In Sickness and in Health?

Dynamics of Health and Cohabitation in the United Kingdom

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Abstract

The purpose of this paper is to estimate the relationship between health and cohabitation status among British adults. It is well established that the two are correlated, and some extensions of Grossman's (1971) model (Bolin et al, 2001) can give us hints as to what this relationship could look like, but yet there are very few econometric studies that analyse the two jointly. In this paper, we use limited dependent variable models to estimate the determinants of health and cohabitation together. By using simulation techniques and applying them to data from the British Household Panel Survey, we are able to distinguish between effects such as confounding factors, spurious relationships, reverse causality and the 'true' causal effect. Our results will have important implications for policy and theory alike.

Keywords: health, cohabitation, maximum simulated likelihood

JEL Classificartion: I11, H51

1 Introduction

Following Grossman's (1972) seminal work, an extensive theoretical literature on the demand for health has developed. Grossman's contribution to the literature may be summarised in two points: firstly, to apply the household production function model of consumer behaviour to health. In this perspective, there is a sharp distinction between commodities such as health, that appear as argument's in the individual's utility function, and market goods and services, that are used as input factors in the production of commodities. Secondly, drawing on human capital theory, Grossman emphasised the dual characteristic of health as being at the same time a consumption commodity and capital that increases our productive ability.

The special twist of the Grossman model that distinguishes it from any other human capital model is that health capital increases the amount of time we have available for work or consumption, and not the efficiency in these functions. Secondly, it can be presumed that the consumption utility of health is higher than the utility of human capital acquired through schooling or on-the-job training; hence, looking at consumption utility from health alongside the investment problem seems more justified for health than for human capital.

The Grossman model has since been extended in various directions, allowing for, amongst other things, uncertainty in the deterioration of health and endogenous choice of length of life. The model has also been subjected to empirical testing using a wide range of techniques and datasets. For an overview, see Grossman (2004).

Amongst the various inputs that supposedly enter the household production function of health; the focus has traditionally been on medical services. Hence, individuals demanding a higher level of health stock should as a consequence, ceteris paribus, also demand a greater amount of medical services. This focus on medical services, as opposed to, for instance, preventative activities, has been unfortunate, since it tends to be rejected in empirical studies.

Another important perspective in empirical studies has been to assess the effects of schooling on health. This issue represents a considerable challenge from a methodological point of view. Firstly, there is the issue as to how education affects health. According to the Grossman model, education increases productive efficiency, i.e. the amount of health produced by a certain amount of inputs. But educated people might also have superior information and make better choices regarding health due to this, which can be called allocative efficiency. Finally, it might be that education changes time preferences so that people with higher education tend to be more patient than others.

Furthermore, there is a possibility of reverse causality. Health can be an important determinant of the level of education that a person chooses to attain, for instance if healthier students are more efficient in the acquisition of knowledge (as less days are lost due to ill health). This reverse causality problem is hopefully less severe than for other socioeconomic variables, since people tend to acquire their education relatively early in life. Besides, there may be confounding factors that influence health and education simultaneously.

Although we take education into account in this paper, the main focus is on how health interacts with cohabitation status. Despite the fact that the Grossman model is based on a household production model, there has been little interest in the effects of the actual organisation of that household. One important exception is a couple of papers by Bolin et al (2001, 2002) that study the health optimisation problem from the point of view of a family.

Taking the cohabitation status into account has several implications for the economic models. One such is that cohabitation affects the efficient allocation of the individual's resources, and since it is a binary choice variable, it tends to alter many predictions of the life cycle model. This is particularly true since a change in the marital status in either direction normally is connected with adjustment costs that will temporarily result a deviation from optimal paths of, for instance, wealth (above all in terms of housing). Quite naturally, these disturbances will have implications for investment in health as well.

So what are the relationships between health and marital status? Again, it is useful to think of the problem in terms of direct causality, reverse causality and confounding factors. Firstly, it is imaginable that cohabitation status has an impact on health in various ways. In terms of allocative efficiency, one can apply Becker's (1973, 1974) theory that spouses exploit comparative advantages and hence reach a more efficient allocation of resources, which also benefits health production. Secondly, the problem of imperfect adjustment mentioned above will lead to changes in marital status having an effect on health. Finally, it is possible that the cohabitation status also affects preferences. Since living in a couple is often a precondition for having children, the cohabitation might lead to changing time preferences (i.e. due to the children the individual derives more utility from a long life).

Concerning the reverse causality, going from health to cohabitation status, it is possible that unhealthy people are more isolated than others, hence having fewer opportunities to find a partner. Secondly, it is possible that an individual with bad health is quite demanding and this might increase the probability of being left. Finally, people with bad health tend to have lower incomes, which in turn might reduce the chances of finding a partner. The “third-variable” problem, i.e. confounding factors that affect both, might be things such as, for instance, inherited wealth.

Unfortunately, the models proposed by Bolin et al (2001, 2002) fail to take these aspects of the problem into account. The authours work with a very simplified model where the two spouses engage in Nash bargaining in order to determine how much to invest in their respective health capital stocks. This decision is influenced, amongst other things, by the wage rate of the partner in question. The threat point is the utility a spouse would have in case of divorce. The utility in this event is assumed to be exogenous and independent of the other variables in the model (such as income or life expectancy). Furthermore, it is assumed that divorce is an irreversible, one-off event, that length of life is certain and also the same for both spouses.

Given these assumptions, the Bolin et al (2001) approach has a weak predictive power. The authors are only able to assess the impact of a change in the ’cost of divorce’, and apart from that the model does not deliver any interesting comparative statics. Hence, further theoretical work in this field would be very useful. Future work should go in the direction of increased generality - such as allowing for different length of lives of the spouses, movements out of an into cohabitation, and including stochastic elements in health and cohabitation alike. Other aspects of the model, however, would benefit from being made more specific, such as the utility function. With more restrictions put on the shape of the function, more powerful predictions could be made.

An alternative, and much less technical, treatment of cohabitation and health is provided by Wilson (2001). Wilson does not intend to explain self-selection into marriage, but decomposes the correlation between health of spouses in a way that is also useful from our point of view. Wilson distinguishes between *assortative mating*, meaning that the marriage market is sorted according to either health directly or other oservables that are correlated with health; *common lifestyle factors*, i.e. that spouses tend to have or develop common risk behaviours; *shared environmental factors*, i.e. exogenous risk factors that both spouses are exposed to; and *direct health effects*, reflecting the direct, causal effect of cohabitation on health.

There is some overlapping between the parameters we estimate in this paper and the effects that Wilson observes. Assortative mating will clearly be picked up with unobserved fixed effects, as will predetermined common lifestyle factors. For the rest, applying the reasoning of the Grossman model, both endogenous risk factors and direct health effects should be regarded as causal effects of cohabitation on health, and hence they will be picked up by the coefficients on the cohabitation variable.

2 Methodological Approach

Our econometric model includes two estimating equations; one for cohabitation and one for health. Concerning the estimation technique, we follow closely the approach taken by Börsch-Supan et al (1993) and adapt it to our problem. This means allowing for various types of intertemporal and cross-equation linkages. Firstly, we allow for unobserved person-specific attributes in both cohabitation and health. Health status varies over time, but it also has an important, time-invariant component reflecting the fact that some people are structurally healthier than others. The same goes for cohabitation status. Furthermore, if there is selection into marriage based on health (or variables correlated with health) we would expect the person-specific attributes of the two estimating equations to be correlated as well.

However, not all intertemporal correlation patterns in unobservables can be captured by time-invariant error components. Hence, we also allow for time-varying disturbances, that are potentially correlated across the equations and potentially exhibiting autoregression. We restrict the autoregressive structure to be of first order, but given the amount of correlations allowed for through time-invariant and time-varying effects, the error structure is very general and allows for a wide range of different correlation structures.

2.1 Estimating Equations

We now define the two estimating equations and then investigate the error structure more closely. The health variable is discrete and takes on four different values: healthy, moderately disabled, severely disabled, and dead. Hence, we chose to estimate an ordered probit model. This involves a latent and continuous health variable H_{it}^*:

$$H_{it}^* = \delta_1 E_{it} + \delta_2 A_{it} + \delta_3 A_{it}^2 + \delta_4 A_{it}^3 + \delta_5 A_{it}^4 + \delta_6 \hat{C}_{it-1} + \delta_7 \hat{H}_{it-1}^1 + \delta_8 \hat{H}_{it-1}^2 + \varepsilon_{it}^H \quad (1)$$

where E_{it} is a vector of education dummies, A_{it} is the age of individual i in year t, $\hat{C}_{it-1}$ is the cohabitation status of individual i in the previous period and $\hat{H}_{it-1}^1$ and $\hat{H}_{it-1}^2$ refer to whether the individual was moderately or severely disabled in the previous year. Hence, we allow for state dependence in both dependent variables, which may be interpreted as individuals being off the optimal path due to the randomness of the processes. One problem with state dependence is that unless the first year of observations is treated differently, there is a potential bias in the estimate since it does not account for the fact that the system might not be in equilibrium in the first period. Remedies to this problem have been proposed by Heckman (1983) and Wooldridge (2000). The problem, however, is that both approaches are unsuitable for our purposes, since the Heckman approach requires estimating a large number of extra parameters, and the Woolridge approach involves estimating fixed effects using an average of the exogenous variables. This is not a very attractive option either, since some of the independent variables are dummies. Hence, we are not able to correct for this problem, but will use a very long sequence of observations in order to mitigate it.

Then, just as in the standard model, the actual state of disability is defined according to a switching function:

$$\widehat{H}_{it} = \begin{cases} 1 & if \quad H_{it}^* \leq \alpha_1 \\ 2 & if \quad \alpha_1 < H_{it}^* \leq \alpha_2 \\ 3 & if \quad \alpha_2 < H_{it}^* \leq \alpha_3 \\ 4 & if \quad \alpha_4 < H_{it}^* \end{cases} \tag{2}$$

where the values of $\widehat{H}_{it} \in \{1, 2, 3, 4\}$ correspond to healthy, moderately disabled, severely disabled and dead, respectively. Needless to say, death is treated as an absorbing state.

For cohabitation status, we estimate a binomial probit. Hence, the latent function is

$$C_{it}^* = c + \beta_1 E_{it} + \beta_2 A_{it} + \beta_3 A_{it}^2 + \beta_4 A_{it}^3 + \beta_5 A_{it}^4 + \beta_6 \hat{C}_{it-1} + \beta_7 \hat{H}_{it-1}^1 + \beta_8 \hat{H}_{it-1}^2 + \varepsilon_{it}^C \tag{3}$$

where c is a constant, and the rest of the independent variables are the same as in equation 1 above. The switching function is then

$$\widehat{C}_{it} = \begin{cases} 1 & if \quad C_{it}^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Finally, we have a look at the error structures. As mentioned above, we allow for a random-effects structure, autoregression and correlation across the two equations (in time-dependent as well as time-invariant disturbances). Hence, we have the error process

$$\varepsilon_{it}^j = \mu_i^j + \eta_{it}^j, \; j = H, C \tag{5}$$

where μ_i^j is the inividual fixed effect. Furthermore, the variable η_{it}^j evolves over time according to

$$\eta_{it}^{j} = \rho_j \eta_{it-1}^{j} + \upsilon_{it}^{j},\ j = H, C \tag{6}$$

Finally, the correlation between the two estimating equations is captured by the assumptions

$$corr\left(\upsilon_{it}^{h}, \upsilon_{it}^{c}\right) = \sigma^{HC} \tag{7}$$

$$cov\left(\mu_{i}^{h}, \mu_{i}^{c}\right) = \omega^{HC} \tag{8}$$

and by the same logic, we denote the variance of the various disturbances with σ^H, σ^C and ω^H, ω^C respectively. Altogether, this implies:

$$m_{ts}^{jk} = cov(\varepsilon_{it}^{j}, \varepsilon_{is}^{k}) = \omega^{jk} + \rho_j^{|t-s|} \frac{\sqrt{\left(1-\rho_j^2\right)}\sqrt{\left(1-\rho_k^2\right)}}{1-\rho_j \rho_k} \sigma^{jk} \tag{9}$$

where $j, k \in \{H, C\}$ and parameters are identified if $\left|\rho_j\right| < 1$. Then, m_{ts}^{jk} is an element of the $2T \times 2T$ covariance matrix M.

2.2 Estimating Procedure: Maximum Simulated Likelihood

The probability of observing the sequences $\widehat{C}_{i1}, \ldots \widehat{C}_{iT}, \widehat{H}_{i1}, \ldots, \widehat{H}_{iT}$ for a particular individual is:

$$\begin{aligned} & \Pr\left(\widehat{C}_{i1}, \ldots \widehat{C}_{iT}, \widehat{H}_{i1}, \ldots, \widehat{H}_{iT}\right) \\ = & \int_{a_{i1}^{c}}^{b_{i1}^{c}} \cdots \int_{a_{iT}^{c}}^{b_{iT}^{c}} \int_{a_{i1}^{h}}^{b_{i1}^{h}} \cdots \int_{a_{iT}^{h}}^{b_{iT}^{h}} f\left(u_{i1}^{c}, \ldots, u_{iT}^{c}, u_{i1}^{h}, \ldots, u_{iT}^{h}\right) du_{i1}^{c} \ldots u_{iT}^{h}. \end{aligned} \tag{10}$$

The upper and lower bounds for integration, a_{i1}^{c} and b_{i1}^{c} are defined as follows. First of all, we acknowledge that death is an absorbing state by setting $b_{it}^{c} = \infty$ and $a_{it}^{c} = -\infty$ as soon as $\widehat{H}_{it} = 4$. Similarly, we have $b_{it}^{h} = \infty$ and $a_{it}^{h} = -\infty$ as soon as $\widehat{H}_{it-1} = 4$. For the rest, we have $b_{it}^{c} = \infty$ and $a_{it}^{c} = -X_{it}'\beta$ if $\widehat{C}_{it} = 1$ and $b_{it}^{c} = -X_{it}'\beta$ and $a_{it}^{c} = -\infty$ if $\widehat{C}_{it} = 0$. For the health variable, we have $b_{it}^{h} = \infty$ and $a_{it}^{h} = -\infty$ if $\widehat{H}_{it-1} = 4$, $b_{it}^{h} = \infty$ if $\widehat{H}_{it} = 4$, $a_{it}^{c} = -\infty$ if $\widehat{H}_{it} = 1$ and for the rest, we have $b_{it}^{h} = \alpha_{\widehat{H}_{it}+1} - X_{it}'\beta$ and $a_{it}^{h} = \alpha_{\widehat{H}_{it}} - X_{it}'\beta$, where the α_i :s are defined according to equation (2). The matrix X_{it} contains the set of independent variables (including lagged dependent variables).

We employ an algorithm proposed by Geweke (1989) that can be used to derive unbiased estimates of the choice probabilities. Univariate truncated normal variables can be drawn according to a straightforward application of the integral transform theorem. Let v be a draw from a univariate standard uniform distribution, $v \in [0, 1]$. Then

$$e_{it}^{j} = G^{-1}(v) = \Phi^{-1}\left\{\left[\Phi\left(b_{it}^{j}\right) - \Phi\left(a_{it}^{j}\right)\right] \cdot v + \Phi\left(a_{it}^{j}\right)\right\} \tag{11}$$

is distributed $N(0, 1)$, subject to $a_{it}^{j} \leq e \leq b_{it}^{j}$ since the cumulative distribution function of a univariate truncated normal distribution is

$$G(z) = \frac{\Phi(z) - \Phi(a)}{\Phi(b) - \Phi(a)} \tag{12}$$

where Φ denotes the univariate normal cumulative distribution function.

Next, we define the matrix L, that is the lower diagonal Cholesky factor of the covariance matrix M (whose elements are defined by equation 9). Hence,

$$LL' = M \tag{13}$$

Then we can draw a random variable

$$v_q \sim N(0, 1) \text{ s.t. } \frac{a_{it}^{j} - \sum_{y=1}^{q-1} l_{yq} v_y}{l_{qq}} \leq v_q \leq \frac{b_{it}^{j} - \sum_{y=1}^{q-1} l_{yq} v_y}{l_{qq}} \tag{14}$$

where $q = t$ if $j = c$ and $q = T + t$ otherwise. The v_q:s can be drawn sequentially. The likelihood contribution of a certain observation is simulated by the probability of $a^* \leq L \cdot v \leq b^*$ and hence we can rewrite the log likelihood function as

$$\begin{aligned} & \ln\left(\Pr\left(\widehat{C}_{i1}, \ldots \widehat{C}_{iT}, \widehat{H}_{i1}, \ldots, \widehat{H}_{iT}\right)\right) \\ = & \sum_{q=1}^{2T} \ln\left(\Pr\left(\frac{a_{it}^{j} - \sum_{y=1}^{q-1} l_{yq} v_y}{l_{qq}} \leq v_q \leq \frac{b_{it}^{j} - \sum_{y=1}^{q-1} l_{yq} v_y}{l_{qq}}\right)\right) \\ = & Q_1 + Q_2(v_1) + Q_3(v_1, v_2) \cdots Q_{2T}(v_1 \cdots v_{2T}) \end{aligned} \tag{15}$$

which can be approximated by the simulator

$$\frac{1}{R} \sum_{r=1}^{R} \sum_{q=1}^{2T} Q_q\left(v_{1r}, \cdots, v_{q-1r}\right) \tag{16}$$

2.2.1 Discussion

In general, the simulation estimator (16) produces consistent estimates of the parameters of the likelihood function (10). Furthermore, Börsch-Supan and Hajivassiliou (1993) find that for $R = 20$, the bias due to simulation is negligible. Hence, the estimator seems to be appropriate for our purposes.

There is, however, one practical problem related to the assumption of state dependence in the two variables. This problem has to do with the treatment of intitial observations, as a simple estimation along the lines outlined above would be based on the erroneous assumption that the system is in equilibrium in the first period. This will lead to inconsistent estimates. Two different approaches have been suggested to remedy this problem. The first one, proposed by Heckman (1981), is to estimate the initial conditions in reduced form and allow for any type of correlation pattern between the initial conditions and any subsequent condition. An alternative strategy has been proposed by Wooldridge An alternative to this is provided by Wooldridge (2005) who proposes modeling the distribution of the heterogeneity conditional on the initial condition and any time varying regressors that may be present. Doing this does not require internal consistency with the underlying statistical model nor does it require computations that are as involved as the previous method, but it does require additional distributional assumptions.

Unfortunately, none of these approaches will be useful for our purposes. Heckman's approach increases the number of parameters to be estimated substantially, and given the size of the dataset this becomes a hopeless task. Concerning Wooldridge's solution, we have the problem that most variables used for estimation, apart from age and the dependent variables themselves, tend to be time-dependent. Hence, using that approach would prevent us from estimating the parameters of interest.

The initial condition problem decreases in the length of the panel, however. Since we have a relatively long panel, the problem is likely to be relatively small in our case. Furthermore, since we are focusing on older people in the population, it could be argued that the model should be close to equilibrium once their conditions are being recorded in the BHPS.

2.3 The Dataset

For the estimation, we use the twelve first waves of the British Household Panel Survey. In this subsection, we define the variables used, report the treatment of missing values and provide some summary statistics.

2.3.1 Variables

The variables used for estimation are presented in *Table 1*. The definition of most of them is obvious, but the health variable H requires some further explanation. For this variable, we make use of information whether the individual is alive in a certain year or not (for dead individuals, the variable takes on the value $H = 4$). For survivors, we use the questions concerning whether the health status of the respondent limits daily activities. The categories allowed for in these questions are roughly equivalent to Activities of Daily Living. Furthermore, as common in Long Term Care Insurance underwriting, we use the definitions that 'moderate disability' corresponds to having two activities failing, and 'severe' disability corresponds to having three or more activities failing. Respondents who report that health does not limit daily activities, are coded as healthy. Furthermore, we have suppressed the education category $E5$, which does not have any of the qualifications mentioned in categories $E1 - E4$. Hence, this is the group with the lowest level of education.

Table 1. Definition of Variables.

Variable	Definition
A	Age (calender year minus birth year)
$E1$	University Degree
$E2$	Teaching/Nursing Qualifications
$E3$	A Levels
$E4$	O Levels or equivalent
C	Individual married or cohabiting
H	health limits daily activities

2.3.2 Treatment of Missing Values

Missing variables are a particularly great problem in this work, as dropping individuals with missing observations is not an option - this would bias he mortality rates. In general, some 2-3 per cent of observations were missing. Some of these were quite easy to impute from earlier or later observations: for instance; somebody who has a university degree in a certain year will have the same university degree in any subsequent year.

In a second step, we assumed that if an individual has the same cohabitation status or health status in two years adjacent to a missing observation, we assume that the missing observation had the same value as the two surrounding ones. This seems reasonable given how slowly health and cohabitation status may change, but it might be problematic since it would bias the estimates if there is a substantial probability of two transitions over that time period. Given, however, the low number of missing observations of this kind, the impact on the parameter estimates must be relatively low.

For all observations that were still missing after this exercise, we simply assumed them to belong to the most common categories (i.e. cohabitation, healthy, no education). This is certainly not unproblematic, but it would be equally problematic to make imputations based on variables used in the estimations. Besides, it can again be argued that the small number of missing cases ensures that this practice has a limited impact on the results.

2.3.3 Descriptive Statistics

In the following, we will provide some summary statistics of the panel. We include all 6,690 permanent members of the panel in the main regressions. Due to the vast size of the panel, however, robustness checks and hypothesis testing has to be performed on a subsample of the panel. We start out by showing the main variable of interest - health - and how it evolves with age in *Table 2*.[1]

Table 2 shows the well documented relationship between health and age. For instance, among people in their twenties, the prevalence of physical impairments is around one percent; around retirement age the figure is around ten percent, and at the highest agest a majority of people have some kind of impairment.

Next, we look at the role of cohabitation. In Table 3, we cross-tabulate the initial wave by health status and cohabitation status. The two seem to be correlated; a person not cohabiting is twice as likely to be unhealthy as a person who is cohabiting.

Furthermore, the cohabitation state of the initial year seems to be a quite good predictor of the health status in subsequent years, including death. In *Table 4* we cross-tabulate the cohabitation status in 1991 with the health status in 2002. Clearly, people who were cohabiting in 1991 had a higher chance of being alive and healthy in 2002.

[1] In principle, the data could also be partitioned by gender. Due to the few observations in some age brackets, however, it is better to present the pooled dataset. Males and females exhibit the same patterns of gradually deteriorating health, but female survivors tend to have slightly worse health than males.

Table 2. Health Status (ADLs) by age, 1999.

Age91	Healthy	Moderate	Severe	Total
15-20	394	2	1	397
	99.24	0.50	0.25	100.00
21-25	487	3	2	492
	98.98	0.61	0.41	100.00
26-30	688	3	7	698
	98.57	0.43	1.00	100.00
31-35	677	6	0	683
	99.12	0.88	0.00	100.00
36-40	593	4	4	601
	98.67	0.67	0.67	100.00
41-45	683	4	6	693
	98.56	0.58	0.87	100.00
46-50	565	15	14	594
	95.12	2.53	2.36	100.00
51-55	411	9	17	437
	94.05	2.06	3.89	100.00
56-60	410	17	22	449
	91.31	3.79	4.90	100.00
61-65	406	18	21	445
	91.24	4.04	4.72	100.00
66-70	409	22	26	457
	89.50	4.81	5.69	100.00
71-75	269	25	35	329
	81.76	7.60	10.64	100.00
76-80	177	13	29	219
	80.82	5.94	13.24	100.00
81-85	107	13	24	144
	74.31	9.03	16.67	100.00
86-90	24	6	9	39
	61.54	15.38	23.08	100.00
91-95	5	1	7	13
	38.46	7.69	53.85	100.00
Total	6,305	161	224	6,690
	94.25	2.41	3.35	100.00

Finally, we look at the relationship between health and education. Figures are presented in *Table 5*. The Education variable reflects the self reported educational attainment, where various types of degrees are ranked according to the years of schooling involved (where 1 representes leaving school at 16 and 5 a full unicersity degree). Just as expected, a higher educational attainment is correlated with better health, although the relationship is not entirely monotonous.

Table 3. Health Status (ADLs) by cohabitation status, 1999.

	Health 1991			
Cohab1991	*Healthy*	*Moderate*	*Severe*	**Total**
0	1,900	69	113	2,082
	91.26	3.31	5.43	100.00
1	4,405	92	111	4,608
	95.59	2.00	2.41	100.00
Total	6,305	161	224	6,690
	94.25	2.41	3.35	100.00

Table 4. Health Status 2002 (ADLs) by cohabitation status 1991.

	Health 2002				
Cohab1991	*Healthy*	*Moderate*	*Severe*	*Dead*	**Total**
0	1,477	57	108	440	2,082
	70.94	2.74	5.19	21.13	100.00
1	3,789	148	180	491	4,608
	82.23	3.21	3.91	10.66	100.00
Total	5,266	205	288	931	6,690
	78.71	3.06	4.30	13.92	100.00

Table 5. Health Status 2002 (ADLs) by educational attainment 1991.

	Health 1991			**Total**
Edu1991	*Healthy*	*Moderate*	*Severe*	
1	2,012	104	167	2,283
	88.13	4.56	7.31	100.00
2	1,844	17	20	1,881
	98.03	0.90	1.06	100.00
3	1,290	32	26	1,348
	95.70	2.37	1.93	100.00
4	512	4	2	518
	98.84	0.77	0.39	100.00
5	6,305	161	224	6,690
	94.25	2.41	3.35	100.00

3 Results

Estimation results for cohabitation are presented in *Table 6*. In the table, the first group of variables are the exogenous variables - constant, age and education. The label Ct-1 refers to state dependence in the cohabitation variable, and 'Mod' and 'Sev' refer to whether the individual was moderately or severely disabled in the previous period. Parameters σ^{HC}, ω^{HC} and ρ_1 refer to the structure of the error terms.

Some aspects of the parameter estimates are surprising. Firstly, all the exogenous explanatory variables are insignificant - i.e. education seems to have very little explanatory power for the cohabitation variable. Concerning age, the estimates are insignificant throughout but jointly significant. We can also reject the hypothesis that the probability of cohabitation changes over time: the year effect is weak and insignificant.

The main part of the explanatory power is instead connected with unobserved heterogeneity. Remarkably, the fixed individual effects are small and insignificant, but there is a strong correlation in unobservables with health for fixed effects as well as transitory shocks. Similarly, there is an extremely strong state dependence in the cohabitation variable. Severe disability also has a significant negative impact on the probability of cohabitation.

Taken together, these findings suggest that observed socioeconomic differences in cohabitation status have little to do with causation, but rather suggest that people of different education groups have unobserved characteristics that influence their probability of cohabitation. It is interesting to notice that health seems to be one of the most important characteristic, as the individual fixed effect becomes insignificant once health is accounted for.

In Table 7, we present parameter estimates for the disability variable. Apart from the constant, the variables are the same as in Table 6 above.

Again, we find that age and education effects are generally insignificant. Only the second lowest education group has significantly better health than the lowest education group. This finding suggests that the relationship between health and education is non-linear, which is also supported by the fact that the point estimates are not increasing monontonically in the level of education. We also find that cohabitation has a positive but insignificant effect on health. State dependence seems to ber very strong in the health variable, where svere and moderate disability in the last year significantly reduces the health prospects of the current year.

One striking finding is that health seems to be deteriorating over time. This is quite at

Table 6. Estimation Results, Cohabitation.

Variable	Coefficient	Std Error	T Stat	P Value
Constant	-0.01652	63.437	-0.0003	0.9998
Age	-0.02725	2.1783	-0.0125	0.9900
A2	-0.07062	0.4393	-0.1608	0.8723
A3	-0.01557	2.0985	-0.0074	0.9941
A4	-0.00247	0.0026	-0.9612	0.3365
Edu1	-0.07062	0.4393	-0.1608	0.8723
E2	0.10121	0.1205	0.8396	0.4012
E3	0.15286	0.2417	0.6185	0.5363
E4	0.00230	0.0931	0.0247	0.9803
Ct-1	3.9877	0.1186	33.627	0.0000
Modt-1	-0.10601	0.1602	-0.6617	0.5082
Sevt-1	-0.10927	0.0964	-1.1330	.02572
Year	0.00924	0.0134	0.6895	0.4905
σ^{hc}	-0.1157	0.0263	-4.401	0.0000
ω^{cc}	0.0056	0.0152	0.3684	0.7126
ω^{hc}	-0.3681	0.0379	-9.701	0.0000
ρ_1	-0.4911	0.0501	-9.794	0.0000
Loglik	-5541.3426			
Loglik0	-56102.0			
Pseudo R2	0.901			
N	7,986			

odds with the general increase in life expectancy that has been observed in the UK as in other countries. This result has two possible interpretations. One possibility is that the observed improvements in health expectancy has been due to a mixture of cohort effects, increasing education levels and changing cohabitation patterns (although the latter seems less likely). If this is the case, there has been a general tendency to worse health amongst older people, that has been counteracted by a general improvement in these factors.

An alternative interpretation is that the model used here simplifies too much. It might not be appropriate to assume that the cutoff values - α_1, α_2 and α_3 - are constant over time. Indeed, data of the development of HLE over the last few decades suggest that a substantial proportion of the gains in life expectancy are spend in moderate disability, whereas the time spent in severe disability has a downward tendency. This might in turn be due to improvements in medical technology. If this is the case, the three alphas might well be diverging over time and this is then the effect picked up by the time coefficient estimated here.

Finally, we find that unobserved heterogeneity is very significant in explaining the dynamics of health. The individual fixed effect (point estimate 0.55) accounts for almost as much variance as the transitory shocks (where variance is set to unity). Again, we can conclude that causal effects from education seem to be dominated by variation in unobservables. This is of course a very policy relevant finding.

Table 7. Estimation Results, Health.

Variable	Coefficient	Std Error	T Stat	P Value
Age	-0.10372	0.7042	-0.1473	0.8829
A2	0.11272	0.6588	0.1711	0.8641
A3	0.00137	0.0013	1.0781	0.2810
A4	-0.00569	0.1689	-0.0337	0.9731
Edu1	-0.2338	0.2540	-0.9203	0.3575
E2	-0.11610	0.0973	-1.1938	0.2326
E3	-0.17442	0.1814	-0.9613	0.3363
E4	-0.19692	0.0857	-2.2983	0.0216
Ct-1	-0.08389	0.0725	-1.1564	0.2476
Modt-1	0.48237	0.0879	5.4865	0.0000
Sevt-1	0.71820	0.1033	6.9517	0.0000
Year	0.05228	0.0095	5.5273	0.0000
σ^{hc}	-0.11573	0.0263	-4.4014	0.0000
ω^{hh}	0.55339	0.0931	5.9462	0.0000
ω^{hc}	-0.3681	0.0379	-9.7008	0.0000
ρ_1	-0.0596	0.0547	-1.0887	0.2763

4 Conclusion

The objective of this paper has been to develop an econometric approach in order to estimate the relationship between cohabitation and health, in order to analyse to what degree observed differences in health between singles and people cohabiting can be attributed to causality, unobserved heterogeneity or persistance. There is a lack of rigorous theoretical treatments of the problem, as well as a dearth of empirical studies that accounts for the full complexity of the problem. By using simulation techniques developed for limited dependent variable models, we are able to derive an estimator that takes all relevant aspects of the problem into account.

We applied the estimator to a subsample of the BHPS, including all men aged 65 and older at the beginning of the panel. In general, we find that the causal relationship from age and education on health is relatively weak, and that most variation in the data is due to correlation in unobservables. Hence, there is a strong correlation in fixed indivdual attributes relevant for health and cohabitation, and there is a strong persistence in the dependent variables. Accordingly, our results suggest that the relationship between education and health is not primarily a causal one, but rather the effect of self-selection. This finding obviously has strong policy implications.

Further checks of robustness and consistency have to be undertaken, however. Firstly, it is desirable to extend the analysis to other subsamples of the population, and to compare the model with state dependence with one without according to available criteria. Furthermore, it would be useful to analyse to what extent simulation bias represents a problem here, using the test proposed by Hajivassiliou (2000).

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