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Discussion Paper Series

No. 13/02

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This version is from May 2013

Abstract

Health care funding decisions in the UK are based on valuations of the general public. However, it has been shown that there is a disparity between a hypothetical valuation of the impact of a specific condition on health and the effect of that health state by someone who experiences it. This paper examines the issue of adaptation to health states, which partially may explain the discrepancy between hypothetical and experienced health state valuations. We use the British Cohort Study (BCS70) which is a longitudinal dataset that tracks a sample of British individuals since their birth in 1970. We use four BCS70 waves containing information on self-assessed health (SAH), morbidity as well as a number of socio-economic characteristics. To estimate the issue of adaptation, we implement a *dynamic ordered probit model* that controls for (health) state dependence. The empirical specification controls for morbidity and also includes a variable for the duration of the illness. We find that, for most chronic conditions, duration has a positive impact on self-assessed health, while for some conditions-such as diabetes- this does not occur. We interpret our results as evidence in support of the hypothesis that adaptation to chronic diseases exists and may explain at least in *part* the differences between general public and patients' health state valuations.

Keywords: Self Assessed Health, Dynamic Ordered Probit, Adaptation to health states

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1. Introduction

Numerous studies show important differences between the pleasure (and displeasure) humans predict they will experience, and that is actually experienced, for a wide range of consumption choices and life decisions (Ayton et al, 2007). Famously, despite most people's strong expectations to the contrary, the life satisfaction of paraplegics and lottery millionaires are barely distinguishable *sometime after* the event (Brickman et al, 1978). Studies of health states reveal large differences between the anticipated intensity and duration of the effect of impairments to health, as considered by the general public assessing health problems hypothetical to them, and the experiences reported by those who actually have those conditions (Ubel et al, 2003). The disparity in the perception of the magnitude of the impact that certain chronic conditions have on self-assessed health (SAH) would not be so relevant if health care funding decisions, such as the National Institute of Clinical Excellence, did not favour one set of valuations (public) over others (patients or carers). It is paramount to understand and establish the magnitude of these health valuation disparities to assess the real implications of funding decisions based on one set of valuations versus another.

As Ubel et al. (2003) point out, even though the disparity between the valuations of healthy control and patients is well established, the reasons behind the disparity are still controversial. At present several theories have been developed to explain the origin of the different quality of life (QoL) results derived from alternative health measurements. The potential explanations range from framing effects to differentials in the interpretation and understanding of health states descriptions, which could be due to response shift, focusing illusion, contrast effects, perspective, etc. One of the most accepted explanations for the dissimilar health measurements relies on the patient *adaptation* and public failure to predict it. That is, people adapt to many of the constraints and discomforts of health states but this is not anticipated by people who do not experience them. This paper, which is part of a bigger project[1], focuses on the particular issue of the existence of adaptation to long-standing illnesses and chronic health states experienced by patients, using a longitudinal panel dataset.

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Our paper is related to two main strains of literature. First of all, to that of *adaptation* to health states for which there is an extensive literature in the multidisciplinary field of experimental economics and psychology. Riis et al. (2005) and Damschroder et al. (2005) review in more detail the research in this area that originated following some early papers reporting the rather counter-intuitive evidence that individuals in severely limiting health states feel their happiness/wellbeing is well above the ratings that healthy subjects attribute to them. Some other example of this stream of work include Brickman et al. (1978), Sackett et al. (1978), Boyd et al. (1990), Buick et al. (2002), and Baron et al. (2003).

The second stream of literature related to our paper is that of the dynamics of SAH over time, frequently studied using longitudinal panel data (Jones et al., 2009). Contoyannis et al. (2004), for instance, focuses on the role that unobserved heterogeneity and socioeconomic status have in explaining changes in health controlling for health state dependence (persistence in health outcomes) and attrition. In a closely related paper, Carro and Taferri (2012) suggest refining this approach by applying a bias-corrected fixed effects estimator. Halliday (2008) analyses the subject of health state dependence and heterogeneity reducing the model to a binary outcome model and applying a different random-effects approach. Buckley et al. (2004) had also used three years of the Canadian Survey of Labor and Income Dynamics to estimate the impact of socioeconomic factors, in particular income, on the health state valuations individuals aged fifty years and older. They found that after controlling for age, education and the endogeneity of wealth, income did affect positively the SAH of men and women above fifty.

Contoyannis and Li (2011) also use a Canadian database, the Canadian National Longitudinal Survey of Children and Youth (NSLCY), to study persistence of health states for children. They find that children living in less structured and poorer households remain in lower health states for longer. Related to the subject of the effect that income has on the persistence in (worse) health states, a series of papers concentrate on issues of *inequality* in the presence of health state persistence. Hauck and Rice (2004) use the British Household Panel Survey to show that health state persistence is greater for those individuals in lower income and less educated groups; Jones and Lopez-Nicolas (2004) propose a health related income mobility index estimator which is further explored in Allanson et. al (2010). Although it does not use self-reported health, Oswald et al. (2008) estimate a hedonic model with fixed effects using the British Household Panel Data to explain self reported life satisfaction of individuals having suffered some sort of disability. They find that individuals recover between 30% to 50% of their pre-disability life-satisfaction sometime after the change in their health.

Therefore, the main focus of the extant literature analysing longitudinal data on SAH has been the relationship between this variable and socio-economic characteristics controlling for the existence of state dependence and unobserved heterogeneity. Nevertheless, these papers do not model explicitly long standing health-related conditions as factors that may explain the dynamics in SAH – despite them being included in the calculation of the probability weights computed to correct for attrition bias (Jones et al., 2006). We think accounting for chronic conditions in particular may be important to understand the issue of adaptation to health states. For instance, if an individual reports the same SAH in two consecutive periods, it may be inferred that her health status has not changed significantly. However, if we have information about, and account for, the onset of a new chronic condition between those two periods, then we would have to conclude that the state-dependence coefficient implicitly captures the process of quick adaptation to the new health condition.

We hypothesize that 1) the impact of the presence of long standing illnesses on SAH can be teased out explicitly from the state dependence estimates obtained by the preceding literature and, therefore 2) the magnitudes of the state dependence estimates are necessarily affected by the process of adaptation to these chronic conditions.

To test our hypotheses and analyse the issue of adaptation, our paper estimates the effect of the presence of long standing illnesses and the 'time since diagnosis' on SAH controlling for state dependence, socioeconomic characteristics, unobserved heterogeneity and attrition as in Contoyannis et al. (2004) and Jones et al. (2006). We use the British Cohort Study, a longitudinal dataset set that surveys periodically a cohort of originally 17,287 individuals born in 1970 in England, Wales and Scotland. This dataset records both self-health assessed health and changes in the health state of the individuals, i.e. onset of chronic diseases and health shocks as well as socioeconomic and demographic characteristics. We are interested in studying if there is a positive relationship between the length of time an individual suffers from a chronic illness and the likelihood of reporting better health while controlling for changes in other socioeconomic factors and co-morbidities. If a positive effect is found, the results will support the existence of adaptation as well as its contribution to explain the state-dependent observable fact.

This paper is organised as follows, in the following section we present our empirical strategy. Section three describes the dataset and the variable included in the empirical specification. Some descriptive statistics are also provided. We report our results in section four and discuss the findings. The final section concludes and also points towards the next steps for future research.

2. Empirical Strategy

As discussed in the previous section, the existence of health state dependence has been documented by various papers showing that there is a strong persistence of health states overtime when using longitudinal panel data. To explore the issue of adaptation to health states and its impact on SAH, we adopt the latent health model framework in Contoyannis et al. (2004) and Jones et al. (2006) and assume the following dynamic structure for the latent self-assessed health overtime:

$$sah^*_{it} = \alpha \cdot sah_{it-1} + \beta \cdot m_{it} + \delta \cdot d_{it} + \gamma \cdot x_{it} + c_i + u_{it} \qquad (1),$$

where sah_{it} and sah_{it-1} are individual *i's* self-assessed health in period *t* and *t-1*, respectively. Our variables of interest are the morbidity variable captured in m_{it} and the variable that denotes duration denoted by d_{it}. We would expect a negative estimate for the morbidity coefficient β while a positive value of the coefficient for duration δ would support our hypotheses on the existence of adaptation. The vector x_{it} includes a number of explanatory variables, containing a measure of morbidity and time since the onset of the illness. The individual time-invariant fixed-effect is captured by c_i , and u_{it} is the error term. The standard assumption of normality of the error term holds here $u_{it} \sim N(0,1)$ as well as the no correlation condition between the error term, the explanatory variables and the unobserved fixed-effect.

Given that sah^*_{it} is a latent variable, we only can observe the category chosen by the individual at each point in time:

$$\begin{aligned} sah_{it} &= 1 \text{ if } -\infty < sah^*_{it} < \lambda_1 \\ sah_{it} &= 2 \text{ if } \lambda_1 < sah^*_{it} < \lambda_2 \\ sah_{it} &= 3 \text{ if } \lambda_2 < sah^*_{it} < \lambda_3 \\ sah_{it} &= 4 \text{ if } \lambda_3 < sah^*_{it} < +\infty \,, \end{aligned}$$

where $\lambda_0 = -\infty$ and $\lambda_4 = +\infty$. Thus, under the assumption of normality of the error term u_{it}, the probability of observing individual choosing category k is:

$$\begin{aligned} P(sah_{it} = k) = \Phi(\lambda_k - \alpha \cdot sah_{it-1} - \beta \cdot m_{it} - \delta \cdot d_{it} - \gamma \cdot x_{it} - c_i) - \\ -\Phi(\lambda_{k-1} - \alpha \cdot sah_{it-1} - \beta \cdot m_{it} - \delta \cdot d_{it} - \gamma \cdot x_{it} - c_i) \end{aligned} \quad (2)$$

The estimation of model (2) presents two challenges unobserved heterogeneity and attrition between waves. First, in a dynamic nonlinear model, treating initial observations as exogenous leads to inconsistent estimators. This is corrected using the approach suggested by Wooldridge (2005) by which the unobserved fixed effect is estimated taking into account the initial self-assessed health:

$$c_i = \sigma + \varphi \cdot sha_{i1} + \kappa \overline{x_i} + \varepsilon_i \,. \quad (3)$$

Accordingly, the new latent variable model for self-assessed health is:

$$sah^*_{it} = \alpha \cdot sah_{it-1} + \beta \cdot m_{it} + \delta \cdot d_{it} + \gamma \cdot x_{it} + \sigma + \varphi \cdot sah_{i1} + \kappa \overline{x_i} + \varepsilon_i + u_{it} \,. \quad (4)$$

Second, as is usual in longitudinal datasets, ours has an important percentage of non-respondents for each wave. If nonresponse is endogenously determined there is bias and the inference is not robust. Thus, as explained in detail below, we test for the presence of endogenous attrition in the dataset using the Verbeek and Nijman (1992) test. Given that the test indicates the presence of attrition, we correct for attrition using the inverse probability weight approach suggested by Wooldridge (2005). To compute the correcting weights we estimate a probit on a variable response variable defined as $R_i = 1$ if individual i responds to wave t and $R_i = 0$ otherwise. The covariates included in the probit are all regressors in our empirical model at the first period, x_{i1996}. The ordered probit in model (4) is then estimated by weighting each observation by the inverse (predicted) probability of being present in each wave. We do not report here the coefficients for the mean of the exogenous variables $\overline{x_i}$ used to parameterise the unobserved effect.

3. Data

The data we use to test the model is the 1970 British Cohort Study (BCS70). The BCS70 data started being compiled from a sample of 17,287 babies born in England, Wales and Scotland at a specific week in April 1970. Since then there have been seven surveys at the ages of 5 (year 1975), 10 (year 1980), 16 (year 1986), 26 (year 1996), 30 (year 2000), 34 (year 2004) and 38 (year 2008). An additional survey of those individuals aged 42 is currently being conducted. The BCS70 contains information on socioeconomic and demographic characteristics and also special questions on specific issues of interest such as health, political positions or attitudes towards risk. Since our variable of interest is SAH and the relevant data started being collected only when the cohort was aged 26 years old, we concentrate on the waves 1996, 2000, 2004 and 2008, i.e. when individuals were 26, 30, 34 and 38 years old.

Each wave poses the question of SAH in terms of how individuals would describe their health in general. However, the 2004 survey includes a different formulation and asks individuals "*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...*". This question introduces an age-contextualization that was not present in the other waves. In addition, it frames the question as it refers to the last 12 months. Differences in the SAH question wording have been analysed in the context of the British Household Panel Survey

(BHPS) and the evidence suggests that there is no significant impact on the estimates (Hernández-Quevedo et al, 2008).

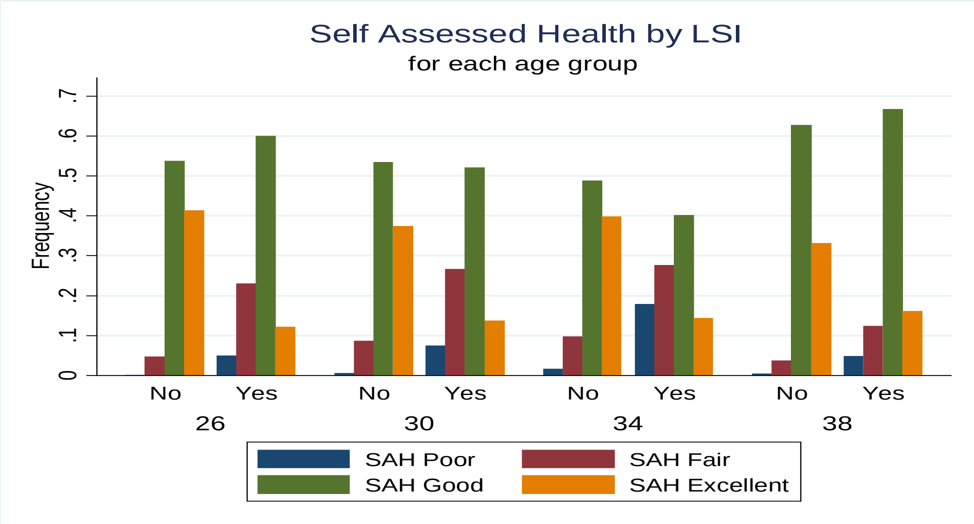
Additionally, the question on self-assessed health across waves changes the number of categories. As shown in Table 1, the 1996 and 2000 surveys have four categories, whereas the 2004 and 2008 surveys have five categories. Evidence from the BHPS suggests that collapsing the categories does not affect the estimations of covariates (Hernández-Quevedo et al, 2008). This approach has been used by several authors (e.g. Lindley and Lorgelly, 2007; Cubi-Molla and Herrero, 2011) and will also be implemented here. Table 1 shows the distribution of frequencies for each category in each of the four waves.

Table 1. Survey Definitions of SAH and re-coding for analysis

SAH Used in Estimations	Waves			
	1996	2000	2004	2008
1 = Poor	Poor (1.1%)	Poor (2.2%)	Very poor (1.4%) Poor (4.8%)	Poor (2.8%)
2 = Fair	Fair (8.5%)	Fair (12.8%)	Fair (14.8%)	Fair (8.3%)
3 = Good	Good (55.2%)	Good (53.1%)	Good (46.4%)	Good (26.5%) Very good (38.3%)
4 = Excellent	Excellent (35.2%)	Excellent (31.9%)	Excellent (32.6%)	Excellent (24.1%)

Figure 1 shows the distribution of SAH for those with or without a long-standing illness (LSI) at each wave for the unbalanced panel; i.e., for those observations that have complete information on all variables, regardless of whether they are in one or more waves. The graph shows that the frequency of respondents with no LSI reporting SAH as being “Excellent” decreases slightly as the cohort ages, whereas for those with a LSI there is an increasing trend that may be indicative of adaptation. Reporting “Good” SAH does not show a considerably lower frequency between those with a LSI and those who don't have a LSI. Poor health increases with age and with having a LSI. Overall, individuals report a lower level of SAH at age 34.

Figure 1. Dynamics of SAH by the existence of LSI



BCS70 also records the age at onset of the disease. This information allows us to compute the duration of time variable d_{it}. The 2008 survey does not include a question on the age at onset of the LSI. Therefore, if an individual has not reported he had a LSI before 2008 but he reports to have an LSI in 2008, we do not have a value for d_{it}. For those observations we will assume an average duration of 2 years.

Table 2 provides a list of the variables we include in our model and some descriptive statistics. Our main variables of interest are a dummy indicating whether the individual has any LSI as well as the length of time the individual has had this LSI. We also control for other socio-economic characteristics: gender, marital status, number of natural children in the household and activity (employed, unemployed, etc). Income is not included in the model given that there are too many missing values and our sample would be reduced by half if it were to be included. As a proxy for income we include a variable that captures the housing tenure, i.e. whether the individual owns, rents or has another type of arrangement.

Table 2 : Variable Names and Descriptive Statistics

Variable	**Categories**	**Indicator Variables**	**Mean**	**Standard Deviation**	**Max**	**Min**

Self Assessed Health	1=Poor	SAHpoor	0.03	0.17	1	0
	2=Fair	SAHfair	0.11	0.31	1	0
	3=Good	SAHgood	0.55	0.50	1	0
	4=Excellent	SAHexcellent	0.31	0.46	1	0
Long Standing Illness	Whether the individual has any long-standing illness, disability or infirmity	LSI	0.30	0.46	1	0
Duration of LSI	Whether the individual has any long-standing illness, disability or infirmity	Duration	2.88	7.43	38	0
Gender	=1 if female	Female	0.53	0.50	1	0
Children	Number of natural children living in the house	Children	0.89	1.07	8	0
Marital Status	1=Single	Single	0.44	0.50	1	0
	2=Married	Married	0.48	0.50	1	0
	3=Separated/Divorced	Sep/div	0.08	0.27	1	0
	4=Widowed	Widow	0.00	0.04	1	0
Activity	1=Employed	Employed	0.82	0.38	1	0
	2=Unemployed	Unemployed	0.03	0.16	1	0
	3=Full Time Education	FT Education	0.01	0.12	1	0
	4=Temporarily Sick/Disabled	TempSickDis	0.00	0.05	1	0
	5=Long term Sick/Disabled	LTSickDis	0.02	0.14	1	0
	6=Other (Looking after family, retired, on government training scheme, etc...)	OtherAct	0.12	0.32	1	0
Tenure	=1 Individual owns home	Own	0.66	0.47	1	0
	=2 Individual rents home	Rent	0.27	0.44	1	0
	=3 Other arrangement (rent-free, squatting or other)	Other	0.08	0.27	1	0
Education	1= No qualifications	NoQual	0.08	0.27	1	0
	2=GCSE or equivalent	GCSE	0.37	0.48	1	0
	3=A Level or equivalent	Alevel	0.17	0.37	1	0
	4=Degree/higher degree	Degree	0.38	0.49	1	0

4. Results

In this section, we present the results of the estimation for different specifications of equation (3) by including the unobserved individual effect parameterised as in equation (2) (Wooldridge, 2005). Estimates are computed using an unbalanced panel adjusted by attrition using Inverse Probability Weights (IPW).

Table 3 contains the results of the ordered dynamic panel. The first column shows the results when no variable for LSI is included in the model. Our results corroborate the evidence that there is a strong state dependence, in line with findings in Contoyannis et al. (2004). The coefficients of the initial state, SAH (t1), are positive and significant with the exception of SAHfair (t1). This is indicative of a positive relationship between the initial levels of SAH and the unobserved individual effect.

Column (2) shows the results when we include the indicator variable on whether the individual has one or more LSIs. Note that in this case, the morbidity variable appears to absorb part of the effect that the SAH (t-1) coefficients capture as they decrease in magnitude. The indicator variable for LSI has a negative and significant effect which, in our dynamic ordered probit context, can be interpreted as follows: having a LSI condition lowers individuals' evaluation of their health state. In order to see if there are higher order dynamics we include a lag of the LSI variable. Column (3) shows the results when the current value of the LSI is included as well as the lagged value of LSI. This can be considered a first approximation to capture adaptation. Unexpectedly, there is a negative and significant effect of the estimate for LSI(t-1). However, this coefficient is considerably smaller in magnitude than the coefficient for LSI(t). The reduced effect of LSI(t-1) may be due to the fact that there are four years between waves and this may not be a long enough time period for the individual to adapt. Therefore we decide to only include the contemporary level of LSI in the regressions. Column (4) shows the results when we account for the presence of LSI and also for the duration of the LSI. The effect of the LSI estimate remains negative and highly significant and there is also evidence of a positive and significant effect of the duration variable. This is in support of the positive adaptation hypotheses. Individuals that have suffered with a LSI for longer are more likely to select higher level of health assessment.

Table 3. Dynamic Pooled Ordered Probit – Full Sample

VARIABLES	(1) No LSI	(2) LSI	(3) LSI (t) & LSI (t-1)	(4) LSI & Duration
SAHfair (t-1)	0.280***	0.223***	0.205***	0.224***
SAHgood (t-1)	0.801***	0.668***	0.634***	0.672***
SAHexcellent (t-1)	1.315***	1.151***	1.111***	1.156***
SAHfair (t1)	0.0669	0.0987	0.0982	0.0891
SAHgood (t1)	0.438***	0.440***	0.435***	0.434***
SAHexcellent (t1)	0.877***	0.869***	0.860***	0.864***
LSI		-0.529***	-0.506***	-0.566***
LSI (t-1)			-0.0881***	
LSI Duration				0.00333**
Female	-0.340**	-0.450***	-0.459***	-0.449***
Married	-0.00932	0.0374	0.0373	0.0390
Sep/div	-0.0197	0.0528	0.0519	0.0570
Widow	-0.0194	0.130	0.135	0.138
Children	-0.0573***	-0.0154	-0.0157	-0.0130
Gcse	0.0201	0.0262	0.0264	0.0277
Alevel	-0.101	-0.0324	-0.0314	-0.0297
Degree	-0.182	-0.0842	-0.0834	-0.0784
Unemployed	0.0859	0.0822	0.0787	0.0823
FTEducation	0.0760	0.0617	0.0621	0.0602
TempSickDis	-0.663***	-0.642***	-0.648***	-0.634***
LTSickDis	-1.308***	-1.177***	-1.196***	-1.172***
Other	0.0366	0.00818	0.00781	0.00764
Own	-0.00906	-0.00408	-0.00155	-0.00305
Rent	-0.0351	-0.0443	-0.0423	-0.0437
Cut 1	-0.6942	-1.0523	-1.1037	-1.0514
Cut 2	0.2713	-0.0495	-0.1001	-0.0485
Cut 3	2.1174	1.8518	1.8026	1.8531
Observations	18,009	18,009	18,009	18,009
Log-likelihood	-20926	-20448	-20439	-20444

*** p<0.01, ** p<0.05, * p<0.1
Reference Categories: SAHpoor, Single, Employed, Othertenure, No qualifications

The next set of results in Table 4 shows the estimates when the model is run separately for those who do not have a LSI and for those who have a LSI. Colum (1) provides the results for those individuals that do not have any condition and column (2) show the results for those individuals that have a LSI. Overall there seems to be higher dependence among those that had a condition than among those who did not have a LSI. There is also a more significant effect of the initial health values SAH (t1) among individuals with at least one LSI. Column (3) shows the results when we include the variable duration to the specification for those that have a LSI. Again the results are supportive of the adaptation hypotheses and this is evident from observing the coefficient of the LSI duration variable which has significant and positive effect.

Table 4. Dynamic Pooled Ordered Probit by LSI condition

VARIABLES	(1) No LSI	(2) Having LSI	(3) Having LSI & Duration
SAHfair (t-1)	-0.00489	0.260***	0.261***
SAHgood (t-1)	0.439***	0.714***	0.720***
SAHexcellent (t-1)	0.937***	1.154***	1.166***
SAHfair (t1)	-0.161	0.197	0.180
SAHgood (t1)	0.172	0.537***	0.526***
SAHexcellent (t1)	0.615***	0.931***	0.928***
LSI Duration			0.00385***
Female	-0.462***	-0.0662*	-0.0592*
Married	0.0109	0.0825	0.0883
Sep/div	0.0111	0.130	0.143
Widow	0.514	-0.190	-0.163
Children	-0.0899***	0.102***	0.109***
Gcse	0.0460	0.0185	0.0198
Alevel	0.0587	-0.158	-0.152
Degree	-0.0614	-0.0735	-0.0597
Unemployed	0.00634	0.188	0.188
FTEducation	0.0296	0.0932	0.0863
TempSickDis	-0.753**	-0.573**	-0.561*
LTSickDis	-0.496	-1.267***	-1.258***
Other	0.0169	-0.00867	-0.00972
Own	-0.00510	0.0119	0.0149
Rent	-0.0165	-0.0802	-0.0781
Cut 1	-1.6188	-0.4054	-0.3567
Cut 2	-0.4915	0.5481	0.5976
Cut 3	1.4202	2.4393	2.4903
Observations	12,164	5,845	5,845
Log-likelihood	-12837	-7535	-7530

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Reference Categories: SAHpoor, Single, Employed, Othertenure, No qualifications

The variable LSI used in the specifications above includes any long-standing illness, infirmity, or disability that an individual may have at any point in time. However, individuals may have conditions that have different health implications. For instance, individuals with chronic conditions may change their attitude towards their personal health assessment given that they have to endure a long-term illness. For this reason, we test if individuals with a chronic condition have a different assessment of their health compared with individuals that have other LSIs. We select two chronic conditions, asthma and diabetes, the aim of which is to determine whether individuals may have a different approach to their health assessment influenced by a chronic situation. For that purpose we have created dummies for asthma (=1 if individual has asthma or asthma and other condition), diabetes (=1 if individual has diabetes or diabetes and other condition), any other LSI (=1 if the individual has any other LSI). The reference category is those who do not have any LSI. Table 6 shows the results when explicitly accounting for chronic conditions. Therefore the results are estimates obtained from the sample of observations that do report to have a LSI. Individuals not having any health problem are excluded from the model.

The specification in the first column of Table 5 includes only dummies for asthma and diabetes. The reference category is those that have any other LSI. State dependence and the effect of the initial SAH level remains consistent with the results we obtained previously. The asthma and diabetes dummies have a negative effect on the evaluation of the health state with respect to those that have another type of LSI. This indicates that these specific chronic conditions have a specific negative impact on SAH. In the second specification we include the duration variable for asthma, diabetes and for the other conditions without including the dummy. The coefficient for duration is positive and significant for asthma and other LSIs, whereas it has a negative effect in the case of diabetes. This is confirmed by the third set of results as shown in column (3). In this specification we include the dummies as well as the duration variables so that the duration does not absorb the effect of the existence of asthma and diabetes. Having a chronic condition is therefore negatively associated with health assessment, but the length of time individuals suffer from the condition leads to a process of adaptation. This adaptation therefore positively affects SAH as individuals become more accustomed to their health situation. There is a negative coefficient for the diabetes duration which could be explained as the condition being more aggravated as individuals age.

Table 5. Dynamic Pooled Ordered Probit for Individuals having a LSI – Chronic Conditions vs. other conditions

VARIABLES	(1) Having LSI - Chronic	(2) Having LSI - Duration	(3) Having LSI -Chronic & Duration
SAHfair (t-1)	0.252***	0.249***	0.246***
SAHgood (t-1)	0.699***	0.705***	0.698***
SAHexcellent (t-1)	1.135***	1.152***	1.141***
SAHfair (t1)	0.202	0.192	0.197
SAHgood (t1)	0.536***	0.536***	0.537***
SAHexcellent (t1)	0.922***	0.935***	0.932***
Asthma	-0.0438		-0.0908*
Diabetes	-0.306***		-0.214*
Asthma Duration		0.00382**	0.00639***
Diabetes Duration		-0.0153**	-0.00641
OtherLSI Duration		0.00699***	0.00547***
Female	-0.0685**	-0.0561*	-0.0560*
Married	0.0870	0.0907	0.0928
Sep/div	0.135	0.141	0.138
Widow	-0.187	-0.139	-0.146
Children	0.102***	0.108***	0.105***
Gcse	0.0207	0.0358	0.0321
Alevel	-0.152	-0.132	-0.139
Degree	-0.0576	-0.0340	-0.0367
Unemployed	0.187	0.190	0.188
FTEducation	0.0875	0.0761	0.0736
TempSickDis	-0.577**	-0.564*	-0.560*
LTSickDis	-1.275***	-1.258***	-1.270***
Other	-0.0121	-0.0124	-0.0165
Own	0.0112	0.00957	0.00869
Rent	-0.0753	-0.0763	-0.0765
Cut 1	-0.4439	-0.3463	-0.3777
Cut 2	0.5116	0.6104	0.5798
Cut 3	2.4056	2.5063	2.4769
Observations	5,845	5,845	5,845
Log-likelihood	-7525	-7518	-7514

*** p<0.01, ** p<0.05, * p<0.1
Reference Categories: SAHpoor, Single, Employed, Othertenure, No qualifications, Other LSIs

We next show the average partial effects (APEs) for the variables of interest, SAH state dependence, SAH at the initial value, LSI, and LSI duration. The APEs are computed by averaging the unobserved component over the distribution of the individual effect and using the sample average coefficients (Wooldridge, 2005; Contoyannis et al, 2004). Table 6 shows the APEs of reporting an excellent SAH using the full sample. The APEs for the impact of the covariates on the probability of reporting poor, fair or good health can also be computed but are not reported here. These are the APEs for the specifications in Table 4 and correspond with columns (2) and (4) which include the dummy for LSI and both LSI and duration, respectively. As stated previously, the variables LSI and LSI Duration have a positive and significant estimate.

Table 6. Average Partial Effect of the probability of reporting Excellent Health – Full Sample

VARIABLES	(1) Having a LSI	(2) Having a LSI & Duration
SAHfair (t-1)	0.0666***	0.0670***
SAHgood (t-1)	0.1999***	0.2009***
SAHexcellent (t-1)	0.3445***	0.3458***
SAHfair (t1)	0.0295	0.0266
SAHgood (t1)	0.1318***	0.1298***
SAHexcellent (t1)	0.2599***	0.2585***
LSI	-0.1583***	-0.1693***
LSI Duration		0.0010**

*** p<0.01, ** p<0.05, * p<0.1

Table 7 shows the APEs for the specifications that compute the results by separating the sample into those not having any LSI (column (1)) and those having a LSI (column (2)). Column (3) shows the impact of including the duration variable for those that have a LSI. The APEs in Table 7 correspond to the specifications shown in Table 4. The APEs for the variable duration in the third column show that there is a modest but significant effect of the duration variable.

Table 7. Average Partial Effect of the probability of reporting Excellent Health by LSI

VARIABLES	(1) Not Having a LSI	(2) Having a LSI	(3) Having a LSI & Duration
SAHfair (t-1)	-0.0017	0.0567***	0.0569***
SAHgood (t-1)	0.1489***	0.1558***	0.1569***
SAHexcellent (t-1)	0.3178***	0.2517***	0.2541***
SAHfair (t1)	-0.0547	0.0430	0.0393

SAHgood (t1)	0.0584	0.1172***	0.1146***
SAHexcellent (t1)	0.2085***	0.2030***	0.2023***
LSI Duration			0.0008***

*** p<0.01, ** p<0.05, * p<0.1

Table 8 shows the APEs when we differentiate between chronic versus other LSIs. Again the results refer to the probability of reporting excellent health. The APEs for the chronic condition dummies is negative, whereas there is a positive duration effect on the estimates in the second and third column. This effect is consistent except for the diabetes duration.

Table 8. Average Partial Effect of the probability of reporting Excellent Health for Individuals having a LSI – Chronic Conditions vs. other conditions

VARIABLES	(1) Chronic Condition	(2) Duration	(3) Chronic & Duration
SAHfair (t-1)	0.0549***	0.0542***	0.0536***
SAHgood (t-1)	0.1523***	0.1534***	0.1518***
SAHexcellent (t-1)	0.2473***	0.2508***	0.2482***
SAHfair (t1)	0.0440	0.0418	0.0428
SAHgood (t1)	0.1169***	0.1165***	0.1168***
SAHexcellent (t1)	0.2008***	0.2035***	0.2027***
Asthma	-0.0095		-0.0197*
Diabetes	-0.0666***		-0.0467*
Asthma Duration		0.0008**	0.0014***
Diabetest Duration		-0.0033**	-0.0014
OtherLSI Duration		0.0015***	0.0012***

*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions and Future Research

We have examined the issue of adaptation to health states in a dynamic framework. To the best of our knowledge, the existing literature has estimated dynamic models of SAH in a state dependent context in which morbidity has not been explicitly accounted for (although morbidity has indeed been used to parameterise the unobserved individual effect). Our interest is not only to incorporate more explicitly morbidity in these models but, primarily to estimate the dynamic impact of LSI duration on SHA and on the magnitude of the SHA state dependence. For this purpose we have used four waves of the BCS70 and estimated several specifications of a dynamic SAH model controlling for state dependence, unobserved heterogeneity, and attrition. Our findings indicate that individuals are likely to report better health states the longer the time period they have experienced their condition. The adaptation to LSI duration appears robust to different specifications and this has prevailed when we teased out the effect of specific LSIs such as asthma and diabetes. Overall our results suggest that, for LSI that do not get aggravated over time, there is a positive adaptation effect.

We acknowledge that having a LSI may also have an impact on the cut-off points that define the selection of a category by an individual. For example, the cut-off point for the "poor" category is different for an individual with a chronic condition versus those with no condition. This also allows for changes in the consecutive cut-off points. Therefore, our aim will be to also determine if having a LSI in general, and a chronic condition in particular, has an effect on the thresholds that individuals impose in order to determine their SAH. Equally interesting would be to check for the existence of index shifts, for example whether there are differences between those having a LSI and those who don't with respect to the location of the cut-off points. Recent evidence using the BHPS explicitly account for heterogeneity in the cut-off points which are determined by SAH (Carro and Traferri, 2012).

The paper uses data on the UK but the extension of the model to other countries will also provide additional insight into the issue of adaptation. In the present work, we have a sample of individuals of the same age, but we do not determine whether adaptation depreciates or appreciates with age. To address this concern, we aim to extend the analysis to a European context using the Survey of Health, Ageing and Retirement in Europe (SHARE), a longitudinal dataset that offers information for representative samples of 19 European countries aged 50 or over.

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