Adaptation to Health States: Sick yet better off?

Patricia Cubí-Mollá[a], Mireia Jofre-Bonet[b], Victoria Serra-Sastre[b,*]

[a]*Office of Health Economics*
7th Floor, Southside, 105 Victoria Street, SW1E 6QT London, UK

[b]*Department of Economics, City University London*

Northampton Square, EC1V 0HB London, UK.

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**Corresponding author*: Department of Economics, City University London, Northampton Square, EC1V 0HB London, UK. Phone Number: +44(0)2070400171. Email: v.serra-sastre@city.ac.uk.

1. Introduction

Adequate evaluation of the costs and benefits associated with any health care technology or intervention has become a requirement in many countries for the purpose of funding, pricing, and reimbursing decisions. Appropriate measurement of health outcomes is paramount to this appraisal process. However, controversy remains on the methodological underpinning of how health outcome measurements are obtained. For instance, health technology assessment in England by the National Institute of Health and Care Excellence (NICE) favors the measurement of health gains in terms of Health-Related Quality of Life (HRQoL) using the EQ-5D. Although evaluations of the underlying health states by members of the general public (as opposed to patients) are preferred, most informative data about the health outcome is derived from patients' subjective and self-reported measures.

The fact that a patient's self-measurement of her health state may be affected by factors other than changes to her objective health is not trivial. Experiencing a new disease, for instance, may affect a patient's underlying health perceptions and state preference valuations. If the new health state is the worst ever experienced by the patient, she may contemplate other bad health states as "not that bad," consequently transforming the internal standards and relativities of health state perception and measurement. Moreover, a change in the true health status may alter a patient's values given to different aspects of life such as being able to move freely, having someone close by, or feeling unhappy. All such modifications in values will have an effect on an individual's self-assessed (subjective) health reporting. Finally, a new disease may also make the patient reinterpret the meaning of the different psychological constructs,[1] which underpin the outcome measure, further affecting her (subjective) health perception, quality of life, or well-being measurement.[2] As a result, we might witness a change in the fundamental meaning of a patient's self-evaluation of her health status (Schwartz & Sprangers, 1999). These "response shifts" are often found to affect the outcome measurement and, consequently, any method that does not account for these shifts will inevitably lead to potential biases (Blome & Augustin, 2015).

[1] That is, not directly observable, non-tangible, and subjective.
[2] For instance, the same EQ-5D profile may be associated with different amounts of HRQoL for patients at different points in time.

A particular realization of the response shift phenomenon is generally identified as "adaptation" to chronic health states, which has been observed in literature (McTaggart-Cowan et al., 2011). The length of time that a patient experiences certain chronic conditions, for example, appears to influence their health-related constructs in a counter-intuitive way. Patients tend to self-report better subjective health over the disease trajectory, even if more objective health measures suggest that their condition is not improving (Daltroy, 1999; Riis et al., 2005; Damschroder et al., 2005; Buick et al., 2002; Baron et al., 2003). Some authors even suggest that patients accommodate a chronic illness to a degree that the average HRQoL value arising from their self-reported measurement ends up being not inferior (and sometimes even superior) to that corresponding to healthy population norms (Breetvelt et al., 1991; Groenvold et al., 1999). This circumstance has been more recently observed in some clinical trials submitted to NICE for appraisal (NICE, 2015a and 2015b). For instance, in a recent NICE technology appraisal (NICE, 2015a) "The Committee agreed that it was not plausible that the utility value for progression-free survival off treatment was higher than the utility value for members of the general public without the disease." A possible explanation for this occurrence could be that adaptation is taking place within the diseased population. Given such findings and that health care funding decisions are increasingly reliant on subjective health state measurements, it is critical that we fully understand the dynamics of health self-reporting. In particular, the fundamental role that *time since diagnosis* in considering chronic disease has on subjective health state measurement is worth the empirical investigation.

Our paper is generally related to relatively extensive literature in the multidisciplinary fields of experimental economics and psychology on *adaptation to health states*. 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/well-being is well above the ratings that healthy subjects attribute to them. Examples 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). These studies rely on small cross-sectional samples from surveys and/or experiments but have not followed individuals over time. In contrast, more recent papers exploit longitudinal datasets to analyze the impact of chronic conditions on life satisfaction. For instance, Powdthavee (2009) finds total adaptation to mild disabilities in terms of health satisfaction, albeit those severely disabled do not restore their health

satisfaction up to their potential. Mendolia and McNamee (2014) also find some evidence adaptation to chronic pain in terms of recovery of life satisfaction after three years. Finally, Oswald and Powdthavee (2008) estimate a hedonic model with fixed effects using the British Household Panel Survey (BHPS) to explain the self-reported life satisfaction of individuals having suffered some sort of disability. They find that individuals recover between 30% and 50% of their pre-disability life-satisfaction sometime after the change in their health.

In this paper, we employ a distinct approach from the above. We hypothesize, given an adaptation response, that there is a positive relationship between the length of time an individual suffers from an illness and the likelihood of reporting better health. To do so, we analyze the issue of adaptation by estimating the effect of the presence of a long-standing illness (LSI) and the *time since diagnosis* on the construct of subjective self-assessed health (SAH). Our objective is to identify actual changes in the perception and measurement of health as a result of the adaptation response-shift mechanism due to the time spent in a chronic disease state. Our research is based on two main assumptions. First, individuals affected by one (and only one) LSI will keep their underlying latent health constant. Having a chronic illness therefore provides a measure of latent objective health (Groot, 2000). The underlying objective health of an individual suffering from a chronic condition is assumed to remain constant over the duration of the disease despite any alleviation that the treatment might provide. Second, any changes in the measurement of subjective SAH will then reflect changes in the perception of health, which will be assumed to be a result of the adaptation process in response to the disease, no matter what factors are contributing to this process. We consider individuals who only have one LSI so that there are no spillover effects across chronic diseases and assume that temporary health shocks to the underlying objective condition do not affect it fundamentally. In addition, we control for individual health state dependency—by which an individual reports better or worse health states by default—by incorporating dynamic modeling of health states, as in Contoyannis et al. (2004) and Jones (2006). We use the British Cohort Study, a longitudinal dataset that periodically surveys a cohort of originally 17,287 individuals born in 1970 in England, Wales, and Scotland. This dataset records both SAH and changes in the health state of the individuals, with data on the onset of chronic diseases and on health shocks, as well as socioeconomic and demographic characteristics. We find that the greater the number of

years of suffering from an LSI, the higher the probability of reporting better SAH. This result also holds for a number of specific, individual chronic conditions.

This paper contributes to the related literature by adding innovative and robust results to the analysis of adaptation: (i) we exploit a longitudinal dataset rather than a cross-section, which helps capture the role of adaptation over time and control for unobserved heterogeneity; (ii) we use a dynamic framework, which allows to adjust for health state dependence; and, (iii) we rely on SAH - a self-reported health construct - rather than utility measures derived from questionnaires such as the EQ-5D or the SF-36. To the best of our knowledge, this is the first paper to examine the role of adaptation on potential changes in SAH. In sum, our paper adds valuable insights to the understanding of the adaptation effect. This may be relevant not only from the health care interventions point of view but also, ultimately, for funding, pricing, and reimbursement exercises if the public is to be informed about the trajectory of patients' health perceptions over the course of a condition before revealing their preferences.

This paper is organized as follows. The next section presents our empirical strategy. Section 3 describes the dataset and the variables included in the empirical specification. Some descriptive statistics are also provided. We report our results in Section 4 and discuss the findings. The final section concludes and suggests next steps for future research.

2. Empirical Strategy

We explore the issue of adaptation to health states and its impact on SAH by adopting the latent health model framework in Contoyannis et al. (2004) and Jones et al. (2006) and assume the following dynamic structure for the latent perceived health:

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

where sah^{*}_{it} and sah_{it-1} are individual *i's* latent SAH in period *t* and reported SAH in *t-1*, respectively. Lagged SAH is included here to capture any state dependence between periods. Our variables of interest are *morbidity*, m_{it}, which captures whether the respondent has a chronic condition and *duration*, d_{it}, which accounts for time since the onset of the condition. We expect a negative sign for β, coefficient associated to m_{it}, whereas a positive value of δ, the coefficient for d_{it}, would support our hypotheses of the

existence of adaptation to chronic health states. The vector x_{it} includes a number of explanatory variables, containing socio-demographic characteristics. The error term is divided in two components: the individual time-invariant effect as captured by c_i and an individual time-varying error term, u_{it}, which is normally distributed.

The true individual health, sah^*_{it}, is a latent variable and thus what we observe is only the self-assessed health category, sah_{it}, reported by the individual at each point in time, such that

$$sah^*_{it} = \quad k \quad if \quad \lambda_{k-1} < sah^*_{it} \quad < \lambda_k \quad for \quad k = 1,2,...,K \quad ,$$

where K represents the number of SAH categories, $\lambda_0 = -\infty$ and $\lambda_K = +\infty$. The λ's are threshold parameters estimated together with the coefficients. Thus, under the assumption of normality of the error term u_{it}, the probability of observing individual reporting category k is

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

where $\Phi(.)$ is the standard normal cumulative distribution function.

The estimation of model (2) presents three challenges: dealing with unobserved individual heterogeneity and the initial conditions problem; the existence of attrition between waves; and the potential response category cut-off point shift. In the following paragraphs, we explain how we address these three concerns.

First, in a dynamic ordered probit model such as that in (2), dealing with the unobserved heterogeneity is not as simple as in the case of linear models, for which differencing can be applied. Moreover, in datasets such as ours, the challenge posed by the presence of unobserved heterogeneity is compounded by the initial conditions problem, that is, we do not have information on the initial period when the individual data-generating process began but only from when the data starts. Using just the first wave sample data realization, instead of the initial one, can lead to inconsistent estimators (Wooldridge, 2005; Contoyannis et al., 2004). To overcome this problem and to account for unobserved heterogeneity, we follow Wooldridge's (2005) approach, which proposes to parameterize c_i

as a function of the first SAH observed in the sample and the average of the exogenous variables, $\overline{x_i}$, over the different waves in the dataset:

$$c_i = \sigma + \varphi' \cdot sah_{i1} + \mu \cdot \overline{m}_i + \nu \cdot \overline{d}_i + \kappa' \cdot \overline{x}_i + \varepsilon_i \qquad (3)$$

Accordingly, we rewrite the latent variable model (1) for self-assessed health as

$$sah_{it}^* = \alpha' \cdot sah_{it-1} + \beta \cdot m_{it} + \delta \cdot d_{it} + \gamma' \cdot x_{it} + \sigma + \varphi' \cdot sah_{i1} + \mu \cdot \overline{m}_i + \nu \cdot \overline{d}_i + \kappa' \overline{x}_i + \varepsilon_i + u_{it}, \quad (4)$$

and estimate the modified dynamic ordered probit model as

$$\begin{aligned} P(sah_{it}^* = k) = \Phi(\lambda_k - \alpha' \cdot sah_{it-1} - \beta \cdot m_{it} - \delta \cdot d_{it} - \gamma' \cdot x_{it} - \sigma - \phi \cdot sah_{i1} - \mu \cdot \overline{m}_i - \nu \cdot \overline{d}_i - \kappa \overline{x}_i) \\ -\Phi(\lambda_{k-1} - \alpha' \cdot sah_{it-1} - \beta \cdot m_{it} - \delta \cdot d_{it} - \gamma' \cdot x_{it} - \sigma - \phi \cdot sah_{i1} - \mu \cdot \overline{m}_i - \nu \cdot \overline{d}_i - \kappa \overline{x}_i) \end{aligned} \qquad (5)$$

Second, attrition from wave to wave may be endogenously determined (for instance, due to health-related issues) and consequently hinder the robustness of the inference. We test for the presence of endogenous attrition in our dataset using the Verbeek and Nijman (1992) test and fail to reject the null hypothesis of random non-response. Therefore, we correct our model using the inverse probability weight (IPW) approach suggested by Wooldridge (2002). This method requires the computation of correcting weights based on the propensity to respond in each wave. To do so, we first estimate a probit model of the response variable, defined as $R_{it} = 1$, if individual i responds to wave t and $R_{it} = 0$ otherwise, on the initial value of all covariates included in (1). The dynamic ordered probit model (5) is then estimated by weighting each observation by the inverse of the predicted probability of being present in each wave. Wooldridge (2002) shows that inverse probability weighting leads to consistent and $\sqrt{N}$-asymptotically normal estimators. Wooldridge (2002) also shows that the estimator asymptotic variance obtained after the IPW correction is larger than the asymptotic variance that we would obtain after adjusting for the use of predicted probabilities; therefore, IPW leads to conservative inference. Without loss of generality, the standard errors reported in this paper are not adjusted for the use of fitted probabilities in the computation of IPW, and we rely on the fact that they are an upper bound of the true standard errors.

Third, the dependent variable of the dynamic probit model is ordinal and based on a subjective assessment of health. The usual assumption for the estimation of these models is that thresholds between health categories are the same across individuals. However, there are reasons to believe that subgroups of individuals may have different health category cut-

off points. Lindeboom and Van Doorslaer (2004) found evidence of such response cut-off point shift across gender and age subgroups, but not when groups were based on income or education. Respondents in our sample all have the same age, so we examine if there exist cut-off point shifts across subgroups based on gender and on having or not having an LSI. The rationale for the latter subgroup analysis is that when assessing their health, individuals with a chronic health condition may use different thresholds compared with those without one.

Lastly, the coefficients estimated from equation (5) inform on the statistical significance of the regressors on the probability of reporting better SAH, but they cannot be interpreted in terms of sign or magnitude. We base our results' interpretation on the partial effect of the variables of interest on the probability of reporting *Excellent, Good, Fair*, or *Poor* SAH. For instance, the partial effect of having a particular LSI, m_{it}, on the probability of choosing SAH k is:

$$\frac{\partial P(sah_{it} = \mathrm{k} | sah_{it-1}, m_{it}, d_{it}, x_{it}, c_i)}{\partial m_{it}} = [f(\lambda_k - A) - f(\lambda_{k-1} - A)] \cdot \beta$$

where $A = \beta \cdot m_{it} + \delta \cdot d_{it} + \gamma' \cdot x_{it} + \sigma + \phi \cdot sah_{i1} + \mu \cdot \bar{m}_i + \nu \cdot \bar{d}_i + \kappa \overline{x_i}$ and ƒ(.) the density function for the normal distribution. In general, the effect of a change in one of the regressors depends on the estimated coefficients, the data, and the SAH category we use to compute the probability (Greene and Hensher, 2010). Thus, to interpret our results, we calculate the average partial effects (APEs), that is, the average of the partial effects for all individuals, which also includes averaging their individual effects c_i. As discussed in Wooldridge (2005) and Contoyannis et al. (2004), the average effects obtained are consistent.

3. Data

The data we use to test our model is the 1970 British Cohort Study (BCS70). The BCS70 began compiling data from a sample of 17,287 babies born in England, Wales, and Scotland during a specific week in April 1970. Since then, there have been seven surveys at the ages of 5 (year 1975), 10, 16, 26, 30, 34, 38, and 42 (year 2012). 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 toward 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 waves 1996, 2000, 2004, and 2008, that is, when the individuals were 26, 30, 34, and 38 years old. We exclude the 2012 survey as it does not contain information on time since the onset of illness.

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 analyzed in the context of the BHPS and there is no evidence of significant impact on the estimates (Hernández-Quevedo et al., 2008).

Additionally, the question on SAH 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., Lorgelly and Lindley, 2008; Cubí-Mollá and Herrero, 2012) and will be implemented here. Table 1 shows the distribution of frequencies for each category in each of the four waves.

[Table 1 about here]

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 one (only) LSI from our list of chronic conditions as well as the length of time the individual has had that LSI (time from the onset of the first LSI to the time of the wave). The LSI indicator variable takes a value of 1 if an individual suffers from only one chronic condition from the following list: diabetes; depression; anxiety; epilepsy; high blood pressure (HBP); migraine; hay fever, rhinitis, and other diseases of the upper respiratory tract (URT); asthma; cancer; ulcer; Crohn's disease; eczema; psoriasis; and back problems.

The selection of LSIs was based on incidence in the sample population and consistency in their definition across waves of the BCS70.[3] In addition, we ensure we include a wide spectrum of chronic conditions with the aim to explore how different LSIs may follow different adaptation patterns. BCS70 records the age at the onset of each disease, which allows us to compute the duration of time variable d_{it} for each of them,. The 2008 survey does not include a question on the age at the onset of the LSI. Therefore, if an individual has not reported she had an LSI in 2004 but reports to have an LSI in 2008, we assume that the duration equals two years.

In addition, we control for individual socio-economic characteristics such as gender, number of natural children in the household, marital status, activity (employed, unemployed, full-time education, other), housing tenure (owner, renting, other type of dwelling), and education (no qualifications, GCSE, A level, degree or higher). Income is not included in the model given that there are too many missing values. Nevertheless, we rely on the fact that education, occupation, and housing tenure are good proxies of income. A reported SAH of *Poor* (SAH_t = *Poor*), being single, being employed, having another type of tenure, and having no qualifications are the reference categories for the *SAH*, marital status, economic activity, tenure, and education variables, respectively.

[Table 2 about here]

A few remarks about Table 2. First of all, about half of the observations declare to have at least one of the LSIs in our list by the end of our sample period. The average duration for those declaring to have at least one LSI is almost 16 years. Only about 9% of the pooled sample reports *SAH* to be *Poor* or *Fair*. About 53% reports an *SAH* category of *Good* and about 38% *Excellent*. About 52% of the sample are females; about 57% are married; 88% are in employment; 78% own the house where they live; and 45% have a university degree or higher.

[3] Inconsistencies in reporting whether an individual has an LSI in a given wave are corrected under the assumption that any reported chronic condition cannot be reversed. Evidence from the Understanding Society survey shows that changes in responses to the question of whether individuals suffer from any LSI are largely owing to modifications in the severity, effectiveness of treatment or daily activities of the respondent, and not to a real change in the LSI status (Jäckle and Pudney, 2015).

In Table 3 below, we provide more detailed information on the frequencies and percentages of observations for each particular LSI. To isolate the effect of specific illnesses on SAH, we differentiate those who have only one particular condition from those who have several conditions simultaneously, that is, there are 41 observations of individuals having *only diabetes*. The indicator variable *Morethan1* in the last row provides the count of those with more than one LSI and so it takes a value of 1 when individuals have at least two of the listed LSIs.

[Table 3 about here]

From Table 3 we observe that for our relatively young BCS sample, the most common LSIs are URT, eczema, and back problems, followed by migraines, asthma, HBP, depression, psoriasis, and depression. Epilepsy, cancer, Crohn's disease, ulcers, and anxiety are relatively infrequent. We also note that 33% of the observations correspond to individuals having more than one chronic condition.

Figure 1 depicts the *average SAH* at different points in time before and after the onset of the disease using pooled data for the list of conditions in our definition of LSI. We can observe a significant drop in the average SAH values reported two years after the onset—or diagnosis—of each disease. However, while epilepsy and, to a lesser extent, depression suggest the existence of adaptation patterns, for the other diseases, adaptation is less clear as the lines rather become flat at a lower SAH. The patterns displayed in this figure, though, do not control for important factors affecting SAH such as aging, gender, or health-state dependence. We analyze adaptation, adjusting for these elements in the following sections.

[Figure 1 about here]

4. Results

4.1 Base case results

In this section, we present the results of the estimation for different specifications of equation (5), which include the parameterized unobserved individual effect in equation (3). Estimates are computed using an unbalanced panel adjusted by attrition using IPWs. Table 4 contains the estimates of the ordered dynamic panel. We only report here the coefficient estimates for the lagged SAH (SAH_{t-1}), SAH in the first sample period (SAH_{t1}), morbidity (LSI), and duration variables (LSI Duration). All other coefficient estimates of the

control variables and the averages of the exogenous variables used in the parameterization of the individual effect can be found in Table A1 of the Appendix. The specification in the first column does not include the existence of *LSI* or its duration. This first set of results corroborates the evidence that there is a strong state dependence, in line with findings by Contoyannis et al. (2004). Moreover, the coefficients associated to SAH_{t1} are positive and increasing in magnitude as we move from *Poor* to *Excellent* health, indicating that the initial SAH determines SAH in consecutive periods.

Column (2) shows the results when we include the indicator variable on whether the individual has one or more LSIs. Interestingly, the morbidity variable, *LSI*, appears to absorb part of the effect of the previous health state as all SAH_{t-1} coefficients decrease in magnitude. The indicator variable *LSI* itself has a negative and significant effect, which, in our dynamic ordered probit context, can be interpreted as evidence that having an LSI condition lowers an individual's own health state valuation. Column (3) shows the results when we account for both the presence of an LSI and also its duration. The estimate of the *LSI* remains negative and highly significant while the estimate for the duration variable is positive and significant. These results are in support of the positive adaptation hypothesis: individuals who have lived with an LSI for longer are more likely to select higher levels of health assessment.

[Table 4 about here]

Table 5 shows the APEs of the specification in column (3) of Table 4. Our specifications show two consistent effects. Firstly, that having a LSI increases the probability of reporting *Poor, Fair or Good* health by 1, 3.6 and 6.4 percentage points, respectively. Contrarily, it decreases the probability of reporting *Excellent* health by 11 percentage points. Secondly, and in accordance to our hypothesis of adaptation, LSI duration has the opposite effect: longer duration brings a higher probability of reporting being in *Excellent* health, and decreases the probability of reporting *Poor, Fair* and *Good*. We observe that the likelihood to report *Excellent* health increases by 8 percentage points for each ten additional years of duration.

Somewhat surprisingly, in Column 1 (corresponding to the likelihood of reporting a *Poor* SAH), the coefficients associated with having an LSI and its duration are smaller than what we might expect. We would have anticipated that having an LSI increases the probability of

reporting *Poor* health in a larger magnitude than it does of reporting categories *Fair* or *Good*. Even though ten additional years of duration decrease the probability of reporting *Fair* and *Good* by approximately 2.6 and 4.6 percentage points respectively, it only increases that of reporting *Poor* health by 0.77. This could be due to a *small sample size* issue as individuals in the sample are relatively young and the proportion of individuals reporting SAH *Poor* is small.

[Table 5 about here]

4.2 Extensions

4.2.1. Cut-off point shift by gender and LSI

As discussed in Section 2, one of the potential challenges to the empirical specification is the presence of heterogeneity in the thresholds parameters by subgroups in the sample. In order to identify a potential response category cut-off point shift, we run separate regressions for those having an LSI versus not and by gender (not reported here). We found no evidence of differences in the composition of the latent error variance when we segregated the samples. In particular, the proportion of variability in the latent error attributable to unobserved heterogeneity is not significantly different when comparing those with an LSI to those who do not have any LSI (0.27 compared with 0.30) and when comparing females to males (0.30 compared with 0.31). If we further split the sample by both presence of LSI and gender, there are no significant differences either: the proportion of variability in the latent error attributable to unobserved heterogeneity is 0.25 for males and 0.28 for females who have an LSI, and 0.33 for males and 0.27 for females without one.

In Table 6, we present the estimates when we divide the sample into two groups: the first includes only those respondents with no LSI, in Column (1), and the second those suffering from one LSI, in Columns (2) and (3). Comparing Columns (1) and (2), we note that, overall, those who have an LSI seem to show a higher state dependence than those who do not have an LSI. The results in Column (3), which include the variable duration for the group with an LSI, are supportive of the adaptation hypotheses, as the coefficient of the LSI duration variable is significant and positive and of similar magnitude than when we used the pooled sample for the estimation in Table 4.

[Table 6 about here]

In Table 7 below, we report the corresponding APEs associated with the specification in Column (3) of Table 6. In Table 7, we notice that, for those reporting an SAH category of *Excellent* in Column (4), the partial effect of duration is significant and positive, as it had been in Table 5 for the pooled sample. This corroborates the previous finding supporting the thesis that adaptation makes it more likely to report their SAH as *Excellent* and less likely to report it to be *Poor,* Fair, or just *Good*. Ten extra years of duration increase the likelihood of reporting *Excellent* health by 7.3 percentage points and decrease the probability of reporting *Poor, Fair* or *Good* by a magnitude of 1.1, 2.9 and 3.3 percentage points, respectively.

[Table 7 about here]

4.2.2 When does adaptation kick in?

As reported in Table 2, the average duration is about 16 years, despite the fact that respondents of the BCS70 are young individuals. A tabulation of the age at the onset of illness for those who report an LSI reveals that 9% are born with a condition and approximately 50% are aged 20 or less when they report to first have a chronic condition. About 60% of those with a condition have a duration of 20 or more years. That explains why our duration variable of interest has such a large average. In order to explore further the dynamics of SAH and the effect of adaptation, we re-estimate the model, restricting the sample so that we capture the effect of different durations more precisely. These estimates are presented in Table 8 below. Column (1) to Column (5) show results when restricting the sample to individuals that have no LSI and plus those who have LSI durations of 5 or less years (LSIDuration5), of 10 years or less (LSIDuration10), of 15 years or less (LSIDuration15), of 20 years or less (LSIDuration20), and of 25 years or less (LSIDuration25), respectively.[4]

[Table 8 about here]

The results in Table 8 are consistent with our previous findings, and the LSI coefficient retains the negative and statistically significant coefficient for all subsamples. However, only specifications in Columns (4) and (5)- corresponding to durations of 20 and 25 years

[4] We have re-estimated this same specification for the subsample that includes only those respondents with one LSI (as in Table 6 Column (3)) and the results are very similar to the results shown in Table 8. Again, statistically significant results are obtained only for the coefficients of LSIDuration20 and LSIDuration25.

or less, respectively -have a statistically significant coefficient for duration. These results suggest that individuals show an adaptation effect on their reported SAH after relatively long LSI durations. The APEs for the specification in Column (5) (shown in Table A2 in the Appendix) corroborate the effects pattern for the diagnosis and the duration we had obtained for the base case. The largest diagnosis effect is on the likelihood of reporting *Excellent SAH,* which is 12.4 percentage points lower than those with no LSI. For ten additional years with an LSI, the probability of reporting *Excellent* SAH increases by 6.8 percentage points while that of reporting *Good* (*Fair*) health is reduced by 4 (2.2) percentage points. As the APEs for the specification in Column (4) are very similar to those in Column (5), they are not reported here.

4.2.3. Does SAH preceding the onset of an LSI determine the path of adaptation?

We now focus our attention to examine if SAH prior to the onset of an LSI influences adaption. Gupta et al. (2015) used the General Health Questionnaire (GHQ) as a measure of subjective wellbeing (SWB) and showed that there is short-term adaptation for those individuals in the 25th percentile of the SWB distribution, whereas there is not much evidence of adaptation in the longer term or in the other percentiles across the SWB distribution.[5] Following Gupta et al. (2015), we examine if the distribution of SAH prior to the onset of the LSI determines a different path of adaptation.

For that purpose, we restrict the sample to those individuals who experience the onset of the LSI on or after 2000.[6] The underlying assumption is that adaptation may differ for those individuals reporting a better SAH before the disease onset. Table 9 below shows the coefficients obtained using this subsample. The first column replicates the analysis in Column (3) of Table 4, including the SAH lags, morbidity, and the duration variable. Column (2) includes an interaction between lagged SAH and duration. However, lagged SAH refers to the previous period for each wave and not the one in the period just before the onset of the LSI. In Column (3), we change the specification to include specifically an indicator variable that captures whether the respondent reported an *Excellent* SAH in the period

[5] Our paper differs from Gupta et al. (2015) mainly in the definition of the dependent variable and the time horizon considered. They use a continuous dependent variable (with higher values indicating higher SWB) whereas our variable of interest is an ordinal categorical variable. Gupta et al. (2015) analyze adaptation only up to five years after the onset of the condition, whereas our dataset allows for any duration.

[6] In all specifications considered so far, respondents could have developed an LSI before the first wave used in our study. The subsample used in this part only includes individuals who report an LSI for the first time in the 2000 wave or later. This restriction ensures we have the reported SAH in the previous wave prior to onset.

before the onset of illness (Exc_PreLSI).[7] Column (3) also includes the interaction of the pre-LSI indicator and the duration variable. Estimates for the morbidity coefficient are in line with those previously obtained. The duration variable is statistically significant only for the specification in Column (1). The coefficients of the duration and interaction terms are not significant in Columns (2) and (3). There is a drop in the sample size and this could also help to obtain imprecise estimates. Given our sample, we cannot conclude from our results that better health prior to diagnosis leads to a different adaptation pattern.

[Table 9 about here]

4.2.4. Analysis by specific chronic conditions

The variable LSI used in the previous analyses was constructed if the individual ever suffered from either diabetes; depression; anxiety; epilepsy; HBP; migraines; hay fever, rhinitis, or other chronic URT; asthma; cancer; ulcers; Crohn's disease; eczema; psoriasis; or back problems. However, conditions may have different implications on the wellbeing of individuals. For this reason, we estimate a model segregating the sample by the chronic condition they suffer from and examine whether adaptation patterns differ among them. To do so, we create indicator variables for each chronic disease as listed above. These indicator variables take a value of 1 if an individual suffers only from a particular chronic disease. To capture the effect of comorbidity, we now include an additional indicator variable that takes a value of 1 if an individual has more than one chronic condition. The objective of separating individuals suffering from only one condition from those with more than one is twofold. First, it allows us to isolate the individual effect of each chronic condition by avoiding compensatory effects that mask real adaptation. Second, it enables disentangling if different patterns arise when individuals suffer from more than one chronic condition. By construction, the reference category is not having any LSI.

Table 10 shows the APEs of the analysis when we allow for a differential effect by chronic condition. For the sake of paucity, we only show the APEs for each of the morbidity indicator variables and its corresponding duration variable. Noticeably, having any chronic disease except for anxiety, epilepsy, migraines, URT, ulcers, and psoriasis has a statistically

[7] Results in Table 5 show that the APE of the morbidity and duration change sign in the gradient between *Excellent* and the rest of the categories. We therefore only differentiate across the health spectrum between those in *Excellent* health prior to onset and the rest of the SAH categories.

significant effect on the likelihood of reporting a specific SAH category. In particular, the effect of having either diabetes, depression, HBP, asthma, cancer, Crohn's disease, eczema, back problems, or more than one LSI increases the probability of reporting a lower SAH category (*Poor*, *Fair*, or *Good*) and decreases that of reporting the *Excellent* category.

Duration has a statistically significant effect for diabetes, anxiety, migraines, URT, asthma, back problems, and having more than one LSI. Moreover, it exhibits the same pattern we observed for the benchmark case, that is, duration lowers the likelihood of declaring to be in a *Poor*, *Fair*, or *Good* health state, but it increases that of reporting to be in *Excellent* health. Remarkably, although having anxiety, migraines, or URT has no significant diagnosis effect, time since the onset of these conditions has a statistically significant effect: negative on the likelihood of reporting the three worse health states and positive on that of selecting the SAH category *Excellent*. Contrarily, having depression, HBP, cancer, Crohn's disease, or eczema have statistically significant impacts on SAH, but we do not find they have a significant adaptation effect. In particular, cancer and Crohn's disease have the largest diagnosis effect with a decrease in the likelihood of reporting *Excellent* health by 74 and 69 percentage points, respectively compared to those with no LSI. The coefficient associated to duration for those conditions that have no diagnosis effect (anxiety, migraines and URT) is similar in magnitude to those that have both diagnosis and duration effects (diabetes, asthma, back problems). Finally, note that having more than one chronic condition has significant coefficients for both diagnosis and duration: suffering from multiple chronic conditions shows a decrease in the probability of reporting *Excellent* health of 11 percentage points compared to those with no LSI. Nevertheless, having multiple chronic conditions shows a weaker adaptation effect as these individuals are 1 percentage point more likely to report *Good* health but 2.4 percentage points less likely to report *Excellent* health for an extra ten years of duration.

[Table 10 about here]

From these results we can conclude that, contrarily to what one would have expected, some diseases that tend to worsen over time (diabetes) or produce flares over an individual's lifetime (migraines, asthma) show the effects of adaptation. Other symptomatic diseases for which we would expect adaptation (depression, cancer, Crohn's disease, eczema) have a significant diagnosis effect, but the time since onset does not contribute to

an increase in the likelihood of reporting the *Excellent* health state, indicating no adaptation effect. The significant diagnosis effect of HBP but no adaptation is less unexpected, as HBP could be rather asymptomatic. Finally, for epilepsy, ulcers, and psoriasis, we do not detect any diagnosis or duration effect. The results for epilepsy may not be surprising given that it tends to be more acute in the early years of life. Also, for epilepsy and psoriasis, the diagnosis could be too remote in time to be remembered and adaptation may not have taken place either because the period without the condition is inexistent or too far back. The case of ulcers is more puzzling but could be the consequence of its low prevalence in this younger cohort.

The lack of definite results for individual chronic conditions may be a result of the relatively young sample we have used in the empirical analysis (the individuals in our sample range between 26 and 38 years of age); thus, the longer-term effects of having some of these chronic diseases may not have really kicked in. Therefore, examining if stronger adaptation effects are evident in older populations facing higher morbidity and longer potential for adaptation is called for. There is also a relatively low prevalence of the individual chronic conditions included in the analysis and therefore there may not be enough variation in our data to capture the diagnosis and adaptation effect. This could explain why some conditions exhibit a diagnosis (adaptation) effect but no adaptation (diagnosis) effect. The analysis of how different duration lengths (as in section 4.2.2) might impact SAH for individuals suffering from specific chronic conditions would be valuable to understand better of adaptation patterns. Again, the low prevalence for a few conditions in our sample naturally limits this extension. Attempting to separate the effect of each chronic condition demands highly detailed data on individual conditions, consistent across waves, and with high enough prevalence in the sample studied. We are unable to pursue this in the current context but it is left in the agenda for future research.

5. Conclusions

In this paper, we examine the issue of adaptation to health states in a dynamic framework. To the best of our knowledge, the existing literature estimated dynamic models of SAH in a state dependent context in which morbidity and its duration were not explicitly accounted for, although morbidity has indeed been used to parameterize the unobserved individual effect. Our interest is not only to incorporate morbidity in these models but also to estimate the dynamic impact of LSI duration on SAH and on the magnitude of the SAH

state dependence. For this purpose, we use four waves of the BCS70 and estimate several specifications of a dynamic SAH model, controlling for state dependence, unobserved heterogeneity, and attrition.

Our findings indicate that, despite the negative impact of suffering from an LSI, individuals are likely to report better health states the longer they experience a chronic condition. In particular, the APEs for each of the SAH categories reveal that differences in the effect of the morbidity and duration variables arise between *Excellent* and all other SAH categories (*Good, Fair*, and *Poor*). Suffering from a chronic illness decreases the likelihood of reporting *Excellent* health, but longer durations counterbalance this effect, that is, duration increases the probability of reporting SAH as *Excellent*. Suffering from a chronic condition makes an individual more likely to report all other SAH categories, with an overall larger decrease in the probability of reporting *Good* health compared with *Poor* or *Fair.* Again, the LSI diagnosis effect is offset by a decrease in the probability of reporting the three lowest categories the longer the individual has suffered from the chronic condition.

We acknowledge that factors such as gender or having a specific LSI may also have an impact on the cut-off points defining the selection of a given category by an individual. For example, the particular point at which an individual with an LSI decides to report an SAH *Poor* category instead of *Fair* may be different from that of a completely healthy individual. Thus, in this paper, we examine the issue of category cut-point shifts by running the dynamic models on subsamples determined by having an LSI and by gender, and we compare the percentage of the variability in the error attributed to the unobserved heterogeneity. Our results show minimal differences.

Additionally, we also explore adaptation patterns by different lengths of LSI. The results suggest that adaptation mainly happens when individuals have suffered from the condition for a long duration, that is, duration only has a significant effect when equal to or over 20 years. We also study whether adaptation differs across individuals who report better health prior to having an LSI. We find no significant evidence supporting this hypothesis, but the lack of significance could be because the sample size of individuals who acquire an LSI within our sample period is small.

In an attempt to explore adaptation for different chronic conditions, we tease out the effects of having specific LSIs and the impact of time since the onset of each LSI. Overall,

our condition estimates support the morbidity and duration effects we had obtained using a generic LSI variable, but disease-specific impacts are diverse. Although some conditions show a significant effect for both diagnosis and adaptation, some conditions show only one or the other and three of them show none. Not surprisingly, the duration effect for those with multiple conditions increase the probability of reporting SAH as *Good* or below and decreases the probability of *Excellent* health, as opposed to the effect shown when considering individuals with only one LSI. Among the reasons that could explain the diversity of effects are the fact that our sample is a young cohort of individuals and the low prevalence of some of the conditions. It is also plausible that adaptation does not have an equal impact across conditions. Conditions that manifest themselves very early in life may have no diagnosis and adaptation effect because of the remoteness of the diagnosis and the lack of a period living without them as a reference. Conditions that are subject to flares but are asymptomatic otherwise (asthma) may have a different adaptation pattern from conditions that cause constant pain/bother. Adaptation to a specific LSI is a process also influenced by the effectiveness of the available lines of treatment and the unobserved individual ability to adopt a different lifestyle. As lines of treatment are fairly standardized in the UK, owing to the existence of medical guidelines, and because we are interested in adaptation to LSIs regardless of the factors that aid the process, this does not undermine our findings but may help to explain some of these differences.

There are some potential limitations posed by the dataset used. We have a sample of relatively young individuals who are aged 26 in the first wave and are followed by three subsequent sweeps up to age 38. Therefore, we cannot study how adaptation evolves over time and varies by individuals in different age groups. Another limitation of our paper is that comorbidities are combined in one single indicator variable that controls only for having more than one condition. Alternative specifications for comorbidities have not been explored here. Finally, the paper does not measure the degree of adaptation and whether respondents partially or fully return to their health level prior to the existence of an LSI. This limitation imposed by the dataset structure does not provide the SAH at the onset of the LSI—individuals may have developed a condition well before the first wave in our sample data and several others developed it during the sample period. In this first attempt to explore the issue of adaptation, we use longitudinal data in a dynamic context of health state dependence. Taken together and despite of the above caveats, our results corroborate with robust estimates the existence of adaptation to chronic diseases.

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Table 1. SAH categories and frequency distribution across waves and SAH 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%)

Table 2. Variables and descriptive statistics

Variable	Definition	Label	Mean	Standard Deviation
Self Assessed Health$_t$[±]	1 = *Poor*	SAH$_t$ = *Poor*	0.013	0.114
	2 = *Fair*	SAH$_t$ = *Fair*	0.074	0.263
	3 = *Good*	SAH$_t$ = *Good*	0.526	0.499
	4 = *Excellent*	SAH$_t$ = *Excellent*	0.385	0.486
Long Standing Illness	Whether the individual has any long-standing illness in our list*	LSI	0.496	0.500
Duration of LSI	Duration of the long-standing illness, disability or infirmity	LSI Duration**	15.950	9.83
Gender	= 1 if female	Female	0.518	0.499
Children	Number of natural children living in the house	Children	1.026	1.070
Marital Status	1 = Single	Single	0.351	0.477
	2 = Married	Married	0.568	0.495
	3 = Separated/Divorced	Sep/div	0.078	0.269
	4 = Widowed	Widow	0.001	0.039
Activity	1 = Employed	Employed	0.877	0.333
	2 = Unemployed	Unemployed	0.017	0.130
	3 = Full Time Education	FT Education	0.008	0.093
	4 = Other (Looking after family, sick/disabled retired, on government training scheme, etc.)	OtherAct	0.101	0.302
Tenure	= 1 Individual owns home	Own	0.783	0.411
	= 2 Individual rents home	Rent	0.158	0.364
	= 3 Other arrangement (rent-free, squatting or other)	Other	0.057	0.233
Education	1 = No qualifications	NoQual	0.030	0.171
	2 = GCSE or equivalent	GCSE	0.336	0.472
	3 = A Level or equivalent	Alevel	0.178	0.382
	4 = Degree/higher degree	Degree	0.455	0.498

Notes:

*The LSI indicator variable takes a value equal to 1 if the individual declares having any of the following conditions: diabetes; depression; anxiety; epilepsy; high blood pressure (HBP); migraines; hay fever, rhinitis, and other chronic upper respiratory tract diseases (URT); asthma; cancer; ulcers; Crohn's disease; eczema; psoriasis; and back problems. It takes a value of 0 otherwise.

[**]*LSI Duration* is calculated as the number of years with at least one of the chronic diseases in the LSI definition. Mean and Standard Deviation of *LSI duration* is computed taking into account only those observations with an LSI.

[±]time *t* being the contemporaneous period (*t)*, lagged period (*t–1*), or at the first wave (*t1*).

Table 3. Percentage and frequency of individual LSIs

Condition	Freq.	Percent	Cum.
Diabetes	41	0.24	33.86
Depression	362	2.09	35.95
Anxiety	74	0.43	36.37
Epilepsy	123	0.71	37.08
HBP	401	2.32	39.4
Migraine	694	4.01	43.41
URT	1,375	7.94	51.35
Asthma	513	2.96	54.31
Cancer	39	0.23	54.53
Ulcer	85	0.49	55.02
Crohn	31	0.18	55.2
Eczema	894	5.16	60.36
Psoriasis	216	1.25	61.61
Back	867	5.01	66.62
Morethan1	5,782	33.38	100

Table 4. The effect of morbidity and duration on SAH

Model specification:	(1) **Dynamic model**	(2) **Dynamic model with morbidity**	(3) **Dynamic model with morbidity & duration**
SAH_{t-1}= Fair	0.220*	0.188	0.168
	(0.120)	(0.119)	(0.116)
SAH_{t-1} = *Good*	0.713***	0.656***	0.640***
	(0.117)	(0.116)	(0.114)
SAH_{t-1} = *Excellent*	1.194***	1.125***	1.112***
	(0.120)	(0.119)	(0.117)
SAH_{t1} = *Fair*	0.575***	0.545***	0.588***
	(0.199)	(0.200)	(0.200)
SAH_{t1} = *Good*	0.913***	0.884***	0.923***
	(0.198)	(0.199)	(0.198)
SAH_{t1} = *Excellent*	1.380***	1.344***	1.384***
	(0.200)	(0.202)	(0.201)
LSI		-0.270***	-0.333***
		(0.061)	(0.064)
LSI Duration			0.0241***
			(0.004)
Cut 1	-0.370	-0.570	-0.551
Cut 2	0.584	0.394	0.416
Cut 3	2.461	2.284	2.307
Observations	11,565	11,565	11,493
Log-likelihood	-12738	-12661	-12562

Notes: Coefficients are estimated using dynamic pooled ordered probit. Estimates are for unbalanced panel are adjusted for attrition using Wooldridge (2002) IPWs. Robust standard errors are in parentheses. Standard errors are clustered by respondent identifier. Control variables are not shown for paucity. Controls included are female, number of natural children living in the house, marital status (single, married, separated/divorced, widowed), activity (employed, unemployed, full-time education, other), tenure (own, rent, other), and education (no qualifications, GCSE or equivalent, A level or equivalent, degree/higher degree). Reference categories: SAH_{t-1} = *Poor*, SAH_{t1} = *Poor*, Single, Employed, Other tenure, No qualifications. The individual effect was parameterized using self-assessed health in *t1* (shown above) and the average over time of the time-varying exogenous variables (number of natural children living in the house, marital status, activity, tenure, and education). Cut 1 to Cut 3 are the estimated threshold cut points. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. APEs on the probability of reporting SAH = *k*

Dynamic model with morbidity & duration	*(1)* *Poor*	*(2)* *Fair*	*(3)* *Good*	*(4)* *Excellent*
SAH_{t-1}= *Fair*	-0.00535	-0.0181	-0.0324	0.0558
	(0.0037)	(0.0125)	(0.0224)	(0.0385)
SAH_{t-1}= *Good*	-0.0205***	-0.0692***	-0.124***	0.213***
	(0.0038)	(0.0124)	(0.0222)	(0.0379)
SAH_{t-1}= *Excellent*	-0.0355***	-0.120***	-0.215***	0.370***
	(0.0042)	(0.0130)	(0.0229)	(0.0387)
SAH_{t1}= *Fair*	-0.0188***	-0.0635***	-0.114***	0.196***
	(0.0065)	(0.0216)	(0.0389)	(0.0667)
$SAH_{t\,1}$= *Good*	-0.0295***	-0.0997***	-0.178***	0.308***
	(0.0066)	(0.0214)	(0.0387)	(0.0661)
$SAH_{t\,1}$= *Excellent*	-0.0442***	-0.149***	-0.268***	0.461***
	(0.0070)	(0.0218)	(0.0394)	(0.0669)
LSI	0.0107***	0.0360***	0.0644***	-0.111***
	(0.0022)	(0.0070)	(0.0125)	(0.0214)
LSI Duration	-0.000770***	-0.00260***	-0.00466***	0.00803***
	(0.0001)	(0.0005)	(0.0008)	(0.0014)
Observations	11,493	11,493	11,493	11,493

Notes: Estimates are for unbalanced panel adjusted for attrition using Wooldridge (2002) IPWs. Robust standard errors are in parentheses. Standard errors are clustered by respondent identifier. APEs of the control variables and parameterization of the individual effect included in the empirical specification are not shown for paucity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. The effect of morbidity and duration by subsample: Without and with an LSI

Sample groups:	Without LSI	With one LSI	
Model Specification:	(1) No LSI	(2) LSI	(3) LSI & Duration
SAH_{t-1} = *Fair*	-0.0708	0.205	0.188
	(0.289)	(0.129)	(0.124)
SAH_{t-1} = *Good*	0.313	0.729***	0.720***
	(0.287)	(0.126)	(0.121)
SAH_{t-1} = *Excellent*	0.808***	1.171***	1.165***
	(0.286)	(0.131)	(0.127)
SAH_{t1} = *Fair*	0.456***	0.526**	0.581***
	(0.145)	(0.221)	(0.223)
SAH_{t1}= *Good*	0.929***	0.780***	0.821***
	(0.142)	(0.216)	(0.218)
SAH_{t1} = *Excellent*	1.349***	1.288***	1.329***
	(0.145)	(0.220)	(0.222)
LSI Duration			0.0232***
			(0.005)
Cut 1	-1.039	-0.195	-0.171
Cut 2	0.0381	0.729	0.755
Cut 3	1.958	2.604	2.627
Observations	5,823	5,740	5,670
Log-likelihood	-6054	-6574	-6486

See notes for Table 4. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7. APEs on the probability of reporting SAH = *k* for the subsample of individuals that have an LSI

	(1)	(2)	(3)	(4)
Dynamic model with duration	*Poor*	*Fair*	*Good*	*Excellent*
SAH_{t-1} = *Fair*	-0.00900	-0.0234	-0.0269	0.0593
	(0.0059)	(0.0154)	(0.0179)	(0.0391)
SAH_{t-1} = *Good*	-0.0345***	-0.0897***	-0.103***	0.227***
	(0.0060)	(0.0153)	(0.0182)	(0.0383)
SAH_{t-1} = *Excellent*	-0.0559***	-0.145***	-0.167***	0.368***
	(0.0068)	(0.0164)	(0.0195)	(0.0397)
SAH_{t1} = *Fair*	-0.0279**	-0.0724***	-0.0833***	0.183***
	(0.0109)	(0.0277)	(0.0323)	(0.0704)
SAH_{t1} = *Good*	-0.0394***	-0.102***	-0.118***	0.259***
	(0.0108)	(0.0272)	(0.0319)	(0.0689)
SAH_{t1} = *Excellent*	-0.0637***	-0.166***	-0.191***	0.420***
	(0.0115)	(0.0278)	(0.0329)	(0.0700)
LSI Duration	-0.00111***	-0.00289***	-0.00332***	0.00732***
	(0.0002)	(0.0006)	(0.0007)	(0.0015)
Observations	5,670	5,670	5,670	5,670

See notes for Table 5. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8. The effect of morbidity and duration on SAH at different duration levels

Model specification:	(1) Morbidity& Duration< = 5	(2) Morbidity& Duration< = 10	(3) Morbidity& Duration< = 15	(4) Morbidity& Duration< = 20	(5) Morbidity& Duration< = 25
SAH_{t-1} = *Fair*	-0.125	0.0212	0.0839	0.141	0.142
	(0.219)	(0.160)	(0.138)	(0.121)	(0.115)
SAH_{t-1} = *Good*	0.282	0.416***	0.484***	0.575***	0.604***
	(0.215)	(0.159)	(0.136)	(0.120)	(0.112)
SAH_{t-1} = *Excellent*	0.772***	0.886***	0.940***	1.035***	1.066***
	(0.217)	(0.161)	(0.139)	(0.123)	(0.115)
SAH_{t1} = *Fair*	0.401	0.566**	0.912***	0.718***	0.627***
	(0.311)	(0.265)	(0.233)	(0.206)	(0.199)
SAH_{t1} = *Good*	0.829***	0.949***	1.272***	1.069***	0.962***
	(0.312)	(0.263)	(0.233)	(0.206)	(0.198)
SAH_{t1} = *Excellent*	1.243***	1.387***	1.731***	1.523***	1.422***
	(0.314)	(0.266)	(0.235)	(0.209)	(0.201)
LSI	-0.296***	-0.395***	-0.387***	-0.383***	-0.372***
	(0.099)	(0.071)	(0.067)	(0.066)	(0.066)
LSI Duration5	-0.0507				
	(0.037)				
LSI Duration10		0.00794			
		(0.011)			
LSI Duration15			0.0103		
			(0.007)		
LSI Duration20				0.0177***	
				(0.005)	
LSI Duration25					0.0203***
					(0.005)
Cut 1	-1.078	-0.807	-0.363	-0.477	-0.569
Cut 2	-0.0973	0.174	0.611	0.502	0.396
Cut 3	1.820	2.067	2.485	2.376	2.288
Observations	6,859	7,762	8,725	9,647	10,387
Log-likelihood	-7274	-8365	-9522	-10545	-11327

See notes for Table 4. *** p < 0.01, ** p < 0.05, * p < 0.1.

Duration variables are restricted at less than or equal to 5, 10, 15, 20, and 25 years. Each column includes in the parameterization of the unobserved individual effect the average across waves of the corresponding definition for the LSI duration variable.

Table 9. Adaptation patterns according to SAH pre-LSI

Model specification:	(1) Dynamic model with morbidity & duration	(2) Dynamic model with interactions	(3) Dynamic model SAH prior to LSI &interaction
SAH_{t-1} = *Fair*	0.0229	-0.322	
	(0.178)	(0.473)	
SAH_{t-1} = *Good*	0.530***	0.139	
	(0.178)	(0.446)	
SAH_{t-1} = *Excellent*	0.965***	0.559	
	(0.186)	(0.452)	
Exc_PreLSI			0.509***
			(0.122)
SAH_{t1} = *Fair*	0.854***	0.863***	1.046***
	(0.271)	(0.280)	(0.286)
SAH_{t1} = *Good*	1.083***	1.106***	1.555***
	(0.246)	(0.257)	(0.244)
SAH_{t1} = *Excellent*	1.566***	1.591***	1.941***
	(0.259)	(0.269)	(0.266)
LSI	-0.965**	-0.961**	-0.783*
	(0.450)	(0.450)	(0.405)
LSI Duration	0.0190*	-0.0389	0.0133
	(0.011)	(0.054)	(0.013)
(SAH_{t-1} = *Fair) x LSI Dur*		0.0516	
		(0.060)	
(SAH_{t-1} = *Good) x LSI Dur*		0.0585	
		(0.054)	
(SAH_{t-1} = *Excellent) x LSI Dur*		0.0617	
		(0.055)	
Exc_PreLSI x LSI Dur			-0.0158
			(0.019)
Cut 1 c1	-0.713	-1.066	-0.572
Cut 2 c2	0.128	-0.226	0.252
Cut 3 c3	2.038	1.685	2.121
Observations	1439	1439	1439
Log-likelihood	-1710	-1709	-1740

See notes for Table 4. *** p < 0.01, ** p < 0.05, * p < 0.1.

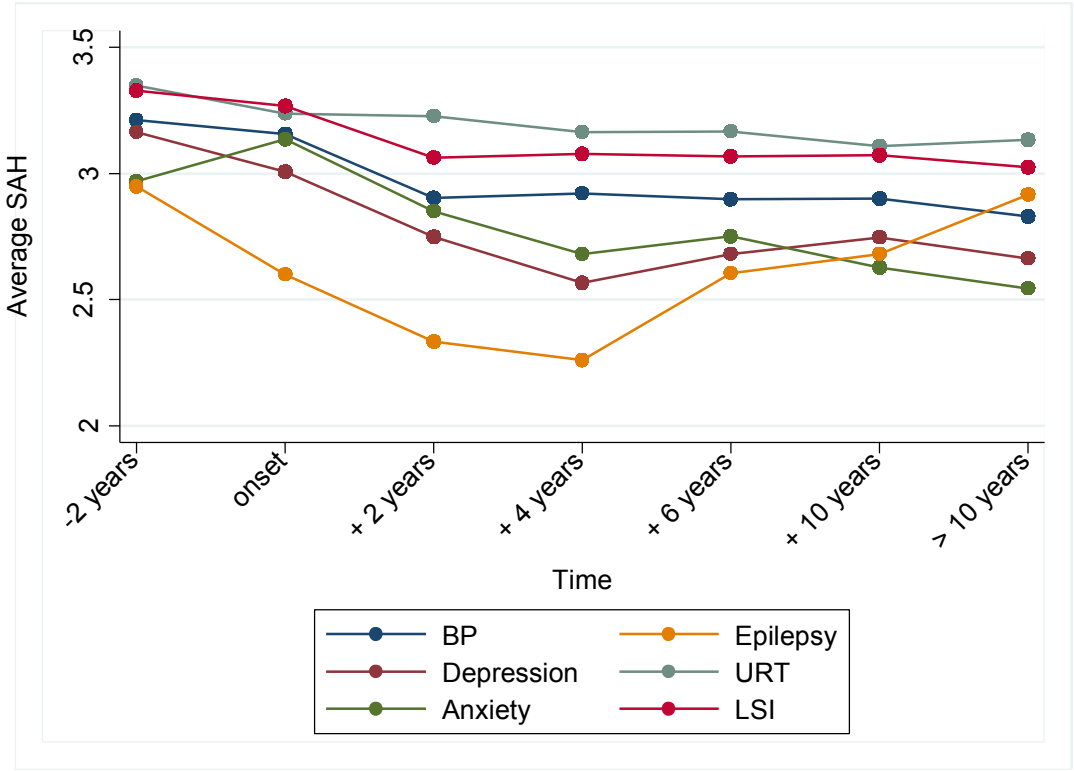
Table 10: APEs for morbidity and duration for selected chronic conditions

	(1) Poor	(2) Fair	(3) Good	(4) Excellent
Diabetes	0.0331**	0.0724**	0.0815**	−0.1870**
	(0.0133)	(0.0288)	(0.0324)	(0.0743)
Depression	0.0329***	0.0719***	0.0810***	−0.1858***
	(0.0094)	(0.0205)	(0.0231)	(0.0528)
Anxiety	0.0216	0.0472	0.0532	−0.1221
	(0.0171)	(0.0372)	(0.0419)	(0.0961)
Epilepsy	−0.0121	−0.0264	−0.0297	0.0682
	(0.0164)	(0.0359)	(0.0404)	(0.0928)
HBP	0.0278***	0.0608***	0.0684***	−0.1569***
	(0.0086)	(0.0188)	(0.0212)	(0.0486)
Migraine	0.0059	0.0129	0.0145	−0.0333
	(0.0063)	(0.0137)	(0.0155)	(0.0355)
URT	0.0064	0.0139	0.0157	−0.0360
	(0.0049)	(0.0107)	(0.0120)	(0.0276)
Asthma	0.0171**	0.0373**	0.0420**	−0.0965**
	(0.0079)	(0.0173)	(0.0194)	(0.0446)
Cancer	0.1320***	0.2885***	0.3247***	−0.7452***
	(0.0369)	(0.0799)	(0.0900)	(0.2061)
Ulcer	−0.0201	−0.0438	−0.0493	0.1132
	(0.0181)	(0.0395)	(0.0445)	(0.1021)
Crohn	0.1224**	0.2673**	0.3009**	−0.6906**
	(0.0484)	(0.1049)	(0.1186)	(0.2713)
Eczema	0.0121*	0.0263*	0.0296*	−0.0680*
	(0.0068)	(0.0148)	(0.0166)	(0.0382)
Psoriasis	0.0147	0.0321	0.0362	−0.0830
	(0.0118)	(0.0257)	(0.0290)	(0.0665)
Back	0.0261***	0.0570***	0.0641***	−0.1471***
	(0.0049)	(0.0106)	(0.0120)	(0.0273)
Morethan1	0.0194***	0.0425***	0.0478***	−0.1097***
	(0.0040)	(0.0085)	(0.0096)	(0.0219)
Diab_dur	−0.0026**	−0.0058**	−0.0065**	0.0149**
	(0.0013)	(0.0028)	(0.0031)	(0.0071)
Depr_dur	−0.0006	−0.0013	−0.0014	0.0033
	(0.0005)	(0.0011)	(0.0012)	(0.0027)
Anx_dur	−0.0017**	−0.0038**	−0.0043**	0.0098**
	(0.0008)	(0.0017)	(0.0019)	(0.0044)
Epil_dur	−0.0011	−0.0024	−0.0027	0.0061
	(0.0007)	(0.0016)	(0.0018)	(0.0041)
HBP_dur	−0.0002	−0.0005	−0.0005	0.0012
	(0.0005)	(0.0010)	(0.0011)	(0.0026)
Mig_dur	−0.0008**	−0.0018**	−0.0020**	0.0045**
	(0.0004)	(0.0009)	(0.0010)	(0.0022)
URT_dur	−0.0006**	−0.0014**	−0.0016**	0.0036**

	(0.0003)	(0.0006)	(0.0007)	(0.0016)
Ast_dur	−0.0006*	−0.0012*	−0.0014*	0.0032*
	(0.0003)	(0.0007)	(0.0007)	(0.0017)
Canc_dur	−0.0019	−0.0041	−0.0046	0.0105
	(0.0014)	(0.0031)	(0.0035)	(0.0079)
Ulcer_dur	−0.0012	−0.0026	−0.0029	0.0066
	(0.0008)	(0.0018)	(0.0020)	(0.0046)
Crohn_dur	0.0001	0.0003	0.0003	−0.0007
	(0.0023)	(0.0051)	(0.0057)	(0.0131)
Ecz_dur	−0.0002	−0.0004	−0.0004	0.0010
	(0.0003)	(0.0007)	(0.0008)	(0.0017)
Pso_dur	0.0001	0.0001	0.0001	−0.0003
	(0.0006)	(0.0013)	(0.0015)	(0.0034)
Back_dur	−0.0007**	−0.0016**	−0.0018**	0.0041**
	(0.0004)	(0.0008)	(0.0009)	(0.0020)
Morethan1_dur	0.0004*	0.0009*	0.0010*	−0.0024*
	(0.0002)	(0.0005)	(0.0006)	(0.0013)
Observations	17,320	17,320	17,320	17,320

See notes for Table 4 and 5. *** p < 0.01, ** p < 0.05, * p < 0.1. Duration for those with multiple chronic conditions (Morethan1_dur) is computed as the duration of the condition they suffered first.

Figure 1. Average SAH for selected chronic conditions



Appendix

Table A1. Dynamic ordered probit model: All coefficients.

Model specification:	(1) Dynamic model	(2) Dynamic model with morbidity	(3) Dynamic model with morbidity & duration
SAH_{t-1}= Fair	0.220*	0.188	0.168
	(0.120)	(0.119)	(0.116)
SAH_{t-1}= |Good	0.713***	0.656***	0.640***
	(0.117)	(0.116)	(0.114)
SAH_{t-1}= Excellent	1.194***	1.125***	1.112***
	(0.120)	(0.119)	(0.117)
LSI		-0.270***	-0.333***
		(0.061)	(0.064)
LSI Duration			0.0241***
			(0.004)
Female	0.123***	0.138***	0.138***
	(0.025)	(0.026)	(0.026)
Married	-0.0411	-0.0396	-0.0674
	(0.047)	(0.048)	(0.048)
Sep/div	-0.0750	-0.0792	-0.134*
	(0.074)	(0.074)	(0.075)
Widow	-0.584*	-0.559*	-0.631**
	(0.338)	(0.327)	(0.317)
Unemployed	0.119	0.114	0.0969
	(0.116)	(0.117)	(0.118)
FT Education	0.000195	0.00338	-0.00495
	(0.128)	(0.128)	(0.127)
OtherAct	-0.0551	-0.0445	-0.0324
	(0.057)	(0.057)	(0.057)
Own	-0.00945	-0.0112	-0.0253
	(0.063)	(0.063)	(0.064)
Rent	-0.0201	-0.0134	-0.0122
	(0.069)	(0.069)	(0.069)
Children	-0.0852***	-0.0841***	-0.112***
	(0.020)	(0.021)	(0.022)
GCSE	-0.203	-0.217	-0.252
	(0.179)	(0.183)	(0.187)
Alevel	-0.228	-0.213	-0.273
	(0.203)	(0.206)	(0.211)
Degree	-0.343*	-0.337	-0.419*
	(0.206)	(0.210)	(0.215)
Estimated coefficients of the individual effect parameterization[8]:			
SAH_{t1}= Fair	0.575***	0.545***	0.588***
	(0.199)	(0.200)	(0.200)
SAH_{t1}= Good	0.913***	0.884***	0.923***

[8] We run an alternative parameterization of the individual effect that include only SAH in t1 and the average of the LSI and LSI Duration variables. The results were virtually identical to those presented here.

	(0.198)	(0.199)	(0.198)
SAH_{t1}= Excellent	1.380***	1.344***	1.384***
	(0.200)	(0.202)	(0.201)
mMarried	0.110*	0.105*	0.137**
	(0.062)	(0.062)	(0.063)
mSep/div	0.0226	0.0133	0.0688
	(0.104)	(0.104)	(0.104)
mWidow	0.878	0.806	0.879
	(0.578)	(0.581)	(0.573)
mUnemployed	-0.309*	-0.306*	-0.261
	(0.163)	(0.164)	(0.164)
mFT Education	0.0253	-0.0138	0.00995
	(0.192)	(0.195)	(0.193)
mOtherAct	-0.0201	-0.0210	-0.0185
	(0.083)	(0.084)	(0.084)
mOwn	-0.0213	-0.00365	0.0181
	(0.092)	(0.093)	(0.093)
mRent	-0.151	-0.146	-0.134
	(0.098)	(0.099)	(0.099)
mChildren	0.0742**	0.0731**	0.103***
	(0.030)	(0.030)	(0.031)
mGCSE	0.286	0.311*	0.346*
	(0.182)	(0.186)	(0.191)
mAlevel	0.397*	0.391*	0.447**
	(0.207)	(0.210)	(0.215)
mDegree	0.570***	0.580***	0.658***
	(0.208)	(0.213)	(0.218)
mLSI		0.0402	0.0161
		(0.083)	(0.099)
mLSI Duration			-0.0244***
			(0.006)
Cut 1	-0.370	-0.570	-0.551
Cut 2	0.584	0.394	0.416
Cut 3	2.461	2.284	2.307
Observations	11,565	11,565	11,493
Log-likelihood	-12738	-12661	-12562

Notes: Coefficients are estimated using dynamic pooled ordered probit. Estimates are for unbalanced panel adjusted for attrition using Wooldridge (2002) IPWs. Robust standard errors are in parentheses. Standard errors are clustered by respondent identifier. Reference categories: SAH_{t-1} = *Poor*, SAH_{t1} = *Poor*, Single, Employed, Other tenure, No qualifications. The individual effect was parameterized using self-assessed health in t1 and the average over time of the time-varying exogenous variables. The averages across all waves of the time-varying variables used to parameterize the individual fixed-effect are denoted using the prefix m- (e.g., mMarried). If we include time constant exogenous variables in the parameterization of the individual effect, we will not be able to identify the corresponding coefficient estimate in γ and κ; therefore, we have excluded the dummy female. Cut 1 to Cut 3 are the estimated threshold cut points. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. APEs on the probability of reporting SAH = k for the subsample of those with a maximum LSI duration of 25 years

Dynamic model with morbidity & duration	(1) *Poor*	(2) *Fair*	(3) *Fair*	(4) *Excellent*
SAH_{t-1}= Fair	-0.0044	-0.0151	-0.0278	0.0473
	(0.0036)	(0.0123)	(0.0227)	(0.0385)
SAH_{t-1}= |Good	-0.0189***	-0.0643***	-0.1187***	0.2019***
	(0.0036)	(0.0121)	(0.0223)	(0.0376)
SAH_{t-1}= Excellent	-0.0333***	-0.1135***	-0.2094***	0.3562***
	(0.0041)	(0.0127)	(0.0230)	(0.0383)
SAH_{t1}= Fair	-0.0196***	-0.0668***	-0.1233***	0.2097***
	(0.0064)	(0.0211)	(0.0393)	(0.0665)
SAH_{t1}= Good	-0.0301***	-0.1024***	-0.1890***	0.3215***
	(0.0065)	(0.0211)	(0.0395)	(0.0664)
SAH_{t1}= Excellent	-0.0445***	-0.1514***	-0.2794***	0.4753***
	(0.0070)	(0.0215)	(0.0403)	(0.0672)
LSI	0.0116***	0.0396***	0.0731***	-0.1244***
	(0.0022)	(0.0070)	(0.0129)	(0.0219)
LSI Duration25	-0.0006***	-0.0022***	-0.0040***	0.0068***
	(0.0002)	(0.0005)	(0.0009)	(0.0015)
Observations	10,387	10,387	10,387	10,387

Notes: APEs for the subsample that includes respondents with an LSI duration of less than or equal to 25 years, as reported in Column 5 of Table 8. Estimates are for unbalanced panel adjusted for attrition using Wooldridge (2002) IPWs. Robust standard errors are in parentheses. Standard errors are clustered by respondent identifier. APEs of the control variables and parameterization of the individual effect included in the empirical specification are not shown for paucity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.