Health-related attrition in the BHPS and ECHP: using inverse probability weighted estimators in nonlinear models

Andrew M Jones[1], Xander Koolman[2], Nigel Rice[3]

May 2004

Abstract

This paper considers models of the association between socioeconomic status and self-assessed health (SAH) based on eleven waves of the British Household Panel Survey (BHPS) and the full eight waves of the European Community Household Panel (ECHP). The objective is to explore the consequences of health-related attrition for these models. Attrition may be important as there is a risk of *survivorship bias*: long-term survivors who remain in the panel are likely to be healthier on average. To address this issue we describe the pattern of health-related attrition revealed by the BHPS and ECHP data. We both test and correct for attrition in our empirical models of the impact of socioeconomic status on self-assessed health. Descriptive evidence shows that there is health-related attrition in the data, with those in poor initial health more likely to drop out, and variable addition tests provide evidence of attrition bias in the panel data models of SAH. Nevertheless a comparison of estimates - based on the balanced sample, the unbalanced sample and corrected for non-response using inverse probability weights - does not show substantive differences in the average partial effects of the variables of interest. So, while health-related attrition exists, it does not appear to distort the magnitudes of the estimated average partial effects of socioeconomic status. Similar findings have been reported concerning the negligible influence of attrition bias in models of various labour market outcomes; we discuss possible explanations for our results.

JEL codes I12 C23

Keywords: Self-assessed health, attrition, selection on observables, inverse probability weighting, BHPS, ECHP

Data from the *British Household Panel Survey* (BHPS) were supplied by the UK Data Archive. Neither the original collectors of the data nor the Archive bear any responsibility for the analysis or interpretations presented here. The ECHP UDB – version of December 2003 was supplied by Eurostat. This paper derives from the project "The dynamics of income, health and inequality over the lifecycle" (known as the ECuity III Project), which is funded in part by the European Community's Quality of Life and Management of Living Resources programme (contract QLK6-CT-2002-02297). Nigel Rice is in part supported by the UK Department of Health programme of research at the Centre for Health Economics.

[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]Department of Health Policy and Management, Erasmus University, The Netherlands
[3]Centre for Health Economics, University of York, United Kingdom

1. Introduction

The objective of this paper is to explore the existence of health-related attrition and its consequences for modelling the association between socioeconomic status (SES) and self-assessed health (SAH). Using panel data, such as the British Household Panel Survey (BHPS) or European Community Household Panel (ECHP), to analyse health models of self-assessed health creates a risk that the results will be contaminated by *survivorship bias*. There is attrition from the panels at each wave and some of it can be expected to be directly related to health: due to deaths, serious illness and people moving into institutional care. In addition, other sources of attrition may be indirectly related to health, for example divorce may increase the risk of non-response and also be associated with poorer health than average. So, the long-term survivors who remain in the panel are likely to be healthier than average. The health of survivors will tend to be higher than the population as a whole and their rate of decline in health will tend to be lower. Also, the socioeconomic status of the survivors may not be representative of the original population who were sampled at wave 1. So, failing to account for attrition may result in misleading estimates of the relationship between health and socioeconomic characteristics.

To address this issue we describe the pattern of health-related attrition revealed by the BHPS and ECHP data and we test and correct for attrition in our empirical models. We apply variable addition tests for attrition bias (Verbeek and Nijman, 1992) and inverse probability weighting to adjust for attrition in estimation of pooled models (Robins *et al.* 1995; Fitzgerald *et al.*, 1998; Moffitt *et al.*, 1999; Wooldridge, 2002a). The association between socioeconomic status and health is presented as average partial effects (Wooldridge, 2002b). Descriptive evidence shows that there is health-related attrition in the data, with those in poor initial health more likely to drop out, and variable addition tests provide evidence of attrition bias in the panel data models of SAH. Nevertheless a comparison of estimates - based on the balanced sample, the unbalanced sample and corrected for attrition using inverse probability weights - does not show substantive differences in the average partial effects of the variables of interest. So, while health-related attrition exists, it does not appear to distort the magnitudes of the estimated effects of socioeconomic status. Similar findings have been reported concerning the negligible influence of attrition bias in models of various labour market outcomes; we discuss possible explanations for our results.

The structure of the paper is as follows. Section 2 introduces the BHPS and ECHP datasets. Section 3 presents a descriptive analysis of health-related attrition in both surveys. In Section 4 we introduce the empirical models for self-assessed health and describe the estimation strategy.

Section 5 reports and discusses the results for the models of socioeconomic status and self-assessed health and a conclusion is provided in Section 6.

2. The Data

2.1 BHPS

The sample

In estimating the empirical models for self-assessed health we first exploit the panel data available in the first eleven waves (1991-2001) of the British Household Panel Survey (BHPS). This includes rich information on socio-demographic and health variables. The BHPS is a longitudinal survey of private households in Great Britain, and was designed as an annual survey of each adult (16+) member of a nationally representative sample of more that 5,000 households, with a total of approximately 10,000 individual interviews. The first wave of the survey was conducted between 1st September 1990 and 30th April 1991. The initial selection of households for inclusion in the survey was performed using a two-stage stratified systematic sampling procedure designed to give each address an approximately equal probability of selection (Taylor *et al.*, 1998). The same individuals are re-interviewed in successive waves and, if they split off from their original households are also re-interviewed along with all adult members of their new households. In this analysis we use both *balanced samples* of respondents, for whom information on all the required variables is reported at each wave, and *unbalanced samples* that exploit all available observations. Both samples do not include new entrants to the BHPS; they only track all of those who were observed at wave 1. In this sense, the analysis treats the sample as a cohort of all those present at wave 1 who were followed-up in the subsequent eleven waves. To be included in the analysis individuals must be original sample members (OSMs) who were aged 16 or over and who provided a valid response for the health measure at wave 1.

Measures of health

The principal health outcome is self-assessed health (SAH), defined by a response to: '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?' SAH should therefore be interpreted as indicating a perceived health status relative to the individual's concept of the 'norm' for their age group. In any case, we condition on a quartic function of age in the empirical analysis.

SAH has been used widely in previous studies of the relationship between health and socioeconomic status (e.g., Ettner, 1996; Deaton and Paxson, 1998; Smith, 1999; Benzeval *et al.*, 2000; Salas, 2002; Adams *et al.*, 2003; Frijters *et al.*, 2003; Contoyannis *et al.,* 2004) and of the relationship between health and lifestyles (e.g., Kenkel, 1995; Contoyannis and Jones, 2004). SAH is a simple subjective measure of health that provides an ordinal ranking of perceived health status. However it has been shown to be a powerful predictor of subsequent mortality (see e.g., Idler and Kasl, 1995; Idler and Benyamini, 1997) and its predictive power does not appear to vary across socioeconomic groups (see e.g., Burström and Fredlund, 2001). Socioeconomic inequalities in SAH have been a focus of research (see e.g., van Doorslaer *et al.*, 1997; van Doorslaer and Koolman, 2002; van Ourti, 2003) and have been shown to predict inequalities in mortality (see e.g., van Doorslaer and Gerdtham, 2003). Categorical measures of SAH have been shown to be good predictors of subsequent use of medical care (see e.g., van Doorslaer *et al.*, 2000; van Doorslaer *et al.,* 2004).

Unfortunately there was a change in the wording of the SAH question at wave 9 of the BHPS. For waves 1-8 and 10-11, the SAH variable represents "health status over the last 12 months". However, the SF-36 questionnaire was included in wave 9. In this questionnaire, the SAH variable for wave 9 represents "general state of health", using the question: "In general, would you say your health is: excellent, very good, good, fair, poor?". Item non-response is greater for SAH at wave 9 than for the other waves and this complicates our analysis of attrition rates. Hernandez *et al.* (2004) have explored the sensitivity of ordered probit models of SAH to this change in the wording, but here we simply exclude wave 9 from the analysis.

Other indicators of morbidity are used as predictors of attrition. The BHPS variable HLLT measures self-reported functional limitations and is based on the question "does your health in any way limit your daily activities compared to most people of your age?" Respondents are left to define their own concepts of health and their daily activities. In contrast, for the variable measuring specified health problems (labelled HLPRB in the BHPS), respondents are presented with a prompt card and asked, "do you have any of the health problems or disabilities listed on this card?" The list is made up of problems with arms, legs, hands, etc; sight; hearing; skin conditions/allergies; chest/breathing; heart/blood pressure; stomach/digestion; diabetes; anxiety/depression; alcohol/drug related; epilepsy; migraine and other (cancer and stroke were added as separate categories in wave 11 but are not included here). Also respondents are asked to report whether they are registered as a disabled person (labelled HLDSBL).

A specific 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. The GHQ can detect disorders of a temporary nature such as depression and anxiety, but also permanent conditions such as schizophrenia and psychotic depression. An advantage of the GHQ is that it does not require a subjective assessment by a specialist clinician and is therefore, more amenable to inclusion in household surveys. A Likert scale is used to form an overall score (GHQ1) for each respondent based on summing across the item specific responses. This provides a variable ranging from 0 (least problems) to 36 (most problems). The predictive validity and content validity of the GHQ are good in comparison to other well-known scaling tests of mental illness. The GHQ also performs well in reliability tests and has proven to be robust against retest effects.

Socioeconomic status

Two dimensions of socioeconomic status are included in our models of SAH: income and education. Income is measured as equivalised and RPI-deflated annual household income (INCOME). This variable is transformed to natural logarithms to allow for concavity of the relationship between health and income (e.g., Ettner, 1996; van Doorslaer and Koolman, 2002; Frijters *et al.*, 2003; Contoyannis *et al.,* 2004). Education is measured by the highest educational qualification attained by the end of the sample period in descending order of attainment (DEGREE, HND/A, O/CSE). NO-QUAL (no academic qualifications) is the excluded category for the educational variable. In addition to income and education variables are included to reflect individuals' demographic characteristics and stage of life: age, ethnic group, marital status and family composition. The marital status distinguishes between WIDOW, SINGLE and DIVORCED/SEPARATED and married or living as a couple is the excluded category. Similarly, We include an indicator of ethnic origin (NON-WHITE), the number of individuals living in the household including the respondent (HHSIZE), and the numbers of children living in the household at different ages (NCH04, NCH511, NCH1218). Age is included as a fourth-order polynomial, (AGE, AGE2 = $AGE^2/100$, AGE3 = $AGE^3/10000$, AGE4 = $AGE^4/1000000$). A vector of time dummies are included to account for aggregate health shocks, time-varying reporting changes, and any effects of age which are not captured by the polynomial.

2.2 ECHP

The sample

The detailed analysis of the BHPS is complemented by a second source of data: the full eight waves, 1994-2001, of the *European Community Household Panel User Database* (ECHP-UDB) designed and coordinated by Eurostat, the European Statistical Office. This puts the UK data in the context of a broader analysis of patterns of health-related attrition across European countries. The ECHP is a standardised multi-purpose annual longitudinal survey carried out the level of the European Union (Peracchi, 2002). The survey is based on a standardised questionnaire that involves annual interviewing of a representative panel of households and individuals of 16 years and older in each of the participating EU member states. It covers a wide range of topics including demographics, income, social transfers, health, housing, education and employment. We use data for the following fourteen member states of the EU for the full number of waves available: Austria (waves 2-8), Belgium (1-8), Denmark (1-8), Finland (3-8), France (1-8), Germany (1-3), Greece (1-8), Ireland (1-8), Italy (1-8), Luxembourg (1-3), Netherlands (1-8), Portugal (1-8), Spain (1-8) and the United Kingdom (1-3). Sweden did not take part in the ECHP. The ECHP-UDB also includes comparable versions of the BHPS and German Socioeconomic Panel (GSOEP) and descriptive evidence is provided for these.

Measures of health

Self-assessed general health status (SAH) is measured as either very good, good, fair, poor or very poor. Unlike the BHPS, respondents are not asked to compare themselves with others of the same age. Responses are also available for the question "Do you have any chronic physical or mental health problem, illness or disability? (yes/no)" and if so "Are you hampered in your daily activities by this physical or mental health problem, illness or disability? (no; yes, to some extent; yes, severely)". In France this question was re-worded to "gene par une maldie chronique, un handicap?". We use two dummy variables to indicate either some limitation or severe limitation.

Socioeconomic status

The ECHP income measure is disposable household income per equivalent adult, using the modified OECD equivalence scale (giving a weight of 1.0 to the first adult, 0.5 to the second and each subsequent person aged 14 and over, and 0.3 to each child aged under 4 in the household). Total household income includes all net monetary income received by the household members during the reference year. It includes income from work (employment and self-employment), private non-labour income (from investments and property and private transfers to the household), pensions and other direct social transfers received. No account has been taken of indirect social transfers (e.g. reimbursement of medical expenses), receipts in kind and imputed rent from owner-occupied accommodation. Education is measure by the highest level of general or higher education completed, i.e. third level education (ISCED 5-7), second stage of secondary level education (ISCED 3-4) or less than second stage of secondary education (ISCED 0-2)). Marital status distinguishes between married/living in consensual union, separated/divorced, widowed and unmarried. Activity status includes employed, self-employed, student, unemployed, retired, doing housework and 'other economically inactive'. Region of residence uses the EU's NUTS 1 level (Nomenclature of Statistical Territorial Units) except for countries where such information was withheld for privacy reasons (The Netherlands, Germany) or because the country is too small (Denmark, Luxembourg).

3. Descriptive analysis of attrition rates

3.1 BHPS

Table 1 shows how the sample size and composition evolves across waves of the BHPS. The table, which gives figures for the whole sample and the sub-samples of men and women, shows the number of observations that are available at each wave and the corresponding number of drop-outs and re-joiners between waves. These are expressed as wave-on-wave survival and attrition rates. The survival rate is the percentage of observations available at wave *t* to the sample at wave 1. The attrition rate is the percentage of the number of drop-outs between waves t and t-1 to the number of observations at t-1. The raw attrition rate excludes re-joiners, while the net attrition rate includes them. Attrition rates are highest between waves 1 and 2, with the rate tending to decline over time. The table also disaggregates the raw attrition rates according to individuals' SAH at wave 1. This shows that attrition rates are inversely related to initial health and, in particular, attrition is highest among those who start the survey in very poor health. This pattern of *health-related attrition* persists throughout the panel and is stronger for men than women.

Table 2 shows that the overall attrition rate across all 11 waves of the panel varies with socioeconomic characteristics. The average rate of attrition over 11 waves is 39%. As expected, attrition increases with individuals' age at the start of the panel, ranging from 36% for those aged under 30 to 73% for those aged over 70. Some of this age-related attrition is likely to be associated with health, through deaths, serious illness and moves to institutional care. Attrition is greater among those with lower income and with less formal education: the poorest quintile have an overall attrition rate of 58%, compared to 32% among the richest quintile; those with no qualifications have an attrition rate of 48% compared to 26% among those with a degree. The table also shows that health-related attrition interacts with individuals' socioeconomic characteristics (some caution is required as some of the cell sizes are very small). So, for example, attrition rates are very high among elderly individuals (aged >70) who start the survey in poor (87%) or very poor health (95%).

Table 3 presents the overall attrition rates split by quartiles of the GHQ score for psychological well-being. This measure does not exhibit a clear-cut health-related gradient in attrition rates – attrition rates only range from 39 to 43% - and no systematic pattern of interactions between health-related attrition and socioeconomic characteristics emerges. Table 4 summarises the three binary measures of functional limitations (HLLT), health problems (HLPRB) and registered disability (HLDSBL). All of these show higher overall attrition among those in poorer health: 54% for those with limited activities, compared to 37% without; 43% for those with health problems, compared to 38% without; and 57% for those with disabilities, compared to 38% without. There is a clear interaction with age: among younger individuals attrition is higher for those who do not report poor health, perhaps reflecting the fact that attrition associated with geographic, occupational and social mobility may be greater among younger people who do not have health problems. The pattern reverses for the more elderly groups, where attrition is higher among those in poorer health. As shown in Table 2, attrition is greater among those on lower incomes and with lower levels of educational qualification. But comparing the difference in attrition rates between the healthy and unhealthy across income quintiles does not reveal a systematic interaction between health-related attrition and income. However the gap in attrition rates is greater for those with no educational qualifications, than those with qualifications.

Tables 1-4 provide only a description of simple bivariate relationships between attrition rates and socioeconomic characteristics. To extend this to a multivariate analysis Tables 5 and 6 present probit models for response/non-response at each wave of the panel, from wave 2 to wave 11, using the full sample of individuals who are observed at wave 1. The dependent variables for these models equal 1 if the individual responds at the wave in question and 0 otherwise and are always defined relative to the full sample at wave 1. The probability of response is modelled as a function of the wave 1 values of all of the regressors that are included in our empirical model of SAH, along with additional wave 1 variables for region (NORTH-WEST, NORTH-EAST, SOUTH-EAST, SOUTH-WEST, MIDLANDS, SCOTLAND, WALES), activity status (SELF-EMPLOYED; UNEMPLOYED; RETIRED; family care and maternity leave, FAMILY-CARE; government training, students and other, EMP-OTHER) and occupational group (UNCLASSIFIED; MANUAL-TECHNICAL; skilled non-manual, SKILL-NON-MAN; skilled manual and armed forces, SKILLED-MANUAL; PART-SKILLED; UNSKILLED, LONG-TERM-SICK) and other indicators of morbidity (HLPRB, HLDSBL, HLLT). These additional observable variables form the basis of the inverse probability weighting approach to correcting for attrition, which is described in more detail below.

The tables show the partial effects of the regressors on the probability of response at each wave, along with an indication of which of these are statistically significant at the 5% level and 1% levels. The partial effects are computed as marginal effects for continuous regressors and average effects for discrete regressors, evaluated at the sample means of the other regressors in the model. These results reveal statistically significant associations between non-response and levels of educational attainment for both men and women. Those with DEGREE, HND/A and O/CSE qualifications are more likely to remain in the sample and the magnitude of this effect increases over the waves. On average, a man with a degree has a 0.07 higher probability of responding at wave 2, relative to one without academic qualifications. By wave 11 they have a 0.176 higher probability of responding. For women the corresponding figures are 0.084 and 0.190. Non-whites are less likely to remain in the sample, and this effect increases in magnitude as time progresses. By wave 11 the probability of responding among non-white men is 0.134 lower and among women it is 0.163 lower. There is no clear evidence of statistically significant income-related attrition.

The pattern of health-related attrition shows that, for both men and women, very poor initial health (SAHVPOOR) reduces response rates, as does functional limitations (HLLT). These effects grow in magnitude and attain statistical significance as the panel lengthens. Disability (HLDSBL) does not show a clear cut pattern in the multivariate analysis and health problems (HLPRB) shows the counter-intuitive effect that those who report health problems are more likely to respond at all waves. This may be because the variable HLPRB encompasses some relatively minor ailments – such that the majority of the sample report having at least one of them – and, after controlling for other more measures of health this variable is capturing other forms of attrition such as geographic mobility among healthy young people.

3.2 ECHP

Table 7 reports the overall attrition rates across the available waves for each of the countries that participated in the ECHP, along with comparable samples from the BHPS and German Socioeconomic Panel (GSOEP) that are included in the ECHP-UDB. The evidence reinforces earlier studies (Peracchi, 2002; Behr *et al.*, 2002; Behr, 2004). In particular the UK and Ireland stand out as having above average rates of attrition, with 45% drop-out after only three waves in the UK and 69% after eight waves in Ireland. The high attrition in the UK is largely attributable to the decision by the national data unit (NDU) to follow only households with complete sets of personal interviews, rather than adopting the standard ECHP following rules. For the other countries that participated for the full eight waves overall attrition rates are broadly similar, ranging from 40% in Italy to 49% in Spain. Germany and Luxembourg only participated for waves 1-3 and have low attrition rates of 13% and 12%. The attrition rates over the comparable period of 29% for the BHPS and 33% for the GSOEP are lower than the ECHP, reflecting the fact that these samples were established prior to 1994. As in the BHPS there is evidence of health-related attrition in the ECHP. When the samples are split by initial levels of self-assessed health a consistent pattern emerges across all countries, with higher rates of attrition among those in poor or very poor initial health. The gradient is not always monotonic, in some countries the lowest attrition rates are for those with good or, in the case of Luxembourg, fair health.

To give a sense of how the attrition rates vary by socioeconomic characteristics the ECHP data is pooled across countries. Table 8 shows the overall attrition rates across the available waves and across all countries split by socioeconomic characteristics at the first wave. The table shows an interaction between health-related attrition and age and marital status, with a clearer health-related gradient among those aged over 70 and among widows and widowers. But it is striking that the gradient in attrition rates across categories of SAH seems stable across income quintiles and levels of education. This has implications for the impact of attrition on the relationship between health and socioeconomic status and is explored in the regression models below. Some caution is required in interpreting these pooled data as it has been shown that the patterns of attrition by income and education are quite different across countries in the North and the South of the EU. In the North those with higher incomes and more education are more likely to remain in the panel, while the reverse is true in the South.

4. Models and estimation methods

4.1 The ordered probit model

To model the association between self-assessed health (SAH) and socioeconomic status (SES) we use pooled ordered probit specifications on both balanced and unbalanced samples. The latent variable specification of the model that we estimate can be written as:

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

where h^*_{it} is a latent variable that underlies reported SAH; x_{it} is a set of observed socioeconomic variables, which may be associated with the health indicator; and ε_{it} is a time and individual-specific error term, which is assumed to be normally distributed. The pseudo-ML estimator of the pooled ordered probit model is consistent even if the error terms are not serially independent and does not require that the regressors are strictly exogenous, so it can accommodate pre-determined variables (see e.g., Wooldridge, 2002b). A robust estimator of the covariance matrix is used to allow for clustering within individuals. As we do not have a natural scale for the latent variable the variance of the error term (ε) is restricted to equal one.

In our data the latent outcome h^*_{it} is not observed. Instead, we observe an indicator of the category in which the latent indicator falls (h_{it}). The observation mechanism can be expressed as,

(2) $$h_{it} = j \quad if \ \mu_{j-1} < h^*_{it} \leq \mu_j \ , \quad j = 1,\ldots\ldots,m$$

where $\mu_0 = -\infty$, $\mu_j \leq \mu_{j+1}$, $\mu_m = \infty$. Given the assumption that the error term is normally distributed, the probability of observing the particular category of SAH reported by individual *i* at time *t* (h_{it}), conditional on the regressors,

(3) $$P_{itj} = P(h_{it} = j) = \Phi(\mu_j - \beta' x_{it}) - \Phi(\mu_{j-1} - \beta' x_{it})$$

where $\Phi(.)$ is the standard normal distribution function. This formulation makes it clear that it is not possible to separately identify an intercept in the linear index (β_0) and the cutpoints (μ), the model only identifies ($\mu_j - \beta_0$). To deal with this we have adopted a conventional normalisation, setting β_0=0 (an alternative is to set μ_1=0). By extension, it is clear that, without *a priori* restrictions, the individual effect (α_i) cannot be distinguished from an individual-specific cut-point shift. The same argument applies to the impact of the regressors on h^*_{it} , so long as the cut-points are a linear function of the regressors. This should be borne in mind when interpreting the results presented below.

We do not impose an explicit error components specification in (1) but, to understand the nature of the attrition problem, it will often be helpful to think in terms of time invariant unobservable heterogeneity (an "individual effect") and idiosyncratic random shocks that vary over time ("health shocks"). Attrition associated with individual effects implies that there are certain "types" of individual who are prone to drop out of the panel and whose health is permanently different from those who stay in. This kind of attrition can therefore be detected by comparing the outcomes that are observed prior to attrition. Attrition associated with idiosyncratic shocks is more problematic. A transient health shock would be reflected in h^*_{it} , and hence in h_{it}, but not necessarily in past health and, if the shock leads to the individual dropping-out of the panel, h_{it} is unobserved.

4.2 Attrition bias

Testing

The descriptive analysis has shown evidence of systematic patterns of attrition by socioeconomic characteristics and previous levels of health, but it remains to be seen whether this will lead to *attrition bias* in our empirical models of SAH. To provide an initial test for attrition bias we use simple variable addition tests as proposed by (Verbeek and Nijman, 1992, p.688). The test variables we use are i) an indicator for whether the individual responds in the subsequent wave (NEXT WAVE), ii) an indicator of whether the individual responds in all 11 waves and, hence, is in the balanced sample (ALL WAVES) and iii) a count of the number of waves that are observed for the individual (NUMBER OF WAVES). Each of these are added to our pooled ordered probit model and estimated with the unbalanced sample. The t-ratios on the added variables give three variants of the test for attrition bias. The intuition behind these tests is that, if attrition is random, indicators of an individual's pattern of survey responses (R) should not be associated with the outcome of interest (h) after controlling for the observed covariates (x): in other words, it is testing a conditional independence condition $E(h|x,R)=E(h|x)$. Additional evidence can be provided by Hausman-type tests that compare estimates from the balanced and unbalanced samples; in the absence of attrition bias these estimates should be comparable, but attrition bias may affect the unbalanced and balanced samples differently leading to a contrast between the estimates. However, in the context of ordered probit models, a simple comparison of the estimated βs is complicated by the fact that the coefficients from the two specifications do not have a common scale. Instead we rely on a comparison of average partial effects, which do share the same scale. It should be noted that the variable addition tests and Hausman-type tests may have low power; they rely on the sample of observed outcomes for h and will not capture attrition associated with idiosyncratic shocks that are not reflected in observed past health (Nicoletti, 2002).

Estimation

To allow for attrition we adopt an inverse probability weighted (IPW) estimator and apply it to the pooled ordered probit model (Robins *et al.,* 1995; Fitzgerald *et al.,* 1998; Moffitt *et al.,* 1999;

Wooldridge, 2002a, 2002b). This approach is grounded in the notion of missing at random or ignorable non-response (Rubin, 1976; Little and Rubin, 1987). Using R as an indicator of response and h and x as the outcome and covariates of interest: missing completely at random (MCAR) is defined by $P(R=1|h,x)=P(R=1)$ and missing at random (MAR) is defined by $P(R=1|h,x)=P(R=1|x)$. The latter implies that, after conditioning on observed covariates, the probability of non-response does not vary systematically with the outcome of interest. By Bayes rule, the MAR condition can be inverted to give $P(h|x,R=1)=P(h|x)$, which provides a rationale for the Verbeek and Nijman (1992) approach to testing.

Fitzgerald *et al.* (1998) extend the notion of ignorable non-response by introducing the concepts of selection on observables and selection on unobservables. This requires an additional set of observables, z, that are available in the data but not included in the regression model for h. Selection on observables is defined by Fitzgerald *et al.* by the conditional independence condition $P(R=1|h,x,z)=P(R=1|x,z)$. Selection on unobservables occurs if this conditional independence assumption does not hold. Selection on unobservables, also termed informative, non-random or non-ignorable response, is familiar in the econometrics literature where the dominant approach to attrition follows the sample selection model (Heckman, 1976; Hausman and Wise, 1979). This approach relies on the z being "instruments" that are good predictors of non-response and that satisfy the exclusion restriction $P(h|x,z)=P(h|x)$. This is quite different from the selection on observables approach that seeks z's which are endogenous to h. The statistics literature has related methods, some of which use the EM algorithm for data imputation (see e.g., Diggle and Kenward, 1994; Fitzmaurice *et al.*, 1996; Molenberghs *et al.*, 1997). It is worth mentioning that linear fixed effects estimators are consistent, in the presence of selection on unobservables, so long as the non-ignorable attrition is due to time invariant unobservables (see e.g., Verbeek and Nijman, 1992).

The validity of the selection on observables approach hinges on whether the conditional independence assumption holds and attrition can be treated as ignorable, once z is controlled for. If the condition does hold, consistent estimates can be obtained by weighting the observed data by the inverse of the probability of response, conditional on the observed covariates (Robins *et al.*, 1995). This gives more weight to groups of individuals who have a high probability of attrition, as they are under-represented in the sample.

Fitzgerald *et al.* (1998) make it clear that this approach will be applicable when interest centres on a structural model for $P(h|x)$ and that the z's are deliberately excluded from the model, even though they are endogenous to the outcome of interest. They suggest lagged dependent variables as an obvious candidate for z. Rotnitzky and Robins (1997) offer a similar interpretation when they describe possible candidates for z being intermediate variables in the causal pathway from x to h. This property implies that it would not be sensible to use solely "field variables" such as changes in interviewer as candidates for the additional observables (see e.g., Behr *et al.,* 2002). These kinds of variables may be good predictors of non-response but are unlikely to be associated with SAH. Horowitz and Manski (1998) show that if the observables (z) are statistically independent of h, conditional on (x, $R=1$), then the weighted estimates reduce to the unweighted ones. This would explain why no difference between weighed and unweighted estimates may be reported in empirical analyses that use inappropriate variables for z.

In our application we are interested in the distribution of self-assessed health conditional on socioeconomic status, rather than the distribution conditional on socioeconomic status, and other indicators of morbidity and the individual's past history of SAH. We use past morbidity as our z variables. Of course, this approach will break-down if an individual suffers an unobserved health shock, that occurs after their previous interview, that leads them to drop out of the survey and that is not captured by conditioning on lagged measures of morbidity. In this case non-response would remain non-ignorable even after conditioning on z.

It is possible to test the validity of the selection on observables approach. The first step is to test whether the z's do predict non-response; this is done by testing their significance in the probit models for non-response at each wave of the panel (Tables 5 and 6). The second is to do Hausman-type tests to compare the weighted and unweighted estimates; the ordered probit models are compared in terms of average partial effects. Finally an inversion test can be used. Following Bayes rule, Becketti *et al* (1988) propose conditioning on patterns of response by splitting the sample into those in the balanced panel and the attriters and then comparing models for the dependent variable in the initial wave estimated on the sub-samples. Here we compare estimates of the pooled ordered probit for the balanced and unbalanced panels and for the available observations on the sample of attriters (those who are not in the balanced panel). In addition we use an augmented version of the Verbeek and Nijman (1992) test. By Bayes rule the conditional independence assumption implies $P(h|x,z,R=1)=P(h|x,z)$, so the test variables (NEXT WAVE, ALL WAVES, NUMBER OF WAVES) can be added to pooled ordered probits that include the full set of observables, treating these variables as indicators of patterns of response. Once again, it should be emphasised that these tests will have power to detect attrition that is associated with heterogeneity and is reflected in individuals' health prior to attrition.

Implementation of the Fitzgerald *et al.* (1998) form of the ignorability condition implies that x is observable when $R=0$. In the case of the kind of unit non-response we are dealing with in the

BHPS and ECHP, attrition means that there is missing data for the current period covariates (x) as well as self-assessed health (h). So we implement a stronger form of conditional independence $P(R=1|h,x,z)=P(R=1|z)$ as proposed by Wooldridge (2002a). To compute the IPW estimator we estimate (probit) equations for response ($R_{it}=1$) versus non-response ($R_{it}=0$) at each wave, t=2,…,T, conditional on a set of characteristics (z_{i1}) that are measured for all individuals at the first wave (as in tables 5 and 6). As described above, this relies on selection on observables and implies that attrition can be treated as ignorable non-response, conditional on z_{i1} (Fitzgerald *et al.*, 1998; Wooldridge, 2002b, p.588). Selection on observables requires that z_{i1} contains variables that predict attrition and that are correlated with the outcome of interest (SAH) but which are deliberately excluded from the structural model (i.e., equation (1)).

In practice z_{i1} includes the initial values of all of the regressors in (1). Also it includes initial values of SAH and of the other indicators of morbidity: whether the individual reports a specific health problem (HLPRB), whether they report that health limits their daily activities (HLLT) and whether they report a disability (HLDSBL). In addition, z_{i1} includes initial values of the respondent's activity status, occupational socioeconomic group and region. The probits for response/non-response are estimated at each wave of the panel, from wave 2 to wave 11 in the case of the BHPS and waves 2 to 8 for the ECHP, using the full sample of individuals who are observed at wave 1. The inverse of the fitted probabilities from these models, $1/\hat{p}_{it}$, are then used to weight observations in the ML estimation of the pooled ordered probit model using:

(4) $$LogL = \sum_{i}^{n} \sum_{t}^{T} \left(R_{it}/\hat{p}_{it}\right) LogL_{it}$$

Wooldridge (2002a) shows that, under the ignorability assumption:

(5) $$\mathrm{P}(R_{it}=1 | h_{it}, x_{it}, z_{i1}) = \mathrm{P}(R_{it}=1 | z_{i1}) \quad , \quad t=2,\ldots,T$$

the IPW estimator is $\sqrt{n}$ consistent and asymptotically normal. Wooldridge (2002a) also shows that using the estimated $\hat{p}_{it}$ rather than the true p_{it} and ignoring the implied adjustment to the estimated standard errors leads to "conservative inference" so that the standard errors are larger than they would be with an adjustment for the use of fitted rather than true probabilities (see also Robins *et al.,* 1995). Therefore we do not adjust the standard errors.

The IPW estimator can be adapted to allow the elements of *z* to be up-dated and change across time, for example adding *z* variables measured at *t-1* to predict response at *t*. This should improve the power of the probit models to predict non-response and hence make the ignorability assumption more plausible. In this case the probit model for attrition at wave t is estimated relative to the sample that is observed at wave *t-1*. This relies on attrition being an absorbing state and is therefore confined to "monotone attrition" where respondents never re-enter the panel. Also, because estimation at each wave is based on the selected sample observed at the previous wave, the construction of inverse probability weights has to be adapted. The predicted probability weights are constructed cumulatively using $\hat{p}_{it} = \hat{\pi}_{i2} \cdots \hat{\pi}_{it}$, where the $\hat{\pi}_{it}$ denote the fitted selection probabilities from each wave. In this version of the estimator the ignorability condition has to be extended to include future values of h and x (see Wooldridge, 2002b, p. 589)). Once again Wooldridge shows that omitting a correction to the asymptotic variance estimator leads to conservative inference so we do not adjust the standard errors.

We have not pursued a selection on unobservables approach in this paper. This stems from the lack of credible exclusion restrictions that would define variables that predict health-related attrition but do not have a direct effect on SAH. Also, the use of fixed effects estimators is not possible for probit and ordered probit models, due to the incidental parameters problem (although we have experimented with models that use Mundlak (1978) type specifications to deal with correlated effects, see also Contoyannis *et al.* (2004)). In using the public use versions of the BHPS and ECHP-UDB we do not have any scope for using methods based on refreshment samples (see e.g., Dolton, 2004). The IPW approach is attractive as it is easy to apply in the context of nonlinear models, such as the ordered probit model, and only requires a re-weighting of the data. Rather than using the published longitudinal weights that are supplied with the datasets, the weights are model-specific and specifically designed for the outcome of interest (SAH) and the associated problem of health-related attrition. Lagged values of SAH, along with other indicators of morbidity, provide promising candidates for the *z*-variables. Although the validity of the approach depends on the credibility of the ignorability assumption.

5. Estimation Results

The results for the various model specifications outlined above are reported in this section. For the detailed analysis of the BHPS, models for men and women are presented separately throughout. For the more parsimonious analysis of the ECHP the samples are pooled.

Tests for attrition

Table 9 presents the variable addition tests for attrition bias in the pooled ordered probit model for the BHPS. The first set of results are for the benchmark pooled ordered probits. The second includes the additional observables (z) that are used to compute the inverse probability weights. The latter can be regarded as a test for the ignorability assumption behind the IPW estimator. All of the test statistics show evidence of attrition bias for both men and women. The positive coefficients on the test variables are consistent with the fact that response rates are positively associated with health. Adding these test variables to the model is not intended to "correct" the estimates for attrition, but it is informative to compare the estimates with the baseline model that does not include the test variables. It is striking that, for key variables such as income and education, the differences between the estimated coefficients are negligible. This suggests that attrition may not bias the estimates of these effects, a result that is reinforced below.

Table 10 presents a summary of the variable addition tests for the ECHP. To conserve space, only tests based on the NUMBER OF WAVES are presented and the table reports the t-statistics for the ordered probits based on the x variables, and on the combination of the x and z variables for each country. With the exception of Luxembourg, the test results show the same pattern as the BHPS.

Estimates of ordered probits

Tables 11 and 12 present the coefficient estimates for the pooled ordered probit estimated with the BHPS data. The models were estimated on the balanced and unbalanced samples. The estimates for the pooled ordered probit models allow for serial correlation in the errors by using a robust estimator of the covariance matrix. In addition we estimated the pooled model using inverse probability weights (IPW) to adjust for attrition. Both variants of the IPW estimator are presented: IPW-1 uses wave 1 regressors to predict non-response, IPW-2 also includes values from the previous wave as well as the initial wave and the sample is restricted by excluding observations that exhibit non-monotone attrition. The results show differences in the coefficients on the age variables and on WIDOW between the weighted and unweighted estimates, reflecting age-related attrition, but the coefficients on ln(INCOME) and the education variables are very similar across all of the specifications.

Average partial effects

The scaling of the ordered probit coefficients is arbitrary. To provide an indication of the magnitude of the associations between SAH and the regressors we present average partial effects (APEs). For continuous regressors, such as income, theses are obtained by taking the derivative of the ordered probit probabilities with respect to the variable in question. For discrete regressors, such as the educational qualifications, they are obtained by taking differences. In general, average partial effects are averaged over the population distribution of heterogeneity and computed using the population averaged parameters (see e.g., Wooldridge, 2002b). In the pooled ordered probit models the total error variance is normalised to 1 and the estimated βs are population averaged parameters by default, so the APEs are given by the standard formula for partial effects.

In the ordered probit model it is possible to compute APEs for each of the five categories of self-assessed health. For parsimony, Table 13 summarises the APEs of income and educational attainment on the probability of reporting excellent health in the BHPS data. In this case the sign of the APE has a clear qualitative interpretation, with a positive sign implying a positive association with health and vice versa. A partial effect is computed for each observation in the sample, evaluated at the observed values of the regressors. The table presents the sample mean of the partial effects – the APE – along with the sample standard deviation, in parentheses, to give a sense of the variability of the partial effects across observations. These are presented for all versions of the model. Comparing the balanced and unbalanced samples gives very similar results, suggesting that non-response does not lead to differences in the estimated APEs. This is reinforced by the fact that the models with and without inverse probability weights are virtually identical.

Table 14 summarises the APEs on the probability of reporting very good health, the highest category in the ECHP, for ln(INCOME) and education estimated with the ECHP-UDB data. The table compares the estimates for the unweighted ordered probit and the (IPW-1) weighted ordered probit, both estimated on the unbalanced sample. In all of the countries there is a positive association between both income and education and SAH. As with the BHPS, the differences between the unweighted and weighted estimates of the average partial effects are very small.

6. Discussion

Descriptive evidence shows that there is health-related attrition in the data, with those in poor initial health more likely to drop out, and variable addition tests provide evidence of attrition bias in the models of SAH. Nevertheless a comparison of estimates based on the balanced samples, the unbalanced samples and corrected for attrition using inverse probability weights do not show substantive differences in the average partial effects of the variables of interests. So, while health-related attrition exists, it does not appear to distort the magnitudes of the estimated relationship between socioeconomic status and self-assessed health. Similar findings have been reported concerning the negligible influence of attrition bias in models of income dynamics and various labour market outcomes (see e.g., Hausman and Wise, 1979; Becketti *et al.,* 1988; Lillard and Panis, 1998; Zabel, 1998; Ziliak and Kniesner, 1998; Jimenez-Martin and Peracchi, 2002; Behr, 2004) and on measures of social exclusion such as poverty rates and income inequality indices (Watson, 2003; Rendtel *et al.,* 2004). To understand our findings for SAH, recall that the descriptive analysis shows little evidence of income-related attrition. There is evidence of strong education-related and some health-related attrition, but the latter is concentrated among those in poor initial health who are relatively few in number. There is no clear interaction between health-related attrition and levels of income or education.

References

Adams, P., Hurd, M.D, McFadden, D., Merrill, A. and Ribeiro, T. (2003) Healthy, wealthy and wise? Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics,* **112**, 3-56.

Becketti, S., Gould, W., Lillard, L. and Welch, F. (1988) The Panel Study of Income Dynamics after fourteen years: an evaluation. *Journal of Labor Economics,* **6**, 472-492.

Behr, A., Bellgardt, E. and Rendtel, U. (2002) A cross-national comparison of panel attrition in the ECHP and its impact on the estimation of wage equations.

Behr, A. (2004) Comparing estimation strategies in the presence of panel attrition. Empirical results based on the ECHP. *Wilhelms-Universitäüt,* Münster.

Benzeval, M., Taylor, J. and Judge, K. (2000) Evidence on the relationship between low income and poor health: Is the Government doing enough? *Fiscal Studies,* **21**, 375-399.

Burström, B. and Fredlund, P. (2001) Self rated health: is it as good a predictor of subsequent mortality among adults in lower as well as in higher social classes? *Journal of Epidemiology and Community Health,* **55**, 836-840

Contoyannis, P. and Jones, A. (2004) Socioeconomic status, health and lifestyle. *Journal of Health Economics,* in press.

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

Deaton, A..S. and Paxson, C.H. (1998) Ageing and inequality in income and health. *American Economic Review, Papers and Proceedings* **88**, 248-253.

Diggle, P. and Kenward, M.G. (1994) Informative drop-out in longitudinal data analysis. *Applied Statistics,* **43**, 49-93.

Dolton, P. (2004) Reducing attrition bias using targeted refreshment sampling and matching. *University of Newcastle upon Tyne.*

Ettner, S. (1996) New evidence on the relationship between income and health. *Journal of Health Economics,* **15**, 67-85

Fitzgerald, J., Gottshalk, P. and Moffitt, R. (1998) An analysis of sample attrition in panel data. The Michigan Panel Study on Income Dynamics. *Journal of Human Resources,* **33**, 251-299.

Fitzmaurice, G.M., Heath, A.F and Clifford, P. (1996) Logistic regression models for binary panel data with attrition. *Journal of the Royal Statistical Society Series A(Statistics in Society),* **159**, 249-263.

Frijters, P., Haisken-DeNew, J.P. and Shields, M.A. (2003) Estimating the causal effect of income on health: evidence from post reunification East Germany, *Centre for Economic Policy Discussion Paper No. 465,* Australian National University.

Hausman, J. and Wise, D. (1979) Attrition bias in experimental and panel data: the Gary Income Maintenance Experiment. *Econometrica,* **47**, 455-474.

Heckman, J.J. (1976) The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *The Annals of Economic and Social Measurement,* **5**, 475-492.

Hernández-Quevedo, C., Jones, A.M. and Rice, N., (2004) Reporting bias and heterogeneity in self-assessed health. Evidence from the British Household Panel Survey

Horowitz, J.L. and Manski, C.F. (1998) Censoring of outcomes and regressors due to survey nonresponse: identification and estimation using weights and imputations. *Journal of Econometrics,* **84**, 37-58.

Idler, E. L. and Benyamini, Y. (1997). Self-rated health and mortality: a review of twenty-seven community studies. *Journal of Health and Social Behavior,* **38**, 21-37.

Idler, E.L. and Kasl, S.V. (1995) Self-ratings of health: do they also predict change in functional ability? *Journal of Gerontology,* **50B**, S344-S353.

Jimenez-Martin, S. and Peracchi, F. (2002) Sample attrition and labor force dynamics: evidence from the Spanish labor force survey. *Spanish Economic Review,* **4,** 79-102.

Kenkel, D. (1995). Should you eat breakfast? Estimates form health production functions. *Health Economics,* **4**, 15-29.

Lillard, L.A. and Panis, C.W.A. (1998) Panel attrition from the Panel Study of Income Dynamics: household income, marital status and mortality. *Journal of Human Resources,* **33**, 437-457.

Little, J.A. and Rubin, D.B. (1987) *Statistical analysis with missing data.* John Wiley and Sons, New York.

Moffitt, R., Fitzgerald, J. and Gottschalk, P. (1999) Sample attrition in panel data: the role of selection observables. *Annales d'Economie et de Statistique,* **55-56**, 129-152.

Molenberghs, G., Kenward, M.G. and Lesaffre, E. (1997) The analysis of longitudinal ordinal data with non-random drop-out. *Biometrika,* **84**, 33-44.

Mundlak, Y. (1978) On the pooling of time series and cross-section data. *Econometrica,* **46**, 69-85.

Nicoletti, C. (2002) Non-response in dynamic panel data models. *Working papers of the Institute for Social and Economic Research,* paper 2002-31, Colchester: University of Essex.

Peracchi, F. (2002) The European Community Household Panel: a review. *Empirical Economics,* **27**, 63-90.

Rendtel, U., Behr, A., Bellgardt, E. and Sisto, J. (2004) Does panel attrition disturb comparative analysis with the European Community Household Panel (ECHP)? Mimeo.

Robins, J., Rotnitzky, A. and Zhao, L.P. (1995) Analysis of semiparametric regression models for repeated outcomes in the presence of missing data. *Journal of the American Statistical Association,* **90**, 106-121.

Rotnitzky, A. and Robins, J. (1994) Analysis of semi-parametric regression models with non-ignorable non-response. *Statistics in Medicine,* **16**, 81-102.

Rubin, D.B. (1976) Inference and missing data. *Biometrika,* **63**, 581-592.

Salas, C. (2002) On the empirical association between poor health and low socioeconomic status at old age. *Health Economics,* **11**, 207-220.

Smith, J.P. (1999) Healthy bodies and thick wallets: the dual relationship between health and economic status. *Journal of Economic Perspectives* **13**, 145-166.

Taylor, M., Brice, J., Buck, N. and Prentice, E. (1998) *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices.* University of Essex, Colchester.

van Doorslaer, E. and Gerdtham, U-G. (2003) Does inequality in self-assessed health predict inequality in survival by income? Evidence from Swedish data. *Social Science and Medicine*, **57**, 1621-1629.

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., Jones, A.M. and Koolman, X. (2004). Explaining income-related inequalities in doctor utilisation in Europe: a decomposition approach. *Health Economics,* in press

van Doorslaer, E., et al. (2000) Equity in the delivery of health care in Europe and the US. *Journal of Health Economics*, **19**, 553-583.

van Doorslaer, E, Wagstaff, A., Bleichrodt, H. *et al*, (1997) Income-related inequalities in health: some international comparisons, *Journal of Health Economics*, **16**, 93-112.

van Ourti, T. (2003). Socio-economic inequality in ill-health amongst the elderly. Should one use current income or permanent income? *Journal of Health Economics,* 22: 187-217.

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

Verbeek, M. (2000) *A guide to modern econometrics.* Wiley, Chichester.

Watson, D. (2003) Sample attrition between waves 1 and 5 in the European Community Household Panel. *European Sociological Review,* **19**, 361-378.

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

Wooldridge, J. (2002b) *Econometric Analysis of cross section and panel data.* MIT Press.

Zabel, J.E. (1998) An analysis of attrition in the Panel Study of Income Dynamics and the Survey of Income and Program Participation with an application to a model of labor market behavior. *Journal of Human Resources,* **33**, 479-506.

Ziliak, J.P. and Kniesner, T.J. (1998) The importance of sample attrition in life cycle labor supply estimation. *Journal of Human Resources,* **33**, 507-530.

Table 1: SAH sample size, drop outs, re-joiners, survival rate (%) and attrition rates (%) by wave and previous period health status, BHPS

			All data				EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. Ind.	Drop outs	Re-joiners	Survival rate	Raw Attrition rate	Net Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	10256		0								
2	8957	1299	254	87.3	12.7	12.7	11.5	12.6	13.0	13.7	23.7
3	8410	801	158	82.0	8.9	6.1	8.1	8.1	9.7	12.6	19.5
4	7978	590	143	77.8	7.0	5.1	6.7	6.6	6.7	10.4	14.2
5	7570	551	189	73.8	6.9	5.1	6.2	6.2	7.8	8.9	16.3
6	7424	335	63	72.4	4.4	1.9	3.1	3.2	5.1	10.5	18.8
7	7162	325	76	69.8	4.4	3.5	3.2	3.9	4.8	8.8	8.8
8	6912	326	-	67.4	4.6	3.5	3.4	3.8	5.3	5.9	17.0
9[†]	-	-	-	-	-	-	-	-	-	-	-
10[‡]	6421	-	122	62.6	-	-	-	-	-	-	-
11	6223	320		60.7	5.0	3.1	4.4	4.0	6.0	6.6	12.4

			Men				EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. Ind.	Drop outs	Re-joiners	Survival rate	Raw Attrition rate	Net Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	4832		0								
2	4180	652	126	86.5	13.5	13.5	12.2	13.5	14.2	14.6	26.9
3	3878	428	82	80.3	10.2	7.2	8.9	9.5	11.5	14.6	24.0
4	3675	285	72	76.1	7.4	5.2	6.7	7.4	7.3	8.5	14.5
5	3464	283	100	73.8	7.7	5.7	5.4	7.4	9.6	9.7	23.0
6	3408	156	31	70.5	4.5	1.6	3.6	3.1	4.8	12.2	25.4
7	3280	159	32	67.9	4.7	3.8	3.3	4.5	4.6	9.7	11.5
8	3137	175	-	64.9	5.3	4.4	4.1	4.4	6.4	7.0	22.9
9[†]	-	-	-	-	-	-	-	-	-	-	-
10[‡]	2899	-	58	60.0	-	-	-	-	-	-	-
11	2820	137		58.4	4.7	2.7	4.5	4.5	4.8	5.2	10.4

			Women				EX at t-1	GOOD at t-1	FAIR at t-1	POOR at t-1	VPOOR at t-1
Wave	No. Ind.	Drop outs	Re-joiners	Survival rate	Raw Attrition Rate	Net Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate	Attrition rate
1	5424		0								
2	4777	647	128	88.1	11.9	11.9	10.8	11.8	12.1	13.2	21.4
3	4532	373	76	83.6	7.8	5.1	7.2	7.0	8.2	11.3	16.4
4	4303	305	71	79.3	6.7	5.1	6.7	5.8	6.3	11.6	14.0
5	4106	268	89	75.7	6.2	4.6	7.1	5.2	6.6	8.3	12.0
6	4016	179	32	74.0	4.4	2.2	2.6	3.4	5.2	9.3	14.3
7	3882	166	44	71.6	4.1	3.3	3.0	3.3	4.9	8.3	7.1
8	3775	151	-	69.6	3.9	2.8	2.7	3.3	4.5	5.2	12.6
9[†]	-	-	-	-	-	-	-	-	-	-	-
10[‡]	3522	-	64	64.9	-	-	-	-	-	-	-
11	3403	183		62.7	5.2	3.4	4.3	3.7	6.8	7.4	13.5

Note:
Raw attrition rates exclude re-joiners; Net attrition rates include re-joiners.
† At wave 9 the self-assessed health question was changed to one based on the SF-36 questionnaire. SF-36 questionnaire response rates appear lower than those for hlstat and therefore are not used as a basis for calculating attrition rates.
‡ Attrition rates conditional on previous wave reporting of self-assessed health are not possible due to the change in the self-assessed health question at wave 9.

Table 2: SAH-related attrition rates (%) over 11 waves by gender, age, income, educational and marital status, BHPS

	ALL	EX at t1	GOOD at t1	FAIR at t1	POOR at t1	VPOOR at t1
ALL DATA	39	36	37	44	48	64
GENDER:						
MEN	42	38	39	49	53	67
WOMEN	37	33	36	40	45	63
AGE GROUP:						
<30	36	40	34	37	22	22
31-50	32	30	31	35	32	47
51-70	39	33	37	41	53	64
>70	73	60	69	77	87	95
INCOME QUINTILE:						
1	58	55	57	59	58	74
2	41	36	39	44	47	62
3	37	35	36	41	45	62
4	36	36	34	39	44	45
5	32	32	32	29	38	71
EDUCATION:						
DEGREE	26	26	27	29	24	0
HND/A LEVEL	30	31	28	32	28	67
O LEVEL / CSE	34	36	32	36	32	49
NO QUALIFICATIONS	48	42	46	52	55	65
MARITAL STATUS:						
WIDOW	62	47	60	64	81	83
SINGLE	42	45	40	44	44	42
DIVORCED/SEPARATED	41	38	37	45	47	60
MARRIED/COUPLE	35	32	34	40	41	64

Note: Survival rates across the 11 waves are calculated as 100%-Attrition rate

Table 3: GHQ-related attrition rates (%) over 11 waves by gender, age, income, educational and marital status, BHPS

	ALL	GHQ 4 at t1	GHQ 3 at t1	GHQ 2 at t1	GHQ 1 at t1
ALL DATA	41	43	41	39	41
GENDER:					
MEN	43	46	42	43	42
WOMEN	39	41	40	36	39
AGE GROUP:					
<30	37	37	36	36	39
31-50	34	35	33	32	36
51-70	40	45	40	39	39
>70	75	83	78	72	67
INCOME QUINTILE:					
1	58	59	58	56	60
2	41	42	39	39	44
3	37	37	37	37	37
4	34	33	33	33	37
5	33	35	34	33	32
EDUCATION:					
DEGREE	29	24	29	30	32
HND/A LEVEL	33	38	32	32	32
O LEVEL / CSE	36	35	36	35	39
NO QUALIFICATIONS	50	53	50	49	50
MARITAL STATUS:					
WIDOW	64	73	64	56	64
SINGLE	43	45	43	40	44
DIVORCED/SEPARATED	42	46	33	45	45
MARRIED / COUPLE	37	37	38	36	37

Note: Survival rates across the 11 waves are calculated as 100%-Attrition rate

Table 4: Summary of health-related attrition rates (%) over 11 waves by gender, age, income, educational and marital status, BHPS

	HLLT NO t1	HLLT YES t1	HLPRB NO t1	HLPRB YES t1	HLDSBL NO t1	HLDSBL YES t1
ALL DATA	37	54	38	43	38	57
GENDER:						
MEN	39	59	41	46	41	56
WOMEN	35	51	34	41	36	58
AGE GROUP:						
<30	36	33	40	35	36	33
31-50	31	35	34	33	32	39
51-70	36	51	38	41	38	52
>70	67	84	62	76	72	83
INCOME QUINTILE:						
1	54	68	57	59	57	68
2	38	53	40	44	40	56
3	36	48	37	40	36	54
4	35	43	37	37	36	46
5	32	43	34	35	32	42
EDUCATION:						
DEGREE	26	39	27	28	26	25
HND/A LEVEL	30	37	32	32	30	62
O LEVEL / CSE	34	39	36	36	34	39
NO QUALIFICATIONS	45	59	45	51	47	57
MARITAL STATUS:						
WIDOW	54	80	49	67	61	72
SINGLE	41	49	44	42	42	48
DIVORCED/SEPARATED	38	51	37	44	40	50
MARRIED/COUPLE	34	47	34	39	35	56

Table 5: Probit models for response/ non-response by wave (results are presented as partial effects on the probability of responding at wave t, evaluated at the sample means of the regressors) – SAH; Men, BHPS

	WAVE								
N = 4543	2	3	4	5	6	7	8	10	11
Ln(INCOME)	.023*	.023*	.034**	.013	.012	.014	.018	-.002	.003
WIDOW	-.034	-.006	-.007	.041	.037	-.0004	.014	-.016	.002
SINGLE	-.018	-.040*	-.037	-.039	-.036	-.038	-.062*	-.069**	-.068**
DIV/SEP	-.014	.003	-.012	.015	.014	-.006	-.022	-.057	-.066
NON-WHITE	-.102**	-.155**	-.155**	-.154**	-.130**	-.137**	-.151**	-.145**	-.134**
DEGREE	.070**	.131**	.156**	.155**	.137**	.160**	.177**	.176**	.176**
HND/A	.057**	.077**	.070**	.077**	.082**	.089**	.107**	.121**	.131**
O/CSE	.027*	.039*	.037*	.038*	.050**	.059**	.069**	.061**	.071**
HHSIZE	-.019**	-.016*	-.029**	-.015	-.006	-.004	-.0005	.002	-.003
NCH04	.068**	.058**	.085**	.065**	.059**	.049*	.045*	.039	.044*
NCH511	.032**	.015	.034*	.009	.003	.006	-.005	-.012	-.003
NCH1218	.041**	.042**	.066**	.038*	.028	.039*	.019	.008	-.003
AGE	-.027	-.041	-.037	-.050	-.039	-.030	-.040	-.049	-.042
AGE2	.102	.140	.125	.166	.138	.108	.138	.168	.133
AGE3	-.146	-.188	-.160	-.207	-.179	-.138	-.167	-.201	-.135
AGE4	.071	.085	.066	.081	.071	.050	.055	.063	.023
NORTH-WEST	.003	.006	-.005	-.003	-.011	.0005	.014	-.005	-.012
NORTH-EAST	.029	.014	.022	.018	.029	.027	.029	.023	.026
SOUTH-EAST	.003	.022	.025	.036	.032	.029	.023	.048	.032
SOUTH-WEST	.062**	.067**	.039	.043	.048	.038	.046	.050	.059
MIDLANDS	.009	.034	.025	.027	.030	.035	.030	.016	.018
SCOTLAND	-.028	-.003	-.005	-.001	-.034	-.025	-.045	-.054	-.059
WALES	.027	.025	.050	.011	.022	.011	-.003	.008	.028
SELF-EMPLOYED	.006	-.005	.022	-.001	.002	-.003	.008	-.022	-.010
UNEMPLOYED	-.017	-.042	-.078	-.101	-.074	-.118	-.111	-.113	-.111
RETIRED	.006	-.006	-.022	-.050	-.026	-.080	-.042	-.085	-.079
FAMILY-CARE	.005	-.039	-.038	-.067	-.063	-.095	-.100	-.075	-.073
EMP-OTHER	.019	.0006	-.013	-.015	-.007	-.013	.006	-.035	-.018
UNCLASSIFIED	.052	.038	.065	.065	.069	.096	.099	.100	.101
MANUAL-TECHNICAL	.042	.030	.007	.004	.027	.024	.021	.030	.026
SKILL-NON-MAN	.041	.042	.047	.019	.031	.041	.053	.085*	.069
SKILLED-MANUAL	.030	.008	.008	-.006	.009	.024	.031	.043	.034
PART-SKILLED	.040	.012	.036	-.014	-.004	.008	.013	.021	.010
UNSKILLED	.058	.072	.053	-.017	.022	.050	.079	-.027	.027
SAHEX	.006	.014	.006	.003	-.021	-.018	-.011	-.004	-.012
SAHFAIR	.003	-.015	-.042*	-.057**	-.073**	-.063**	-.068**	-.064**	-.052*
SAHPOOR	.015	.012	.004	.013	-.014	-.017	-.017	-.035	-.046
SAHVPOOR	-.032	-.053	-.079	-.079	-.154**	-.153*	-.175**	-.172**	-.167*
HLPRB	.002	.027*	.052**	.055**	.042**	.039*	.043*	.037	.029
HLDSBL	-.014	.003	.003	-.023	.004	.040	.014	-.024	-.006
HLLT	-.025	-.039	-.041	-.084**	-.076**	-.084**	-.091**	-.071*	-.078*
Log-likelihood	-1660.9	-2200.1	-2357.7	-2568.3	-2590.1	-2677.6	-2747.8	-2830.2	-2878.5

Note: * denotes significance at $p \leq 0.05$, ** denotes significance at $p \leq 0.01$,
All regressors represent wave 1 responses, there were no men in the long-term sick category in our sample at wave 1.

Table 6: Probit models for response/ non-response by wave (results are presented as partial effects on the probability of responding at wave t, evaluated at the sample means of the regressors) – SAH; Women, BHPS

	WAVE								
N = 5247	2	3	4	5	6	7	8	10	11
Ln(INCOME)	.005	.012	.013	.015	.005	.001	.002	.002	.001
WIDOW	.033*	.035	.029	.019	.011	.012	.009	.005	-.008
SINGLE	-.027	-.036	-.061**	-.065**	-.066**	-.056*	-.053*	-.060*	-.058*
DIV/SEP	-.030	-.031	-.016	-.013	-.031	-.051*	-.049	-.052	-.045
NON-WHITE	-.069**	-.128**	-.143**	-.139**	-.130**	-.136**	-.157**	-.164**	-.163**
DEGREE	.084**	.127**	.130**	.174**	.174**	.179**	.181**	.209**	.190**
HND/A	.049**	.096**	.081**	.102**	.094**	.099**	.114**	.125**	.124**
O/CSE	.030**	.038**	.039*	.047**	.047**	.054**	.050**	.072**	.072**
HHSIZE	-.010	-.011	-.015*	-.011	-.004	.004	.005	.006	.010
NCH04	.045**	.037*	.055**	.037*	.039*	.033	.038*	.027	.026
NCH511	.027**	.024*	.025*	.015	.005	-.004	-.004	-.014	-.017
NCH1218	.026*	.019	.022	.025	.021	.016	.007	.006	-.012
AGE	.021	.041*	.024	.035	.030	.027	.019	.019	.031
AGE2	-.067	-.139*	-.085	-.118	-.100	-.084	-.069	-.068	-.109
AGE3	.094	.202*	.134	.176	.147	.126	.127	.126	.189
AGE4	-.050	-.108*	-.079	-.100	-.086	-.078	-.090	-.094	-.130
NORTH-WEST	.018	.021	.008	.015	-.001	.015	.020	.025	.041
NORTH-EAST	.024	.014	.025	.020	.021	.046	.041	.072**	.073**
SOUTH-EAST	.019	.014	.022	.051*	.046*	.060*	.053*	.085**	.098**
SOUTH-WEST	.045*	.051*	.035	.047	.050*	.043	.030	.067*	.093**
MIDLANDS	.014	.010	.005	.008	.011	.027	.005	.029	.040
SCOTLAND	.006	-.031	-.034	-.022	-.055	-.029	-.037	-.036	-.021
WALES	.019	-.038	-.003	.014	.026	.044	.032	.046	.046
SELF-EMPLOYED	.005	.003	.011	-.009	.008	-.026	-.019	-.017	-.031
UNEMPLOYED	-.005	-.035	-.052	.014	-.016	.007	.005	-.155*	-.109
RETIRED	.020	.025	.051	.124*	.086	.116*	.119*	.024	.068
FAMILY-CARE	-.013	-.005	-.007	.057	.024	.052	.060	-.045	-.016
LONG-TERM-SICK	-.147	-.101	-.084	-.021	-.129	-.098	-.082	-.156	-.129
EMP-OTHER	-.027	-.033	-.050	.023	.004	.041	.037	-.044	-.061
UNCLASSIFIED	.021	-.011	-.005	.020	.027	-.019	-.082	.116	.023
MANUAL-TECHNICAL	.017	.011	.028	.085	.059	.043	.001	.062	.009
SKILL-NON-MAN	.031	.016	.032	.099	.079	.067	.031	.104	.031
SKILL-MANUAL	.035	.037	.057	.109	.109	.104	.058	.144*	.084
PART-SKILLED	.037	-.001	.010	.090	.063	.057	.023	.102	.039
UNSKILLED	.015	-.008	.007	.066	.045	.020	-.030	.041	-.032
SAHEX	.008	.009	.0007	-.006	-.002	.0005	.010	.027	.008
SAHFAIR	.004	-.001	-.005	.004	.002	-.004	-.001	.028	.006
SAHPOOR	.005	-.027	-.024	-.010	-.018	-.022	-.031	-.004	.010
SAHVPOOR	-.045	-.058	-.055	-.051	-.083	-.099*	-.152**	-.111*	-.131*
HLPRB	.039**	.046**	.046**	.039**	.033*	.040**	.041**	.028	.037*
HLDSBL	.015	.037	.027	.019	.009	-.001	.007	-.023	-.026
HLLT	-.012	-.009	-.007	-.021	-.020	-.040	-.016	-.020	-.031
Log-likelihood	-1801.3	-2411.4	-2566.6	-2780.6	-2790.0	-2891.4	-2963.4	-3116.4	-3170.3

Note: * denotes significance at $p \le 0.05$, ** denotes significance at $p \le 0.01$,
All regressors represent wave 1 responses.

Table 7: Summary of SAH-related attrition rates (%) over all available waves by country, ECHP-UDB

Country (waves)	ALL	VGOOD	GOOD	FAIR	POOR	VPOOR
AUSTRIA (2-8)	41	41	38	40	50	65
BELGIUM (1-8)	48	44	46	54	61	73
DENMARK (1-8)	49	44	47	58	66	75
FINLAND (3-8)	47	43	45	50	55	65
FRANCE (1-8)	44	42	42	44	53	61
GERMANY (1-3)	13	15	11	13	23	36
GERMANY (GSOEP 1-8)	33	34	30	31	37	50
GREECE (1-8)	41	39	41	40	46	59
IRELAND (1-8)	69	69	68	68	73	78
ITALY (1-8)	40	37	39	40	49	59
LUXEMBOURG (1-3)	12	13	12	10	15	37
NETHERLANDS (1-8)	44	42	43	48	57	63
PORTUGAL (1-8)	30	29	26	29	35	51
SPAIN (1-8)	49	47	48	49	53	65
UK (1-3)	45	43	44	48	52	56
UK (BHPS 1-8)	29	27	26	32	35	53

Table 8: Summary of SAH-related attrition rates(%) over all available waves by gender, age, income, educational and marital status pooled across countries, ECHP-UDB

	ALL	VGOOD	GOOD	FAIR	POOR	VPOOR
ALL DATA						
GENDER:						
MEN	42	43	40	42	48	61
WOMEN	40	41	37	39	44	56
AGE GROUP:						
<=30	45	47	43	44	40	41
31-50	36	38	35	35	35	43
51-70	36	37	34	35	39	51
>70	60	52	54	58	66	78
INCOME QUINTILE:						
1	45	48	41	43	47	58
2	36	38	33	36	41	53
3	41	41	38	42	48	59
4	40	39	38	40	44	58
5	42	41	41	42	49	62
EDUCATION:						
TERTIARY (ISCED5-7)	38	40	36	38	36	57
SECONDARY (ISCED3-4)	40	43	38	38	43	56
PRIMARY (ISCED0-2)	42	41	39	42	47	59
MARITAL STATUS:						
WIDOW	51	44	45	50	59	70
SINGLE	47	49	45	46	49	55
DIVORCED/SEPARATED	41	41	39	43	45	53
MARRIED/COUPLE	37	37	35	38	41	55

Table 9: Verbeek and Nijman tests for attrition: based on pooled ordered probit models, BHPS

	Men				Women			
	β	SE	t-test	p-value	β	SE.	t-test	p-value
	1. Based on regressors in pooled ordered probit models							
NEXT WAVE*	.147	.026	5.64	.000	.070	.026	2.69	.007
ALL WAVES	.160	.027	5.82	.000	.101	.025	4.03	.000
NUMBER OF WAVES	.027	.005	5.64	.000	.019	.005	3.98	.000
	2. Based on regressors in pooled ordered probit plus those in probits for item response/non-response**							
NEXT WAVE*	.160	.027	5.97	.000	.057	.026	2.20	.028
ALL WAVES	.115	.024	4.78	.000	.087	.022	3.95	.000
NUMBER OF WAVES	.022	.004	5.74	.000	.016	.004	4.26	.000

* Based on sample for wave 1 to wave 8 only.

** Variable addition tests run on ordered probits of SAH conditioned on X_{it} and Z_{i1} , where Z_{i1} consists of all period 1 regressors used in probits of response / non-response (refer to Tables 5 & 6).

Table 10: Verbeek and Nijman tests for attrition using NUMBER OF WAVES: based on pooled ordered probit models, ECHP-UDB

Country (waves)	Model based on regressors x (t ratio)	Model based on regressors x and z_1 (t ratio)
AUSTRIA (2-8)	6.02	5.79
BELGIUM (1-8)	5.58	5.11
DENMARK (1-8)	5.58	3.68
FINLAND (3-8)	2.17	1.70
FRANCE (1-8)	8.14	6.39
GERMANY (1-3)	6.45	*
GREECE (1-8)	7.84	4.88
IRELAND (1-8)	7.11	6.85
ITALY (1-8)	12.21	6.78
LUXEMBOURG (1-3)	0.11	-0.18
NETHERLANDS (1-8)	6.43	2.94
PORTUGAL (1-8)	10.62	8.71
SPAIN (1-8)	7.98	6.09
UK (1-3)	3.08	*

* Convergence not achieved

Table 11: Static ordered probit models with inverse probability weights – Men, BHPS

	(1) Balanced sample NT = 23,980	(2) Attrition sample NT = 10,671	(3) Unbalanced sample NT = 34,651	(4) Inverse probability weights IPW-1 NT = 33,792	(5) Inverse probability weights IPW-2 NT=27,162
Ln(INCOME)	.254 (.023)	.168 (.025)	.220 (.018)	.220 (.020)	.242 (.020)
WIDOW	-.021 (.091)	.050 (.097)	-.008 (.068)	.005 (.071)	-.070 (.102)
SINGLE	-.101 (.050)	-.049 (.061)	-.100 (.039)	-.107 (.041)	-.123 (.044)
DIV/SEP	.014 (.074)	-.178 (.085)	-.074 (.057)	-.086 (.058)	-.100 (.068)
NON-WHITE	-.265 (.079)	-.214 (.077)	-.253 (.057)	-.245 (.059)	-.256 (.074)
DEGREE	.361 (.056)	.322 (.074)	.358 (.045)	.372 (.046)	.352 (.049)
HND/A	.256 (.046)	.264 (.062)	.271 (.037)	.293 (.038)	.267 (.041)
O/CSE	.220 (.047)	.214 (.055)	.227 (.036)	.226 (.037)	.231 (.040)
HHSIZE	.045 (.017)	-.007 (.021)	.022 (.014)	.024 (.014)	.019 (.016)
NCH04	.027 (.032)	-.014 (.045)	.014 (.026)	.012 (.027)	.031 (.031)
NCH511	.022 (.025)	-.017 (.035)	.016 (.021)	.006 (.022)	.021 (.026)
NCH1218	.040 (.027)	.014 (.038)	.030 (.022)	.025 (.023)	.042 (.030)
AGE	.066 (.058)	.002 (.062)	.008 (.042)	.010 (.044)	.011 (.055)
AGE2	-.219 (.187)	.021 (.203)	-.031 (.137)	-.038 (.142)	-.061 (.181)
AGE3	.273 (.253)	-.115 (.273)	.017 (.185)	.025 (.81)	.085 (.252)
AGE4	-.114 (.122)	.094 (.130)	.006 (.089)	.0009 (.091)	-.041 (.124)
Cut 1	.800 (.680)	-.670 (.711)	.129 (.491)	-.107 (.525)	.086 (.616)
Cut 2	1.554 (.679)	.028 (.713)	.589 (.492)	.605 (.525)	.780 (.616)
Cut 3	2.426 (.678)	.827 (.713)	1.425 (.491)	1.448 (.525)	1.583 (.615)
Cut 4	3.761 (.678)	2.070 (.714)	2.727 (.491)	2.746 (.525)	2.863 (.615)
Log Likelihood	-28652.8	-13730.3	-42577.5	-41919.0	-34139.6

1. Standard errors are reported in parentheses.
2. Cut 1 – 4 are estimated cut points or thresholds.
3. Coefficients for the year dummies are not reported.
4. Attrition sample defined as individuals within unbalanced sample minus individuals within balanced sample.
5. IPW – 1 weights based on wave specific probits of response/non-response on set of regressors appearing in Tables 5 and 6 including health variables.
6. Descriptive summary of IPW – 1 with health variables weights for sample above: Mean = 1.347, SD = 0.377, Min = 1, Max = 14.52. Summary of IPW – 1 weights without wave 1 values (all unity): Mean = 1.402, SD = 0.377, Min = 1.01, Max = 14.52.
7. IPW – 2 weights based on wave specific probits of response/non-response on set of regressors appearing in Tables 5 and 6.
8. Descriptive summary of IPW – 2 with health variables weights for sample above: Mean = 1.381, SD = 0.583, Min = 1, Max = 45.9. Summary of IPW – 2 weights without wave 1 values (all unity): Mean = 1.460, SD = 0.611, Min = 1.01, Max = 45.93.

Table 12: Static ordered probit models with inverse probability weights – Women, BHPS

	(1) Balanced sample NT = 28,980	(2) Attrition sample NT = 11,835	(3) Unbalanced sample NT = 40,815	(4) Inverse probability weights IPW-1 NT = 40,297	(5) Inverse probability weights IPW-2 NT = 32,165
Ln(INCOME)	.213 (.019)	.141 (.024)	.190 (.015)	.176 (.018)	.178 (.018)
WIDOW	.047 (.051)	-.084 (.063)	-.016 (.040)	-.018 (.042)	-.029 (.048)
SINGLE	.018 (.044)	.064 (.060)	.035 (.035)	.021 (.038)	.033 (.043)
DIV/SEP	-.109 (.053)	-.140 (.072)	-.126 (.043)	-.137 (.045)	-.146 (.052)
NON-WHITE	-.307 (.088)	-.295 (.090)	-.310 (.063)	-.311 (.068)	-.365 (.080)
DEGREE	.384 (.052)	.444 (.083)	.403 (.044)	.435 (.045)	.462 (.047)
HND/A	.277 (.045)	.434 (.064)	.322 (.037)	.347 (.037)	.365 (.041)
O/CSE	.294 (.041)	.325 (.052)	.309 (.032)	.333 (.033)	.345 (.036)
HHSIZE	-.011 (.016)	.007 (.020)	-.009 (.012)	-.0009 (.013)	-.011 (.015)
NCH04	.051 (.029)	.037 (.041)	.051 (.023)	.031 (.024)	.046 (.026)
NCH511	.089 (.024)	.016 (.036)	.072 (.020)	.059 (.020)	.073 (.024)
NCH1218	.063 (.025)	.062 (.035)	.062 (.020)	.053 (.021)	.060 (.026)
AGE	.015 (.058)	.053 (.060)	-.025 (.041)	.024 (.043)	-.024 (.043)
AGE2	-.076 (.183)	-.108 (.190)	.082 (.130)	-.085 (.132)	.080 (.130)
AGE3	.155 (.243)	.049 (.247)	-.101 (.170)	.130 (.171)	-.100 (.164)
AGE4	-.105 (.115)	.014 (.114)	.036 (.080)	-.077 (.078)	.035 (.073)
Cut 1	-.013 (.667)	.078 (.702)	-.520 (.480)	-.128 (.514)	-.583 (.509)
Cut 2	.753 (.668)	.780 (.701)	.214 (.480)	.615 (.518)	.128 (.510)
Cut 3	1.624 (.668)	1.601 (.702)	1.064 (.480)	1.470 (.518)	.988 (.508)
Cut 4	2.980 (.668)	2.910 (.704)	2.403 (.481)	2.799 (.519)	2.301 (.509)
Log Likelihood	-35913.5	-15414.6	-51489.4	-51375.2	-41171.5

1. Standard errors are reported in parentheses.
2. Cut 1 – 4 are estimated cut points or thresholds.
3. Coefficients for the year dummies are not reported.
4. Attrition sample defined as individuals within unbalanced sample minus individuals within balanced sample.
5. IPW – 1 weights based on wave specific probits of response/non-response on set of regressors appearing in Tables 5 and 6 including health variables.
6. Descriptive summary of IPW – 1 with health variables weights for sample above: Mean = 1.304, SD = 0.648, Min = 1, Max = 100.0. Summary of IPW – 1 weights without wave 1 values (all unity): Mean = 1.35, SD = 0.684, Min = 1.01, Max = 100.0.
7. IPW – 2 weights based on wave specific probits of response/non-response on set of regressors appearing in Tables 5 and 6.
8. Descriptive summary of IPW – 2 with health variables weights for sample above: Mean = 1.356, SD = 1.752, Min = 1, Max = 295.4. Summary of IPW – 2 weights without wave 1 values (all unity): Mean = 1.427, SD = 1.910, Min = 1.01, Max = 295.4.

Table 13:Average partial effects (APE) on the probability of reporting excellent self-assessed health for income and education, BHPS

a) Men

	(1) Balanced sample	(2) Attrition sample	(3) Unbalanced sample	(4) Inverse probability weights IPW-1	(5) Inverse probability weights IPW-2
Ln(INCOME)	.081 (.015)	.050 (.013)	.069 (.014)	.068 (.014)	.076(.016)
DEGREE	.123 (.017)	.102 (.021)	.120 (.018)	.124 (.020)	.118 (.020)
HND/A	.084 (.013)	.082 (.017)	.088 (.015)	.095 (.016)	.087 (.016)
O/CSE	.072 (.012)	.065 (.015)	.073 (.013)	.072 (.013)	.075 (.014)

b) Women

	(1) Balanced sample	(2) Attrition sample	(3) Unbalanced sample	(4) Inverse probability weights IPW-1	(5) Inverse probability weights IPW-2
Ln(INCOME)	.060 (.013)	.036 (.012)	.053 (.013)	.048 (.012)	.050 (.013)
DEGREE	.120 (.021)	.129 (.033)	.124 (.024)	.134 (.026)	.145 (.028)
HND/A	.083 (.016)	.124 (.031)	.096 (.020)	.101 (.021)	.110 (.023)
O/CSE	.086 (.016)	.088 (.024)	.089 (.019)	.094 (.020)	.101 (.021)

1. The partial effects are computed for each individual using their observed values of the regressors. The table presents the sample mean of the partial effects – the APE – along with the sample standard deviations in parentheses.

Table 14:Average partial effects on the probability of reporting very good self-assessed health for income and education, ECHP-UDB

Country (waves)	Unbalanced sample	Inverse probability weights IPW-1
AUSTRIA (2-8)		
Ln(INCOME)	0.065 (0.028)	0.069 (0.027)
SECONDARY (ISCED3-4)	0.071 (0.030)	0.070 (0.027)
TERTIARY (ISCED5-7)	0.144 (0.048)	0.139 (0.043)
BELGIUM (1-8)		
Ln(INCOME)	0.034 (0.013)	0.035 (0.014)
SECONDARY (ISCED3-4)	0.042 (0.016)	0.043 (0.016)
TERTIARY (ISCED5-7)	0.099 (0.033)	0.097 (0.032)
DENMARK (1-8)		
Ln(INCOME)	0.076 (0.013)	0.078 (0.012)
SECONDARY (ISCED3-4)	0.104 (0.016)	0.105 (0.015)
TERTIARY (ISCED5-7)	0.166 (0.022)	0.162 (0.020)
FINLAND (3-8)		
Ln(INCOME)	0.037 (0.020)	0.033 (0.019)
SECONDARY (ISCED3-4)	0.036 (0.020)	0.032 (0.018)
TERTIARY (ISCED5-7)	0.108 (0.053)	0.103 (0.051)
FRANCE (1-8)		
Ln(INCOME)	0.024 (0.012)	0.024 (0.012)
SECONDARY (ISCED3-4)	0.029 (0.014)	0.027 (0.013)
TERTIARY (ISCED5-7)	0.039 (0.018)	0.037 (0.017)
GERMANY (1-3)		
Ln(INCOME)	0.028 (0.016)	0.029 (0.016)
SECONDARY (ISCED3-4)	0.023 (0.013)	0.023 (0.013)
TERTIARY (ISCED5-7)	0.065 (0.034)	0.065 (0.034)
GREECE (1-8)		
Ln(INCOME)	0.038 (0.013)	0.039 (0.012)
SECONDARY (ISCED3-4)	0.064 (0.020)	0.065 (0.019)
TERTIARY (ISCED5-7)	0.096 (0.030)	0.095 (0.029)
IRELAND (1-8)		
Ln(INCOME)	0.089 (0.015)	0.089 (0.015)
SECONDARY (ISCED3-4)	0.089 (0.013)	0.090 (0.013)
TERTIARY (ISCED5-7)	0.125 (0.017)	0.126 (0.016)
ITALY (1-8)		
Ln(INCOME)	0.017 (0.010)	0.016 (0.009)
SECONDARY (ISCED3-4)	0.037 (0.021)	0.036 (0.019)
TERTIARY (ISCED5-7)	0.074 (0.038)	0.074 (0.036)
LUXEMBOURG (1-3)		
Ln(INCOME)	0.066 (0.026)	0.060 (0.020)
SECONDARY (ISCED3-4)	0.092 (0.033)	0.099 (0.029)
TERTIARY (ISCED5-7)	0.139 (0.044)	0.150 (0.039)
NETHERLANDS (1-8)		
Ln(INCOME)	0.042 (0.015)	0.042 (0.015)
SECONDARY (ISCED3-4)	0.027 (0.009)	0.027 (0.009)
TERTIARY (ISCED5-7)	0.065 (0.021)	0.065 (0.020)
PORTUGAL (1-8)		
Ln(INCOME)	0.012 (0.014)	0.012 (0.015)
SECONDARY (ISCED3-4)	0.025 (0.027)	0.024 (0.027)
TERTIARY (ISCED5-7)	0.037 (0.040)	0.039 (0.043)
SPAIN (1-8)		
Ln(INCOME)	0.024 (0.015)	0.025 (0.015)
SECONDARY (ISCED3-4)	0.055 (0.030)	0.054 (0.030)
TERTIARY (ISCED5-7)	0.070 (0.038)	0.070 (0.038)
UK (1-3)		
Ln(INCOME)	0.058 (0.012)	0.058 (0.012)
SECONDARY (ISCED3-4)	0.065 (0.012)	0.066 (0.012)
TERTIARY (ISCED5-7)	0.140 (0.021)	0.140 (0.021)