

Using longitudinal data to investigate socioeconomic inequality in health

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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 socioeconomic characteristics, as revealed by longitudinal survey data. This chapter provides an overview of methods for the analysis of health inequalities and health mobility when such longitudinal data are available.

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1 Introduction

Over the last twenty years the UK has enjoyed increased prosperity; despite this there remain striking inequalities in health across geographical areas and between socio-economic groups within society: evidence suggests that such inequalities are widening. Concern over the level of health inequalities prompted the commission of Sir Donald Acheson's *Independent Inquiry into Inequalities in Health* (Acheson, 1998). This summarised 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 (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 of 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) seeks to place 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 calls for 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. The disciplines of public health and epidemiology have contributed greatly to this end. The aim of this chapter 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 to illuminate 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 chapter concentrates 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”. 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 chapter is to highlight 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 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 45-degree 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 convex curve on the figure - the concentration curve. In the example shown, the poorest 20% of income earners receive less than 20% of the health available. 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 (C), 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,

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

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. Concentration indices are sometimes criticised for being hard to interpret: what does a value of, say, 0.04 mean? A recent contribution by Koolman and van Doorslaer (2004) helps to clarify the situation. They show that, if the concentration index is interpreted in terms of a hypothetical linear redistribution from rich to poor, it can be given a Robin Hood-type interpretation. This interpretation implies that 75 times the concentration

index is the percentage of total y that would have to be redistributed from individuals in the richest half to individuals in the poorest half of the population to achieve an equal distribution

Recent work by Bommier and Stecklov (2002) argues that concentration curves, and by implication the concentration index, are a more appropriate way to measure socioeconomic inequality in health than inequality indices derived from social welfare functions that have health and income as arguments. This is the case if equity is defined according to a social justice approach: that defines “the health distribution in the ideal equitable society as one where access to health has not been determined by socioeconomic status or income” (Bommier and Stecklov (2002, p. 502)).

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 of inequality, and that measurement should focus on total health inequality (e.g., Gakidou et al., 2000). This can be analysed using 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: the concentration index is proportional to the Gini coefficient, where the factor of proportionality is given by the ratio between the correlation coefficient for health and income rank and the correlation coefficient between health and health rank (Kakwani, 1980; van Doorslaer and Jones, 2003). This means that it is easy to move between these measures of socioeconomic and pure health inequality.

The inequality literature makes a distinction between partial orderings, based on Lorenz or concentration curves, and complete orderings, based on index numbers such as the Gini and concentration indices. A partial ordering means that some combinations of distributions can be ranked unambiguously, but not all. The ambiguity arises if the Lorenz or concentration curves for two distributions cross each other. In order to obtain a complete ordering of distributions, Gini coefficients and concentration indices embed particular normative judgements about the weight given to individuals at different points in the income distribution and, hence, they embody a particular degree of inequality aversion. Sensitivity of the results to inequality aversion can be assessed by using extended Gini or concentration indices (Yitzhaki, 1983; Lerman and Yitzhaki,

1984; Wagstaff, 2002). These add an extra parameter that can range from inequality neutrality (no concern for inequality) to extreme inequality aversion (Rawlsian lexi-min).

Gini and concentration indices are measures of relative inequality and do not address the equity-efficiency trade-off. This trade-off can be captured by generalized Lorenz or concentration curves. These multiply the Lorenz or concentration curve by the absolute level of health. A classic result from the income equality literature – the Kakwani-Kolm-Shorrocks theorem – shows that generalized Lorenz dominance is equivalent to a distribution having a greater level of social welfare, for any welfare function that is increasing and concave in income. The generalized concentration index, $\mu(1-C)$, gives a single index that captures the trade-off between the mean of the distribution (μ) and the level of inequality. This can be combined with different degrees of inequality aversion, through the extended concentration index, to give what Wagstaff (2002) calls an index of health achievement. This index summarises the equity-efficiency trade-off for different degrees of inequality aversion.

The preceding analysis assumes that a cardinal measure of health is available. This is relatively 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 re-scale 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 their case the Canadian National Population Health Survey (NPHS), which includes SAH and the McMaster health utility index (HUI). 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. 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.

Figure 2, 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 Watanabe (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,

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

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_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 3 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.

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 differences in need: 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 from 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 sample as a whole as the vertical equity norm and horizontal inequity is measured by systematic deviations from this norm by income level.

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 specified as a nonlinear function of the regressors: for example, 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. So long as the model 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 López Nicolás (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 periods. 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 (1978).

The aim of the paper by Jones and López Nicolás (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 levels of health 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). This shows that, after nine waves, the weighted average of short-run measures underestimates the long-run measure by 15% for men and 5% for women

The distinction between the short-run and long-run will be of interest to policy makers whose ethical concern is with inequalities in long-run health. For example, the “fair innings” perspective suggests that equity should be defined in terms of a person’s lifetime experience of health (Williams and Cookson [28, p.1899]). In practice, this lifetime experience could be measured using DALYs (Murray and Lopez [29]) or QALYs (Williams [30]).

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 2.4 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.

As in Jones and López Nicolás (2003), 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:

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

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 estimation.

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:

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

where h_{it} , X_{it} , Z_{it} , 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_{it}). 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 persistence for men and women. Gradients across the categories of the socio-economic groups are clearly apparent. Less persistence 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, estimates of persistence for women are larger 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 so that the differences in estimates as one moves from the 1st (youngest) to the 5th (oldest) age quintile are: men: 51% for $\hat{\rho}$ and 68% for $\hat{\lambda}$; women: 106% and 78% respectively. 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 persistence 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, as for the GHQ score, the BHPS reveals evidence of considerable persistence in individual's health status. So for example, 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 individual's previous experience of health influences their current health outcomes.

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 (2004) 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 ($t = 1 \dots T$) for a sample of individuals ($i = 1 \dots n$). This is modelled using a latent variable specification

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

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, will 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 (2002a) 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

correlated 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 probability weights are used to attempt to control for attrition (Wooldridge,2002b). This works by estimating separate probit equations for 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. . The appropriateness of this approach relies on the assumption 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 do not 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

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 analyst. The successful evaluation of policy initiatives aimed at the reduction in health inequalities should be afforded a prominent role in the future agenda on tackling inequalities in health.

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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:				
1 st Quintile	.477 (.015)	.567 (.011)	.436 (.014)	.519 (.011)
2 nd Quintile	.435 (.015)	.539 (.011)	.400 (.014)	.508 (.010)
3 rd Quintile	.386 (.016)	.453 (.012)	.397 (.014)	.494 (.010)
4 th Quintile	.367 (.015)	.472 (.012)	.327 (.013)	.439 (.011)
5 th Quintile	.329 (.015)	.451 (.012)	.295 (.013)	.417 (.011)
AGE:				
1 st Quintile	.285 (.014)	.385 (.012)	.266 (.012)	.353 (.011)
2 nd Quintile	.354 (.015)	.456 (.012)	.316 (.014)	.425 (.011)
3 rd Quintile	.399 (.015)	.494 (.012)	.349 (.014)	.469 (.011)
4 th Quintile	.432 (.016)	.537 (.011)	.463 (.014)	.567 (.010)
5 th 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 (.012)
RETIRED	.585 (.014)	.651 (.010)	.522 (.012)	.629 (.009)
SCOTHER	.482 (.029)	.605 (.020)	.425 (.037)	.535 (.026)
HEALTH:				
HEALTHY	.128 (.006)	.236 (.007)	.134 (.006)	.245 (.007)
UNHEALTHY	.208 (.009)	.348 (.009)	.160 (.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 (2004))

a) Men

Wave	No. individuals	FULL SAMPLE			EX	GOOD	FAIR	POOR	VPOOR
		Survival rate	Drop outs	Attrition rate	at t-1	at t-1	at t-1	at t-1	at t-1
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%

b) Women

Wave	No. individuals	FULL SAMPLE			EX	GOOD	FAIR	POOR	VPOOR
		Survival rate	Drop outs	Attrition rate	at t-1	at t-1	at t-1	at t-1	at t-1
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 (2004))

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)

Figure 1: The concentration curve

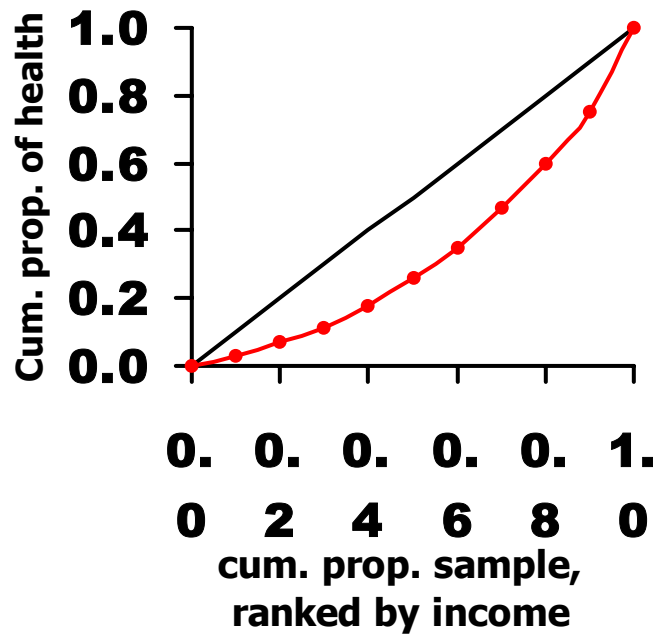


Figure 2: Income and health inequality in Europe
(Source: van Doorslaer and Koolman (2002))

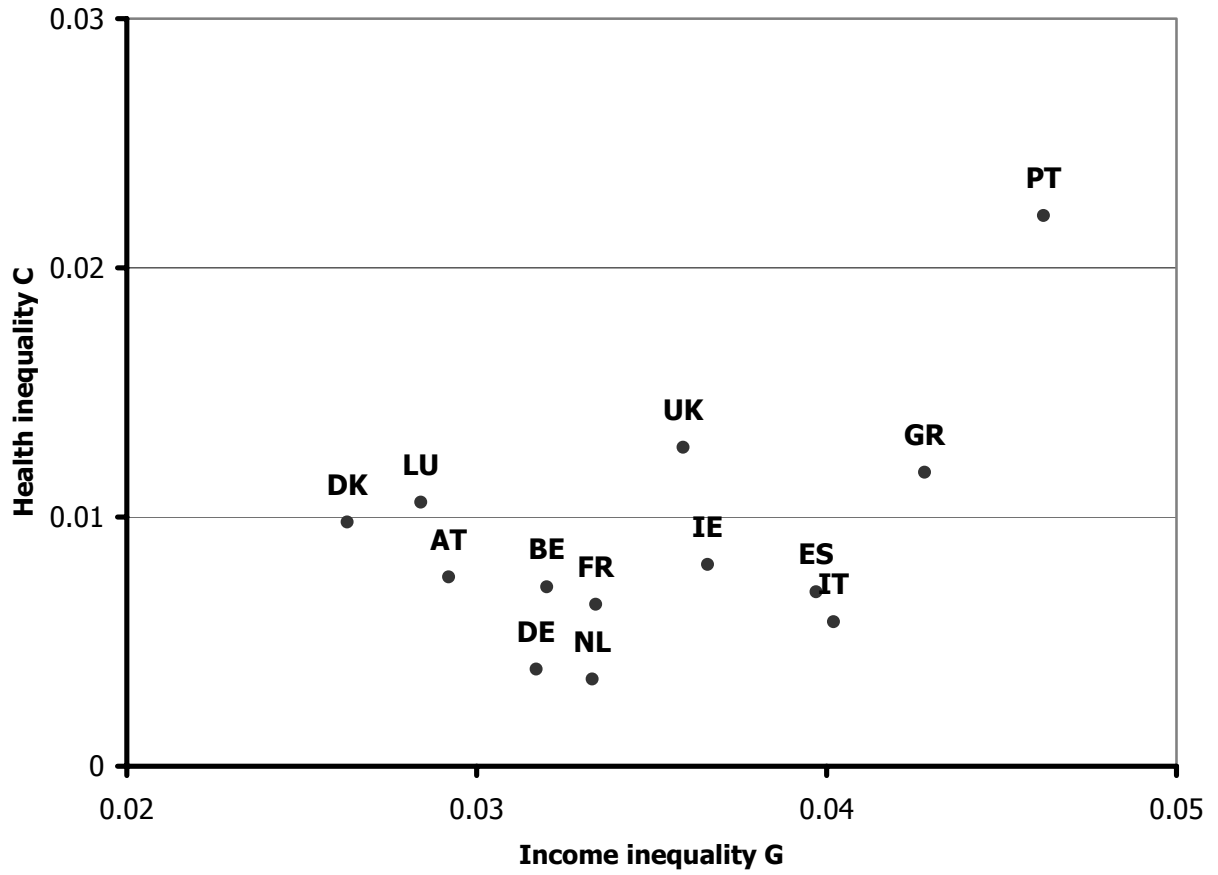


Figure 3: Decomposition of socioeconomic inequality in health in Europe
 (Source: van Doorslaer and Koolman (2002))

