Incidence-based Estimates of Healthy Life Expectancy for the United Kingdom: Coherence between Transition Probabilities and Aggregate Life Tables*

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Abstract

Will the United Kingdom's ageing population be fit and independent, or suffer from greater chronic ill health? Healthy life expectancy represents the expected number of years of healthy well-being a life table cohort would experience if age specific rates of mortality and disability prevailed throughout the cohort's lifetime. Robust estimation of healthy life expectancy is thus essential for examining whether additional years of life are spent in good health and whether life expectancy is increasing faster than the decline of disability rates. This paper examines a means of generating estimates of healthy and unhealthy life expectancy for the United Kingdom that are consistent with exogenous population mortality data. The method takes population transition matrices and adjusts these in a statistically coherent way so as to render them consistent with aggregate life tables.

Keywords: Healthy Life Expectancy, Health State Transitions, Least-squares Adjustment

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1 Introduction

While it is plain that life expectancy has increased considerably over the last thirty years or so in many advanced countries, it is much less clear how healthy life expectancy has developed. Questions have therefore arisen about the quality of life. Are we living longer but in worse health? Are the increases in life expectancy at older ages because we are keeping sick or disabled people alive longer or because we are saving people from death but leaving them in states of disability? These are important questions both for individuals and also for government policies on social and health services provision for the elderly.

A shift in emphasis, from increasing survival to improving both the length and quality of people's lives, has led to a greater policy interest in the issue in the UK. The government projects that the overall number and proportion of older people will rise significantly in the coming decades, primarily due to increased longevity. However, there is a debate over whether these people will live longer, healthier lives, longer but more disabled lives, or something in between (Wanless 2002). The Treasury's long-term projections of the costs of an ageing population assume that the proportion of life spent in long-term care will remain constant but acknowledge that this is a cautious assumption and do not rule out an expansion of morbidity in the future (Treasury 2004).

A crucial question therefore is whether the proportion of life spent in disability is rising or declining. Existing data can be used to support either case. While there have been clear rises in overall life expectancy over time, there are concerns that not all years gained are in healthy well-being and that a proportion of extra years lived are being spent in ill-health (Bissett (2002) and Breakwell & Bajekal (2005)). The conclusions from UK data sources appears to point to these trends reflecting increased years of mild disability, and a decline in severe disability (Bajekal et al. (2004) and Kelly et al. (2000)).

Traditional estimations of healthy life expectancy based on single-state life tables, more popularly termed Sullivan's method, have served reasonably well as tools of measurement and projections of healthy life (Sullivan (1966) and Sullivan (1971) - see appendix A for a detailed account of the Sullivan method and its uses). In his seminal article, Sullivan (1971) developed a method for combining mortality and morbidity rates into a single summary measure of a population's health status. The concern about his method however is the fact that it uses current morbidity prevalence rates, and not current incidence rates. The Sullivan method assumes the current mortality prevalence rates will prevail in future cohorts as they reach the same age. The state of well-being of the elderly today may indeed reflect damage done in the past - such as injuries sustained by soldiers and civilians during the Second World War. Hence, Sullivan's method cannot reflect sudden changes in disability transition rates. It may therefore be a poor indication of the risks of ill-health

faced by the younger generation.

However, multi-state models based on transition probabilities between health states differentiate current and future stocks and flows of individuals by previous health states of existence (Rogers et al. (1990) and Brouard & Robine (1992)) and thus allow the construction of incidence-based measures of healthy life expectancy. Panel data are required for their construction; this typically requires either occasional epidemiological studies (Spiers et al. (2005) and Jagger et al. (2003)) which, because they are occasional, cannot provide a regular indication of any change in the pattern of healthy life expectancy, or the inclusion of questions about health in a portmanteau panel survey. This paper focuses on the construction of incidence-based measures of healthy life expectancy from the questions about health states included in the British Household Panel Survey, which has been conducted annually in Great Britain since 1991, and the coherence between these measures and information on survival contained in the official life tables for the United Kingdom.

The structure of the paper is as follows. Section 2 introduces the British Household Panel Survey and sets out our preferred measure of healthy life expectancy. Section 3 presents a means of generating estimates of healthy and unhealthy life expectancy consistent with exogenous population mortality data. In section 4 we set out the method of least-squares that takes population transition matrices and adjusts these in a statistically coherent way so as to render them consistent with death rates in aggregate life tables. Section 5 reports and discusses the results from our models and section 6 concludes.

2 Data and Measures

2.1 The British Household Panel Survey Dataset

Our study focuses on the panel data that are available for the first fourteen waves, 1991-2004, of the British Household Panel Survey. The British Household Panel Survey is a standardised multi-purpose annual longitudinal survey of each person aged 16+ in a nationally representative sample of more than five thousand private households comprising about ten thousand individuals in Great Britain. The same individuals are re-interviewed each successive year and, if they split off from their original households to form new households, they are followed and also re-interviewed along with all adult members of their new households. New households are introduced in each year to compensate for attrition.

While the British Household Panel Survey serves as a useful tool in providing information on socioeconomic and health variables, there are a number of drawbacks of its uses. First, sub-groups, such as ethnic minorities, with relatively low prevalence in the general population are too small for robust inference. Second, age cohorts within the pan-

els, including those formed from panel members' children, have to be too broadly defined for the effective assessment of cohort effects. If they are focused on single ages the data have to be aggregated over many years confounding the cohort effects with period effects. Finally, the issue of sample attrition over the life of the panel has reduced numbers in the main panel and is a potential source of bias. This concern is tackled in detail below.

2.2 Self-Assessed Health

From the range of health status variables available in the British Household Panel Survey we have chosen as our measure of healthy life expectancy the self-assessed health variable which is given as a response to: 'Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been (i) excellent; (ii) good; (iii) fair; (iv) poor; or (v) very poor?' This matches, as closely as possible, the question used in the General Household Survey which provides the basis for the official estimates of healthy life expectancy (although with the important difference that the General Household Survey does not invite people to compare themselves with people of their own age). The British Household Panel Survey also attempts to identify people who have died since the previous interview, distinguishing them from people who drop out for other reasons; we treat death as a sixth 'health state' ranked below "very poor".

Whilst self-assessed health is the closest possible match of healthy life expectancy to official estimates, a number of concerns have been raised about the validity of this subjective measure of health. It has long been argued that perceived health does not correspond with actual health (Bound (1990) and Crossley & Kennedy (2002)). An individual's own understanding of his health may not accord with the appraisal of not only medical experts but also other individuals of the same age.

Nevertheless whilst self-assessed health has been used frequently in previous studies in examining health dynamics (e.g. Ettner (1996), Benzeval et al. (2000), Contoyannis et al. (2004*a*), Deaton & Paxson (1998) and Smith (1999)) not much work has been devoted to estimate transition probabilities using self-assessed health (see Bebbington & Shapiro (2005) for an application with European Household Panel Survey data). It can be widely thought of as a simple subjective measure of health that provides an ordinal ranking of perceived health status. It has received extensive coverage in recent years largely attributed to the authority deriving from the robustness of its predictive capacity for mortality (Idler & Benyamini 1997). Also, categorical measures of self-assessed health have been shown to be good predictors of subsequent use of medical care (van Doorslaer et al. 2000). Nevertheless there are obvious concerns that changes over time may be a result of changing perceptions and expectations rather than a true deterioration or

improvement in health.

As mentioned, the self-assessed health question at each wave of the British Household Panel Survey is measured following an ordinal scale, with polychotomous response categories. However, in wave 9 there was a notable change in the wording of the self-assessed health question. For waves 1-8 and 10-14, the self-assessed health variable represents 'health status over the last 12 months'. In wave 9 the self-assessed health variable uses the question: 'In general, would you say your health is (i) excellent, (ii) very good, (iii) good, (iv) fair, or (v) poor?'. Two important differences can be distinguished between the wordings of the self-assessed health measure in wave 9 and the other waves. First, the question is not framed in terms of a comparison with cohorts of the same age. Secondly, the five possible responses are labelled differently. Hernandez-Quevedo et al. (2004) have examined the sensitivity of ordered probit models of self-assessed health to this change in wording and have suggested that item non-response is greater for self-assessed health at wave 9 than for the other waves. They argue that there tends to be a bias in reporting better health status in wave 9, in that, individuals who report their health status as "poor" in wave 9, may well have assessed their health as "very poor" had this option been offered. In order to avoid our estimated transition probabilities being corrupted by this, we omit the transitions from 1998 to 1999 and 1999 to 2000 from our data, with the consequence that healthy life expectancy estimates are not available for 1999 and 2000.

3 Initial Transition Matrix Estimates

3.1 Modelling transitions in health

Were the sample of the British Household Panel Survey large enough it would be possible to draw transition matrices for each age separately directly from the panel. However the number of people classified by age and health category is not large with the consequence that such an approach would yield very erratic estimates of the transition matrices. Instead therefore we treat underlying health status as a latent variable and fit a dynamic ordered probit model to the panel data, explaining health status in one year as a function of age, age^2 and health state in the previous year. We also introduce time dummies. The resulting probit equations can be used to produce initial estimates of the transition probabilities as a function of initial health state and age.

The latent variable specification of the reduced form model that we estimate can be written as

$$h^*_{i,t} = \boldsymbol{\beta}'\mathbf{x}_{i,t} + \boldsymbol{\gamma}'\mathbf{h}_{i,t-1} + \eta_i + \mathbf{w}'\boldsymbol{\zeta}_t + e_{i,t} \tag{1}$$

$(i = 1, ..., N_t; t = 1992, ..., 2004)$, where $h^*_{i,t}$ is an underlying continuous latent variable for

the ith individual that underlies reported self-assessed health at wave t. The observed variables, age and age^2, which may be associated with the health indicator are captured by the vector $\mathbf{x}_{i,t}$. $\mathbf{h}_{i,t-1}$ is a six dimensional vector of dummies for the individual's health state in the previous wave (in estimation one dummy is excluded to avoid the dummy variable trap) and $\boldsymbol{\gamma}$ are coefficients to be estimated. The element of $\boldsymbol{\gamma}$ relating to death is constrained to $-\infty$. This ensures death is an absorbing state in the sense that once a person dies she will remain in that state. η_i is an individual specific time-invariant random effect and $\boldsymbol{\zeta}_t$ is a vector of time dummies included to capture cross-sectional dependence explained by common (aggregate) shocks, with $\mathbf{w}$ denoting the associated vector of estimable coefficients. Finally, $e_{i,t}$ is a random independently distributed error term following a $N(0,1)$ distribution. The variance is set to unity for identification given the categorical nature of the observed health outcome.

Unfortunately, as mentioned above, there was a change in the wording of the self-assessed health question at wave nine of the British Household Panel Survey which has led to wave nine being dropped from our analysis. Given the consideration of lagged health $\mathbf{h}_{i,t-1}$ in (1), this means wave ten is considered only when explaining $h^*_{i,t}$ in wave eleven. Since $h^*_{i,t}$, is unobserved but the self-assessed health data indicate the category in which the latent indicator fell, we use ordered discrete choice models based on the latent regression (1). Specifically, the observed health states, $h_{i,t}$, are triggered by $h^*_{i,t}$ as it crosses unknown cut points (thresholds) α_j $(j = 1, ..., 5)$ such that:

$$h_{i,t} = j \text{ if } \alpha_j < h^*_{i,t} \leq \alpha_{j+1}, \ (j = 0, 1, ..., 5), \tag{2}$$

corresponding to "death", "very poor", "poor", "fair", "good" and "excellent", respectively, where $\alpha_0 = -\infty$, $\alpha_j \leq \alpha_{j+1}$ and $\alpha_6 = \infty$. So each observed health state corresponds to a value range within the unobserved latent distribution for health, such that the entire range of the distribution is covered by one health state. The transition probabilities derived from the conditional distribution of $h_{i,t+1}$ given the state k $(k = 1, ..., 5)$, corresponding to "very poor" through to "excellent" health, at time t are

$$P(h_{i,t+1} = j \mid h_{i,t} = k) = \Phi(\alpha_{j+1} - \boldsymbol{\beta}'\mathbf{x}_{i,t} - \boldsymbol{\gamma}'\mathbf{e} - \eta_i - \mathbf{w}'\boldsymbol{\zeta}_t) - \Phi(\alpha_j - \boldsymbol{\beta}'\mathbf{x}_{i,t} - \boldsymbol{\gamma}'\mathbf{e} - \eta_i - \mathbf{w}'\boldsymbol{\zeta}_t), \tag{3}$$

where $\Phi(\cdot)$ denotes the cumulative standardised normal distribution and $\mathbf{e}$ is a six dimensional vector of zeros with unity on the $k+1$-th element, relating to the dummy variable on the k-th lagged health state $(k = 1, ..., 5)$.

When estimating the dynamic ordered probit model, (1), following Wooldridge (2005) the initial conditions problem is dealt with by letting $\eta_i = \boldsymbol{\gamma}_1'\mathbf{h}_{i,1991} + \upsilon_i$, where $\mathbf{h}_{i,1991}$ is a five dimensional vector of dummies for the individual's health state in the first wave

(1991). Note that since an individual must be alive in this first wave, $\mathbf{h}_{i,1991}$ is of lower dimension than $\mathbf{h}_{i,t-1}$ $(t = 1993, ..., 2004)$. The five dimensional vector of coefficients $\boldsymbol{\gamma}_1$ indicates the relationship between the individual effect and initial health. It is assumed that $\upsilon_i \sim N(0, \sigma_\upsilon^2)$. Again in estimation one of the dummy variables is excluded to avoid multi-collinearity.

To account for possible health-related sample attrition in the data, with individuals in poor health perhaps more likely to drop out of the British Household Panel Survey leading to upwardly biased estimates of life expectancy, we also consider dynamic panel ordered probit models that correct for sample selection. See Appendix B for a detailed account of the modelling procedure and model estimates. In fact, in line with Contoyannis et al. (2004*b*), comparisons of estimates based on models with and without a correction for sample attrition, suggest that differences are relatively small. But there is statistical evidence of heterogeneity across individuals, in the sense that $\sigma_\upsilon^2 > 0$, and we therefore prefer a random effects rather than a pooled specification.

At time $t = 1991$ an individual must be in one of the health states $h_{i,1991} = j$ $(j = 1, ..., 5)$. Over time $(t = 1992, ..., 2004)$ she may remain where she is or enter and leave any other state, and she may well reach the state of death, $h_{i,t} = 0$.

3.2 Estimation of transition matrices

We calculate transition matrices as a function of age from equation (3). Since time dummies are included in the probit model these transition probabilities are functions of time and age. $\mathbf{M}^{r,t}$ is the transition probability matrix for someone aged r in year t, where the elements of $\mathbf{M}^{r,t} = \{m_{jk}^{r,t}\} = P(h_{i,t+1} = j \mid h_{i,t} = k)$, $(j = 1, ..., 5; k = 1, ..., 5)$, where r is the age of the i-th individual in year t and due to the homogeneity restrictions (across i) imposed on (1) essentially we consider a representative individual of each age r. We express the population vector as $\mathbf{y}_{T,t}$; its pth element, $y_{T,t,p}$ shows the number of people in health state j $(j = 1, ..., 5)$ at age T in year t. If we denote by $\mathbf{i}$ a vector of 1s with length equal to the number of health states, then from an initial population $\mathbf{y}_{T,t}$ at age T in year t, the proportion surviving to age $T + 1$ depends on the proportion of people in each health state in year T and is given as

$$s_{T+1,T,t} = \frac{\mathbf{i}'\mathbf{M}^{T+1,t}\mathbf{y}_{T,t}}{\mathbf{i}'\mathbf{y}_{T,t}} \tag{4}$$

More generally, the proportion surviving to age T^* is

$$s_{T^*,T,t} = \frac{\mathbf{i}'\Pi_{r=T}^{T^*-1}\mathbf{M}^{r,t}\mathbf{y}_{T,t}}{\mathbf{i}'\mathbf{y}_{T,t}} \tag{5}$$

This is unlikely to match the corresponding proportion derived from the official life table

which we denote $s^*_{T^*,T,t}$. In order to produce transition matrices and thus healthy life expectancy estimates consistent with the official data we need to find new transition matrices, ideally not too different from the existing ones. As equation (5) shows, the survival rates generated by any set of transition matrices depend on the actual population vector of people aged T in year t and thus the required transition matrices depend on the age, T, for which survival rates and thus healthy life expectancies are to be calculated.

We denote the adjusted transition matrices $\tilde{\mathbf{M}}^{r,T,t}$ indicating that these are specific to the population aged T in year t and relate to all ages $r \geq T$. These need to satisfy the relationships

$$s^*_{T^*,T,t} = \frac{\mathbf{i}'\Pi_{r=T}^{T^*-1}\tilde{\mathbf{M}}^{r,T,t}\mathbf{y}_{T,t}}{\mathbf{i}'\mathbf{y}_{T,t}} \quad T^* > T \tag{6}$$

It is obvious that $s_{T^*,T,t}$ can be driven to $s^*_{T^*,T,t}$ only by adjusting the transition matrices $\mathbf{M}^{r,t}$ where $r \leq T^* - 1$. But an adjustment to one of these matrices has implications for $s_{r,T,t}$ for all $r > T^*$. Thus, although it is obviously possible to address the problem sequentially, it is unlikely that sequential adjustment will offer the most satisfactory solution.

4 A Least-Squares Approach

The adjustment of the transition matrices, $\mathbf{M}^{r,t}$, so that conditions (6) are met, raises a number of issues. With only one survival rate for each age but with each transition matrix being a five by five array there is obviously an infinite number of possible adjustments which could be made. It seems desirable to choose adjustments which are as small as possible bearing in mind the constraints which need to be met. We define "as small as possible" by looking at the sum of the squared adjustments made to all the elements of all the transition matrices, measured relative to the magnitudes of the elements themselves. Thus we tolerate a large adjustment to a large element more than a large adjustment to a small element. This is the common weighted least squares criterion. Such an approach has been widely used in a variety of contexts– by statisticians following Deming & Stephan (1940) who first proposed its use to estimate cell probabilities in a contingency table subject to certain marginal constraints (a procedure known as raking) and also by economists (Stone et al. (1942), Byron (1978) and Solomou & Weale (1993)) to enhance estimates of data which should satisfy linear constraints. Zieschang (1990) sets out the least-squares problem very clearly while DeVille et al. (1993) consider alternative loss functions. However they all looked at situations where the constraints to be satisfied were linear functions of the variables to be adjusted. In such a case there is an analytical solution which takes a simple matrix form although it can be awkward to work out if the problem is of large dimension.

Our constraints are non-linear as equation (6) makes clear. The survival rate at any given age depends on all of the transition matrices up to and including that age and in a manner which is the outcome of matrix multiplication. This means that it is a multiplicative function of the individual matrix elements in contrast to the linear function which would be required for an analytical solution. We therefore derive an algorithm to find the least-squares solution. The process uses the solution to the linear least squares problem at each step on the way, making use of a Taylor series expansion at each interation. The procedure works so that, at each step an extra increment to the transition matrices is calculated. This is nevertheless done so as to minimise the overall weighted sum of squares of the adjustments and not the weighted sum of squares of each increment.

We denote by the vector $\mathbf{n}_r$ the vector constructed from the columns of transition matrix $\mathbf{M}^{r,t}$ stacked in order. We omit the year subscript t since it is not needed in this section; all variables are specific to year t. We further consider the vector

$$\mathbf{n} = \begin{bmatrix} \mathbf{n}_T \\ \dots \\ \mathbf{n}_r \\ \dots \\ \mathbf{n}_{99} \end{bmatrix} \tag{7}$$

We write the vector of survival proportions generated by the vector $\mathbf{n}$ as $\mathbf{s}_T(\mathbf{n}, \mathbf{y}_T)$ with its rth element $s_r(\mathbf{n}, \mathbf{y}_T) = s_r$. Since the different health states have different death rates associated with them, the proportion surviving to any age is a function of the initial population vector, $\mathbf{y}_T$. The observed survival proportions are denoted $\mathbf{s}_T^*$. We then aim to find $\mathbf{n}^* = \mathbf{n}^0 + \boldsymbol{\Delta}\mathbf{n}$ to minimise

$$\frac{1}{2}\boldsymbol{\Delta}\mathbf{n}'\mathbf{V}^{-1}\boldsymbol{\Delta}\mathbf{n} + \boldsymbol{\lambda}\left\{\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^0 + \Delta\mathbf{n}, \mathbf{y}_T\right)\right\} \tag{8}$$

where $\mathbf{V}^{-1}$ is a weighting matrix with V_{fg} indicating the fth row and gth column of $\mathbf{V}$ with n_l the lth element of $\mathbf{n}^0$. We set $V_{ff} = n_l^2$ and $V_{fg} = 0$ $(f \neq g)$. Differentiating with respect to the elements of $\mathbf{n}$

$$\mathbf{V}^{-1}\boldsymbol{\Delta}\mathbf{n} - \left(\frac{\partial \mathbf{s}_T}{\partial \mathbf{n}}\right)' \boldsymbol{\lambda} = \mathbf{0} \tag{9}$$

where $\frac{\partial \mathbf{s}}{\partial \mathbf{n}}$ denotes a matrix whose fth row and gth column consists of $\frac{\partial s_f}{\partial n_g}$. This gives

$$\boldsymbol{\Delta}\mathbf{n} = \mathbf{V}\left(\frac{\partial \mathbf{s}}{\partial \mathbf{n}}\right)' \boldsymbol{\lambda} \tag{10}$$

We also note that by applying a Taylor series expansion we have

$$\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^0 + \Delta\mathbf{n}, \mathbf{y}_T\right) \cong \mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^0, \mathbf{y}_T\right) - \left(\frac{\partial \mathbf{s}_T}{\partial \mathbf{n}}|_{\mathbf{n}^0}\right)\boldsymbol{\Delta}\mathbf{n} \tag{11}$$

Given that

$$\mathbf{s}_T^* - \mathbf{s}_T(\mathbf{n}^0, \mathbf{y}_T) - \left(\frac{\partial \mathbf{s}}{\partial \mathbf{n}}|_{\mathbf{n}^0}\right)\boldsymbol{\Delta}\mathbf{n} \cong \mathbf{0} \tag{12}$$

The exogenous survival rates will be approximately delivered if

$$\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^0, \mathbf{y}_T\right) \cong \left(\frac{\partial \mathbf{s}}{\partial \mathbf{n}}|_{\mathbf{n}^0}\right)\boldsymbol{\Delta}\mathbf{n} \tag{13}$$

We then set $\frac{\partial \mathbf{s}}{\partial \mathbf{n}}|_{\mathbf{n}^0} = \mathbf{S}_0$ and $\lambda_0 = \left\{\mathbf{S}_0\mathbf{V}\mathbf{S}_0'\right\}^{-1}\left(\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}_0, \mathbf{y}_T\right)\right)$. Therefore

$$\boldsymbol{\Delta}\mathbf{n}_0 = \mathbf{V}\mathbf{S}_0'\left\{\mathbf{S}_0\mathbf{V}\mathbf{S}_0'\right\}^{-1}\left(\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}_0, \mathbf{y}_T\right)\right) \tag{14}$$

This finalises the first stage of the iteration process.

We now put $\mathbf{n}^1 = \mathbf{n}^0 + \Delta\mathbf{n}^0$ and seek to find a vector $\Delta\mathbf{n}^1$ to minimise

$$\frac{1}{2}\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1\right)'\mathbf{V}^{-1}\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1\right) + \boldsymbol{\lambda}\left\{\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^0 + \Delta\mathbf{n}^0 + \Delta\mathbf{n}^1, \mathbf{y}_T\right)\right\} \tag{15}$$

Thus, with $\frac{\partial \mathbf{s}}{\partial \mathbf{n}}|_{\mathbf{n}^1} = \mathbf{S}_1$, we then have

$$\mathbf{V}^{-1}\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1\right) - \mathbf{S}_1'\boldsymbol{\lambda} = 0 \tag{16}$$

and approximately

$$\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^1, \mathbf{y}_T\right) \cong \mathbf{S}_1\boldsymbol{\Delta}\mathbf{n}^1 \tag{17}$$

This then yields

$$\mathbf{S}_1\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1\right) = \mathbf{S}_1\mathbf{V}\mathbf{S}_1'\boldsymbol{\lambda} \tag{18}$$

whence we have

$$\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1\right) = \mathbf{V}\mathbf{S}_1'\left\{\mathbf{S}_1\mathbf{V}\mathbf{S}_1'\right\}^{-1}\left\{\mathbf{S}_1\boldsymbol{\Delta}\mathbf{n}^0 + \mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^1, \mathbf{y}_T\right)\right\} \tag{19}$$

A further increment $\Delta\mathbf{n}^2$ is chosen to satisfy

$$\mathbf{V}^{-1}\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1 + \Delta\mathbf{n}^2\right) - \mathbf{S}_2'\boldsymbol{\lambda} = \mathbf{0} \tag{20}$$

and approximately

$$\mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^2, \mathbf{y}_T\right) \cong \mathbf{S}_2\boldsymbol{\Delta}\mathbf{n}^2 \tag{21}$$

giving

$$\left(\boldsymbol{\Delta}\mathbf{n}^0 + \Delta\mathbf{n}^1 + \Delta\mathbf{n}^2\right) = \mathbf{V}\mathbf{S}_2' \left\{\mathbf{S}_2\mathbf{V}\mathbf{S}_2'\right\}^{-1} \left\{\mathbf{S}_2\left(\boldsymbol{\Delta}\mathbf{n}^0 + \boldsymbol{\Delta}\mathbf{n}^1\right) + \mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^2, \mathbf{y}_T\right)\right\} \quad (22)$$

A recursive algorithm can be constructed

$$\boldsymbol{\Delta}\mathbf{n}^x = \mathbf{V}\mathbf{S}_x' \left\{\mathbf{S}_x\mathbf{V}\mathbf{S}_x'\right\}^{-1} \left\{\mathbf{S}_x \sum_{w=0}^{x-1} \boldsymbol{\Delta}\mathbf{n}^w + \mathbf{s}_T^* - \mathbf{s}_T\left(\mathbf{n}^x\right)\right\} - \sum_{w=0}^{x-1} \boldsymbol{\Delta}\mathbf{n}^w \quad (23)$$

with $\mathbf{n}^x = \mathbf{n}^0 + \sum_{w=0}^{x-1} \boldsymbol{\Delta}\mathbf{n}^w$ and subsequently, for any x, $\frac{\partial \mathbf{s}}{\partial \mathbf{n}}|_{\mathbf{n}^x} = \mathbf{S}_x$. When the process has converged, the adjusted transition matrices are constructed by appropriate partitions of $\mathbf{n}^x$.

Since the least-squares minimand is evaluated afresh at each value of $\mathbf{n}^x$ an optimum is reached as $\boldsymbol{\Delta}\mathbf{n}^x$ converges towards zero and the iterations can be stopped when it is close to zero as defined by an appropriate tolerance level. The adjusted vector $\mathbf{n}^x$ provides the transition matrices at the xth iteration and when these are consistent with observed survival rates, so too will be the healthy and unhealthy life expectancies derived from them. The least-squares adjustment set out here must be looked upon as a systematic procedure for deriving appropriate results of the conditions imposed.

One important consequence of the approach should be mentioned. As the functional specification $\mathbf{s}(\mathbf{n}, \mathbf{y}_T)$ makes clear, the adjusted transition matrices depend on the initial population vector $\mathbf{y}_{T,t}$, a point also discussed above. In any year, this has to be based on the contemporaneous observation. The health mix of people currently of age T is unlikely to match that of people currently aged $T - v$ when they reach age T; indeed that is the reason for focusing on incidence-based measures of healthy life expectancy. It follows that the adjusted transition matrices at any age will depend on the current age of the cohort in question. Ideally one would work with cohort rather than interim life tables, with the survival rates being appropriate to the cohort in question. However official cohort life tables are not available.

5 Application to British Household Panel Survey Data

We focus on the results for healthy life expectancy at age sixty-five for men and women, although the method can obviously be applied to any age. Life expectancy in each health state is calculated as set out in appendix A.2 and the results we present are generated by equation (29) there, with $T = 65$. The initial population estimates are taken from the proportions reporting each health state in the British Household Panel Survey of the year in question. However, since the number of sixty-five year olds is small, we smooth

the figures in two ways. First of all we use in place of the proportion of people aged sixty-five, the mean of the proportions of people in each health state at each age from sixty-three to sixty-seven. Secondly, as with the calculation of official life tables, in place of the proportion in each year, we use the mean of the proportions for the year in question and the year on either side. Even after this smoothing the proportions of people in each health state appears erratic as table 1 shows.

Women	Excellent	Good	Fair	Poor	Very Poor
1992	0.027	0.076	0.262	0.451	0.184
1993	0.028	0.073	0.257	0.460	0.182
1994	0.026	0.067	0.235	0.487	0.186
1995	0.025	0.063	0.237	0.489	0.186
1996	0.021	0.066	0.242	0.489	0.181
1997	0.025	0.075	0.269	0.457	0.175
1998	0.043	0.131	0.280	0.398	0.149
2001	0.047	0.150	0.273	0.370	0.160
2002	0.037	0.108	0.254	0.410	0.190
2003	0.030	0.100	0.267	0.416	0.187
Men	Excellent	Good	Fair	Poor	Very Poor
1992	0.017	0.096	0.235	0.427	0.225
1993	0.016	0.086	0.243	0.443	0.213
1994	0.020	0.081	0.263	0.423	0.213
1995	0.023	0.083	0.268	0.415	0.211
1996	0.030	0.094	0.279	0.388	0.209
1997	0.039	0.100	0.280	0.388	0.194
1998	0.042	0.111	0.290	0.387	0.170
2001	0.030	0.109	0.283	0.396	0.182
2002	0.029	0.102	0.274	0.399	0.195
2003	0.024	0.094	0.274	0.420	0.188

Table 1: Proportion of People in Each Health Category. Age 65 after Smoothing

The unadjusted transition matrices for men and women are used as set out in appendix A.2 to calculate average expected number of years in each health state shown in table 2. There is appreciable variation over time although the time dummies in the probit equations in tables 5 and 6 are for the most part not statistically significant. The results show life expectancy declining over time but at levels which are, except for men in 2002 and 2003, higher than those in the official life tables presented subsequently in table 3. The associated low mortality rates may be due to three factors. First of all, the British Household Panel Survey has trouble in identifying deaths, since they have to be reported by some other household member. Secondly, the survey covers people living in households and not those living in residential care; the death rate is likely to be higher among the latter. Thirdly, following Contoyannis et al. (2004*b*) and Contoyannis et al. (2006) we

have estimated transition rates using an ordered probit model. This smooths out what would otherwise be erratic transformation rates. However this standard approach may not be very good at representing death - our sixth "health state". In any case it is clear from table 2 that one would be reluctant to trust the estimates of even the proportion of time spent in each health state, given that the overall expected life span differs substantially from that shown in the life tables.

We now move on to the estimates of expected time in each health state calculated after adjusting the transition matrices to be consistent with the life tables centred round each year in question. These are shown in table 3. The estimates of overall expected life are the same as those shown in the life tables, and our figures decompose this into the average amount of time expected to be spent in each health state. For women these figures suggest that, over the period 1992-2003, although total life expectancy at sixty-five has increased by 1.3 years, the increase in time expected to be spent in excellent, good or fair health is negligible. For men the picture is more optimistic. Total life expectancy rose by 2.2 years and expected time in excellent, good or fair health rose by 1.0 years. However, it is still the case that the majority of the increased expected life span is spent in poor or very poor health.

6 Comparison with Official Estimates

As noted earlier, the Office for National Statistics compiles estimates of healthy life expectancy based on responses to a question in the General Household Survey (Kelly et al. 2000). The estimates are based on prevalence rather than incidence of poor health and are calculated using Sullivan's method. Direct comparison with our results is complicated by the fact that the question in the General Household Survey differs from that in the British Household Panel Survey. The question asked is 'Over the last 12 months would you say your health has on the whole been good, fairly good or not good?'. Thus people are asked an absolute question rather than one about their health relative to people of their own age and they are given only three response categories as compared to the 'excellent', 'good', 'fair', 'poor' and 'very poor' of the British Household Panel Survey. The estimates for 2001 and 2002 are adjusted in the light of the results of a question about health in the 2001 Census to allow for the health states of people living in institutions; these are disproportionately women and a reasonable assumption is that they live in residential care because their health is poor.

The comparison is shown in table 4. For men the match between our results and the official figures is remarkable given the very different ways in which they were calculated. For women our figures suggest a longer expected period of healthy life in the 1990s al-

though the two are much closer from 2001 onwards. The sharp jump in officially estimated expected healthy life between 1999 and 2001 for women might, however, have some cause other than a change in the underlying health of the population, given that none of the other data are erratic.

7 Conclusions

The purpose of this paper is two-fold. First to provide estimates of healthy life expectancy based on the self-reported health assessment provided in the British Household Panel Survey and secondly to assess the implications of adjusting these estimates so as to be consistent with figures for overall life expectancy provided by the official life tables. Working from the raw data we find that, while we can use ordered probit methods to estimate transition matrices between health states as a function of age, with death treated as a state ranked below very poor health, the results point to a life expectancy at age sixty-five which was generally considerably higher than the official figures. This casts obvious doubt on the validity of the resulting estimates of healthy life.

However we use a non-linear least-squares method to adjust the transition matrices derived from our probit equations so that the resulting overall life expectancy estimates conform to the official figures. Having made this adjustment we then find a much more satisfactory and stable pattern to the estimates of healthy life. For men our figures are remarkably similar to the official estimates produced using prevalance-based measures of poor health. For women our figures point to a healthy life expectation of about a year longer in the early 1990s although the gap had substantially closed by 2002 because the official figures show rising healthy life expectancy which we do not find.

Overall our results point to a healthy life expectancy for men aged sixty-five which has risen less rapidly between 1992 and 2002 than the official estimates of total life expectancy. For women unlike the official figures we find no increase in healthy life expectancy over the period. A broad general conclusion which follows interpreting both our figures and the official data together is that, while healthy life expectancy may have risen between 1992 and 2002, any increase is probably considerably smaller than the increase in overall life expectancy; hence confirming the expansion of morbidity hypothesis (Gruenberg (1977) and Olshansky et al. (1991)). If this pattern continues it has obvious implications for the pressures on medical expenditure as the population ages.

Women	Excellent	Good	Fair	Poor	Very Poor	Total
1992	1.5	9.0	8.1	4.1	1.5	24.1
	(6.2)	(37.3)	(33.6)	(17.0)	(6.2)	(100)
1993	1.3	8.2	7.7	4.1	1.5	22.7
	(5.7)	(36.1)	(33.9)	(18.1)	(6.6)	(100)
1994	1.2	7.9	7.6	4.1	1.5	22.3
	(5.4)	(35.4)	(34.1)	(18.4)	(6.7)	(100)
1995	1.1	7.5	7.4	4.1	1.5	21.7
	(5.1)	(34.6)	(34.1)	(18.9)	(6.9)	(100)
1996	1.0	7.1	7.3	4.1	1.5	21.0
	(4.8)	(33.8)	(34.8)	(19.5)	(7.1)	(100)
1997	1.1	7.4	7.4	4.1	1.5	21.4
	(5.1)	(34.6)	(34.6)	(19.2)	(7.0)	(100)
1998	1.0	6.9	7.1	4.0	1.5	20.4
	(4.9)	(33.8)	(34.8)	(19.6)	(7.4)	(100)
2001	1.0	7.1	7.2	3.9	1.5	20.7
	(4.8)	(34.3)	(34.8)	(18.8)	(7.2)	(100)
2002	0.9	6.6	7.0	3.9	1.5	20.0
	(4.5)	(33.0)	(35.0)	(19.5)	(7.5)	(100)
2003	0.9	6.7	7.0	4.0	1.5	20.2
	(4.5)	(33.2)	(34.7)	(19.8)	(7.4)	(100)
Men	Excellent	Good	Fair	Poor	Very Poor	Total
1992	1.3	7.1	6.2	3.1	1.1	18.8
	(6.9)	(37.8)	(33.0)	(16.5)	(5.9)	(100)
1993	1.2	6.8	6.1	3.1	1.1	18.3
	(6.6)	(37.2)	(33.3)	(16.9)	(6.0)	(100)
1994	1.1	6.5	5.9	3.1	1.1	17.7
	(6.2)	(36.7)	(33.3)	(17.5)	(6.2)	(100)
1995	1.0	6.0	5.7	3.0	1.1	16.8
	(6.0)	(35.7)	(33.9)	(17.9)	(6.5)	(100)
1996	1.1	6.2	5.8	3.0	1.1	17.1
	(6.4)	(36.3)	(33.9)	(17.5)	(6.4)	(100)
1997	1.1	6.3	5.9	3.0	1.1	17.3
	(6.4)	(36.4)	(34.1)	(17.3)	(6.4)	(100)
1998	0.9	5.6	5.6	3.0	1.0	16.1
	(5.6)	(34.8)	(34.8)	(18.6)	(6.2)	(100)
2001	1.0	5.9	5.7	3.0	1.0	16.7
	(6.0)	(35.3)	(34.1)	(18.0)	(6.0)	(100)
2002	0.9	5.5	5.5	3.0	1.1	15.9
	(5.7)	(34.6)	(34.6)	(18.9)	(6.9)	(100)
2003	0.8	5.2	5.4	3.0	1.0	15.4
	(5.2)	(33.8)	(35.1)	(19.5)	(6.5)	(100)

Notes: The expected percentage of total expected life is shown in parentheses below the figures indicating the number of years spent in each state.

Table 2: Unadjusted Estimates of Expected Time in each Health State at Age 65 (in years and percentages)

Women	Excellent	Good	Fair	Poor	Very Poor	Total
1992	1.3	7.1	5.8	2.7	0.9	17.9
	(7.3)	(39.7)	(32.4)	(15.1)	(5.0)	(100)
1993	1.1	6.9	6.0	3.0	1.0	18.0
	(6.1)	(38.3)	(33.3)	(16.7)	(5.6)	(100)
1994	1.1	6.8	6.1	3.0	1.1	18.0
	(6.1)	(37.8)	(33.9)	(16.7)	(6.1)	(100)
1995	1.0	6.7	6.2	3.2	1.1	18.2
	(5.5)	(36.8)	(34.1)	(17.6)	(6.0)	(100)
1996	1.0	6.6	6.3	3.3	1.2	18.2
	(5.5)	(36.3)	(34.6)	(18.1)	(6.6)	(100)
1997	1.0	6.7	6.3	3.2	1.2	18.4
	(5.4)	(36.4)	(34.2)	(17.4)	(6.5)	(100)
1998	0.9	6.5	6.4	3.4	1.2	18.4
	(4.9)	(35.3)	(34.8)	(18.5)	(6.5)	(100)
2001	1.0	6.8	6.6	3.4	1.3	19.0
	(5.3)	(35.8)	(34.7)	(17.9)	(6.8)	(100)
2002	0.9	6.6	6.7	3.6	1.4	19.1
	(4.7)	(34.6)	(35.1)	(18.8)	(7.3)	(100)
2003	0.9	6.7	6.7	3.6	1.4	19.2
	(4.7)	(34.9)	(34.9)	(18.8)	(7.3)	(100)
Men	Excellent	Good	Fair	Poor	Very Poor	Total
1992	1.1	5.6	4.6	2.1	0.7	14.2
	(7.7)	(39.4)	(32.4)	(14.8)	(4.9)	(100)
1993	1.1	5.6	4.7	2.2	0.7	14.4
	(7.6)	(38.9)	(32.6)	(15.3)	(4.9)	(100)
1994	1.0	5.5	4.8	2.3	0.8	14.5
	(6.9)	(37.9)	(33.1)	(15.9)	(5.5)	(100)
1995	0.9	5.4	5.0	2.5	0.8	14.7
	(6.1)	(36.7)	(34.0)	(17.0)	(5.4)	(100)
1996	1.0	5.6	5.0	2.5	0.8	14.8
	(6.8)	(37.8)	(33.8)	(16.9)	(5.4)	(100)
1997	1.0	5.7	5.0	2.5	0.8	15.0
	(6.7)	(38.0)	(33.3)	(16.7)	(5.3)	(100)
1998	0.9	5.5	5.2	2.7	0.9	15.2
	(5.9)	(36.2)	(34.2)	(17.8)	(5.9)	(100)
2001	1.0	5.9	5.4	2.7	0.9	15.9
	(6.3)	(37.1)	(34.0)	(17.0)	(5.7)	(100)
2002	0.9	5.7	5.6	2.9	1.0	16.1
	(5.6)	(35.4)	(34.8)	(18.0)	(6.2)	(100)
2003	0.9	5.7	5.7	3.1	1.0	16.4
	(5.5)	(34.8)	(34.8)	(18.9)	(6.1)	(100)

Notes: The expected percentage of total expected life is shown in parentheses below the figures indicating the number of years spent in each state. In 1994, 1996, 1998 and 2003 the total computed life expectancies are 0.1 years below the published figures. The reason for this discrepancy is discussed in section A.2.

Table 3: Adjusted Estimates of Expected Time in each Health State at Age 65 (in years and percentages)

Women	Total life expectancy	Healthy life expectancy	
		Good or fairly good (GHS) Official Estimates	Very Good, Good or Fair (BHPS)
1992	17.9	13.0	14.2
1993	18.0	13.0	14.0
1994	18.1	12.9	13.9
1995	18.2	13.0	13.9
1996	18.3	...	13.8
1997	18.4	13.1	14.0
1998	18.5	...	13.9
1999	18.6	13.1	
2000	18.8	...	
2001	19.0	14.0*	14.3
2002	19.1	14.0*	14.2
2003	19.3		14.3
Men	Total life expectancy	Healthy life expectancy	
		Good or fairly good (GHS)	Very Good, Good or Fair (BHPS)
1992	14.2	10.8	11.4
1993	14.4	10.9	11.4
1994	14.5	11.0	11.4
1995	14.7	11.3	11.3
1996	14.8	...	11.5
1997	15.0	11.7	11.7
1998	15.2	...	11.6
1999	15.4	11.5	
2000	15.7	...	
2001	15.9	11.9*	12.3
2002	16.1	12.0*	12.2
2003	16.4		12.3

Notes: Healthy life expectancy estimates for 2001 and 2002 are derived from the General Household Survey and use a new methodology adopted by the Office for National Statistics which adjusts for the actual size and age distribution of the communal establishment population from the 2001 Census.

Table 4: Life expectancy and healthy life expectancy estimates at age 65 between 1991 and 2003 (in years). Official General Household Survey estimates compared with British Household Panel Survey incidence-based estimates.

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A Appendix: Estimation of Healthy Life Expectancy

Healthy life expectancy measures which combine mortality and morbidity into a single composite indicator are a very useful tool for monitoring long term trends in the evolution of population health and for addressing the question of compression or expansion of morbidity in populations. Over the last thirty years there has been a dramatic increase

in the number of health expectancy calculations carried out, almost all using the Sullivan method, which is dependent on past flows. More recently, multi-state life table methods have been developed which require information on transitions between health states. It has been claimed that Sullivan's method produces biased estimates and so it is an incorrect method of monitoring health expectancies over time (Rogers et al. (1990) and van de Water et al. (1995)). This section reviews the techniques used to incorporate healthy life expectancy based on single-state life tables (Sullivan's method based on the prevalence of disability that is a stock that is dependent on past history) and incidence-based transition probabilities (multi-state method which can adjust to represent current health problems by accounting reversible transitions between health states).

A.1 The Single-State Method

The single-state approach requires only a population life table, constructed for a population using the observed mortality rates at each age for a given time period, and prevalence data for the health states of interest (see Bebbington (1991), Mathers et al. (1994) and Mathers (1996) for an extensive discussion). Such prevalence rates can be obtained readily from cross-sectional health or disability surveys carried out for a population at a point in time. Surveys of this type are carried out regularly in the UK, both at the national (Robine & Ritchie (1991) and Matthews et al. (2006)) and regional level (Congdon (2006)), and indeed across the European Union member states (Robine & Jagger (2003) and Robine et al. (2004)). Its interest lies in its simplicity, the availability of its basic data and its independence of the size and age structure of the population.

Sullivan's method calculates the expected life expectancy of individuals currently at specified ages if they lived the rest of their lives experiencing the age specific mortality rates observed for the population at a specific time. It uses age specific mortality figures to calculate the proportion of individuals alive at the beginning of an age interval that die before reaching the next age group. The method has proven to be an powerful tool for estimating the remaining years of life that a group of individuals can expect to live once they reach a certain age. The procedure for calculating Sullivan's method is outlined below. Once again, the results are specific to the year to which the data relate, although we do not include time subscripts.

First, the population at each age in the life table needs to be separated into the proportion experiencing an unhealthy condition, π^{T+v}, and those considered as healthy, $1 - \pi^{T+v}$. The number of healthy people of age $T + v$ is given by

$$z_H^{T+v} = z^{T+v}(1 - \pi^{T+v}) \tag{24}$$

where z^{T+v} is the size of the population of age $T+v$.

The expected number of healthy life years for people aged T is then given as

$$e_T = \frac{1}{z^T} \sum_{T}^{T^{\max}} z_H^{T+v} \text{ where } T^{\max} \text{ is the maximum life-span.} \tag{25}$$

Hence equation (25) presents the proportion of years lived in a healthy state. However, if multiple health states are given, the prevalence at each age for each of those states must be computed which are then used to estimate separately the expected duration of life in those health status.

Problems relating to the validity of the Sullivan method were first pointed out by Bebbington (1992) and Barendregt et al. (1995). They suggest that Sullivan's method underestimates healthy life expectancy weighed against the multi-state method because the bias in the estimation of disability prevalence reflects past experience of each cohort and not the current incidence rates. Past wars, for instance, may continue to affect current disablement rates, as may the past state of health care, as conditions such as polio and thalidomide illustrate. The problems with Sullivan's method arise not because it uses prevalence and mortality data averaged over all health states, but because the data it uses are dependent on past conditions in the population. Therefore, if public health is changing, present prevalence may be a poor guide in predicting future long term care needs.

While the Sullivan method cannot deal with interstate transfers and so it is not suitable for detecting abrupt adjustments in health trends, Mathers & Robine (1997) develop simulation models using French data which suggest that it does however provide accurate estimates of the multi-state value if there are smooth and relatively regular changes over the longer term. They argue that Sullivan's method is an acceptable method for monitoring relatively smooth long term trends in health expectancies at the population level in non-stationary populations.

A.2 The Multi-State Method

Our understanding of patterns and behaviour of mortality, fertility and life expectancy is enhanced by a focus on occurrences of events and transfers and on their association with the populations that are exposed to the risk of experiencing them. The use of the multi-state method which accounts for such an association, were first proposed by Newman (1988), Rogers, Rogers & Branch (1989) and Rogers, Rogers & Belanger (1989) who modelled reversible transitions of individuals of a specific cohort among non-absorbing states. More recently, other authors have widely discussed the multi-state approach of transitions among health states over age (see among others, Crimmins et al. (1994),

Crimmins et al. (1996), Davis et al. (2001), Ledent (1990) and Diehr & Patrick (2001)).

Both theoretically and technically, the multi-state life table method is to be preferred for calculating health expectancies since it is based on period transition rates and will thus detect sudden or gradual changes in disability incidence rates over time. However, since its implementation requires longitudinal data which are expensive and time consuming there are very few countries where national data are available. Whilst the British Household Panel Survey, along with the European Household Panel Survey, has opened up new prospects for calculating interstate transition probabilities, it does not cover the institutional population.

The multi-state method applied here provides the critical link between information on mortality and information on the spectrum of non-fatal health experiences among the living. Whereas the Sullivan method gives only the average health expectancy for the entire population at a given age, the multi-state approach provides transition probabilities differentiated by origins and destinations at an individual level at a given age.

We set out here the calculation of expected time in each health state for the adjusted transition matrices, $\tilde{\mathbf{M}}^{r,T,t}$ for individuals aged T in year t; when the life expectancies are calculated for the unadjusted transition matrices these are simply replaced by $\mathbf{M}^{r,t}$. Given that each element of $\tilde{\mathbf{M}}^{r,T,t} = \{\widetilde{m}_{q,p}^{r,T,t}\}$ represents the probability that an individual in health state p at age r in year $t + r - T$ will be in health state q a year later ($p = 1, ..., 5; q = 1, ..., 5$), we define

$$\mathbf{N}^{T+1,T,t} = \tilde{\mathbf{M}}^{T,T,t} \tag{26}$$

$$\mathbf{N}^{T+v+1,T,t} = \tilde{\mathbf{M}}^{T+v,T,t}\mathbf{N}^{T+v,T,t} \tag{27}$$

where $\{n_{q,p}^{T+v,T,t}\}$, the element in row q and column p of $\mathbf{N}^{T+v,T,t}$, is the probability that an individual is in state q at age $T + v$ conditional being in state p at age T. Hence given $\left\{n_{q,p}^{T+v,T,t}\right\}$, one can obtain the proportion of survivors at age $T + v$ who are in state q at age $T + v + 1$.

Following standard UK practice, we make the assumption that transitions occur evenly throughout the year. Since we are concerned about healthy life expectancy of adults we do not need to take account of the death rates, month by month of babies under one year old. The official UK life tables do, however, incorporate an adjustment for this. We denote by $\mathbf{Z}^{T+v,T,t}$ the total number of years lived in each health state of the population alive at age $T + v$ as a function of its health state at age T predicted from the data and transition matrices for year t. This satisfies the recursion

$$\mathbf{Z}^{T+v,T,t} = \mathbf{Z}^{T+v+1,T,t} + (\mathbf{N}^{T+v,T,t} + \mathbf{N}^{T+v+1,T,t})/2 \tag{28}$$

with $\mathbf{Z}^{T^*,T,t} = \mathbf{N}^{T^*,T,t} = 0 \,\forall\, T^* \geq T^{\max}$, the maximum life-span. We denote $\mathbf{l}^{T+v,T,t} = \mathbf{i}'\mathbf{N}^{T+v,T,t}$ and $\widehat{\mathbf{l}^{T+v,T,t}}$ the matrix with $\mathbf{l}^{T+v,T,t}$ on its leading diagonal and zeros elsewhere. Then the matrix $\mathbf{Z}^{T+v,T,t}\ \widehat{\mathbf{l}^{T+v,T,t}}^{-1}$ indicates the expected number of years to be spent in each health state at age i as a function of initial health state at age T.

However, the actual expected time in each category depends on the actual health of the population at time T. With our vector $\mathbf{y}_{T,t}$ showing the number of people in each health state at age T in year t, the expected amount of time spent in each state averaged across the population, is given as

$$\mathbf{e}^{T+v,T,t} = \frac{\mathbf{Z}^{T+v,T,t}\widehat{\mathbf{l}^{T+v,T,t}}^{-1}\mathbf{y}_{T,t}}{\mathbf{i}'\mathbf{y}_{T,t}} \tag{29}$$

The official life tables are published only for ages from 0 to 100. However they embody assumptions about survival rates of people over 100. Since these are not publicly available, we assume that no one survives beyond one hundres. As a consequence the life expectancies that we calculate can be slightly lower than those published, even though our survival rates for people up to one hundred match the official figures once the transition matrices are adjusted. However the error not of practical importance. To one decimal place there is no effect on male life expectancy. Female life expectancy at age sixty-five is, however, in some years computed to be 0.1 years below the published figure. The figures for women are affected more than those for men because more women survive beyond one hundred.

B Appendix: Ordered Probit Equations used to Construct Transition Probabilities

To account for possible health-related sample attrition in the British Household Panel Survey we consider augmenting (1) with the following sample selection equation

$$\begin{aligned} sel^*_{i,t} &= 1 \text{ if } \boldsymbol{\beta}^{s\prime}\mathbf{x}^s_{i,t} + \boldsymbol{\gamma}^{s\prime}\mathbf{h}_{i,t-1} + \eta^s_i + \mathbf{w}^{s\prime}\boldsymbol{\zeta}_t + e^s_{i,t} > 0, \\ &= 0, \text{ otherwise} \end{aligned} \tag{30}$$

so that $sel^*_{i,t}$ is a selection (binary) indicator, equal to one when the $i-$th individual is present in the British Household Panel Survey at time t, zero otherwise, and the vector $\mathbf{x}^s_{i,t}$ comprises $\mathbf{x}_{i,t}$ plus the logarithm of annual individual income. It is assumed that $e^s_{i,t} \sim N(0,1)$. Only when $sel^*_{i,t} = 1$ is $h^*_{i,t}$ observed and $h_{i,t} = j$ $(j = 0, 1, ..., 5)$. ρ denotes the correlation between $e^s_{i,t}$ and $e_{i,t}$. (1) and (30) are jointly estimated by maximum

likelihood. In practice this was achieved by adopting a generalised latent mixed modelling framework (Skrondal & Rabe-Hesketh (2004)). This involves assuming the dependence between $e_{i,t}$ and $e^s_{i,t}$ is determined by a common factor $f_{i,t}$, such that

$$e_{i,t} = \lambda f_{i,t} + \tau_{i,t} \tag{31}$$

$$e^s_{i,t} = f_{i,t} + \kappa_{i,t} \tag{32}$$

where $f_{i,t}$, $\tau_{i,t}$ and $\kappa_{i,t}$ are independently distributed standard normal random variables and λ is an estimable (factor loading) parameter. This implies the correlation coefficient, ρ, equals

$$\rho = \frac{\lambda}{\sqrt{2(\lambda^2+1)}}. \tag{33}$$

A test of $\lambda = 0$ ($\rho = 0$) then amounts to a test for sample attrition. When $\lambda = 0$ consistent estimators of the parameters in (1) are obtained by estimating (1) without reference to (30). The Stata programme gllamm, and the associated ssm 'wrapper', was used for estimation (Skrondal & Rabe-Hesketh (2004) and Miranda & Rabe-Hesketh (2006)).

We also follow Contoyannis et al. (2004*b*) and Contoyannis et al. (2006) in their analysis of health related attrition in the British Household Panel Survey and employ an inverse probability (IPW) estimator to correct for sample attrition; see Wooldridge (2002) and Wooldridge (2005). This estimator cannot be applied to the random effects model ($\sigma^2_v > 0$), only to the pooled model ($\sigma^2_v = 0$). Again this relies on estimation of probit models for $sel^*_{i,t}$.

Tables 5 and 6 present the coefficient estimates for the ordered dynamic probit models based on pooled and random effects specifications for men and women respectively. In both tables column (i) gives the estimates for the pooled ordered probit model based on estimation of (1) alone. Column (ii) then applies the IPW estimator to accommodate sample attrition. Column (iii) then estimates (1) and (30) jointly for the pooled model. Attempts to estimate jointly using gllamm allowing $\sigma^2_v > 0$ proved computationally too burdensome. Results for the random effects model are therefore presented in column (iv) based on estimation of (1) alone.

In both tables the estimated coefficients on the lagged categories of $\mathbf{h}_{i,t}$ are highly statistically significant. There is an upward gradient across these lagged categories (starting with "very poor" health and moving to "excellent" health). This evidence of positive state dependence is consistent with related work on the dynamics of health in the British Household Panel Survey; see Contoyannis et al. (2004*b*). Note that the baseline category used here is "good" health. The dummies for the state of health in the initial wave (year

1991) are also statistically significant and, like the dummies for the lagged health state, current period health improves with better initial health. The statistical significance of the squared term in age implies health deteriorates in a quadratic manner with older age. Inspection of the time dummies reveals there is a tendency for health to decline over the sample period 1991-2004. The time dummies tend to be more statistically significant for the random effects specification (column (iv)) and for earlier waves.

Tables 5 and 6 reveal that one can reject the null hypothesis that $\lambda = 0$ at a 95% level of significance for both men and women. This suggests there is health related sample attrition. But in-line with Contoyannis et al. (2004*b*) and Contoyannis et al. (2006) this does not appear to influence the parameter estimates in Tables 5 and 6. One can also reject the hypothesis that $\sigma_v^2 = 0$ using a likelihood-ratio test comparing column (i) against column (iv). This is consistent with the statistical significance of σ_v^2. Column (iv) is therefore the preferred model since accommodating individual-level heterogeneity delivers an improved statistical fit relative to pooled comparators.

	(i) Pooled with no sample selection	(ii) Pooled sample selection IPW	(iii) Pooled sample selection joint estimation of (1) and (30)	(iv) Random effects with no sample selection
Dependent Var:	*No. obs.*	*No. obs.*	*No. obs.*	*No. obs.*
$h^*_{i,t}$	38553	36663	101301	38553
$\text{AGE}_{i,t-1}$	0.011 (0.002)	0.011 (0.002)	0.012 (0.002)	0.030 (0.004)
$\text{AGE}^2_{i,t-1}$ ($\times 10^{-4}$)	-1.976 (0.189)	-1.957 (0.224)	-2.023 (0.195)	-4.394 (0.358)
Health status for individual i at year $t-1$ (base=Good)				
EXCELLENT	0.852 (0.017)	0.869 (0.020)	0.865 (0.020)	0.481 (0.025)
FAIR	-0.760 (0.017)	-0.773 (0.018)	-0.771 (0.020)	-0.461 (0.021)
POOR	-1.470 (0.027)	-1.500 (0.030)	-1.492 (0.033)	-0.944 (0.037)
VERYPOOR	-1.997 (0.457)	-2.001 (0.048)	-2.025 (0.052)	-1.361 (0.059)
DEATH	$-\infty$	$-\infty$	$-\infty$	$-\infty$
Health status for individual i in 1991 (base=Good)				
EXCELLENT	0.322 (0.015)	0.327 (0.017)	0.326 (0.016)	0.589 (0.032)
FAIR	-0.267 (0.018)	-0.261 (0.018)	-0.273 (0.019)	-0.545 (0.036)
POOR	-0.472 (0.030)	-0.469 (0.029)	-0.470 (0.031)	-1.032 (0.054)
VERYPOOR	-0.582 (0.052)	-0.604 (0.050)	-0.585 (0.053)	-1.318 (0.104)
Time dummy effects				
year 1992	0.027 (0.029)	0.029 (0.030)	0.056 (0.032)	0.178 (0.031)
year 1993	0.028 (0.029)	0.017 (0.030)	0.047 (0.031)	0.148 (0.032)
year 1994	0.015 (0.029)	0.017 (0.030)	0.027 (0.030)	0.112 (0.031)
year 1995	-0.020 (0.030)	-0.020 (0.030)	-0.015 (0.030)	0.054 (0.032)
year 1996	0.017 (0.030)	0.016 (0.030)	0.021 (0.030)	0.073 (0.031)
year 1997	0.033 (0.030)	0.033 (0.031)	0.035 (0.030)	0.085 (0.031)
year 1998	-0.037 (0.030)	-0.041 (0.031)	-0.040 (0.030)	0.005 (0.031
year 2001	0.034 (0.031)	0.036 (0.032)	0.022 (0.032)	0.044 (0.032)
year 2002	-0.021 (0.031)	-0.028 (0.032)	-0.037 (0.032)	-0.005 (0.030)
year 2003	-0.042 (0.031)	-0.039 (0.032)	-0.062 (0.033)	-0.037 (0.032)
Cut-Point 1	-3.08 (0.059)	-3.104 (0.072)	-3.048 (0.061)	-3.095 (0.107)
Cut-Point 2	-2.61 (0.058)	-2.640 (0.067)	-2.573 (0.059)	-2.586 (0.102)
Cut-Point 3	-1.818 (0.056)	-1.844 (0.064)	-1.768 (0.058)	-1.701 (0.098)
Cut-Point 4	-0.722 (0.055)	-0.726 (0.062)	-0.655 (0.061)	-0.462 (0.096)
Cut-Point 5	0.951 (0.055)	0.954 (0.062)	1.043 (0.072)	1.441 (0.097)
Log likelihood	-37512.378	-34707.715	-70605.968	-36554.280
λ			0.195 (0.083)	
σ^2_v				0.415 (0.020)

Notes: Robust estimated standard errors are reported in parentheses. Cut-Point 1 to Cut-Point 5 are the estimated threshold parameters α_j ($j = 1, ..., 5$). Estimates for the pooled model with sample selection, based on joint estimation of (1) and (30), and the random effects model are re-scaled so that the (composite) error term has a variance of unity. This ensures comparability across columns (i)-(iv).

Table 5: Dynamic ordered probit models with pooled and random effects specifications - men

	(i) Pooled with no sample selection	(ii) Pooled sample selection IPW	(iii) Pooled sample selection joint estimation of (1) and (30)	(iv) Random effects with no sample selection
Dependent Var:	*No. obs.*	*No. obs.*	*No. obs.*	*No. obs.*
$h^*_{i,t}$	45127	43581	117437	45127
$\text{AGE}_{i,t-1}$	0.011 (0.002)	0.010 (0.002)	0.012 (0.002)	0.030 (0.003)
$\text{AGE}^2_{i,t-1}$ ($\times 10^{-4}$)	-1.834 (0.184)	-1.761 (0.200)	-1.956 (0.178)	-4.086 (0.286)
Health status for individual i at year $t-1$ (base=Good)				
EXCELLENT	0.851 (0.016)	0.878 (0.020)	0.867 (0.019)	0.496 (0.024)
FAIR	-0.720 (0.015)	-0.739 (0.016)	-0.734 (0.017)	-0.427 (0.020)
POOR	-1.361 (0.022)	-1.383 (0.025)	-1.387 (0.028)	-0.880 (0.031)
VERYPOOR	-1.776 (0.037)	-1.819 (0.041)	-1.810 (0.043)	-1.147 (0.049)
DEATH	$-\infty$	$-\infty$	$-\infty$	$-\infty$
Health status for individual i in 1991 (base=Good)				
EXCELLENT	0.295 (0.143)	0.284 (0.016)	0.301 (0.015)	0.555 (0.030)
FAIR	-0.285 (0.154)	-0.292 (0.016)	-0.289 (0.016)	-0.511 (0.029)
POOR	-0.484 (0.023)	-0.496 (0.025)	-0.485 (0.024)	-0.935 (0.045)
VERYPOOR	-0.617 (0.042)	-0.638 (0.043)	-0.624 (0.043)	-1.226 (0.074)
Time dummy effects				
year 1992	0.070 (0.026)	0.069 (0.027)	0.096 (0.028)	0.206 (0.028)
year 1993	0.018 (0.026)	0.015 (0.027)	0.035 (0.027)	0.134 (0.028)
year 1994	0.015 (0.026)	0.013 (0.027)	0.024 (0.027)	0.110 (0.028)
year 1995	0.003 (0.027)	0.003 (0.027)	0.006 (0.027)	0.079 (0.028)
year 1996	-0.017 (0.027)	-0.016 (0.027)	-0.016 (0.027)	0.043 (0.027)
year 1997	0.017 (0.027)	0.010 (0.028)	0.015 (0.027)	0.064 (0.028)
year 1998	-0.032 (0.027)	-0.034 (0.028)	-0.038 (0.028)	0.077 (0.027)
year 2001	0.016 (0.028)	0.025 (0.029)	0.002 (0.029)	0.020 (0.027)
year 2002	-0.023 (0.028)	-0.025 (0.029)	-0.041 (0.029)	-0.013 (0.027)
year 2003	-0.007 (0.028)	-0.002 (0.028)	-0.029 (0.029)	-0.003 (0.028)
Cut-Point 1	-3.200 (0.055)	-3.252 (0.069)	-3.177 (0.058)	-3.115 (0.093)
Cut-Point 2	-2.582 (0.053)	-2.633 (0.063)	-2.547 (0.055)	-2.441 (0.087)
Cut-Point 3	-1.755 (0.052)	-1.812 (0.060)	-1.704 (0.053)	-1.521 (0.084)
Cut-Point 4	-0.666 (0.051)	-0.703 (0.059)	-0.594 (0.055)	-0.299 (0.083)
Cut-Point 5	1.032 (0.051)	1.003 (0.059)	1.137 (0.065)	1.618 (0.085)
Log likelihood	-46070.606	-43161.870	-82487.680	-44956.598
λ			0.222 (0.067)	
σ^2_v				0.382 (0.017)

Notes: Robust estimated standard errors are reported in parentheses. Cut-Point 1 to Cut-Point 5 are the estimated threshold parameters α_j ($j = 1, ..., 5$). Estimates for the pooled model with sample selection, based on joint estimation of (1) and (30), and the random effects model are re-scaled so that the (composite) error term has a variance of unity. This ensures comparability across columns (i)-(iv).

Table 6: Dynamic ordered probit models with pooled and random effects specifications - women