Education and its Effects on the Income, Health and Survival of those aged Sixty-five and Over

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31st October 2011

Abstract

We explore the effects of income and, additionally education on the income, self-reported health and survival of people aged sixty-five and over in order to identify benefits resulting from education which are omitted in the conventional analysis with its focus on labour income excluding employer contributions. We find that well educated people enjoy substantially higher incomes and longer healthy lives. However our estimates of the magnitudes of these are sharply reduced if we imposed on our model, estimated from British Household Panel Survey Data, the restrictions that the mortality rates it generates should be consistent with aggregate official data. Nevertheless, discounted back to age 21 we estimate that men with higher education qualifications receive on average, after the age of sixty-five, benefits worth £42,000. For women the comparable figure is £26,000.

JEL Codes: C33, C35, J17, J24

Keywords: Returns to Education; Income, Education and Healthy Life Expectancy; Mortality

*We are grateful to the Economic and Social Research Council for financial support.

1 Introduction

The purpose of this paper is to explore a hitherto neglected component of the return to education- its impact post-retirement. There are two aspects to this. One is that there is a well-established link between health, mortality, income and education. If life and good health are valued, then any estimate of the return to education ought to take account of both the direct effect of education and any indirect influence through income on life expectancy a health.

A second influence which is little discussed is that the focus of most studies of the effect of education is on wage income as reported in surveys such as the Labour Force Survey (see for example McIntosh (2006)). To the extent that retirement income is the combination of state benefits and private pensions or other income generated by savings out of wage income, such an approach is perfectly adequate. But historically most private pension schemes have included employer contributions as well as employee contributions and information on the former is not typically collected in the wage data provided by household surveys. Employer contributions in fact form the majority of pension saving. These are usually wage-related and have the consequence of augmenting the absolute values of the wage differentials generated by different types of education. Thus a failure to take any account of them must have the effect of depressing estimated returns to education below their true values. In this paper we estimate both these effects and indicate their discounted value to people who are just completing their education.

While the connections between education, income, health and mortality are well-established (Smith 1999, Marmot Review 2010), there are obvious questions about the pattern of causation. Do education and income have direct effects on health and mortality or are they the consequences of possibly unobserved driver variables which affect both education and health? The problem is very similar to that involved in trying to produce estimates of the effect of education on earnings which are not contaminated by underlying ability. In this latter case the current view (Blundell et al. 2005) is that the biases arising from reporting errors and the omission of ability effects largely offset each other so that estimates of the returns to education generated using ordinary least squares are not subject to significant overall bias. A number of studies have similarly attempted to establish whether education and income have causative power with respect to health and mortality. Lindahl (2005) finds that the impact of lottery winnings on health is similar to that of other forms of income, suggesting that income has a causative influence. Frijters et al. (2005) uses the effect of German unification on the incomes of the people in East Germany to identify a link between an exogenous change in income and health, although this has the drawback that there were many other changes which took place at the same time, and one cannot be sure that the effect identified is that of income. Economou & Theodossiou (2011) find that, for people aged forty-five to sixty-five, both education and income affect health status, after using instrumental variables to correct for the possible role of health as a driver of income.

Of course there may be a common causes driving both income and health. Barker et al. (2002) argue that adult disease is strongly influenced by foetal experience, although in studies of twins both Fujiwara & Kawachi (2009) and Madsen et al. (2009) find that education plays a separate role as a determinant of adult health. Gould et al. (2011) show the importance of childhood circumstances on adult outcomes. Case & Paxson (2011) establish a link between birth-weight, childhood health subsequent career success. Related work shows a connection between childhood factors and subsequent mortality. Thus Whalley & Deary (2001) find a link between IQ at age 11 and the risk of death before the age of 76 but, in the absence of other control variables, this of course does not say anything about the possible magnitude of income and education effects. Batty et al. (2006) find that the effects of income on mortality are attenuated but not removed if one takes account of respondents' IQ measured at the age of 56. But of course this, itself, may be a consequence of past education and income. Lager et al. (2009) find, on taking account of childhood IQ, education and income that the latter two that the impact of the latter to explain health and mortality is not much affected by the inclusion of childhood IQ as an explanatory variable.

In this paper we explore the relationship between health, income and educational status in the United Kingdom for people aged sixty-five and over. This has the obvious benefit that because relatively few people in this age group work, income is unlikely to be strongly influenced by current health status, although it may of course be influenced by past health status. Similarly, income is likely to be strongly influenced by past education; as noted above people are likely to receive pensions which reflect their past earnings. In most of Europe it is unlikely that income has a significant influence on access to medical care but it is easy to imagine other ways in which it can influence health, for example by affecting expenditure on heating in the winter. Education may, however, have a separate influence on both health and mortality, perhaps because ability to make good use of the National Health Service depends on education.

We carry out our study using the British Household Panel Survey. This makes it possible to represent the individual effects such as those arising from childhood experience, by including health status when first observed in our analysis exploring the role of income and education on health and mortality (Wooldridge 2005). Our estimation approach also takes account of the effects of non-response, and in particular the risk that mortality is under-reported in the British Household Panel Survey because it is often difficult to trace respondents who have died.

After estimating our model, we then simulate it to establish the effects of education on morbidity and mortality. The results of this exercise depend on the conditioning assumptions. For example, it is known that smoking is more prevalent among poorly-educated people and this is also an influence on morbidity and mortality. While it is unlikely that smoking behaviour is a determinant of educational outcomes, one may nevertheless be interested in the effects of education conditional on someone not smoking and our simulation method makes it possible to examine this. Similarly, we can examine the combined effect of education, taking account of both its direct effect and its influence on income and separately the influence of education conditional on a given level of income. Standard estimates of the value of a quality-adjusted life year then make it possible to estimate the present discounted value of the effect of education on morbidity and mortality to a twenty-one year old. Adding this to the component of pension income attributed to employer rather than employee contributions, and thus not shown in conventional measures of returns to education, then makes it possible to estimate the full value of the post employment benefits of education. We repeat the exercise after adjusting our model parameters to ensure that the mortality rates generated by the model are consistent with those reported in official statistics.

2 The Data

The British Household Panel Survey (BHPS) started in 1991[1]. It is an annual survey that provides a panel of socio-economic data set over time. It interviewed each member of a household aged 16 and over, from an initial sample of over 5000 households. The same household members are then re-interviewed in the following waves. If a member leaves the original sample household, that person, as well as the other members of the new household (aged 16 and over) are recruited for the panel. New households are also

[1] University of Essex. Institute for Social and Economic Research, British Household Panel Survey: Waves 1-17, 1991-2008 [computer file]. 6th Edition. Colchester, Essex: UK Data Archive [distributor], May 2009. SN: 5151.

included in the survey each year in order to compensate for attrition. Deaths and non-responses are recorded. Our interest centered on the following information the BHPS provides.

1. The response to the question on self-assessed health, "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...?" Respondents are requested to report "Excellent", "Good", "Fair", "Poor", or "Very Poor". Although this is a question about relative health, the results presented by Khoman et al. (2008) suggested it could be interpreted as a proxy for a question on absolute health. In order to avoid the numerical problems which would arise if we attempted to estimate an ordered probit model to explain health status as part of our system, we aggregate the health categories, treating someone who reports their health as fair, good or excellent as having good health, with everyone else regarded as having poor health.

2. Whether an individual did not respond or was reported dead.

3. Information on household income; this is described in more detail below.

4. The response of an individual to the question "Do you smoke cigarettes?" Respondents are required to report "Yes" or "No".

5. Information on qualifications; this is also set out in more detail below.

We were interested in the penultimate question because smoking is generally believed to be an important determinant of mortality; it was nevertheless not included in the variables considered by Contoyannis et al. (2004) in their study.

These data were collected in all waves except wave 9 in 1999; on that occasion there were marked differences in the way people were asked to describe their health state; secondly and perhaps more importantly, people were not asked to compare their health with that of others of the same age. Since our analysis uses both the current and lagged responses to the question on health we omit waves 9 and 10, from 1999 and 2000 from our analysis.

Non-response and death are recorded in BHPS, in the variable that states "Individual interview outcome"[2] that is recorded in two data sets of the BHPS, first the data

[2] This is given by variable wIVFIO.

set that contains individual-level data for respondents (i.e. record type wINDRESP) and secondly the data set that contains individual-level data for issued households (i.e. record type wINDSAMP). The former, although containing individuals' responses to the questions of our interest, covers only individuals who were actually interviewed (either in full, by proxy or by telephone). In order to obtain full information on respondents, non-respondents, and those reported dead, we merged the two data sets.

It is household income rather than individual income which should be expected to influence health and mortality. In any case for retired people the concept of individual income is not defined in the precise way that it is for employment income. State benefits, whoever they are paid to, reflect domestic circumstances and private pensions may include survivor benefits and thus are, in some sense, joint income rather than individual income. The BHPS provides a gross measure of the household income. However, the net measure of household income is more appropriate for our purposes (see Jenkins (2010)). We therefore use the unofficial supplement to the income variables in the official BHPS release, the "British Household Panel Survey Derived Current and Annual Net Household Income Variables, BHPS waves 1-16, 1991-2007" constructed by the Institute of Social and Economic Research, University of Essex (see Levy & Jenkins (2008)) in our analysis. This supplementary data set contains information for those BHPS households in which all eligible household members have participated in a full interview. Those households in which one or more members refused participation in the BHPS or whose information were given by a proxy respondents are excluded. The data set provides estimated currently weekly household net income and annual household net income for each wave. It also provides variables that classify individual according to their family type and economic status of their family. For more detail, see Levy & Jenkins (2008). Current weekly household net income and the annual household net income are recorded in the variable "whhnetde2" and "whhnyrde2" in the ISER supplement, respectively. Both variables measure total household net income which is equivalised using the Modified OECD scale (with a single adult counting as one person and a couple as 1.5 people) to adjust for differences in household composition and size. The variables are also adjusted to January 2008 prices using a "before housing cost" price index.

The data on educational attainment in the survey are very detailed. These were classified to match, with one exception[3], the national scale which ranges from 0 (for those with no or only minimal qualifications) to 5 for those with post-graduate degrees. The

[3] Our classification differs slightly from the National Qualifications Framework which classes GSCEs at grades D to G as level 1 and grades A* to C as level 2.

system was originally designed to represent national vocational qualifications (NVQs) but academic qualifications have also been calibrated against it, allowing most qualifications to be represented on an equal basis. In common with other work (e.g. Blanden et al. (2010)) we merge categories 4 and 5. Our classification of qualifications is shown in table 1.

To construct our sample, we merge, wave by wave, the combined wINDRESP and wINDSAMP data set of the BHPS from above to the ISER supplement using the household identifier. Since the last available wave we consider in the ISER supplement is wave 16 (year 2006), our study thus uses the data of original sample members (OSM) between 1991 to 2006, aged 65 and over.

3 Education, Income, Health and Survival in the British Household Panel Survey

In this section we present a summary of the data from the British Household Panel Survey showing, in broad terms, the relationships we subsequently explore in greater detail. Table 2 shows the mean income classified by educational level for our pooled data set. We can see clearly that the incomes of people aged sixty-five and older are increasing in their qualification level, with the exception that men qualified to level 3 receive lower incomes than those qualified only to level 2.

Just as qualification level is related to income, so too qualification level is related to health. In table 3 we show the proportion of respondents reporting poor or very poor health classified by their qualification levels. We also show the proportion of people classified by qualification level who report that they smoke. Among men it is clear that health status improves with qualifications. The effect is less obvious with women but after one allows for the fact that there are rather few women qualified to level 3, as table 2 shows, it does appear that health status is generally improving with qualification level. Smoking is widely believed to be a cause of poor health, so we also show the relationship between smoking behaviour and qualification level. For both men and women one can observe the general pattern than smoking prevalence declines with qualification level.

Given the relationship between health and mortality one might expect to see higher mortality rates for people with low-level qualifications. So as to summarise the data compactly, we show in table 4 the mortality rates identified in the British Household Panel Survey for men and women distinguish those educated to levels 0 or 1 from those education to level 2 or higher. We can see that, for both men and women and for all age

Level 1
Youth training certificate
Trade appenticeship
Clerical and commercial qualifications
City and Guilds Certification Part I
SCOTVEC National Certiciate Modules
NVQ/SVQ level 1
GCSEs
SCEs grade D-E or 4-5
O grades A-C or 1-3
Standard grades 4-7
CSEs
O-levels (pre-1975), OLs (post-1975)
SLCs
Level 2
City and Guilds Certification Part II
SCOTVEC Higher National Units
NVQ/SVQ level 2
CPVE
1 A level
Standard grades 1-3
GNVQ
AS level
School Certificate or Matriculation
1 Higher School Certificate
Level 3
City and Guilds Certification Part III
SCOTVEC National Certificate or Diploma
ONC, OND, BEC/TEC/BTEC General Certificate
NVQ/SVQ level 3
2 or more A levels
2 or more Higher School Certificates
Higher grades
Certificate of 6th year studies
Level 4
HNC, HND, BEC/TEC/BTEC/SCOTVEC Higher Certificate or Higher Diploma
NVQ/SVQ level 4
Nursing qualifications (e.g. SEN, SRN, SCM, RGN)
Teaching qualification
University diploma or Foundation degree
University or CNAA First Degree (e.g. BA, B.Ed, BSc)
University or CNAA Higher Degree (e.g. MSc, PhD)

Table 1: The Classification of Qualifications

	Annual Equivalised Household Income		Number	
	Women	Men	Women	Men
Qual. Level 0	9,766	10,598	6,409	3,490
Qual. Level 1	11,322	12,321	1,500	1,607
Qual. Level 2	13,398	15,975	864	732
Qual. Level 3	13,617	14,458	167	430
Qual. Level 4	15,628	18,793	1,276	1,059

Table 2: Mean Annual Income (£2008 prices) and Qualifications

	Proportion in Poor Health		Proportion Smoking	
	Women	Men	Women	Men
Qual. Level 0	16.9%	15.7%	15.3%	18.9%
Qual. Level 1	14.2%	10.5%	9.6%	15.1%
Qual. Level 2	7.1%	10.2%	10.5%	9.3%
Qual. Level 3	19.2%	8.4%	7.7%	12.3%
Qual. Level 4	9.3%	4.0%	7.1%	5.5%

Table 3: Qualfication, Self-reported Health and Smoking Behaviour

categories except women aged 70-74, mortality rates are lower for those with at least level 2 education than for the rest of the survey population.

Finally, we are concerned about the relationship between income, health and mortality. An indication of the connection between health status and income is provided in table 5. Here we show the proportion of the male and female population reporting poor health (poor or very poor in the original classification) distinguishing respondents by whether their income was above or below the median. Table 6 shows mortality rates calculated on the same basis, but with the income classification based on the year before death was reported.

As the introductory discussion makes clear, we also need to address the issue of non-response. Table 7 summarises the probability of non-response as a function of age and education. Non-response rates are generally below mortality rates. Nevertheless, to the

Mortality Rates	Men		Women	
Age	Qual. Level 0-1	Qual Level 2-4	Qual. Level 0-1	Qual Level 2-4
65-69	1.8%	1.3%	1.8%	1.3%
70-74	4.1%	2.9%	2.5%	2.5%
75-79	6.2%	3.0%	3.4%	3.0%
80-84	9.5%	5.1%	5.9%	3.6%
85+	15.7%	10.1%	13.5%	9.3%

Table 4: Mortality Rates and Education

	Men	Women
Below median	14.3%	15.7%
At or above median	9.5%	13.8%

Table 5: Proportion Reporting Poor Health classified by Income

	Men		Women	
Age	Below median	At or above median	Below median	At or above median
65-69	2.33%	1.24%	1.89%	1.34%
70-74	3.03%	4.19%	2.18%	2.25%
75-79	4.93%	4.29%	2.79%	3.90%
80-84	11.19%	3.88%	6.01%	5.50%
85+	15.35%	13.07%	12.59%	12.22%

Table 6: Mortality Rates by Income Category

extent that unreported mortality is a substantial source of non-response, a failure to address non-response appropriately could be a substantial source of error in the component of our model which represents the risk of death.

These data show clear relationships between education, health and mortality in old age. However, since the proportion of smokers is generally higher among poorly-educated people, this effect may be a consequence of smoking behaviour. The relationship between income and health is more clearly marked for men than for women and this is also true of the possible connection between income and mortality. However, while these tables summarise the data they do not allow us to identify the magnitudes of the different effects and in order to explore this we develop an econometric model of the data.

	Men		Women	
Age	Qual. Level 0-1	Qual Level 2-4	Qual. Level 0-1	Qual Level 2-4
65-69	1.65%	1.75%	1.30%	0.76%
70-74	2.78%	0.84%	2.24%	0.92%
75-79	2.42%	2.09%	2.66%	1.31%
80-84	2.24%	2.67%	4.10%	3.54%
85+	4.34%	5.20%	4.48%	5.45%

Table 7: The Probability of Non-response given a Reply in the Previous Wave

4 Econometric model

We use a trivariate system to model health state transition, mortality and non-response, in which logarithmic annual net household income is included as an explanatory variable in all three equations. Mortality and non-response are introduced as distinct equations in the model. This contrasts with other work which has treated death as a form of non-response (Contoyannis et al. 2004) or looked at death as the lowest possible health state in an ordered probit model (Khoman et al. 2008).

We define GH_{it} as the binary variable which takes a value 1 if individual i reports good health (on our dichotomous measure) in year t, where $t = 1992, \cdots 1998, 2001, \cdots 2007$. GH_{it-1} indicates good health in the previous period. Similarly D_{it} takes a value 1 if an individual is reported dead in year t and 0 otherwise and NR_{it} takes a value 1 if an individual does not respond in year t, and 0 otherwise, LY_{it} denotes log annual equivalised net household income with LY_i^1 its value when first observed; S_{it} is a dummy to indicate whether an individual is a smoker. A_{it}^{τ} and T_t are age and year dummies respectively.

We address the initial conditions problem by including variables describing the individual's state when first observed (Wooldridge 2005). To resolve the initial conditions problem, we include in our model the dummies, H_{it}^k $(k = 1..3, 5)$, that correspond to the 4 health categories ("Very poor", "Poor", "Fair", "Excellent") reported initially, with the dummy for the most common category, good omitted for identification reasons. Thus, H_i^1 takes the value of 1 if the person's health is "very poor" in wave 1, and 0 otherwise.

We define gh_{it}, d_{it} and nr_{it} as the latent variables that underlie the health state, mortality and participation in the survey. Thus, $GH_t = 1$ if $gh_{it} > 0$. $D_{it} = 1$ if $d_{it} > 0$, and $NR_{it} = 1$ if $nr_{it} > 0$.

Our trivariate model is represented by three equations as follows

$$gh_{it} = \alpha_1 GH_{it-1} + \sum_{k=1,3}^{5} \beta_{1k} H_i^k + \vartheta_1 LY_{it-1} + \kappa_1 LY_i^1 + \gamma_1 S_{it-1} + \sum_{\tau=65}^{90+} \delta_{1\tau} A_{it}^{\tau} + \sum_{t=1992}^{2007} \theta_{1t} T_t + \varepsilon_{1,it} \tag{1}$$

$$d_{it} = \alpha_2 GH_{it-1} + \sum_{k=1,3}^{5} \beta_{2k} H_{i,t}^k + \vartheta_2 LY_{it-1} + \kappa_2 LY_i^1 + \gamma_2 S_{it-1} + \sum_{\tau=65}^{90+} \delta_{2\tau} A_{it}^{\tau} + \sum_{t=1992}^{2007} \theta_{2t} T_t + \varepsilon_{2,it} \tag{2}$$

$$nr_{it}=\alpha_3 GH_{it-1}+\sum_{k=1,3}^{5}\beta_{3k}H_{i,t}^{k}+\vartheta_3 LY_{it-1}+\kappa_3 LY_i^1+\gamma_3 S_{it-1}+\sum_{\tau=65}^{90+}\delta_{3\tau}A_{it}^{\tau}+\sum_{t=1992}^{2007}\theta_{3t}T_t+\varepsilon_{3,it} \tag{3}$$

We have been able to rely on the non-linear nature of the model to identify the parameters.

Parameter subscripts, taking the values 1 to 3 correspond to the parameters of equations (1), (2), and (3), respectively. The error terms in the three equations are drawn from a multivariate normal distribution, with

$$\begin{bmatrix}\varepsilon_{1,it}\\ \varepsilon_{2,it}\\ \varepsilon_{3,it}\end{bmatrix}\sim N\left(0,\mathbf{\Sigma}\right)$$

where

$$\mathbf{\Sigma}=\begin{bmatrix}1 & \sigma_{12} & \sigma_{13}\\ \sigma_{12} & 1 & \sigma_{23}\\ \sigma_{13} & \sigma_{23} & 1\end{bmatrix}$$

since variances of the error terms are not identified by the model and are set to unity.

The trivariate system is estimated as a trivariate probit using maximum simulated likelihood via the STATA routine *MVPROBIT* of Cappellari & Jenkins (2003), on pooled data. *MVPROBIT* routine uses the GHK (Geweke-Hajivassiliou-Keane) smooth recursive simulator (see Geweke (1989), Hajivassiliou & Ruud (1994) and Keane (1994)) to approximate the trivariate normal density. The conditional means of the above equations can be written as

$$m_j=\alpha_j GH_{it-1}+\sum_{k=1}^{5}\beta_{jk}H_{i,t}^{k}+\vartheta_j LY_{it}+\kappa_j LY_{it-1}+\gamma_j S_t+\sum_{T=65}^{90+}\delta_j A_{it}^{(T)}+\sum_{t=1992}^{2007}\theta_j Y_t \tag{4}$$

where $j = 1, 2$, or 3, the log-likelihood function for the sample of N individuals is

$$\ln L=\sum_{i=1}^{N}\ln\left(\Phi_3\left(\mathbf{m},\mathbf{\Lambda}\right)\right) \tag{5}$$

with $\mathbf{m}=(\nu_{1i}m_1,\ \nu_{2i}m_2,\ \nu_{3i}m_3)$. Λ is a 3x3 matrix, with diagonal element of Λ_{jj} are unity. The off-diagonal elements $\Lambda_{jk}=\Lambda_{kj}=v_{ji}v_{ki}\sigma_{jk}$, where $k\neq j,\ j,\ k=\ 1,\ 2,$ or 3. ν_{ji} is a sign variable of which

$$\begin{aligned}\nu_{ji} &= 1 \text{ if } gh_{it},\ d_{it},\ nr_{it}\ >0\\ \nu_{ji} &= -1 \text{ if } gh_{it},\ d_{it},\ nr_{it}\ \leq 0\end{aligned}$$

Rather than having eight possible outcomes in a trivariate case, there are only six possible outcomes in our sample due to the fact that it is impossible for non-respondents to be both dead and in either good or poor health. But this restriction does not affect our estimation. Computing the log-likelihood function thus involves evaluating the trivariate normal integrals to obtain the trivariate normal CDF. In the case when an individual is in good health, alive and responding to the survey, the joint probability of these circumstances is given by

$$\begin{aligned}
& \Pr\left(GH_{it}=1,\ D_{it}=0,\ NR_{it}=0\right) \qquad (6)\\
= \ & \Pr\left(\varepsilon_{1it}>-m_1,\ \varepsilon_{2it}\leq -m_2,\ \varepsilon_{3it}\leq -m_3\right)\\
= \ & \int_{-\infty}^{m_1}\int_{-\infty}^{-m_2}\int_{-\infty}^{-m_3}\phi_3\left(\varepsilon_{1it},\varepsilon_{2it},\varepsilon_{3it};-\sigma_{12},-\sigma_{13},\sigma_{23}\right)d\varepsilon_{3it}d\varepsilon_{2it}d\varepsilon_{1it}\\
= \ & \Phi_3\left(m_1,-m_2,-m_3;-\sigma_{12},-\sigma_{13},\sigma_{23}\right)
\end{aligned}$$

The *MVPROBIT* routine of Cappellari & Jenkins (2003) uses the GHK (Geweke-Hajivassiliou-Keane) smooth recursive simulator to evaluate multivariate normal distribution function. The GHK simulator applies Cholesky decomposition to the covariance matrix of the errors and also the Bayesian rules, to rewrite the joint trivariate normal density as a product of the univariate normal densities, conditional on some unobserved normal variables. Simulation is used to find values of the unobserved normal variables from truncated normal distribution, and thus to obtain the conditional univariate normal densities. The joint trivariate normal probability is then computed as the arithmetic mean of the product of the simulated univariate normal densities. Maximum likelihood estimation is then applied to evaluate the joint trivariate normal probability. For more detail description of maximum simulated likelihood estimation via GHK simulator on probit models, see Cappellari & Jenkins (2003), Terracol (2002), and Greene (2003).

5 Results

We show in tables 8 and 9 the results, for men and women, of our trivariate probit model which explores the drivers of i) whether someone is in good health, ii) whether they are reported as dead and iii) whether they respond to the survey. The only continuous variable in the three equations is log of income; otherwise all variables are dummies. Thus *Smoke* takes the value 1 if an individual smokes and 0 otherwise, the variables

Qual Level 1 to Qual Level 4 take a value 1 if that particular level of qualification is the individuals highest level and 0 otherwise. *Good Health*$_{t-1}$ takes a value 1 if the individual reports good health in the previous period and the *Initial Health* terms indicate into which of the health categories people gave in their initial responses. Since these are not modelled, there is no need to aggregate them and extra information may be gained by not doing so. The remaining dummies indicate age, with ages 90 and above represented by a single dummy. Year dummies were also included in the model but these have been omitted from the tables to save space. A positive coefficient in the first equation indicates that the respondent with the attribute represented by the related variable is more likely to be in good health; a positive coefficient in the second equation indicates that the respondent is more likely to die and a positive coefficient in the third equation indicates that the respondent is less likely to respond.

The pattern is similar for both men and women although there are nevertheless some substantial differences of magnitude. We can see that, at a 5% significance level, men's health is positively related to income and to previous good health. Initial health status is important, showing the need to take account of the individual effects it represents. Men with qualifications at levels 2 and 4 are significantly more likely to be in good health than are other men; we have no explanation of the lower health status of the relatively small number of men educated to level 3, but note that the coefficient is not significantly different from that for men educated to level 2. Smoking has an effect on health which is adverse but not statistically significant. The risk of death is significantly declining in income but significantly augmented by smoking. Indeed the effect of smoking on both health and mortality requires an increase in almost one log unit of income to offset it.

Turning to the mortality equation, we see that qualifications do not affect the mortality rate of men directly. However death is less likely if the respondent reported good health in the previous year and since qualifications influence the chance of being in good health and, as we subsequently and not surprisingly show, income, they have an indirect influence on death through this route. Any influence of income on mortality is also likely to be a route by which qualifications can influence mortality. Thus the absence of a direct effect after controlling for income and previous health state does not mean that qualifications would have no effect on mortality in single probit regression where these indirect routes were not represented. The chance of non-response is declining in income and increased if men smoke. Qualifications at all levels higher than 0 make men more likely to respond as does good health in the previous period.

The age dummies in the health equation are erratic but suggest that good health is less likely to reported above the age of eighty than at younger ages. Turning to the mortality equation we can see a marked effect for the probability of death to increase with age; the year dummies, which are not shown, indicate no obvious tendency for it to decline with time despite a widely-observed (and historically unprecedented) decline in mortality present in the aggregate statistics. Non-response becomes more likely as men age but again, it is hard to say there is a clear drift with time. Thus the health and mortality equation shows the expected age, but not the expected time effects; the non-response equation identifies a number of factors associated with non-response- low income, smoking, age, absence of qualifications and poor health. In this there are, not surprisingly, a number of items also associated with risk of mortality.

In broad terms the set of influences on women is similar to that on men. Health is significantly positively influenced by income, qualifications at level 4 and initial and previous good health. Mortality is significantly decreasing in income and increased if women smoke. . As with men, qualifications do not have a direct effect on mortality. However, the income effect on health is only two thirds that found with men while than on mortality is only one third that for men. The role of qualifications on health is only about one third that for men. Thus, although the indirect channels by which qualifications can influence mortality are significantly present for women as well as for men, they must be expected to be appreciably weaker. Non-response among women is, however, more rapidly declining in income for women than for men and smoking is not a significant predictor of non-response. As with men there is a pattern of the probability of good health declining with age and, slightly, over time. Mortality risk is increasing with age but there is no clear time effect. The upward drift on non-response with age is more marked for women than for men and there is, once again, no obvious temporal pattern.

In table 10 we show the estimates of the correlations between the disturbances to the three equations. We can see that all three are statistically significant for men and that the disturbances of the non-response equation are significantly correlated with those of both other equations for women, pointing to the importance of estimating the model as a system of equations rather than equation by equation. It is also, of course, striking that there is a very substantial negative correlation between the disturbances to the mortality and non-response equations for both sexes. This indicates that the expected unconditional relationship between mortality and non-response is not fully removed by

	Health		Mortality		Non-response	
	Coeff.	z-stat	Coeff.	z-stat.	Coeff.	z-stat
Ln Income$_{t-1}$	0.101	2.17	-0.285	-6.23	-0.074	-1.91
Ln Initial Income	-0.057	-1.09	0.089	1.41	-0.147	-3.39
Smoke	-0.105	-1.86	0.250	3.77	0.158	3.25
Qual Level 1	0.075	1.36	-0.002	-0.03	-0.200	-4.08
Qual Level 2	0.167	2.09	-0.018	-0.19	-0.365	-4.84
Qual Level 3	0.064	0.63	0.007	0.05	-0.130	-1.53
Qual Level 4	0.275	3.24	-0.067	-0.64	-0.238	-3.58
Good Health$_{t-1}$	1.856	36.47	-0.582	-8.87	-0.113	-1.98
Initial Health Very Poor	-0.916	-7.19	0.358	2.27	0.210	1.61
Initial Health Poor	-0.617	-8.49	0.145	1.52	0.129	1.75
Initial Health Fair	-0.409	-7.72	0.248	3.82	0.123	2.53
Initial Health Excellent	0.181	2.93	-0.102	-1.44	0.058	1.25
Age 66	0.020	0.15	0.028	0.13	0.019	0.18
Age 67	-0.012	-0.09	0.234	1.16	-0.071	-0.64
Age 68	-0.103	-0.76	0.177	0.86	-0.007	-0.06
Age 69	-0.170	-1.29	0.015	0.07	0.061	0.57
Age 70	-0.206	-1.58	0.244	1.23	-0.012	-0.11
Age 71	-0.248	-1.9	0.452	2.39	0.018	0.17
Age 72	-0.099	-0.75	0.011	0.05	-0.031	-0.29
Age 73	-0.275	-2.14	0.312	1.6	-0.047	-0.43
Age 74	-0.293	-2.24	0.603	3.29	-0.067	-0.59
Age 75	-0.089	-0.64	0.596	3.2	-0.054	-0.47
Age 76	-0.295	-2.16	0.556	2.9	-0.109	-0.91
Age 77	-0.256	-1.83	0.610	3.18	-0.040	-0.33
Age 78	-0.290	-2.02	0.527	2.61	-0.069	-0.55
Age 79	-0.179	-1.17	0.555	2.68	-0.129	-0.97
Age 80	-0.472	-3.28	0.767	3.92	-0.215	-1.56
Age 81	-0.370	-2.49	0.725	3.6	-0.034	-0.26
Age 82	-0.123	-0.76	0.861	4.34	-0.046	-0.34
Age 83	-0.487	-3.09	0.816	3.93	0.089	0.65
Age 84	-0.418	-2.56	0.802	3.81	0.162	1.15
Age 85	-0.322	-1.93	0.970	4.74	0.199	1.44
Age 86	-0.600	-3.65	1.044	5.02	0.272	1.89
Age 87	-0.587	-3.18	0.687	2.79	0.337	2.16
Age 88	-0.526	-2.68	0.872	3.7	0.567	3.63
Age 89	-0.466	-2.15	1.170	5.1	0.535	3.15
Age 90+	-0.308	-2.03	1.470	8.18	0.695	6.17
Constant	-0.189	-0.38	0.019	0.03	0.685	1.66
Year dummies were also included; 200 draws						
Log likelihood = -6379.8437			Wald χ^2_{147}		3023.41	

Table 8: Estimation Results: Men

	Health		Mortality		Non-response	
	Coeff.	z-stat	Coeff.	z-stat	Coeff.	z-stat
Ln Income$_{t-1}$	0.082	2.26	-0.098	-2.54	-0.186	-5.93
Ln Initial Income	-0.021	-0.52	0.013	0.26	-0.160	-4.56
Smoke	-0.171	-3.69	0.250	4.07	-0.030	-0.66
Qual Level 1	-0.064	-1.27	-0.008	-0.11	-0.095	-2.01
Qual Level 2	0.062	0.9	-0.018	-0.19	-0.205	-3.23
Qual Level 3	-0.081	-0.63	-0.241	-0.98	-0.293	-1.91
Qual Level 4	0.087	1.44	0.020	0.26	-0.236	-4.17
Good Health$_{t-1}$	1.723	44.17	-0.286	-5.07	-0.124	-2.87
Initial Health Very Poor	-0.911	-10.68	0.267	2.38	0.019	0.21
Initial Health Poor	-0.729	-12.89	0.280	3.63	0.166	2.89
Initial Health Fair	-0.312	-7.85	0.081	1.47	0.011	0.3
Initial Health Excellent	0.286	5.17	-0.095	-1.42	-0.068	-1.6
Age 66	-0.023	-0.19	0.065	0.32	-0.046	-0.43
Age 67	-0.138	-1.15	-0.005	-0.02	-0.132	-1.21
Age 68	-0.076	-0.63	0.082	0.4	-0.194	-1.76
Age 69	-0.004	-0.03	0.098	0.49	-0.148	-1.39
Age 70	-0.117	-0.99	0.255	1.35	-0.156	-1.46
Age 71	-0.151	-1.29	-0.081	-0.37	-0.173	-1.6
Age 72	-0.106	-0.89	0.113	0.57	-0.214	-1.98
Age 73	-0.113	-0.95	0.169	0.87	-0.070	-0.67
Age 74	-0.242	-2.08	0.386	2.1	-0.094	-0.9
Age 75	-0.242	-2.05	0.377	2.03	-0.086	-0.8
Age 76	-0.129	-1.07	0.361	1.93	-0.053	-0.5
Age 77	-0.284	-2.42	0.423	2.29	-0.044	-0.41
Age 78	-0.148	-1.22	0.490	2.66	-0.030	-0.28
Age 79	-0.250	-2.09	0.514	2.78	0.040	0.37
Age 80	-0.366	-3.1	0.289	1.47	-0.005	-0.05
Age 81	-0.121	-0.99	0.597	3.28	0.094	0.89
Age 82	-0.259	-2.11	0.635	3.49	0.200	1.9
Age 83	-0.144	-1.12	0.647	3.52	0.362	3.46
Age 84	-0.434	-3.48	0.676	3.65	0.281	2.59
Age 85	-0.343	-2.68	0.708	3.77	0.352	3.17
Age 86	-0.439	-3.27	0.871	4.64	0.402	3.5
Age 87	-0.403	-2.87	0.933	4.9	0.511	4.37
Age 88	-0.556	-3.87	0.882	4.47	0.712	5.96
Age 89	-0.179	-1.15	1.017	5.14	0.692	5.5
Age 90+	-0.196	-1.71	1.157	7.05	1.065	11.65
Constant	-0.253	-0.66	-1.627	-3.17	1.882	5.49
Year dummies were also included; 200 draws						
Log likelihood = -9692.0435			Wald χ^2_{147}		5140.14	

Table 9: Estimation Results: Women

	Men		Women	
	Coef	z-stat	Coef	z-stat
ρ_{12}	-0.113	-2.55	-0.065	-1.72
ρ_{13}	0.092	2.35	0.067	2.29
ρ_{23}	-0.770	-12.28	-0.807	-18.77

Table 10: Correlations between Disturbances

the introduction of the explanatory variables which we have used.

6 Model Simulation

In order to explore the implications of these estimates we resort to simulation. By simulating the experience of an appropriately constructed sample, we can identify the influence of education on the variables of interest to us. However, in order to do this it is first necessary to model the determination of income and we focus on that first in this section. Secondly, we discuss the appropriate choice of other variables, such as smoking behaviour and initial health state for use in our simulations. Thirdly, we explain how we construct estimates of life expectancy, healthy life expectancy and post-sixty-five income from our model.

6.1 Income

Simulation of income requires some model of the error structure of the disturbances which affect people's incomes after their retirement. Most work on income dynamics has focused on employed people with low risk of unemployment or non-participation in the labour market. We draw on the framework proposed by Guvenen (2007). The specification, described by equation (7), explains income of individual i in year t, $y_{i,t}$ in terms of the vector $\mathbf{X}_{it}$ of exogenous variables also used to explain health[4] and mortality and an innovation process that is commonly considered to provide a good balance between

[4]Although, in keeping with most work on returns to education, we do not include first observed or previous health state or smoking behaviour.

parsimony and the complexity that characterises reality.

$$
\begin{aligned}
LY_{it} &= \mathbf{X}_{it}\boldsymbol{\psi} + \omega_i + \varepsilon_{it}^y + z_{it} && \text{(7a)}\\
z_{it} &= \rho_b z_{it-1} + \eta_{it} && \text{(7b)}\\
\omega_i &\sim iidN\left(0, \sigma_\omega^2\right) && \text{(7c)}\\
\varepsilon_{it}^y &\sim iidN\left(0, \sigma_\varepsilon^2\right) && \text{(7d)}\\
\eta_{it} &\sim iidN\left(0, \sigma_\eta^2\right) && \text{(7e)}
\end{aligned}
$$

The error structure includes a fixed effect, ω_i, a serially uncorrelated effect, ε_{it}^y and a serially correlated term, z_{it}. If ρ takes the value 1, then the model has a unit root in individual income. Unlike Guvenen, however, we cannot include cohort or year dummies as influences on the error process and nor can we include individual-specific trends in earnings because our sample size is limited. As we noted earlier, Blundell et al. (2005) argue that estimation of (7a) by ordinary least squares is satisfactory, because endogeneity biases associated with education effects are more or less cancelled out by reporting errors. Thus correcting for the first worsens rather then ameliorates problems.

We denote the earnings residual after controlling for population average effects of individual i in year t by $u_{it} = y_{it} - \mathbf{X}_{it}\boldsymbol{\psi}$,. with $\boldsymbol{\psi}$ now taking its estimated value. We set the indicator variable $I_{i,t}$ to 1 if earnings (and thus residuals) are observed for individual i in year t, and to 0 otherwise. We then evaluated the $\frac{T(T+1)}{2}$ elements of the covariance matrix in time of the population earnings residuals:

$$v_{t,t+k} = \frac{\sum_i u_{i,t}u_{i,t+k}I_{i,t}I_{i,t+k}}{\sum_i I_{i,t}I_{i,t+k}}, \qquad 1 \leqslant t \leqslant T, 0 \leqslant k \leqslant T-t.$$

Elements of the theoretical covariance matrix implied by the model described by equations (7a) and (7e) were also evaluated as:

$$E\left[u_{i,t}u_{i,t+k}\right] = \sigma_\omega^2 + J_k\sigma_\varepsilon^2 + \rho^k\sigma_\eta^2\frac{1-\rho^{2\tau+2}}{1-\rho^2}$$

where J_k takes a value 1 if $k = 0$ and 0 otherwise, and τ is the number of years elapsed since individual i reached the age of sixty-five. We then computed the theoretical counterpart of $v_{t,t+k}$, as:

$$\tilde{v}_{t,t+k} = \frac{\sum_i E\left[u_{i,t}u_{i,t+k}\right]I_{i,t}I_{i,t+k}}{\sum_i I_{i,t}I_{i,t+k}}, \qquad 1 \leqslant t \leqslant T, 0 \leqslant k \leqslant T-t$$

We used a Gauss-Newton algorithm to adjust the four model parameters $\left(\sigma_\omega^2, \sigma_\varepsilon^2, \sigma_\eta^2, \rho_\alpha\right)$ to minimise the sum of the squared difference between the fitted and theoretical values of the covariance terms:

	Men		Women	
	Coef.	t/z-stat	Coef.	t/z-stat
Qual Level 1	0.089	6.24	0.089	6.56
Qual Level 2	0.361	18.96	0.257	15.18
Qual Level 3	0.248	10.21	0.275	7.49
Qual Level 4	0.509	30.67	0.425	29.37
Constant	9.413	305.9	9.478	341.58
σ^2_ω	0.058	3.18	0.076	5.11
σ^2_ε	0.064	6.97	0.069	6.99
σ^2_η	0.031	5.55	0.027	4.17
tanh ρ_α	1.396	6.54	1.289	5.70
ρ_α	0.885		0.859	
R^2	0.186		0.174	
Adjusted R^2	0.182		0.171	
Root MSE	0.484		0.485	
Number of observations	7318		10216	

Table 11: Coefficients of the Income Process

$$\sum_{t,k} (v_{t,t+k} - \tilde{v}_{t,t+k})^2$$

ρ_α is restricted to the interval [-1,1] by estimating a model specified in terms of $\tanh \rho_\alpha$.

The results are shown in table 11 but with age and year dummies omitted from the table. The coefficients show that, not surprisingly, education-related income differences persist beyond the age of sixty-five; they are, however, smaller than those implied by McIntosh (2006) for people of working age. We do not have any explanation of why men educated to level 2 shown have higher post-sixty-five incomes than those educated to level 3. The error terms show a combination of fixed effects, short-term noise and persistent, but not unit root errors.

This model then allows us to construct simulated values for LY_{it} where $LY_{it} = \mathbf{X}_{it}\boldsymbol{\psi} + \omega_i + \varepsilon^y_{it} + z_{it}$; $\hat{LY}_{it}$ is the time, age and qualification dependent fitted value of log income and the three error terms are sampled randomly from distributions with the structures as described above.

The initial values of income generated in this way are of course different from those first observed in the data, LY^1_{it}. However, to ensure that our initial income values co-vary correctly with qualifications, smoking behaviour and initial health state, it is necessary that they are the same as those observed. We therefore allocate the discrepancy across the three error terms, weighting the adjustment by the variance of the term in question and making the assumption that the autoregressive process runs from age 65. The resulting values of values $\hat{z}_i$ and $\hat{\omega}_i$ are used in propagating the error process forward.

Our overall model reduces to the form shown in equations (8 - 10). Here $\mathbf{X}_{it}$ is the vector of exogenous variables (age, year, smoking status and health state when first observed), y_{it} is the log of income and GH_{t-1} is the dummy taking the value 1 if the respondent reports good health at time $t-1$.

$$gh_{it} = \mathbf{X}_{it}\beta_1 + \gamma_1 y_{it-1} + \delta_1 GH_{it-1} + \varepsilon_{it}^h; \qquad Cov(\varepsilon_{it}^h, \varepsilon_{it}^d) = \rho_{12}, \tag{8}$$

$$d_{it} = \mathbf{X}_{it}\beta_2 + \gamma_2 y_{it-1} + \delta_2 GH_{it-1} + \varepsilon_{it}^d. \qquad Var(\varepsilon_{it}^h) = Var(\varepsilon_{it}^d) = 1 \tag{9}$$

$$LY_{it} = \mathbf{X}_{it}\boldsymbol{\psi} + u_{i,t} \qquad u_{i,t} \text{ defined in (7)} \tag{10}$$

To simulate the model we require appropriate values for $\mathbf{X}_{it}$ and appropriate values for the relevant error terms. it should be noted that the probability of death depends on the fitted value given by equation (9) which we denote $\hat{d}_{it}$ rather than the perturbed value. This probability is given by $\pi_{it} = \Phi\left(\hat{d}_{it}\right)$ where $\Phi()$ is the cumulative normal density function. The mean probability of death at age τ, π_τ, is then given as the average of the π_{it} over the appropriate population. The probability of good health is similarly defined. Because of the relatively small size of our sample in any particular year, we focus our attention on an average of mortality rates (and healthy life) computed for all years of our sample.

We compare the mortality rates generated by our model with those of the interim life tables. These, and the associated life expectancies, are calculated from the cross-section of mortality rates by age in any given year. In order to do this we keep the year dummies of our model unchanged as we simulate our population from the age of sixty-five to its assume maximum age of one hundred.

6.2 Exogenous Variables

We begin our simulations at age sixty-five and have to determine the appropriate values of $\mathbf{X}_{it}$ for the simulated individuals. We do this separately for each year of our sample. With a sample size of n_t in year t and a simulated population of N we draw N individuals with uniform probability with replacement from the sample and use the values of $\mathbf{X}_{it}$ associated with them. This ensures that the simulated population has the same covariance of characteristics as does the sample itself. It might be thought desirable, of course, to use only those aged sixty-five as a basis for constructing the simulated population. However the small sample size suggested that, on balance, it might be better to use a larger group from which to sample repeatedly and we draw from the population of those aged between sixty-five and sixty-nine. The initial value of GH_{t-1} is of course consistent with the first-observed value of health status present in $\mathbf{X}_{it}$.

6.3 Simulation of Mortality Rates, Life Expectancy, Healthy Life Expectancy and Expected Income

We are now in a position to simulate jointly income and the two latent variables which determine health state and the probability of mortality. For each individual i with specified $\mathbf{X}_{i0}$ at age 65 we draw a vector of the four required error terms $[\varepsilon_{it}^h, \omega_i, \varepsilon_{it}^y, z_{it}]$ from the distributions specified above. This allows us to compute values of gh_{it}, providing us with the value of GH_{it} to be used subsequently, and $\hat{d}_{it}$. The latter allows us to calculate the probability of death as discussed above.

The probability of surviving from age sixty-five to the τth birthday $(\tau \geq 65)$ is

$$s_{i\tau} = \prod_{\kappa=65}^{\tau-1} (1 - \Phi\left(\hat{d}_{i\kappa}\right))$$

Life expectancy at age 65 for individual i is

$$e_{i65} = 1 + \sum_{\kappa=65}^{\infty} s_{i\kappa}.$$

There are a number of possible ways of calculating simulated expected time in good health. One is to consider the expected time spent alive with $GH = 1$, much as proposed by Sullivan (1971) and European Health Expectancy Monitoring Unit (2007). However, this does not reflect the full gamut of possible health and Cutler & Richardson (1998) prefer a transformation of the unbounded variable gh_{it} into the interval [0,1] as a measure of health state. The approach they adopt, working with a six-point health scale is to assume that all individuals reporting the top health state have health measured as 1 while all those in the lowest state have health measured as 0. Thus, in effect they truncate the distribution at the cut points for the top and bottom categories. Those with intermediate health are allocated values computed as the difference of their latent health variable from the lowest cut point scaled by the interval between the lowest and highest cut points. We prefer to use a probit transformation of gh_{it}, computed of course after including the random term ε_{it}^h. Then the probability that someone is alive to enjoy the level of health indicated by $\Phi\left(gh_{it}\right)$ is s_{it} so that health-adjusted life expectancy at age sixty-five is

$$h_{i65} = \Phi(gh_{i65}) + \sum_{\kappa=65}^{\infty} s_{i\kappa} \Phi\left(gh_{i\kappa}\right)$$

and similarly discounted for a twenty-one year old

$$h^*_{i65} = \delta^{44} \left\{ \Phi(gh_{i65}) + \sum_{\kappa=65}^{\infty} \delta^{k-65} s_{i\kappa} \Phi\left(gh_{i\kappa}\right) \right\}.$$

We noted earlier that it is household rather than individual income which should be expected to influence health and mortality. However, one of our aims is to identify the influence of education on income post-65. As we mentioned earlier, income shown in survey data may not be clearly attributable to either individual in a couple. In particular many pensions pay survivor benefits, but it is not in practice possible to attribute the income received by a survivor to the person whose pension contributions led to that income. We therefore allocate household income equally between the two members of a couple. The normal cumulant of the deterministic part of our probit equation defines the probability of a person living in a household of two people; since the dataset we used provided equivalised income, this allows us to scale the income allocated to any individual by the expected size of the household to which she or he belongs.

We model the size of the households to which our individuals belong by means of probit equations which explain the probability of someone belonging to a household with two people. We have included the small number living in households of more than two people with those in households of two people. in it. The probit equations are estimated separately for men and women, and explain household size on the basis of age, year of observation, smoking behaviour and educational status. They are shown in appendix A. If we denote as π^m_{it} as the probability that someone belongs to a household of more than one person, then the household income $e^{LY_{it}}$ is scaled by the expected scaling factor $(1{+}0.5\pi^m_{it})/(1+\pi^m_{it})$ for an individual with characteristics i.This reflects the fact that a household with two adults has an equivalence scale of 1.5 in the measure used to computed household equivalised income.

Thus the discounted value of income from sixty-five onwards[5] to a twenty-one year old is given as

$$Y^*_{i65} = \delta^{44} \left\{ e^{y_{i65}} + \sum_{\kappa=65}^{\infty} \delta^{k-65} s_{i\kappa} e^{LY_{ik}} (1 + 0.5\pi^m_{i\kappa})/(1 + \pi^m_{i\kappa}) \right\}.$$

The values of these variables for any subgroup, such as those with a specified level of education, are calculated as the mean value of each variable for that subgroup. Formally,

[5]There is a question whether in assessing the benefits of education, one should take into account the risk of mortality before the age of sixty-five. We have followed general practice in not doing so.

if I_i is an indicator which takes a value 1 when individual i is a member of subgroup S and 0 otherwise then

$$e^*_{S65} = \sum_i I_i e^*_{i65} / \sum_i I_i; \quad i \in S$$

with similar calculations for h^*_{i65} and Y^*_{i65}.

6.4 Parameter Uncertainty

The calculations above are performed for a fixed set of model parameters, those estimated when fitting our trivariate model and, separately, the model which provides estimates of the relationship between education and retirement income. But the standard errors associated with these parameters do not provide any direct indication of the uncertainty surrounding our estimates of the group averages of the variables of particular interest to us. These have to be estimated by simulation.

The procedure we use is to simulate the model repeatedly with random values for the model parameters drawn from the distribution implied by their variance-covariance matrices and the assumption that they are jointly normally distributed. For any given set of model parameters, $\mathbf{z}=[\boldsymbol{\beta}_1, \gamma_1, \delta_1, \boldsymbol{\beta}_2, \gamma_2, \delta_2, \ \rho_{12} \ \boldsymbol{\psi}, \sigma^2_\omega, \sigma^2_\varepsilon, \sigma^2_\eta, \rho_a]$, we compute the aggregates of interest, $e^*_{S65}(\mathbf{z})$, $h^*_{S65}(\mathbf{z})$ and $Y^*_{S65}(\mathbf{z})$. Comparison of the mean value of these across the simulations with the estimates produced from the estimated coefficients provides an indication of whether there are more than trivial biases arising from the fact that the aggregates are non-linear functions of the elements of $\mathbf{z}$. The standard errors of the simulations provide an indication of the reliability of the estimates. In these calculations we have treated the stochastic model of income disturbances and the probit model of household size as having deterministic coefficients.

In order to asses whether differences between aggregates for subpopulations, R and S are significant, it is necessary to take account of possible covariances between the disturbances to the two variables. This is most easily done by computing, for each simulation, the different between the two aggregates, for example $e^*_{R65}(\mathbf{z}) - e^*_{S65}(\mathbf{z})$. The standard deviation of this can then be compared with either its simulated mean or its value computed using the originally estimated parameters so as to indicate whether $e^*_{R65}(\mathbf{z}) - e^*_{S65}(\mathbf{z})$ is likely to be of statistical significance. This allows us to estimate both the differences between income, healthy life expectancy and life expectancy for people of different educational attainment and also provides z- statistics for these estimates.

7 Post-retirement Benefits of Education

Using the methods described in section 6.4, we calculate the values of discounted life expectancy, discounted health-adjusted life expectancy and discounted income for people with each of the five levels of education which we identify. These calculations are performed for a non-smokers and smokers separately, who are in good health at age sixty-five. Were we to attribute differential smoking habits and health status at age sixty-five to education, then the computed benefits of education would be larger than those shown here. We also present estimates of the differences in these aggregates for someone educated to level 4 relative to someone education to levels 0 to 3. Thus this part of the table shows the benefits of higher education relative to the lower qualification levels. The results are presented computed using both the initial parameter estimates and those constrained to be coherent with the aggregate data.

We present our results in two ways. First of all, we show the simulated life-time discounted income, computed using a real discount rate of 3% p.a. from the age of sixty-five onwards. We also show the discounted healthy life expectancy and the undiscounted overall life expectancy. These results are presented for our five educational categories and we also show the differences relative to people who have not been educated even as far as level 0. In tables 12i and 12ii we show results calculated from a simulated population whose characteristics are designed, in the way set out above, to match those of our sample. These results are therefore in some sense analogous to the studies which compare life expectancies of populations living in different areas. They describe the populations as they actually are.

The second set of simulations, shown in tables 12iii and 12iv is designed to show the effects of education conditioning on health and smoking status at the age of sixty-five. Of course there is a wide range of ways in which we could have specified the characteristics of this population; we have chosen to look at people not in poor health and non-smokers. We can see that the very substantial differences present in the actual population, shown in table 12i and 12ii, are considerably attenuated when we control for smoking status and initial health. It remains the case than men educated to level 4 enjoy a healthy life expectancy which is probably significantly higher than that of men not educated beyond level 0. But for women the effect could no longer be described as significant. However discounted income of both men and women remains clearly higher after controlling for smoking status and initial health. Obviously an important factor behind this difference is the direct impact of education on income discussed in section 6.1.

i) Men, Representative Population

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	121425	143528	196197	171416	245880	22103	74773	49992	124456
z-stat	32.6	20.9	13.2	11.8	16.6	3.1	5.0	3.3	8.0
Discounted HLE (years)	10.8	12.6	13.8	13.3	15.2	1.8	3.1	2.5	4.5
z-stat	38.2	25.7	18.8	15.3	22.9	3.5	4.0	2.8	6.0
Life Expectancy (years)	17.1	19.1	20.8	20.2	22.7	1.9	3.7	3.1	5.6
z-stat	33.0	21.3	15.1	12.4	18.8	2.1	2.6	1.7	4.2

ii) Women, Representative Population

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	135940	153370	188285	210141	226661	17431	52345	74201	90722
z-stat	38.6	22.4	15.8	7.2	19.1	2.3	4.3	2.5	7.9
Discounted HLE (years)	12.5	13.2	14.6	14.9	14.4	0.7	2.1	2.4	1.9
z-stat	44.6	27.2	21.6	9.6	23.5	1.2	2.9	1.5	3.1
Life Expectancy (years)	20.8	21.8	22.8	26.4	22.6	1.0	1.9	5.6	1.7
z-stat	39.8	22.8	18.4	8.9	18.7	0.9	1.4	1.9	1.4

iii) Men, Non-smokers in Good Health at Age 65

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	136951	149970	202329	175562	247984	13020	65378	38612	111033
z-stat	27.1	21.5	13.7	11.8	14.8	1.8	4.6	2.4	6.4
Discounted HLE (years)	13.2	13.7	14.6	13.8	15.4	0.5	1.4	0.5	2.2
z-stat	32.6	25.3	19.5	13.5	18.4	0.9	1.9	0.5	2.4
Life Expectancy (years)	20.0	20.5	21.7	20.6	22.9	0.5	1.7	0.7	2.9
z-stat	29.0	19.6	15.9	10.7	14.1	0.5	1.3	0.3	1.7

iv) Women, Non-smokers in Good Health at Age 65

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	144284	157490	193992	211158	229731	13206	49708	66874	85447
z-stat	40.3	21.8	15.4	7.3	21.1	1.7	4.0	2.3	7.9
Discounted HLE (years)	14.5	14.2	15.1	15.7	15.1	-0.3	0.7	1.2	0.6
z-stat	46.2	28.1	21.0	10.3	29.2	-0.5	0.9	0.8	1.1
Life Expectancy (years)	22.7	22.7	23.6	26.3	23.1	0.0	0.9	3.6	0.4
z-stat	37.2	23.0	17.2	8.0	22.6	0.0	0.7	1.1	0.4

Table 12: The Impact of Education on Discounted Retirememt Income, Discounted Healthy Life Expcetancy at age 65 and Life Expectancy at Age 65

Our simulation technique makes it possible to explore how far the differences in healthy life expectancy are attributable to income differences rather than directly due to education differences. If we simulate the model again with individual incomes following the stochastic pattern used in computing the results above, but with all the education dummies set to zero, this allows us to remove the direct effect of income on healthy life expectancy. We find that for the representative population of men the excess of healthy life expectancy of people educated to level 4 declines from 4.5 to 2.2 years while the increase in total life expectancy declines from 5.6 to 2.4 years. For the representative population of women the excess of healthy life expectancy declines from 1.7 to 0.4 years while that of total life expectancy falls from 1.9 to 0.6 years. Thus health and smoking behaviour at age sixty-five are important influences on these measures of life expectancy independently of income after the age of sixty-five..

There is, nevertheless, a substantial concern about the results shown in table 12. The simulations, of course, make it possible to estimate the average life expectancy of the male and female populations generated in the sample. The life expectancies generated by our model should be similar to those shown by interim rather than cohort life tables. We carry out separate simulations for populations with fixed year dummies. Thus the mortality rates generated should be those of the cross-section population in the year in question.[6]. The mean life expectancy generated by our model was 19.1 years for men and 20.7 years for women while the life expectancies generated by the average mortality rates in the years in question were only 15.9 years for men and 18.3 for women. This suggests that, despite the highly significant relationship between mortality and non-response, our treatment of non-response may have not have fully resolved the problem.

8 Simulated and Observed Aggregate Mortality Rates

One way of addressing this issue is to explore restricting the parameters of the model so that the mortality rates generated in a simulation are consistent with those observed for the population at large. The exercise can be seen as imposing appropriate non-linear constraints on the model parameters, such that the simulated mortality rates generated by the model, for each age but averaged across the thirteen years of estimation (1992-2006 excluding the two missing years of 1999 and 2000) are the same as the average

[6]We are unable to work with cohort life expectancies since that would involve projecting the year dummies; however, as we noted there was no obvious trend in the year dummies in the mortality equation.

mortality rates observed in the official life tables[7] for those years.

This is done in the following way. We focus on the subset of $\mathbf{z}$ which contains the parameters of the healthy transition and mortality equations, (8) and (9). We denote this subset $\tilde{\mathbf{z}}$ We denote the simulated vector of mean probabilities, $\boldsymbol{\pi}^s(\tilde{\mathbf{z}})$ reflecting the fact that it is a function of the model parameters. We then choose an adjusted set of parameters, $\tilde{\mathbf{z}}^*$ such that $\boldsymbol{\pi}^s(\tilde{\mathbf{z}}^*) = \bar{\boldsymbol{\pi}}^*$, the observed mortality rates by age averaged across the years relevant to our sample. The obvious criterion is to choose $\tilde{\mathbf{z}}^*$ to minimise the variance-weighted sum of the squared adjustments to the original $\boldsymbol{\beta}$. Thus, with $\mathbf{V}$=$Var(\tilde{\mathbf{z}})$, we solve the Lagrangian problem

$$Min\ (\tilde{\mathbf{z}} - \tilde{\mathbf{z}}^*)'\mathbf{V}^{-1}(\tilde{\mathbf{z}} - \tilde{\mathbf{z}}^*) + \boldsymbol{\lambda}'\left\{\boldsymbol{\pi}^s(\tilde{\mathbf{z}}^*) - \bar{\boldsymbol{\pi}}^*\right\}$$

Noting that there are only twenty-six mortality rates while there are ninety-five parameters, we should expect to be able to find an exact solution to this problem. We solve it using a Gauss-Newton routine with the required derivatives calculated numerically[8]. With both women and men we find that convergence is rapid, requiring no more than five iterations. The variance matrix of $\tilde{\mathbf{z}}^*$ is given as

$$\tilde{\mathbf{V}} = \mathbf{V} - \mathbf{VJ}\left(\mathbf{J}'\mathbf{VJ}\right)^{-1}\mathbf{J}'\mathbf{V}$$

where $\mathbf{J}$ is the Jacobian of $\boldsymbol{\pi}^s(\tilde{\mathbf{z}}^*)$ with respect to $\tilde{\mathbf{z}}$. evaluated at $\tilde{\mathbf{z}}^*$. It may of course be objected that these results are bound to depend on the random disturbances and initial values which define the simulations. But we found that the results in terms of parameter adjustments were robust to this potential source of disruption, even if one looked at as few as five hundred simulated individuals in each year.

With the initial parameter estimates normally distributed, then, with r restrictions imposed, it follows that, at the solution

$$(\tilde{\mathbf{z}} - \tilde{\mathbf{z}}^*)'\mathbf{V}^{-1}(\tilde{\mathbf{z}} - \tilde{\mathbf{z}}^*) \sim \boldsymbol{\chi}^2_r.$$

In our example we are imposing twenty-six restrictions for both men and women. We find that for men $\chi^2_{26} = 83.2$ while for women $\chi^2_{26} = 58.9$. Thus the required restrictions are both rejected despite our use of a standard and widely-used treatment of non-response. We now proceed to explore the implications of using the model adjusted to cohere with aggregate mortality rates so as to examine whether the restrictions implied by this coherence have important implications for our findings.

[7] The life tables are calculated for three-year moving averages. We assume that the mortality rates they show apply to the central year of each three-year window.

[8] Using a perturbation of 10^{-10} so as to avoid problems with numerical errors.

9 A Simulated Population with Constrained Parameters

We show in table 13 simulated values of discounted income and discounted healthy life expectancy at age sixty-five together with overall life expectancy computed without any discounting calculated after the model coefficients have been restricted to be consistent with the aggregate mortality rates shown in the life tables. Looking at tables 13i and ii, it is clear that the education-related differences are attenuated as compared to those estimated from the unrestricted model. This need not have been a consequence of the imposition of the restrictions; indeed, had they been delivered solely by adjusting the age-specific dummies shown in tables 8 and 9 then, despite the non-linear nature of the model, one might have expected the differentials between the different education levels to have been reduced only in proportion. But the adjustment method reflects the covariance structure of the parameters and it is this which had led to more marked downward adjustments on the life expectancy and healthy life expectancy of people educated to level 4 than to those not educated as far as level 1. For men the differences in discounted healthy life expectancy remain significant both in the representative population and in population controlled for smoking behaviour and initial health status. For women, however, the difference is not statistically significant in the former and is closed completely in the latter. Not surprisingly, given the results of section 6.1 the income differences remain highly significant

To form an overall picture of the benefits of education accruing at age sixty-five and it is necessary to value the increment in healthy life expectancy. Mason et al. (2009) draw our attention to a range of valuations between £30,000 and £70,000 at 2005 prices while the National Institute of Clinical Excellence used £30,000 at current prices in 2008 (National Institute of Clinical Excellence 2008, Chapter 8, p.54) while Muller et al. (2011) use the much larger figure of £160,000 (US$265,000) in their study of the costs of pollution damage in the United States. Nevertheless, in the light of this range we adopt a value of £40,000 per health-adjusted year of life. This builds an element of caution into our figures[9].

[9] An alternative approach to valuing life is provided by Murphy & Topel (2006). They base theirs on the utility enjoyed by people who are alive. But the practical problem with this approach is that it requires a cardinal utility function. The widely used CES function is negative unless some constant is added back on. The appropriate constant can be estimated only by forming a view about the level of consumption at which life becomes not worth living. Given the judgements involved it is not clear that the approach is superior to the methods surveyed by Mason et al. (2009)

i) Men, Representative Population

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	112985	125418	176578	142573	199169	12433	63593	29588	86184
z-stat	35.4	23.7	13.2	12.0	16.5	2.0	4.5	2.4	6.5
Discounted HLE (years)	10.0	11.2	12.6	11.1	12.4	1.2	2.6	1.0	2.4
z-stat	44.9	28.4	18.4	13.1	19.9	2.6	3.5	1.1	3.4
Life Expectancy (years)	15.6	16.2	18.4	15.7	17.2	0.7	2.8	0.2	1.6
z-stat	39.7	25.9	15.0	11.3	16.0	0.8	2.1	0.1	1.3

ii) Women, Representative Population

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	129391	138333	173293	169690	204635	8942	43901	40299	75244
z-stat	49.8	26.9	15.5	6.8	21.5	1.4	3.7	1.6	7.7
Discounted HLE (years)	11.9	12.0	13.4	12.2	13.1	0.1	1.5	0.3	1.1
z-stat	60.7	27.4	21.5	8.1	25.8	0.2	2.1	0.2	2.0
Life Expectancy (years)	19.5	19.0	20.2	20.0	19.5	-0.5	0.7	0.5	0.1
z-stat	58.3	23.7	17.9	7.0	21.7	-0.5	0.6	0.2	0.1

iii) Men, Non-smokers in Good Health at Age 65

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	127475	135171	185812	148126	203956	7696	58338	20652	76481
z-stat	30.7	21.7	13.6	10.3	17.4	1.2	4.3	1.3	6.3
Discounted HLE (years)	12.4	12.3	13.5	11.7	12.7	-0.1	1.1	-0.7	0.3
z-stat	31.2	22.8	19.6	12.9	17.4	-0.2	1.6	-0.6	0.4
Life Expectancy (years)	18.1	17.6	19.4	16.5	17.6	-0.5	1.2	-1.7	-0.6
z-stat	28.5	19.8	16.4	10.8	14.5	-0.6	1.0	-1.0	-0.4

iv) Women, Non-smokers in Good Health at Age 65

	Education Level					Difference Relative to Level 0			
	0	1	2	3	4	1	2	3	4
Discounted Income (£)	138411	144707	175394	173621	212059	6296	36983	35210	73648
z-stat	42.2	21.1	16.6	6.8	21.8	0.8	3.4	1.3	7.3
Discounted HLE (years)	13.8	13.0	13.8	13.0	13.8	-0.8	0.0	-0.8	0.0
z-stat	43.9	27.7	21.0	8.3	26.5	-1.4	0.0	-0.5	0.0
Life Expectancy (years)	21.1	19.9	20.6	20.4	20.5	-1.2	-0.5	-0.7	-0.6
z-stat	38.4	22.4	16.3	6.6	21.1	-1.1	-0.4	-0.2	-0.6

Table 13: The Impact of Education on Discounted Retirememt Income, Discounted Healthy Life Expcetancy at age 65 and Life Expectancy at Age 65: Parameters Constrained by Average Mortality Rates

Differences Relative to Level 0	Education Level			
	1	2	3	4
Men (£)	55083	148854	62657	157017
Percentage due to quality-adjusted life years	84%	70%	67%	62%
Women (£)	9968	88745	40793	98010
Percentage due to quality-adjusted life years	37%	65%	31%	46%

Table 14: Discounted Welfare Differences at Age 65

The second adjustment needed is to the income differential associated with education. As explained in the introduction, this is largely a consequence of differences in occupational pensions. These are financed both by employee contributions, which are included in conventional analysis of the returns to education, and employer contributions which are omitted. Thus the income differential needs to be multiplied by the ratio of employer contributions to total contributions in order to correct for this. The national accounts show that, on average employers contributed about 70% of the total cost of pensions[10] and we therefore use this ratio to identify the impact of education on post-retirement income after allowing for saving out of income accruing during working life.

After valuing healthy life in this way and adding on 70% of the post-retirement income differential to produce an indicator of the differences in discounted welfare at age sixty-five as a function of the differences in levels of education, we find the differences summarised in table 14. We also show in the table the proportion of this difference which is attributed to the duration of healthy life rather than to post-retirement income. We also show the percentage of the difference which is attributed directly to the value put on the incremental healthy life expectancy associated with the education level concerned. This percentage is not shown where the two components have opposite signs; such a situation does not arise for men but does arise in some circumstances for women.

These results are consistent with the initial picture visible in section 3. The summary statistics there suggest that there is a stronger relationship between education and health for men than for women and, as we have seen, using the adjusted model coefficients, the link between education and health is much less marked in women rather than men, even if one looks at the representative population instead of controlling for health state. To discount these effects back to age twenty-one, our discount factor of 3% p.a. means that

[10] The average share of employer contributions in the total over the period 1974-1996 was 73%. Since 1997 the national accounts do not distinguish employee contributions from individual purchases of life insurance policies. Pensioners also typically received lump sums on retirement and we have implicitly assumed that these account for the large part of investment income received by those over sixty-five.

they are multiplied by 0.27. Thus even after discounting, the effects for the representative population are £42,000 for men and £26,000 for women. However, if one looks solely at the non-smoking population in good health at age sixty-five, then the discounted value falls to £18,000 for men and £14,000 for women. Had the estimates been computed before imposing the restriction that the mortality rates generated by the model should be consistent with observed mortality rates, the discounted post-retirement benefit for men at age twenty-one would be £71,000 while that for women would be £38,000.

10 Conclusions

In this paper we have explored the relationship between income, health, mortality and education in the population aged sixty-five and over. Econometric estimates of a probit model which jointly explains health status, mortality and non-response point to statistically significant influences of income and education on health status even after individual effects are allowed for by including initial health state and income as explanatory variables. Income is found to have a direct influence on mortality and an indirect influence because income influences health status and health status influences mortality. The fact that, for both men and women, income is a statistically significant influence on health and mortality while initial income is insignificant points strongly to the effect coming from income itself rather than from other individual effects linked to income. Education had a separate and additional influence on the health status of men over and above influences arising from its effect on income. However, education did not have a significant direct effect on mortality. The influences of education on health and mortality of women were not statistically significant.

A separate ordinary least squares analysis showed the influences of education on income which one would expect to find, bearing in mind that, for the survey sample, pension arrangements were typically defined-benefit with benefits related to earnings close to retirement. Other studies have suggested that such an analysis provides a satisfactory indicator of the influence of education on income. Thus, by simulating jointly, income, health state and mortality we are able to construct a stochastic model of people's individual retirement experience, and thereby to estimate the expected post-retirement income and healthy life expectancy. A standard valuation of the latter makes it possible to aggregate these into a monetary welfare indicator and then to discount this back to the age of sixty-five so as to provide an indicator of the relationship between educational status and post-retirement welfare.

However, despite use of the standard correction for non-response in our model, we find that the mortality rates it simulates are generally lower than those shown in the official life tables. We restrict our parameters so as to produce a model consistent with the observed mortality rates while minimising variance-weighted squared deviations of the model parameters from their initial estimates. Despite our standard treatment of non-response, we find that the restrictions required to deliver mortality rates in our simulations consistent with the official statistics are rejected. Thus the study points to the need for further work to understand the limitations of standard methods for dealing with selection and non-response.

When we nevertheless simulate the model with these restrictions imposed, we find that the link between education and post-retirement welfare is attenuated. Despite this, we find that, for men, the additional post-retirement welfare accruing to men educated to level 4 is, discounted back to age 21, £42,000 while for women it is £26,000. Thus the conclusion from the micro-economic evidence is that there are substantial post-retirement benefits which accrue to those educated to high levels. While these are reduced on taking account of aggregate demographic data, the effects, particularly for men, remain substantial.

A A Probit Analysis of Household Size

The coefficients of the probit equation which explain whether respondents belong to households of one or two people are shown in table 15.

	Men		Women	
	Coef.	Std. Err.	Coef.	Std. Err.
Smoke	-0.368	0.046	-0.166	0.038
$Qual_1$	0.181	0.043	0.001	0.038
$Qual_2$	0.450	0.061	-0.083	0.048
$Qual_3$	0.047	0.072	-0.102	0.104
$Qual_4$	0.157	0.051	-0.254	0.041
Age 66	0.004	0.100	-0.085	0.084
Age 67	-0.012	0.100	-0.180	0.083
Age 68	0.047	0.102	-0.209	0.083
Age 69	0.025	0.102	-0.289	0.082
Age 70	-0.010	0.103	-0.311	0.082
Age 71	-0.118	0.101	-0.398	0.081
Age 72	-0.157	0.099	-0.515	0.080
Age 73	-0.264	0.098	-0.607	0.081
Age 74	-0.271	0.100	-0.612	0.082
Age 75	-0.390	0.101	-0.718	0.084
Age 76	-0.387	0.103	-0.837	0.085
Age 77	-0.417	0.105	-0.925	0.086
Age 78	-0.436	0.108	-0.950	0.087
Age 79	-0.539	0.111	-1.063	0.089
Age 80	-0.466	0.112	-1.122	0.090
Age 81	-0.708	0.113	-1.172	0.092
Age 82	-0.691	0.116	-1.228	0.094
Age 83	-0.760	0.121	-1.367	0.101
Age 84	-0.868	0.127	-1.479	0.105
Age 85	-1.105	0.130	-1.444	0.110
Age 86	-1.243	0.139	-1.517	0.121
Age 87	-1.274	0.154	-1.684	0.137
Age 88	-1.304	0.170	-1.712	0.153
Age 89	-1.426	0.194	-1.598	0.160
Age 90+	-1.809	0.140	-1.657	0.111
1993	0.022	0.082	-0.307	0.066
1994	-0.018	0.083	-0.366	0.068
1995	-0.023	0.083	-0.349	0.068
1996	0.006	0.084	-0.310	0.068
1997	0.005	0.083	-0.266	0.068
1998	0.002	0.084	-0.197	0.068
2001	0.132	0.085	-0.205	0.068
2002	0.125	0.085	-0.074	0.069
2003	0.136	0.085	-0.045	0.069
2004	0.121	0.086	-0.058	0.069
2005	0.158	0.086	-0.047	0.070
2006	0.156	0.086	0.003	0.070
Constant	0.906	0.093	0.881	0.079
Log likelihood	-3817		-6366	
No of Obs	7318		10216	

Table 15: A Probit Model of Household Size

References

Barker, D., Eriksson, J., Forsen, T. & Osmond, C. (2002), 'Foetal origins of adult disease: Strength of effects and biological basis', *International Journal of Epidemiology* **31**, 1235–1239.

Batty, G., Derr, G., Macintyre, S. & Deary, I. (2006), 'Does IQ explain Socioeconomic Inequalities in Health? Evidence from a Population-based COhort Study in the West of Scotland', *British Medical Journal* . doi:10:1136/bmj.38723.660637.AE.

Blanden, J., Buscha, F., Sturgis, P. & Urwin, P. (2010), Measuring the Returns to Lifelong Learning. Centre for the Economics of Education Discussion Paper No 110.

Blundell, R., Dearden, L. & Sianesi, B. (2005), 'Evaluation the Effect of Education on Earnings: Models, Methods and Results from the National Child Development Survey', *Journal of the Royal Society: Series A* **168**, 473–512.

Cappellari, L. & Jenkins, S. (2003), 'Multivariate probit regression using simulated maximum likelihood', *The Stata Journal* **3**(3), 278–294.

Case, A. & Paxson, C. (2011), 'The long reach of childhood health and circumstance: Evidence from the whitehall ii study', *Economic Journal* **121**, F183–F204.

Contoyannis, P., Jones, A. & Rice, N. (2004), 'The dynamics of health in the british household panel survey', *Journal of Applied Economics* **19**, 473–503.

Cutler, D. & Richardson, E. (1998), Your money and your life: the value of health and what affects it. NBER Working paper No 6895.

Economou, A. & Theodossiou, I. (2011), 'Poor and Sick: Estimating the Relationship between Household Income and Health', *Review of Income and Wealth* **57**, 395–411.

European Health Expectancy Monitoring Unit (2007), Health Expectancy Calculation by the Sullivan Method: a Practical Guide. http://www.ehemu.eu/pdf/Sullivan_guide_final_jun2007.pdf.

Frijters, P., Haisken-DeNew, J. & Shields, M. (2005), 'The causal effect of income on health: Evidence from german re-unification', *Journal of Health Economics* **24**, 997–1017.

Fujiwara, T. & Kawachi, I. (2009), 'Is education causally related to better health? a twin fixed-effect study in the usa', *International Journal of Epidemiology* **38**, 1310–1322.

Geweke, J. (1989), 'Bayesian inference in econometric models using monte carlo integration', *Econometrica* **57**, 1317–1339.

Gould, E., Lavy, V. & Paserman, M. (2011), 'Sixty Years after the Magic Carpet Ride: the Long-run Effect of the Early Childhood Environment on Social and Economic Outcomes', *Review of Economic Studies* **78**, 938–973.

Greene, W. H. (2003), *Econometric Analysis*, Fifth edition, Prentice Hall, New Jersey.

Guvenen, F. (2007), 'Learning your Earning: are Labour Income Shocks really very Persistent', *American Economic Review* **97**, 687–712.

Hajivassiliou, V. & Ruud, P. (1994), Classical estimation methods for LDV models using simulation, *in* R. Engle & D. McFadden, eds, 'Handbook of Econometrics, Volume IV', Elsevier Science Publishers, North Holland, pp. 2383–2441.

Jenkins, S. (2010), The british household panel survey and its income data. Institute for Social and Economic Research, University of Essex Working paper No 2010-33.

Keane, M. (1994), 'A computationally practical simulation estimator for panel data', *Econometrica* **62**, 95–116.

Khoman, E., Mitchell, J. & Weale, M. (2008), 'Incidence-based estiamtes of life expectancy of the healthy for the uk: Coherence between transition probabilities and aggregate life tables', **171**, 203–222.

Lager, A., Bremberg, S. & Vagero, D. (2009), 'The association of early iq and education with mortality: 65-year longitudinal study in malmo, sweden', *British Medical Journal* **339**, b5282. doi:10.1136/bmj/b5282.

Levy, H. & Jenkins, S. (2008), Bristish household panel survey dervied current and annual net household income variables, wave 1-16, 1991-2007. UK Data Archive Study Number 3909.

Lindahl, M. (2005), 'Estimating the Effect of Income on Health and Mortality using Lottery Prizes as an Exogenous Source of Variation in Income', *Journal of Human Resources* **40**, 144–168.

Madsen, M., Andersen, A.-M., Christensen, K., Andersen, P. & Osler, M. (2009), 'Does educational status impact adult mortality in denmark? a twin approach', *American Journal of Epidemiology* **172**, 225–234.

Marmot Review (2010), Fair Society, Healthy Lives. Report of the Strategic Review of Health Inequlaities in England post-2010.

Mason, H., Jones-Lee, M. & Donaldson, C. (2009), 'Modelling the Money Value of a QALY: a New Approach based on UK Data', *Health Economics* **18**, 933–950.

McIntosh, S. (2006), 'Further analysis of the returns to academic and vocational qualifications', *Oxford Bulletin of Economics and Statistics* **68**, 225–251.

Muller, N., Mendelsohn, R. & Nordhaus, W. (2011), 'Environment Accounting for Pollution in the United States Economy', *American Economic Review* **101**, 1649–1675.

Murphy, K. & Topel, R. (2006), 'The Value of Health and Longevity', *Journal of Political Economy* **114**, 871–904.

National Institute of Clinical Excellence (2008), The Guidelines Manual. http://www.nic.org.uk/niceMedia/pdf/GuidelinesManualChapter8.pdf.

Smith, J. (1999), 'Healthy Bodies and Thick Wallets: the Dual Relation between Health and Economic Status', *Journal of Economic Perspectives* **13**, 145–166.

Sullivan, D. (1971), 'A Single Index of Mortality and Morbidity', *HSMHA Health Reports* pp. 347–354.

Terracol, A. (2002), Triprobit and the ghk simulator: a short note. Annex a la commande Stata triprobit.

Whalley, L. & Deary, I. (2001), 'Longitudinal Cohort Study of Childhood IQ and Survival up to Age 76', *British Medical Journal* **322**, 1–5.

Wooldridge, J. (2005), 'Simple Solutions to the Initial Conditions Problem in Dynamic, Non-linear Panel Data Models with Unobserved Heterogeneity', *Journal of Applied Econometrics* **20**, 39–54.