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

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Abstract

This paper considers health-related non-response in the first eleven waves of the British Household Panel Survey (BHPS) and the full eight waves of the European Community Household Panel (ECHP) and explores its consequences for dynamic models of the association between socioeconomic status and self-assessed health (SAH). We describe the pattern of health-related non-response revealed by the BHPS and ECHP data. We both test and correct for non-response in empirical models of the impact of socioeconomic status on self-assessed health. Descriptive evidence shows that there is health-related non-response in the data, with those in very poor initial health more likely to drop out, and variable addition tests provide evidence of non-response 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 (IPW) – shows that, on the whole, there are not substantive differences in the average partial effects (APE) of the variables of interest. The main differences are between unweighted and one form of IPW-weighted estimates for the APE of income and education in those countries that have fewer than eight waves of data. Similar findings have been reported concerning the limited influence of non-response bias in models of various labour market outcomes; we discuss possible explanations for our results.

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

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1. Introduction

The objective of this paper is to explore the existence of health-related non-response in panel data 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 longitudinal models of health creates a risk that the results will be contaminated by bias associated with longitudinal non-response. There are drop-outs from the panels at each wave and some of these may be related directly to health: due to deaths, serious illness and people moving into institutional care. In addition, other sources of non-response 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. The long-term survivors who remain in the panel are likely to be healthier on average compared to the sample at wave 1. 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. Failing to account for non-response may result in misleading estimates of the relationship between health and socioeconomic characteristics. To address this issue we describe the pattern of health-related non-response revealed by the BHPS and ECHP data and we test and correct for non-response in empirical models of self-assessed health (SAH).

There are many recent studies that have used the BHPS, ECHP and other similar panels to estimate models involving measures of health and that have used regression analyses based on balanced or unbalanced panels which may be prone to problems of non-response. Examples include: Benzeval and Judge (2001) who analyse health and SES with the BHPS; Meer et al, (2003) who analyse health and SES with the US PSID; Buckley et al (2004) who analyse SAH and SES with the Canadian SLID; Contoyannis et al (2004a) who analyse health limitations in the BHPS; Wildman (2003) who analyses the relationship between mental health and SES in the BHPS; and Riphahn (1999) who analyses retirement and health with the GSOEP.

The paper adopts a broad definition of longitudinal non-response, that encompasses any observations that "drop-out" from the original wave 1 sample over the subsequent T waves. To borrow the taxonomy of reasons for non-participation used by Nicoletti and Peracchi (2005), non-response can arise due to:

1. Demographic events such as death.
2. Movement out of scope of the survey such as institutionalization or emigration.
3. Refusal to respond at subsequent waves.

4. Absence of the person at the address.
5. Other types of non-contact.

To these points, we would add item non-response for any of the variables used in the model of health, which eliminates these observations from the sample. The notion of attrition, commonly used in the survey methods literature, is usually restricted to points 3, 4 and 5. However our concern is with any longitudinal non-response that leads to missing observations in the panel data regression analysis. In fact it is points 1 and 2 – death and incapacity – that are likely to be particularly relevant as sources of health-related non-response. The original sample consists of those who provide a full interview and usable information on SAH at the first wave of the panels. Non-response encompasses all of those who fail to provide usable observations for the model of SAH at subsequent waves.

Our aim is to estimate models that focus on the relationship between health (SAH) and socioeconomic status (SES). We take a representative sample of individuals at wave 1 and follow them for the 11 or 8 years of the BHPS and ECHP panels. The sample of interest is those n original individuals observed over a full T-year period (T=11 for BHPS and T=8 for ECHP). A fully observed sample from this population would consist of nT observations. Due to non-response we only observe $\sum_{i=1}^{n} T_i$ observations. The reasons for having incomplete observations include attrition (as conventionally defined in the survey methods literature) as well as individuals becoming ineligible, due to incapacity or death. This creates a problem of *incidental truncation*: we are interested in the association between SAH and SES for our n individuals over the full T waves. However the more frail individuals are more likely to die or drop-out before the end of the observation period, and their levels of SAH and SES are unobservable. This means that the remaining observed sample of survivors may contain less frail individuals – this is the source of potential bias in the relationship between SAH and SES across our sample of n individuals.

We apply variable addition tests for attrition bias (Verbeek and Nijman, 1992) and inverse probability weighting to adjust for non-response in estimation of pooled models (Robins *et al.* 1995; Fitzgerald *et al.*, 1998; Moffitt *et al.*, 1999; Wooldridge, 2002a). Descriptive evidence shows that there is health-related non-response in the data, with those in poor initial health more likely to drop out, and variable addition tests provide evidence of non-response bias in panel data models of SAH. Nevertheless a comparison of estimates - with and without correcting 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 non-response exists, it does not appear to distort the magnitudes of the estimated effects of socioeconomic status. Similar findings have been reported concerning the limited influence of non-response 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 non-response 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

We first exploit the panel data available in the first eleven waves (1991-2001) of the British Household Panel Survey (BHPS). The BHPS is a longitudinal survey of private households in Great Britain that provides rich information on socio-demographic and health variables. It 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 clustered 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 for wave 1 respondents. 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 consisting of all those present at wave 1. 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. Our broad definition of non-response encompasses all individuals who are missing at subsequent waves.

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. 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.,* 2004b) 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 Ourti, 2003; van Doorslaer and Koolman, 2004) 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?". Note that the question is not framed in terms of a comparison with people of one's own age and the response categories differ from the other waves. Item non-response is greater for SAH at wave 9 than for the other waves and these factors would complicate the analysis of non-response rates. Hernandez *et al.* (2004) have explored the sensitivity of ordered probit models of SAH to this change in the wording, but for simplicity we exclude wave 9 from the analysis.

Other indicators of morbidity are used to describe health-related non-response and as predictors of non-response. 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 (HLPRB), 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 (HLDSBL).

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; Frijters *et al.*, 2003; van Doorslaer and Koolman, 2004; Contoyannis *et al.,* 2004a,b). 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 reference 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. Marital status distinguishes between WIDOW, SINGLE (never married) and DIVORCED/SEPARATED, with married or living as a couple as the reference 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 wave dummies is 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 non-response across European countries. The ECHP is a standardised multi-purpose annual longitudinal survey carried out at 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 for each: 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 although the living conditions panel is included with the UDB. 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. In France a six-category scale was used but this is recoded to the five-category scale in the ECHP-UDB. 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)". 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. 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 confidentiality reasons (The Netherlands, Germany) or because the country is too small (Denmark, Luxembourg).

3. Descriptive analysis of non-response rates

3.1 BHPS

Table 1 shows how the sample size and composition evolves across the waves of the BHPS for respondents who provided information on SAH. The table, which gives figures men and women separately, 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 drop-out rates. The survival rate is the percentage of original sample members remaining at wave *t*. The drop-out rate is the percentage of the number of drop-outs between waves t-1 and t to the number of observations at t-1. The raw drop-out rate excludes re-joiners, while the net drop-out rate includes them. Drop-out rates are highest between waves 1 and 2, with the rate tending to decline over time. The table also disaggregates the raw drop-out rates according to individuals' SAH at wave t-1. This shows that drop-out rates are inversely related to past health and, in particular, non-response is highest among those who were in very poor health prior to dropping-out. This pattern of *health-related non-response* persists throughout the panel and is stronger for men than women.

Table 2 shows that the overall drop-out rate across all 11 waves of the panel varies with socioeconomic characteristics measured at wave 1. The average rate of drop-out over 11 waves is 39%. As expected, non-response 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 non-response is likely to be associated with health, through deaths, serious illness and moves to institutional care. Non-response is greater among those with lower income and with less formal education: the poorest quintile have an overall drop-out rate of 58%, compared to 32% among the richest quintile; those with no qualifications have an overall drop-out rate of 48% compared to 26% among those with a degree. The table also shows that health-related non-response interacts with individuals' socioeconomic characteristics (some caution is required as some of the cell sizes are very small). So, for example, drop-out rates are very high among elderly individuals (aged >70) who start the survey in poor (87%) or very poor health (95%).

Tables 1 and 2 provide a description of simple bivariate relationships between drop-out rates and socioeconomic characteristics. To extend this to a multivariate analysis Table 3 presents probit models for response/non-response at each wave of the panel, from wave 2 to wave 11, using the full sample of men who are observed at wave 1 (the results for women are similar and are available from the authors on request). 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 (where a response is defined as providing a usable observation for the ordered probit regression models). 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 non-response, which is described in more detail below.

The table shows 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 0.169 higher probability of responding. For women the corresponding figures are 0.084 and 0.202. 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 0.141 lower and among women it is 0.175 lower. There is no clear evidence of statistically significant income-related non-response.

The pattern of health-related non-response shows that, for both men and women, very poor initial health (SAHVPOOR) is associated with lower response rates, as is functional limitations (HLLT). These associations 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 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 measures of health this variable may be capturing other forms of non-response such as geographic mobility among healthy young people and the ease of making contact with interviewees.

3.2 ECHP

Table 4 reports the overall drop-out 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 drop-out, with 45% drop-out after only three waves in the UK and 69% after eight waves in Ireland. The high non-response 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 drop-out 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 drop-out rates of 13% and 12%. The drop-out 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 non-response 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 non-response among those in poor or very poor initial health. The gradient is not always monotonic, in some countries the lowest drop-out rates are for those with good or, in the case of Luxembourg, fair health.

To provide a sense of how drop-out rates vary by socioeconomic characteristics, Table 5 shows the overall drop-out rates across the available waves and across the countries split by socioeconomic characteristics at the first wave. The table shows the drop-out rates across all available waves for the upper and lower categories of income and education. However the results should be treated with caution as the number of observations in some of the cells are quite small. Patterns of overall non-response by income and education are different across countries: with a positive income gradient in Greece, Ireland, Italy, Portugal and Spain and a positive education gradient in Belgium, Denmark, Finland, France Germany, Netherlands and the UK. Generally the pattern of health-related drop-outs are similar across income and education groups, taking account of the small cell sizes in some cases for very poor health..

4. Models and estimation methods

4.1 The ordered probit model

To model the association between the current level of self-assessed health (SAH) and socioeconomic status (SES) we use pooled ordered probit specifications of a dynamic model (see e.g., Contoyannis *et al.,* 2004b). The latent variable specification of the model can be written as:

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

where i denotes individuals and t denotes the waves of the panel; h^*_{it} is a latent variable that underlies reported SAH; x_{it} is a set of regressors, that includes dummy variables for each category of SAH in the previous year (to capture dynamics), along with observed socioeconomic variables; 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). This makes the estimator more robust in comparison to a random effects specification. 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) $$h_{it} = j \quad if \ \mu_{j-1} < h^*_{it} \le \mu_j \ , \quad j = 1,\ldots\ldots,m$$

where $\mu_0 = -\infty$, $\mu_j \le \mu_{j+1}$, $\mu_m = \infty$. 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 is,

(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 (μ_j -β_0). To deal with this we have adopted a conventional normalisation by setting β_0=0 (an alternative is to set μ_1=0).

We do not impose an explicit error components specification in (1) but, to understand the nature of the non-response 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"). Non-response 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 non-response can therefore be detected by comparing the outcomes that are observed prior to drop-out. Non-response 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. The fundamental identification problem arises if the transient shock leads to the individual dropping-out of the panel, as h_{it} is unobservable for those who have dropped-out.

4.2 Non-response bias

Testing

The descriptive analysis has shown evidence of systematic patterns of non-response by socioeconomic characteristics and previous levels of health, but it remains to be seen whether this will lead to *non-response bias* in our empirical models of SAH. To provide an initial test for non-response bias we use the simple variable addition test proposed by Verbeek and Nijman (1992, p.688). The test variable we use is a count of the number of waves that are observed for the individual (NUMBER OF WAVES). This is added to our pooled ordered probit model and estimated with the unbalanced sample. The t-ratio on the added variables provides a test for non-response bias. The intuition behind the test is that, if non-response 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 tests 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 - for whom we have complete information at all waves - and unbalanced - for whom we have incomplete information for some individuals - samples. In the absence of non-response bias these estimates should be comparable, but non-response bias may affect the unbalanced and balanced samples differently leading to a contrast between the estimates. 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_{it} and will not capture non-response associated with idiosyncratic shocks that are not reflected in observed past health (Nicoletti, 2002).

Estimation

To allow for non-response 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 ($R=1$ if observed, 0 otherwise) 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 non-response, is familiar in the econometrics literature where the dominant approach to non-response 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 for non-ignorable non-response, 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). Also it is worth mentioning that linear fixed effects panel estimators are consistent, in the presence of selection on unobservables, so long as the non-ignorable non-response 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 non-response 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 individuals who have a high probability of non-response, as they are under-represented in the observed 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 on other indicators of morbidity. We use past morbidity among 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 (as in Table 3). The second is to do Hausman-type tests to compare the coefficients from the weighted and unweighted estimates. In addition the ordered probit models are compared in terms of the magnitudes of estimated average partial effects.

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, non-response 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 Table 3). As described above, this relies on selection on observables and implies that non-response 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 non-response and that are correlated with the outcome of interest (SAH) but which are deliberately excluded from the model for health.

In practice z_{i1} includes the initial values of all of the regressors in the health equation. Also it includes initial values of SAH and of the other indicators of morbidity: for the BHPS, 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); for the ECHP, whether the individual was mildly or severely hampered in their daily activities. 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 IPW-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) $$P(R_{it} = 1 \mid h_{it}, x_{it}, z_{i1}) = P(R_{it} = 1 \mid z_{i1}) \ , \quad t=2,\ldots,T$$

the IPW-ML 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).

The IPW-ML 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 non-response at wave t is estimated relative to the sample that is observed at wave *t-1*. This relies on non-response 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 $\hat{p}_{it} = \hat{\pi}_{i2} \times \hat{\pi}_{i2} \ldots \times \hat{\pi}_{it}$, 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.

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 non-response but are not associated with 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 and this had little impact on our findings concerning non-response (see also Contoyannis *et al.,* 2004b). With 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. In contrast to the published longitudinal weights that are supplied with the BHPS and ECHP, our IPW weights are model-specific and specifically designed for the outcome of interest (SAH) and the associated problem of health-related non-response. Past 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. For comparison, we present estimates based on the published BHPS and ECHP weights alongside estimates based on our own weights.

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.

5.1 Tests for non-response

Table 6 presents the Verbeek and Nijman (1992) variable addition tests for non-response bias in the pooled ordered probit model for SAH in the BHPS and ECHP. This is based on adding the NUMBER OF WAVES to the model. The first set of results are for the benchmark pooled ordered probits with covariates x. 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. With the exception of Austria and Luxembourg, all of the test statistics show evidence of non-response bias. Adding these test variables to the model is not intended to "correct" the estimates for non-response, 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 small (these results are available on request).

5.2 Estimates of ordered probits for SAH

Table 7presents the coefficient estimates for the dynamic pooled ordered probits for SAH estimated with the BHPS data for men (the results forwomen are available from the authors on request). The models were estimated on the balanced, the unbalanced sample and the available observations for the sample of drop-outs. The estimates for the pooled ordered probit models allow for clustering within individuals in the errors by using a robust estimator of the covariance matrix. In addition we estimated the model using the published longitudinal weights supplied with the BHPS, along with our own inverse probability weights (IPW) to adjust for non-response. Both variants of the IPW-ML estimator are presented: IPW-1 uses the full sample and wave 1 regressors to predict non-response, with IPW-2 the sample is restricted by excluding observations that exhibit non-monotone attrition and previous period regressors are used. The unbalanced sample is selected so that the same observations are used for the unweighted and all of the unweighted estimators, to allow a direct comparison of the estimators.

The LR tests reject the poolability of the unweighted models for the balanced and drop-outs samples when they are compared to the combined results for the unbalanced panel. The coefficients on lagged SAH show a clear gradient in the magnitude of the coefficients, running from good to very poor SAH (excellent is the omitted category), across all of the models. The results in Table 7 show differences in the sign and size of the coefficients on the age variables and on WIDOW between the three samples and between the weighted and unweighted estimates for the unbalanced sample, reflecting age-related non-response. The sign and size of the coefficients on the education variables are similar across all samples and comparing the weighted and unweighted estimates. The coefficients for ln(INCOME) are also similar across all of the specifications, but with a larger coefficient for the balanced sample than the sample of drop-outs and with the unbalanced sample bracketed between them. Pairwise comparisions of the contrasts between weighted and unweighted estimates of the coefficients on ln(INCOME) and the education variables shows that the differences are small in magnitude, relative to the size of the coefficients, with the largest differences when the IPW-2 weights are used. Pairwise Hausman-type t-tests suggest that the differences between coefficients from the unweighted, BHPS-weighted and IPW-1 weighted estimates are not significantly different. But they do reject the null that there is no statistically significant difference between the unweighted estimates and the IPW-2 estimates. Although this may be due, in part, to the smaller sample size when the sample is restricted to monotone attrition.

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, these 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 8 summarises the APEs of lagged SAH, 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 sample, drop-outs sample 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 estimates with and without weights are very similar in magnitude. The largest differences are between the unweighted and the IPW-2 estimates in the sample of women for educational qualifications.

Table 9 summarises the APEs on the probability of reporting very good health, the highest category in the ECHP, for the lagged SAH variables, estimated with the ECHP-UDB data. While Table 10 presents the APEs for ln(INCOME) and education. The tables compare the estimates for the unweighted ordered probit and the weighted (ECHP published weights and IPW-2 weights) ordered probit estimated on the unbalanced sample. The estimates for lagged SAH, in Table 9, are very stable across all three estimators in all of the countries. Table 10 shows that, in all of the countries, there is a positive association between both income and education and SAH in the unweighted estimates and those based on the published . The average partial effects of income are lowest in Portugal, Italy and Spain and highest in Denmark, Ireland and Luxembourg. The average partial effect of completing tertiary education is lowest in Portugal and France and highest in Ireland and Denmark. As with the BHPS, the quantitative differences between the unweighted and weighted estimates of the average partial effects are small for most countries when the published ECHP weights are used. However there is more difference when the IPW-2 weights are used in place of the published weights and in some cases the partial effects change sign. This occurs in the countries where less than eight waves are available (Austria, Germany, Luxembourg, UK). In all of these cases the underlying coefficients for income and education are not statistically significant.

6. Discussion

This analysis shows that there is clear evidence of health-related non-response in both the BHPS and ECHP. In general, individuals in poor initial health are more likely to drop out, although for younger groups non-response is associated with good health. Furthermore, variable addition tests provide evidence of non-response bias in the models of SAH. Nevertheless a comparison of estimates based on the balanced samples, the unbalanced samples and corrected for non-response using inverse probability weights shows that, in many cases, substantive differences in the magnitudes of the average partial effects of lagged health, income and education are small. The largest differences in the BHPS results are for the comparison of the weighted and IPW-2 weighted estimates of the APEs for education among women. For the ECHP the estimates of dynamics are unaffected by weighting but the IPW-2 estimates for income and education are substantially different than the unweighted estimates in the countries where less than eight waves are available (Austria, Germany, Luxembourg, UK). So, while health-related non-response clearly exists, on the whole it does not appear to distort the magnitudes of the estimated dynamics of SAH and the relationship between socioeconomic status and self-assessed health. Similar findings have been reported concerning the limited influence of non-response 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, recall that the descriptive analysis for the BHPS shows little evidence of income-related non-response. There is evidence of strong education-related and health-related non-response, 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 non-response and levels of income or education. The finding that non-response has a limited impact on the estimates of health dynamics and, to a lesser extent, estimates of the association between socioeconomic status, measured by income and education, and self-assessed health holds for the BHPS and for many of the countries within the ECHP.

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

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 Drop-out rate	Net Drop-out Rate*	Drop-out rate	Drop-out rate	Drop-out rate	Drop-out rate	Drop-out rate
1	4832										
2	4180	652	0	86.5	13.5	13.5	12.2	13.5	14.2	14.6	26.9
3	3878	428	126	80.3	10.2	7.2	8.9	9.5	11.5	14.6	24.0
4	3675	285	82	76.1	7.4	5.2	6.7	7.4	7.3	8.5	14.5
5	3464	283	72	73.8	7.7	5.7	5.4	7.4	9.6	9.7	23.0
6	3408	156	100	70.5	4.5	1.6	3.6	3.1	4.8	12.2	25.4
7	3280	159	31	67.9	4.7	3.8	3.3	4.5	4.6	9.7	11.5
8†	3137	175	32	64.9	5.3	4.4	4.1	4.4	6.4	7.0	22.9
10‡	2899	-	-	60.0	-	-	-	-	-	-	-
11	2820	137	58	58.4	4.7	2.7	4.5	4.5	4.8	5.2	10.4
Women											
1	5424										21.4
2	4777	647	0	88.1	11.9	11.9	10.8	11.8	12.1	13.2	16.4
3	4532	373	128	83.6	7.8	5.1	7.2	7.0	8.2	11.3	14.0
4	4303	305	76	79.3	6.7	5.1	6.7	5.8	6.3	11.6	12.0
5	4106	268	71	75.7	6.2	4.6	7.1	5.2	6.6	8.3	14.3
6	4016	179	89	74.0	4.4	2.2	2.6	3.4	5.2	9.3	7.1
7	3882	166	32	71.6	4.1	3.3	3.0	3.3	4.9	8.3	12.6
8†	3775	151	44	69.6	3.9	2.8	2.7	3.3	4.5	5.2	-
10‡	3522	-	-	64.9	-	-	-	-	-	-	13.5
11	3403	183	64	62.7	5.2	3.4	4.3	3.7	6.8	7.4	

Notes:
Drop-outs – respondents at wave t-1, non-respondents at wave t.
Re-joiners – non-respondents at wave t-1, respondents at wave t.
* Raw drop-out rates exclude re-joiners; Net drop-out 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 drop-out rates.
‡ Drop-out 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 drop-out 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

Table 3: Probit models for response/non-response by wave; Men, BHPS

N = 4543	2	3	4	5	WAVE 6	7	8	10	11
Ln(INCOME)	.023*	.026*	.034**	.020	.021	.025	.027	.011	.016
WIDOW	-.034	-.010	-.032	.010	.009	-.030	-.022	-.044	-.042
SINGLE	-.018	-.040	-.048*	-.051*	-.046*	-.053*	-.065**	-.074**	-.070**
DIV/SEP	-.014	-.007	-.031	-.005	.002	-.020	-.034	-.061	-.075
NON-WHITE	-.102**	-.161**	-.158**	-.160**	-.152**	-.151**	-.160**	-.152**	-.141**
DEGREE	.070**	.132**	.161**	.157**	.143**	.154**	.169**	.163**	.169**
HND/A	.057**	.083**	.090**	.093**	.092**	.100**	.115**	.121**	.134**
O/CSE	.027*	.042*	.055**	.054**	.058**	.064**	.073**	.066**	.075**
HHSIZE	-.019**	-.017*	-.031**	-.019*	-.011	-.009	-.0001	.002	-.001
NCH04	.068**	.064**	.089**	.072**	.057**	.044*	.035	.027	.034*
NCH511	.032**	.018	.036*	.012	.011	.014	-.003	-.013	-.005
NCH1218	.041**	.043**	.069**	.051**	.043	.042*	.017	.012	.0008
AGE	-.027	-.047	-.041	-.042	-.043	-.030	-.031	-.029	-.013
AGE2	.102	.166	.144	.147	.130	.122	.120	.117	.052
AGE3	-.146	-.229	-.193	-.188	-.178	-.166	-.156	-.146	-.041
AGE4	.071	.106	.085	.076	.074	.068	.055	.043	-.051
NORTH-WEST	.003	-.009	-.021	-.008	-.013	.002	.016	-.006	-.010
NORTH-EAST	.029	.002	.011	.024	.030	.027	.029	.024	.030
SOUTH-EAST	.003	.015	.018	.035	.033	.027	.025	.042	.034
SOUTH-WEST	.062**	.074**	.049	.060*	.072*	.062	.072*	.065	.068
MIDLANDS	.009	.025	.024	.038	.040	.035	.035	.026	.026
SCOTLAND	-.028	-.018	-.017	-.010	-.042	-.046	-.077*	-.082	-.086*
WALES	.027	.014	.028	.021	.020	-.002	-.022	-.006	.009
SELF-EMPLOYED	.006	-.0001	.018	.001	.005	-.002	.002	-.036	-.027
UNEMPLOYED	-.017	-.035	-.047	-.092	-.063	-.110	-.100	-.090	-.096
RETIRED	.006	.025	-.029	-.008	.018	-.044	.004	-.014	-.034
FAMILY-CARE	.005	-.026	-.0004	-.032	-.030	-.064	-.048	-.019	-.029
EMP-OTHER	.019	.024	.036	.018	.032	-.010	.042	.013	.014
UNCLASSIFIED	.052	.039	.036	.055	.049	.083	.072	.060	.066
MANUAL-TECHNICAL	.042	.046	.018	.017	.039	.033	.033	.044	.033
SKILL-NON-MAN	.041	.053	.058	.039	.045	.053	.065	.091*	.077
SKILLED-MANUAL	.030	.024	.018	.013	.016	.023	.036	.052	.041
PART-SKILLED	.040	.038	.057	.023	.038	.039	.045	.046	.034
UNSKILLED	.058	.073	.068	-.0008	.014	.017	.043	-.007	.022
SAHEX	.006	.019	.010	.010	-.001	.003	.003	.013	.009
SAHFAIR	.003	-.007	-.027*	-.044*	-.060**	-.051*	-.060**	-.066**	-.053*
SAHPOOR	.015	.022	.020	.010	-.011	-.022	-.032	-.072	-.076
SAHVPOOR	-.032	-.033	-.043	-.059	-.112	-.120	-.137*	-.151*	-.129
HLPRB	.002	.026	.049**	.054**	.049**	.045**	.045**	.040	.037*
HLDSBL	-.014	-.002	-.008	-.027	-.011	.021	.002	-.024	-.023
HLLT	-.025	-.044	-.049	-.087**	-.088**	-.095**	-.097**	-.062*	-.071*
Log-likelihood	-1660.9	-2293.5	-2472.3	-2671.8	-2730.1	-2677.6	-2846.2	-2897.1	-2927.8

1. * denotes $p \leq 0.05$, ** denotes $p \leq 0.01$.
2. All regressors represent wave 1 responses, there were no men in the long-term sick category in our sample at wave 1.
3. Results are presented as partial effects on the probability of responding at wave t, evaluated at the sample means of the regressors.

Table 4: Summary of SAH-related drop-out 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 5: Summary of SAH-related drop-out rates(%) over all available waves by income quintile amd educational status by country, ECHP-UDB

	ALL	VGOOD	GOOD	FAIR	POOR	VPOOR
AUSTRIA (2-8)						
INCOME QUINTILE 1	43	41	41	40	51	60
INCOME QUINTILE 5	43	45	42	38	37	67
PRIMARY EDUCATION	45	48	43	44	33	50
TERTIARY EDUCATION	42	41	38	40	53	64
BELGIUM (1-8)						
INCOME QUINTILE 1	57	54	54	60	66	74
INCOME QUINTILE 5	43	41	40	51	66	71
PRIMARY EDUCATION	41	39	40	46	47	71
TERTIARY EDUCATION	53	45	50	57	68	76
DENMARK (1-8)						
INCOME QUINTILE 1	60	54	59	65	72	83
INCOME QUINTILE 5	37	35	38	48	50	83
PRIMARY EDUCATION	37	35	36	48	55	69
TERTIARY EDUCATION	60	57	57	63	71	78
FINLAND (3-8)						
INCOME QUINTILE 1	49	45	45	52	58	65
INCOME QUINTILE 5	44	43	42	46	57	67
PRIMARY EDUCATION	41	40	41	44	45	100
TERTIARY EDUCATION	53	49	52	53	59	68
FRANCE (1-8)						
INCOME QUINTILE 1	49	49	46	48	59	63
INCOME QUINTILE 5	40	37	38	43	52	67
PRIMARY EDUCATION	37	34	35	39	45	65
TERTIARY EDUCATION	46	43	42	46	55	61
GERMANY (1-3)						
INCOME QUINTILE 1	18	20	15	20	24	32
INCOME QUINTILE 5	12	14	10	11	19	38
PRIMARY EDUCATION	11	15	9	10	14	35
TERTIARY EDUCATION	15	16	12	15	24	36
GREECE (1-8)						
INCOME QUINTILE 1	35	34	31	35	41	57
INCOME QUINTILE 5	48	46	48	53	59	67
PRIMARY EDUCATION	49	47	52	57	56	100
TERTIARY EDUCATION	36	29	34	37	45	57

IRELAND (1-8)						
INCOME QUINTILE 1	66	65	66	66	71	72
INCOME QUINTILE 5	71	70	71	79	57	100
PRIMARY EDUCATION	70	69	69	73	89	.
TERTIARY EDUCATION	66	65	64	68	72	80
ITALY (1-8)						
INCOME QUINTILE 1	37	33	33	37	44	57
INCOME QUINTILE 5	45	46	45	42	55	65
PRIMARY EDUCATION	40	39	40	39	48	100
TERTIARY EDUCATION	40	36	38	40	48	58
LUXEMBOURG (1-3)						
INCOME QUINTILE 1	19	28	17	15	7	42
INCOME QUINTILE 5	13	11	17	10	14	50
PRIMARY EDUCATION	12	7	17	11	33	0
TERTIARY EDUCATION	12	15	11	9	13	37
NETHERLANDS (1-8)						
INCOME QUINTILE 1	47	46	43	51	63	68
INCOME QUINTILE 5	44	39	42	52	53	67
PRIMARY EDUCATION	40	35	39	50	38	60
TERTIARY EDUCATION	53	48	51	55	63	65
PORTUGAL (1-8)						
INCOME QUINTILE 1	31	24	23	29	38	54
INCOME QUINTILE 5	37	47	36	35	41	56
PRIMARY EDUCATION	40	35	38	44	58	100
TERTIARY EDUCATION	28	25	23	28	35	50
SPAIN (1-8)						
INCOME QUINTILE 1	48	43	48	49	50	62
INCOME QUINTILE 5	49	51	48	46	61	68
PRIMARY EDUCATION	51	51	50	52	60	92
TERTIARY EDUCATION	49	45	47	49	53	65
UK (1-3)						
INCOME QUINTILE 1	49	46	49	50	53	51
INCOME QUINTILE 5	42	41	42	44	56	78
PRIMARY EDUCATION	38	38	38	39	40	62
TERTIARY EDUCATION	48	45	47	50	55	55

Table 6: Verbeek and Nijman tests for non-response, BHPS and ECHP-UDB

Country (waves)	Model based on regressors x (t ratio)	Model based on regressors x and z (t ratio)
<u>BHPS (IPW-1)</u>		
Men:	6.42	6.27
Women:	3.53	3.24
<u>BHPS (IPW-2)</u>		
Men:	4.76	4.95
Women:	2.03	2.10
<u>ECHP (IPW-2)</u>		
AUSTRIA (2-8)	0.39	0.27
BELGIUM (1-8)	5.45	4.16
DENMARK (1-8)	4.02	3.15
FINLAND (3-8)	5.28	4.74
FRANCE (1-8)	6.03	4.95
GERMANY (1-3)	3.15	2.79
GREECE (1-8)	3.69	2.80
IRELAND (1-8)	6.81	6.27
ITALY (1-8)	6.54	5.82
LUXEMBOURG (1-3)	-0.64	-0.44
NETHERLANDS (1-8)	3.22	2.03
PORTUGAL (1-8)	7.25	5.89
SPAIN (1-8)	6.07	4.88
UK (1-3)	2.04	1.94

Table 7: Dynamic ordered probit models for SAH – Men, BHPS

	(1) Balanced sample NT = 18,616	(2) Drop-outs sample NT = 6,593	(3) Unbalanced sample NT = 25,209	(4) BHPS longitudinal weights NT = 25,209	(5) Inverse probability weights IPW-1 NT = 25,209	(6) Inverse probability weights IPW-2 NT=21,630
SAHGOOD(t-1)	-.981 (.029)	-.939 (.050)	-.970 (.025)	-.954 (.026)	-.966 (.025)	-.953 (.030)
SAHFAIR(t-1)	-1.867 (.039)	-1.794 (.064)	-1.845 (.033)	-1.820 (.035)	-1.841 (.034)	-1.808 (.041)
SAHPOOR(t-1)	-2.757 (.062)	-2.597 (.081)	-2.723 (.049)	-2.701 (.051)	-2.725 (.050)	-2.677 (.065)
SAHVPOOR(t-1)	-3.356 (.126)	-3.309 (.124)	-3.383 (.089)	-3.385 (.086)	-3.414 (.087)	-3.305 (.114)
Ln(INCOME)	.146 (.016)	.103 (.023)	.130 (.013)	.125 (.015)	.129 (.015)	.149 (.016)
WIDOW	.004 (.055)	.048 (.070)	.015 (.044)	-.012 (.044)	.011 (.047)	.012 (.057)
SINGLE	-.079 (.033)	.004 (.049)	-.067 (.027)	-.066 (.028)	-.075 (.028)	-.083 (.033)
DIV/SEP	.046 (.048)	-.063 (.063)	-.003 (.039)	-.004 (.042)	-.009 (.041)	.014 (.048)
NON-WHITE	-.174 (.048)	-.161 (.072)	-.165 (.040)	-.181 (.041)	-.160 (.041)	-.118 (.057)
DEGREE	.180 (.035)	.166 (.053)	.177 (.029)	.182 (.030)	.180 (.030)	.170 (.034)
HND/A	.144 (.028)	.156 (.045)	.153 (.024)	.163 (.025)	.159 (.024)	.130 (.027)
O/CSE	.110 (.029)	.145 (.039)	.121 (.023)	.124 (.024)	.120 (.024)	.103 (.027)
HHSIZE	.030 (.013)	-.018 (.018)	.013 (.010)	.004 (.011)	.015 (.011)	.019 (.013)
NCH04	.001 (.025)	.019 (.043)	.007 (.022)	.012 (.024)	.013 (.022)	.004 (.025)
NCH511	-.009 (.020)	.046 (.034)	.008 (.017)	.008 (.018)	.0005 (.017)	.008 (.022)
NCH1218	.026 (.023)	.035 (.041)	.030 (.020)	.038 (.021)	.022 (.020)	.041 (.025)
AGE	-.013 (.045)	-.024 (.054)	-.030 (.034)	-.022 (.037)	-.041 (.039)	-.014 (.042)
AGE2	.028 (.144)	.100 (.170)	.081 (.107)	.054 (.117)	.120 (.125)	.025 (.134)
AGE3	-.035 (.193)	-.180 (.224)	-.103 (.142)	-.069 (.156)	-.159 (.168)	-.024 (.179)
AGE4	.020 (.093)	.102 (.104)	.046 (.067)	.031 (.074)	.074 (.081)	.007 (.086)
Cut 1	-2.789 (.531)	-2.956 (.634)	-3.009 (.400)	-2.980 (.435)	-3.136 (.459)	-2.664 (.495)
Cut 2	-1.728 (.531)	-2.040 (.633)	-2.019 (.400)	-1.984 (.434)	-2.148 (.458)	-1.667 (.491)
Cut 3	-.561 (.529)	-.952 (.633)	-.883 (.400)	-.849 (.434)	-1.004 (.457)	-.548 (.490)
Cut 4	1.117 (.529)	.641 (.633)	.770 (.399)	.789 (.433)	.643 (.457)	1.092 (.490)
Log Likelihood	-18568.9	-7139.7	-25782.0	-26,058.2	-26041.9	-22450.2
LR test for pooling			146.8 (0.000)			
Hausman test:						
Ln(INCOME)				-0.668	-0.134	2.037
DEGREE				0.651	0.391	-0.394
HND/A				1.429	1.034	-1.859
O/CSE				0.438	-0.146	-1.273

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. Descriptive summary of BHPS longitudinal weights for above sample: Mean = 1.056, SD = 0.351, Min = 0.190, Max = 2.5.
5. Descriptive summary of IPW – 1 with health variables weights for sample above: Mean = 1.440, SD = 0.388, Min = 1.01, Max = 15.73.
6. Descriptive summary of IPW – 2 with health variables weights for sample above: Mean = 1.908, SD = 1.173, Min = 1.01, Max = 33.89
7. The LR test for pooling compares the unrestricted estimates (balanced+drop-outs samples) with the restricted estimates (unbalanced sample). The statistic is chi-squared.
8. The Hausman test reports the t-test for pairwise comparisons of the contrast between the weighted estimates of the coefficients (models 4-6) with those from the unweighted estimate (model 3).
1.

Table 8: Average partial effects (APE) on the probability of reporting excellent SAH, BHPS.

a) Men

	(1) Balanced sample	(2) Drop-outs sample	(3) Unbalanced sample	(4) BHPS longitudinal weights	(5) Inverse probability weights IPW-1	(6) Inverse probability weights IPW-2
SAHGOOD(t-1)	-.277 (.141)	-.234 (.144)	-.266 (.143)	-.262 (.140)	-.265 (.142)	-.264 (.139)
SAHFAIR(t-1)	-.337 (.178)	-.297 (.178)	-.327 (.179)	-.325 (.176)	-.326 (.178)	-.326 (.176)
SAHPOOR(t-1)	-.295 (.205)	-.260 (.197)	-.286 (.203)	-.286 (.201)	-.286 (.203)	-.289 (.202)
SAHVPOOR(t-1)	-.276 (.208)	-.238 (.200)	-.267 (.207)	-.267 (.205)	-.266 (.206)	-.270 (.206)
Ln(INCOME)	.038 (.018)	.024 (.014)	.033 (.016)	.032 (.016)	.033 (.016)	.038 (.019)
DEGREE	.049 (.021)	.040 (.022)	.046 (.022)	.048 (.022)	.047 (.022)	.045 (.021)
HND/A	.038 (.017)	.037 (.021)	.040 (.019)	.042 (.020)	.041 (.020)	.034 (.016)
O/CSE	.029 (.013)	.034 (.019)	.031 (.015)	.032 (.015)	.031 (.015)	.027 (.013)

b) Women

	(1) Balanced sample	(2) Drop-outs sample	(3) Unbalanced sample	(4) BHPS longitudinal weights	(5) Inverse probability weights IPW-1	(6) Inverse probability weights IPW-2
SAHGOOD(t-1)	-.252 (.148)	-.197 (.133)	-.239 (.146)	-.240 (.146)	-.240 (.146)	-.237 (.141)
SAHFAIR(t-1)	-.296 (.177)	-.250 (.157)	-.286 (.172)	-.284 (.173)	-.287 (.173)	-.283 (.168)
SAHPOOR(t-1)	-.246 (.191)	-.216 (.173)	-.239 (.187)	-.237 (.187)	-.240 (.187)	-.242 (.185)
SAHVPOOR(t-1)	-223 (.191)	-.195 (.174)	-.216 (.187)	-.215 (.187)	-.217 (.188)	-.220 (.186)
Ln(INCOME)	.028 (.015)	.010 (.006)	.023 (.013)	.022 (.013)	.021 (.012)	.017 (.009)
DEGREE	.057 (.029)	.059 (.034)	.057 (.030)	.062 (.032)	.061 (.032)	.071 (.036)
HND/A	.033 (.018)	.055 (.033)	.040 (.021)	.039 (.021)	.040 (.022)	.053 (.028)
O/CSE	.040 (.021)	.027 (.017)	.037 (.021)	.039 (.022)	.040 (.022)	.049 (.026)

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 9: Average partial effects on the probability of reporting very good SAH, ECHP-UDB

Country (waves)	Unbalanced sample	ECHP published weights	Inverse probability weights IPW-2
AUSTRIA (w2-8, N*T 26368)			
VERY POOR HEALTH	-0.172 (0.190)	-0.171 (0.190)	-0.170 (0.183)
POOR HEALTH	-0.187 (0.189)	-0.185 (0.190)	-0.184 (0.183)
FAIR HEALTH	-0.270 (0.171)	-0.269 (0.173)	-0.266 (0.166)
GOOD HEALTH	-0.208 (0.155)	-0.213 (0.158)	-0.202 (0.149)
BELGIUM (w1-8, N*T 31699)			
VERY POOR HEALTH	-0.209 (0.206)	-0.212 (0.207)	-0.227 (0.209)
POOR HEALTH	-0.225 (0.206)	-0.228 (0.208)	-0.244 (0.210)
FAIR HEALTH	-0.301 (0.192)	-0.304 (0.193)	-0.323 (0.193)
GOOD HEALTH	-0.268 (0.164)	-0.270 (0.165)	-0.272 (0.162)
DENMARK (w1-8, N*T 26848)			
VERY POOR HEALTH	-0.442 (0.264)	-0.440 (0.262)	-0.455 (0.269)
POOR HEALTH	-0.453 (0.248)	-0.450 (0.245)	-0.462 (0.248)
FAIR HEALTH	-0.466 (0.176)	-0.460 (0.173)	-0.460 (0.172)
GOOD HEALTH	-0.255 (0.117)	-0.249 (0.113)	-0.257 (0.113)
FINLAND (w3-8, N*T 34439)			
VERY POOR HEALTH	-0.309 (0.270)	-0.308 (0.267)	-0.351 (0.282)
POOR HEALTH	-0.325 (0.259)	-0.324 (0.256)	-0.366 (0.266)
FAIR HEALTH	-0.364 (0.210)	-0.364 (0.207)	-0.396 (0.202)
GOOD HEALTH	-0.260 (0.154)	-0.255 (0.151)	-0.254 (0.142)
FRANCE (w1-8, N*T 66988)			
VERY POOR HEALTH	-0.117 (0.116)	-0.116 (0.116)	-0.111 (0.108)
POOR HEALTH	-0.116 (0.116)	-0.115 (0.115)	-0.110 (0.107)
FAIR HEALTH	-0.183 (0.111)	-0.181 (0.110)	-0.168 (0.100)
GOOD HEALTH	-0.124 (0.099)	-0.124 (0.099)	-0.107 (0.085)
GERMANY (w1-3, N*T 16403)			
VERY POOR HEALTH	-0.127 (0.142)	-0.128 (0.143)	-0.124 (0.134)
POOR HEALTH	-0.137 (0.143)	-0.139 (0.144)	-0.131 (0.132)
FAIR HEALTH	-0.188 (0.137)	-0.191 (0.139)	-0.165 (0.121)
GOOD HEALTH	-0.179 (0.125)	-0.180 (0.126)	-0.121 (0.090)
GREECE (w1-8, N*T 63826)			
VERY POOR HEALTH	-0.483 (0.312)	-0.477 (0.306)	-0.505 (0.336)
POOR HEALTH	-0.471 (0.264)	-0.463 (0.257)	-0.503 (0.292)
FAIR HEALTH	-0.417 (0.176)	-0.407 (0.170)	-0.483 (0.213)
GOOD HEALTH	-0.225 (0.112)	-0.219 (0.108)	-0.292 (0.154)
IRELAND (w1-8, N*T 37699)			
VERY POOR HEALTH	-0.444 (0.251)	-0.446 (0.251)	-0.452 (0.253)
POOR HEALTH	-0.447 (0.239)	-0.448 (0.237)	-0.455 (0.240)
FAIR HEALTH	-0.456 (0.155)	-0.454 (0.152)	-0.457 (0.152)
GOOD HEALTH	-0.251 (0.100)	-0.251 (0.098)	-0.252 (0.098)
ITALY (w1-8, N*T 96509)			
VERY POOR HEALTH	-0.173 (0.180)	-0.174 (0.178)	-0.183 (0.200)
POOR HEALTH	-0.190 (0.176)	-0.191 (0.174)	-0.203 (0.197)
FAIR HEALTH	-0.236 (0.153)	-0.238 (0.151)	-0.264 (0.177)
GOOD HEALTH	-0.173 (0.128)	-0.171 (0.126)	-0.205 (0.154)
LUXEMBOURG (w1-3, N*T 3503)			
VERY POOR HEALTH	-0.214 (0.198)	-0.217 (0.201)	-0.243 (0.212)
POOR HEALTH	-0.226 (0.194)	-0.229 (0.197)	-0.252 (0.204)
FAIR HEALTH	-0.282 (0.160)	-0.286 (0.162)	-0.272 (0.152)
GOOD HEALTH	-0.191 (0.126)	-0.195 (0.128)	-0.183 (0.109)
NETHERLANDS (w1-8, N*T 55673)			
VERY POOR HEALTH	-0.177 (0.164)	-0.178 (0.166)	-0.182 (0.159)
POOR HEALTH	-0.189 (0.166)	-0.190 (0.168)	-0.193 (0.159)
FAIR HEALTH	-0.255 (0.157)	-0.257 (0.159)	-0.256 (0.145)
GOOD HEALTH	-0.232 (0.135)	-0.235 (0.137)	-0.205 (0.119)
PORTUGAL (w1-8, N*T 69236)			
VERY POOR HEALTH	-0.030 (0.054)	-0.033 (0.058)	-0.034 (0.073)
POOR HEALTH	-0.042 (0.059)	-0.047 (0.065)	-0.056 (0.085)
FAIR HEALTH	-0.065 (0.075)	-0.074 (0.083)	-0.088 (0.107)
GOOD HEALTH	-0.076 (0.091)	-0.086 (0.102)	-0.112 (0.134)
SPAIN (w1-8, N*T 85111)			

VERY POOR HEALTH	-0.173 (0.148)	-0.174 (0.147)	-0.177 (0.148)
POOR HEALTH	-0.184 (0.137)	-0.184 (0.136)	-0.187 (0.135)
FAIR HEALTH	-0.183 (0.110)	-0.183 (0.110)	-0.189 (0.109)
GOOD HEALTH	-0.086 (0.059)	-0.083 (0.057)	-0.071 (0.048)
UK (w1-3, N*T 12587)			
VERY POOR HEALTH	-0.317 (0.239)	-0.316 (0.239)	-0.321 (0.224)
POOR HEALTH	-0.337 (0.233)	-0.335 (0.233)	-0.334 (0.213)
FAIR HEALTH	-0.397 (0.187)	-0.396 (0.188)	-0.368 (0.161)
GOOD HEALTH	-0.257 (0.146)	-0.257 (0.147)	-0.225 (0.118)

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 10: Average partial effects on the probability of reporting very good SAH, ECHP-UDB

Country (waves)	Unbalanced sample	ECHP published weights	Inverse probability weights IPW-2
AUSTRIA (w2-8, N*T 26368)			
Ln(INCOME)	0.010 (0.008)	0.014 (0.011)	-0.002 (0.001)
SECONDARY (ISCED3-4)	0.012 (0.009)	0.013 (0.010)	0.017 (0.013)
TERTIARY (ISCED5-7)	0.044 (0.033)	0.045 (0.034)	0.045 (0.033)
BELGIUM (w1-8, N*T 31699)			
Ln(INCOME)	0.015 (0.010)	0.012 (0.008)	0.012 (0.007)
SECONDARY (ISCED3-4)	0.014 (0.009)	0.016 (0.010)	0.007 (0.004)
TERTIARY (ISCED5-7)	0.039 (0.024)	0.042 (0.026)	0.048 (0.027)
DENMARK (w1-8, N*T 26848)			
Ln(INCOME)	0.033 (0.013)	0.030 (0.012)	0.039 (0.015)
SECONDARY (ISCED3-4)	0.036 (0.014)	0.036 (0.014)	0.020 (0.008)
TERTIARY (ISCED5-7)	0.067 (0.026)	0.069 (0.026)	0.049 (0.018)
FINLAND (w3-8, N*T 34439)			
Ln(INCOME)	0.030 (0.017)	0.029 (0.017)	0.022 (0.011)
SECONDARY (ISCED3-4)	0.029 (0.017)	0.036 (0.021)	0.031 (0.016)
TERTIARY (ISCED5-7)	0.053 (0.029)	0.062 (0.033)	0.088 (0.042)
FRANCE (w1-8, N*T 66988)			
Ln(INCOME)	0.011 (0.008)	0.010 (0.008)	0.009 (0.007)
SECONDARY (ISCED3-4)	0.014 (0.011)	0.013 (0.011)	0.019 (0.015)
TERTIARY (ISCED5-7)	0.018 (0.014)	0.018 (0.014)	0.017 (0.014)
GERMANY (w1-3, N*T 16403)			
Ln(INCOME)	0.011 (0.008)	0.006 (0.005)	-0.017 (0.014)
SECONDARY (ISCED3-4)	0.004 (0.004)	0.002 (0.002)	-0.007 (0.006)
TERTIARY (ISCED5-7)	0.026 (0.020)	0.021 (0.016)	0.044 (0.034)
GREECE (w1-8, N*T 63826)			
Ln(INCOME)	0.019 (0.009)	0.020 (0.009)	0.014 (0.007)
SECONDARY (ISCED3-4)	0.045 (0.021)	0.046 (0.020)	0.049 (0.023)
TERTIARY (ISCED5-7)	0.053 (0.024)	0.051 (0.023)	0.054 (0.027)
IRELAND (w1-8, N*T 37699)			
Ln(INCOME)	0.040 (0.014)	0.043 (0.015)	0.031 (0.010)
SECONDARY (ISCED3-4)	0.049 (0.016)	0.053 (0.017)	0.064 (0.020)
TERTIARY (ISCED5-7)	0.062 (0.020)	0.066 (0.021)	0.061 (0.019)
ITALY (w1-8, N*T 96509)			
Ln(INCOME)	0.007 (0.005)	0.005 (0.004)	-0.001 (0.000)
SECONDARY (ISCED3-4)	0.019 (0.014)	0.020 (0.014)	0.036 (0.026)
TERTIARY (ISCED5-7)	0.034 (0.024)	0.031 (0.022)	0.041 (0.028)
LUXEMBOURG (w1-3, N*T 3503)			
Ln(INCOME)	0.044 (0.029)	0.045 (0.029)	0.083 (0.046)
SECONDARY (ISCED3-4)	0.044 (0.028)	0.054 (0.034)	-0.066 (0.039)
TERTIARY (ISCED5-7)	0.038 (0.024)	0.044 (0.027)	-0.043 (0.025)
NETHERLANDS (w1-8, N*T 55673)			
Ln(INCOME)	0.022 (0.014)	0.018 (0.012)	0.025 (0.016)
SECONDARY (ISCED3-4)	0.012 (0.007)	0.016 (0.010)	0.025 (0.015)
TERTIARY (ISCED5-7)	0.027 (0.017)	0.032 (0.019)	0.019 (0.011)
PORTUGAL (w1-8, N*T 69236)			
Ln(INCOME)	0.006 (0.008)	0.006 (0.009)	0.003 (0.005)
SECONDARY (ISCED3-4)	0.011 (0.015)	0.010 (0.014)	0.006 (0.009)
TERTIARY (ISCED5-7)	0.013 (0.018)	0.012 (0.016)	0.007 (0.011)
SPAIN (w1-8, N*T 85111)			
Ln(INCOME)	0.013 (0.009)	0.015 (0.010)	0.005 (0.004)
SECONDARY (ISCED3-4)	0.037 (0.024)	0.038 (0.025)	0.049 (0.031)
TERTIARY (ISCED5-7)	0.040 (0.026)	0.038 (0.025)	0.028 (0.018)
UK (w1-3, N*T 12587)			
Ln(INCOME)	0.029 (0.015)	0.027 (0.014)	0.054 (0.024)
SECONDARY (ISCED3-4)	0.028 (0.014)	0.029 (0.015)	-0.011 (0.005)
TERTIARY (ISCED5-7)	0.052 (0.026)	0.056 (0.027)	0.022 (0.010)

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.