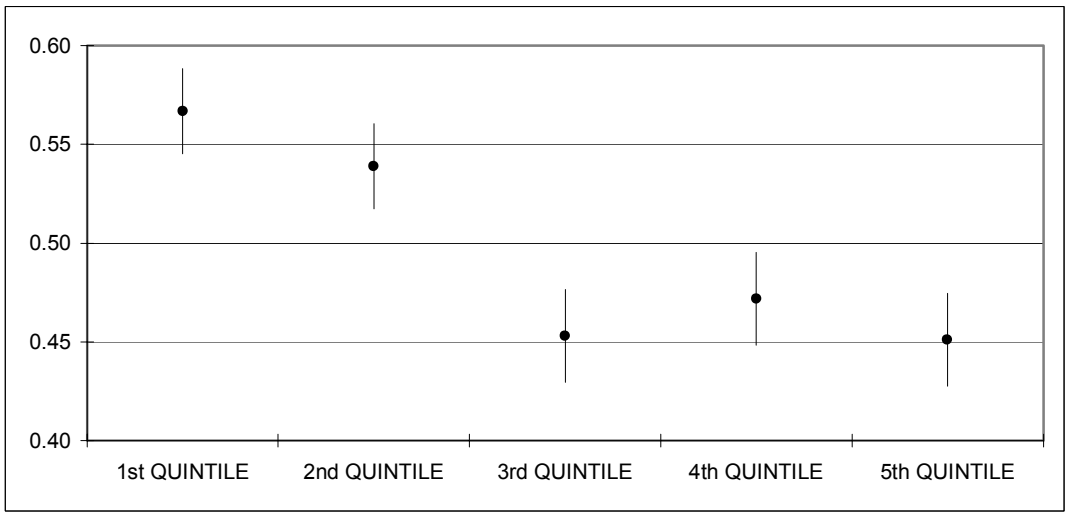


Income quintile

Figure 9: OLS estimates of mobility (λ)
(Source: Hauck and Rice (2003))



Educational attainment



Income quintile

Figure 10: Self-assessed health at wave 2 by self-assessed health at wave 1 (Source: Contoyannis, Jones and Rice (2004)

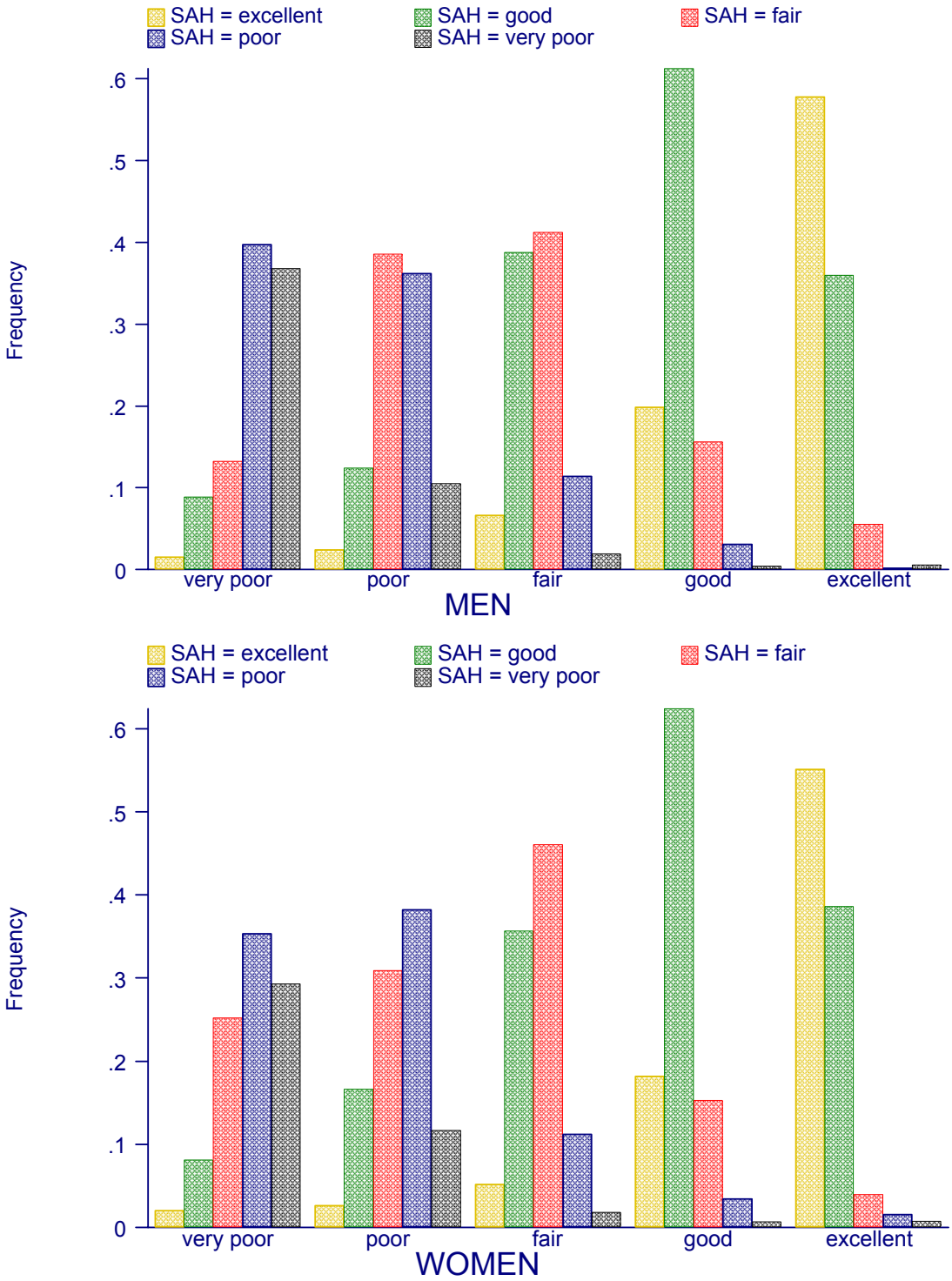


Figure 11: Empirical CDFs of mean income by self-assessed health status (Source: Contoyannis, Jones and Rice (2004))

