Empirical assessment of adaptation to chronic illness

Can time heal all wounds?

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Abstract

Introduction
In health state evaluations, members of the general public are inclined to estimate a larger negative impact of a health impairment compared to patients themselves. This adds to the controversy about the type of health state preferences that should be used. The difference in the patient's experience and the public's ideation is often attributed to adaptation. This master thesis studies adaptation to chronic disability in a large longitudinal data set.

Method
I select over 5000 respondents of the Survey of Health, Ageing and Retirement in Europe (SHARE) who develop a chronic illness and disabilities during the span of the 5 waves of data collection. Adaptation is analyzed for outcome variables self-perceived health and life satisfaction. Self-perceived health is measured on a 5 point Likert scale, with anchors poor to excellent health and life satisfaction on a numbered scale ranging 1 to 11, with anchors very dissatisfied, very satisfied. In order to examine the effect of time since the onset of disability on self-perceived health and life satisfaction, a fixed effects ordered probit model and a fixed effects linear model are recommended in the literature. I use a fixed effects ordered logit model as the dependent variable is measured on an ordinal scale and the probit model is prone to misspecification. For comparison reasons, I also analyze the fixed effects probit and linear model.

Results
Over 13000 observations for life satisfaction and over 15000 for self-perceived health are used. Self-perceived health significantly decreases when the disabilities occur, but life satisfaction remains the same. Supportive evidence for adaptation in the life satisfaction analysis was found, but not in that for self-perceived health.

Discussion
It is possible that the effect of adaptation to chronic disability in self-perceived health can only be found after a longer duration than that measured here. The difference might also be explained by the contextualization of the response variables, where the question on self-perceived health is more focused on health limitations and the question on life satisfaction on general well-being.

Contents

1 Introduction

Health state evaluations have become increasingly important to policy makers concerned with the allocation of health care resources (Menzel, Dolan, Richardson & Olsen, 2002; Versteegh & Brouwer, 2016). These economic evaluations are requested in many countries to inform pricing, reimbursing and funding decisions (Cubí-Mollà, Jofre-Bonet & Serra-Sastre, 2016). The evaluations are usually based on respondents' preferences for being in an impaired health state compared to being completely healthy. Interestingly, health state preferences of the general public (consisting of generally healthy individuals) do not necessarily coincide with those of patients. Members of the general public are inclined to estimate a larger negative impact of health impairments compared to the health state appraisals of the patients themselves (Sackett & Torrance, 1978; Krahn et al., 2003; Peeters & Stiggelbout, 2010). Thus, the discussion dedicated to the question which group of people should be consulted to obtain these measurements is not trivial.

In the Netherlands, health state evaluations of the general public are preferred (Zorginstituut Nederland, 2016), even though patient health state evaluations are more informative about the subjective impact of a certain health state. The general concern with patient health state evaluations is that they are potentially biased due to "response shifts". The idea being that the meaning of a patient's self-evaluation has changed due to a change in internal standards, values, or conceptualization of quality of life, leading to a shift in the patient's reference point (Sprangers & Schwartz, 1999). In contrast, members of the general public reason from the same reference point of being in full health and are thought to have a uniform representation of the 'distance' between their own healthy state and the health impairment. Thus, an argument in favour of health state preferences of the general public is that they lend themselves to universally applicable valuations.

Adaptation to impaired health states is a particular realization of response shift (Cubí-Mollà, Jofre-Bonet & Serra-Sastre, 2016). The difference in the patient's experience and the public's ideation of certain health states is often attributed to adaptation. Frederick and Loewenstein describe adaptation as "a reduction in the affective intensity of favorable and unfavorable circumstances" (1999, p.302). A proper understanding of the dynamics governing the health state preferences of patients could be highly beneficial to the discussion on health state measurements. In particular, the empirical assessment of the adaptation process could help explain the difference between patient and public health state measurements and create insight into the changes of patients' self-perceived health over the course of the disability.

Adaptation to health states has been widely studied by psychologists and experimental economists. However, there only appears to be a small (yet growing) set of high-quality studies that have empirically examined adaptation. Early studies investigating adaptation to impaired health states predominantly employ cross-sectional methods. Note that this means no conclusions can be drawn regarding the effect of time since diagnosis on subjective health and hence these results cannot be used as evidence for adaptation within patients. However, the cross-sectional analyses enable a comparison of health state measurements across different groups of people. The counter-intuitive results show that patients with serious health limitations report well-being or self-reported health levels that are notably above the health state appraisals of healthy subjects as was previously mentioned (Sackett & Torrance, 1978; Krahn et al., 2003; Peeters & Stiggelbout, 2010). Moreover, certain studies even found that patient well-being is only marginally lower than that of healthy subjects (Brickman, Coates & Janoff-Bullman, 1978; Schulz & Decker, 1985; Tyc, 1992).

Recent studies have used panel data in order to examine adaptation to chronic infirmity from the moment of diagnosis. Their empirical evidence does not provide unambiguous support for the occurrence or level of adaptation. Lucas (2007) does not find any adaptation in two large panel data sets. In his study, multilevel models were used to measure adaptation in long-term disabled subjects on life satisfaction. On the other hand, Oswald and Powdthavee (2008) cannot replicate Lucas' findings using a fixed effects model for self-reported life satisfaction, whilst analyzing the same data sets. They find a considerable level of adaptation and suggest that the differing results are due to a difference in the respective methodologies, with the multilevel model used by Lucas being technically closer to a random effects model. Finally, Cubí-Mollà, Jofre-Bonet and Serra-Sastre (2016) do find some evidence for adaptation to self assessed health. They make use of a dynamic fixed effects probit model by utilizing Wooldrigde's (2005) approach. The authors only find a significant effect of duration since the onset of a long-standing illness after 20 years.

It is the objective of this thesis to study adaptation to chronic health limitations. I hypothesize that time since the onset of the chronic disability is positively related to the probability of reporting better health and life satisfaction. To this aim, the effect of adaptation, assessed through the time an individual has experienced limitations with instrumental activities of daily living (IADL) and the severity of these limitations, is analyzed for both self-perceived health and life satisfaction. I hope to establish changes in either of these constructs that can be attributed to the adaptation response shift process as a function of time spend with a chronic disability. The main assumption is that changes in either self-perceived health or life satisfaction can indeed be attributed to the adaptation mechanism, whatever the nature of the contributing factors. The intensity of the underlying impaired health condition is controlled for by the number of limitations with (IADL), which is indicative of the severity of the chronic disability. In doing so, the health state of the respondents is allowed to fluctuate over time. Furthermore, I control for potential other shocks to subjective health and life satisfaction by adding socioeconomic covariates like marital status and labour-force status.

The data used for this analysis is obtained from the SHARE (Survey of Health, Ageing and Retirement in Europe) database. It is a panel data set consisting of individuals aged 50 and over spanning 6 waves. I find that a longer duration is related to a higher probability of being satisfied with life, but not with the probability of reporting a better self-perceived health.

This thesis contributes to the existing literature in that it uses panel data as opposed to a cross-sectional model. In doing so, the trajectory of adaptation over time can be studied and I can control for individual heterogeneity. I employ a fixed effects ordered logit model, which has to my knowledge not been used for studying adaptation. This nonlinear model exploits the ordering of the dependent variable whilst allowing it to be discrete. It consistently estimates the parameters. Furthermore, the duration of the chronic disability is measured by dummy variables, permitting the effect of adaptation since the onset of the chronic limitations to be nonlinear. In addition, adaptation is analyzed for both self-perceived health and life satisfaction, since the effect could differ per outcome measure and no research has looked into this potential difference. Finally, the analysis is not limited to individuals whose latent health is assumed to stay constant. By broadening my selection to those reporting differing levels in the number of limitations with IADL, I can apply the results to a wider scope of health conditions, like diseases that deteriorate over time. In sum, this thesis aims to add new insights to the investigation of adaptation to chronic disability. The results can be used to inform members of the general public about the changes in the health perception of patients, so that they can incorporate this into their health state preferences.

This thesis consists of the following sections. The next section contains the methodology focusing on three econometric models of interest. Section 3 presents the data set and results, including an investigation regarding the robustness of the results. The final section provides a conclusion and a discussion on the limitations with suggestions for future research.

2 Methods

A perusal of the adaptation literature brings to light the myriad of choices involved in the econometric modelling of the adaptation process. In order to explain my preference for the fixed effects ordered logit specification, I will first generally compare and contrast two methods employed in the literature with my proposed model. The two particular empirical strategies under consideration here are presented in Clark, D'Ambrosio and Ghislandi (2016) and Cubí-Mollà, Jofre-Boner and Serra-Sastre (2016).

A schematic overview of the most important features of the logit model and the two models from the literature can be found in table 1. First of all, note that all model specifications here assume fixed effects, meaning that the individual heterogeneous terms might be correlated with the regressors. Secondly, both the ordered logit model proposed in this thesis and the ordered probit model presented by Cubí-Mollà, Jofre-Boner and Serra-Sastre are nonlinear. These nonlinear model specifications are attractive, since they account for the discrete nature of the outcome variable (subjective health or life satisfaction), whilst still incorporating its ordered structure. However, in the estimation of these model coefficients, the unobserved heterogeneity cannot simply be removed by performing a linear transformation, like the within transformation that can be applied to the OLS fixed effects model proposed by Clark, D'Ambrosio and Ghislandi. As a consequence, the fixed effects cannot be estimated consistently under a fixed number of time periods. Even as the number of individuals grows without bound, the number of parameters to be estimated also goes to infinity.

This is referred to as the incidental parameters problem (Neyman & Scott, 1948). In short panels (a small number of observed time periods), this can lead to severe bias in the estimation of the regression parameters (Green, 2004). The ordered logit and ordered probit approaches discussed here both have distinct ways of handling this problem.

The ordered probit model put forward by Cubí-Mollà, Jofre-Boner and Serra-Sastre has, in addition to fixed effects, a dynamic structure. In order to deal with both the incidental parameters problem and the initial conditions problem created by the dynamics, they make use of a parameterization of the fixed effects as a function of the regressors following Wooldridge (2005). Even though their solution is parsimonious and easy to implement, the parameterization is prone to misspecification. Hence, I propose a technique based on the principles of the conditional logit estimator. The estimator in question is described in Baetschmann, Staub, and Winkelmann (2015). It effectively eliminates the fixed effects in an ordered logit model and yields consistent estimates, without having to parameterize the fixed effects.

Finally, the analyses by Clark, D'Ambrosio and Ghislandi and Cubí-Mollà, Jofre-Boner and Serra-Sastre assume a different functional form for the adaptation process. Both methodologies measure adaptation by means of the duration since the onset of the life event, but only Clark, D'Ambrosio and Ghislandi allow the effect to be nonlinear by constructing dummy variables. These dummy variables correspond to consecutive time segments indicative of how long ago somebody experienced the negative life event. I also believe that the continuous functional form for adaptation of Cubí-Mollà, Jofre-Boner and Serra-Sastre is too restrictive and use the dummy specification outlined here.

Table 1: Econometric strategies for modelling adaptation

	FE ordered logit	Clark, D'Ambrosio & Ghislandi (2016)	Cubí-Mollà, Jofre-Boner & Serra-Sastre (2016)
Model specification	FE ordered logit	FE OLS	FE ordered probit
Functional form adaptation	Dummy variables	Dummy variables	Continuous
Parameterization of FE	No	No	Yes

Note. FE stands for fixed effects.

In sum, the main features of my proposed fixed effects ordered logit specification can be found in the first column of table 1. Next, an in depth discussion devoted to the econometric theory of this ordered logit model is provided.

2.1 Fixed effects ordered logit model

The fixed effects ordered logit estimation utilized here is based on the "blow-up and cluster" (BUC) estimator proposed by Baetschmann, Staub and Winkelmann (2015). The ordered logit specificaiton assumes the existence of a latent response variable according to:

$$Y_{it}^{*} = C_{it}'\theta + D_{it}'\delta + IADL_{it}\gamma + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T. \tag{1}$$

Here, Y_{it}^{*} is the respondent's latent self-perceived health or life satisfaction. The variables of interest are the number of limitations with instrumental activities of daily living (IADL), $IADL_{it}$, and duration, D_{it}, measured by dummies indicating the time since the onset of the limitations. I expect a negative effect for $IADL_{it}$, but a positive effect for at least one of the dummies contained by D_{it}. C_{it} consists of a number of sociodemographic covariates. For the remainder of this discussion, I shorten the notation by grouping the regressors in the vector $X_{it} = (C_{it}', D_{it}', IADL_{it})'$ and the parameters by $\beta = (\theta', \delta', \gamma)'$. Lastly, α_i is the individual specific fixed effect and I assume that the error term follows a logistic distribution:

$$F(\varepsilon_{it}|X_{it}, \alpha_i) = \frac{exp(\varepsilon_{it})}{1 + exp(\varepsilon_{it})} \equiv \Lambda(\varepsilon_{it}) \tag{2}$$

The observed self-perceived health or life satisfaction, denoted by Y_{it}, is constructed from Y_{it}^{*} as follows:

$$Y_{it} = k \quad \text{if } \tau_{ik-1} < Y_{it}^{*} \leq \tau_{ik}, \quad k = 1, \ldots, K. \tag{3}$$

The thresholds between categories $k-1$ and k can be individual specific, with $\tau_{i0} = -\infty$ and $\tau_{iK} = \infty$.

The probability for individual i at time t of reporting outcome k is given by

$$P(Y_{it} = k|X_{it}, \alpha_i) = \Lambda(\tau_{ik} - X_{it}'\beta - \alpha_i) - \Lambda(\tau_{ik-1} - X_{it}'\beta - \alpha_i). \tag{4}$$

Clearly, equation 4 not only depends on X_{it} and β, but also on α_i, τ_{ik-1} and τ_{ik}. Hence, we are first of all faced with an identification problem, since only $\tau_{ik} - \alpha_i$ is identified. Secondly, under fixed T, the incidental parameters problem persists as was discussed earlier. These two concerns are addressed by means of conditional maximum likelihood estimation on a binary variable constructed from the original multinomial variable Y_{it}. The binary variable, d_{it}^{k}, is constructed by dichotomizing the response variable at a cut-off point k: $d_{it}^{k} = 1(Y_{it} \geq k)$. Here, the cut-off point can lie anywhere between 2 and K. The joint probability of observing $d_i^k = (d_{i1}^k, \ldots, d_{iT}^k)' = (j_{i1}, \ldots, j_{iT})' = j_i$, where $j_{it} \in \{0, 1\}$, is given by

$$P_i^k(\beta) = P(d_i^k = j_i | \sum_{t=1}^{T} d_{it}^k = g_i) = \frac{exp(j_i' X_i \beta)}{\sum_{j \in B_i} exp(j' X_i \beta)}. \tag{5}$$

Here, the sum of all the outcomes over time, $\sum_{t=1}^{T} d_{it}^k = g_i = \sum_{t=1}^{T} j_{it}$, is a sufficient statistic for α_i, since the probability in equation 5 is independent of α_i and the thresholds. Moreover, X_i is a $T \times M$ matrix, with M the number of regressors and row t equal to X_{it}. The sum in the denominator of equation 5 concerns the set B_i which consists of all vectors j of length T that have as many elements equal to one as the observed vector j_i of individual i:

$$B_i = \left\{ j \in \{0,1\}^T | \sum_{t=1}^{T} j_t = g_i \right\}.$$

The resulting conditional log likelihood is given by

$$LL^k(b) = \sum_{i=1}^{N} log(P_i^k(b)). \tag{6}$$

The maximization of this likelihood function for a dichotomized dependent variable at any cut-off point k has been shown to be consistent by Chamberlain (1980) and will therefore be referred to as the Chamberlain estimator denoted by $\hat{\beta}^k$. The first order derivatives and individual Hessians used for this optimization can be found in appendix A.1.

Note that individuals with constant d_{it}^k do not contribute to the conditional log likelihood, since $P(d_{it}^k = 1| \sum_{t=1}^T d_{it}^k = T) = P(d_{it}^k = 0| \sum_{t=1}^T d_{it}^k = 0) = 1$. Hence, it is worthwhile to obtain β estimates acquired with Chamberlain estimators using different cut-off points k, since the group of individuals contributing to the likelihood function is likely to change for different cut-off points. In fact, if we employ all possible $K-1$ Chamberlain estimators of β, each individual will contribute at least once to a likelihood function, as long as the observed Y_{it}'s of the individual in question are not constant.

The BUC estimator proposed by Baetschmann, Staub and Winkelmann (2015) is based on the maximization of the sum of all possible $K-1$ Chamberlain likelihood functions:

$$LL^{BUC}(b) = \sum_{k=2}^{K} LL^k(b), \tag{7}$$

where $LL^k(b)$ is defined in equation 6. By exploiting the information provided by the different configurations of individuals for different cut-off points, the BUC estimator is more efficient than the Chamberlain estimator. The BUC estimator, $\hat{\beta}^{BUC}$, maximizes the likelihood in equation 7 under the restriction that $\hat{\beta}^2 = \ldots = \hat{\beta}^K$. Since the individual Chamberlain estimators are consistent, it is easy to verify the consistency of the BUC estimator. The first order derivatives of the Chamberlain estimators converge to 0 at the true parameter, which means that the sum of the derivatives - equalling the first order derivative of the BUC log likelihood - will converge to 0 as well at its optimum. Given the concavity of the objective function, this ensures that $\hat{\beta}^{BUC}$ converges to β.

We need to cluster the standard errors at the individual level, due to the constructed dependency between the observations. Hence, the information matrix equality used for the regular maximum likelihood approach is not valid and a cluster robust variance estimator should be used based on the following asymptotic variance (the limiting variance of $\sqrt{n}(\hat{\beta}^{BUC} - \beta)$):

$$Avar(\hat{\beta}^{BUC}) = \left\{ \sum_{k=2}^{K} E(H_i^k(\beta)) \right\}^{-1} \left[\sum_{k=2}^{K} \sum_{l=2}^{K} E(s_i^k(\beta) s_i^l(\beta)') \right] \left\{ \sum_{k=2}^{K} E(H_i^k(\beta)) \right\}^{-1}. \tag{8}$$

Here, $H_i^k(\beta)$ denote the individual Hessians and $s_i^k(\beta)$ the first order derivatives with respect to the Chamberlain likelihood function in equation 6. In the analysis, the expectations are replaced by their sample analogs and the parameters by their estimated values.

Finally, from the β estimates we can derive the statistical significance of the effect of the regressors on the probability of reporting better self-perceived health or life satisfaction. They cannot, however, be interpreted in terms of the size of this effect. Unfortunately, average marginal effects for $P(Y_{it} > k) = 1 - \Lambda(\tau_{ik} - X_{it}'\beta - \alpha_i)$ cannot be calculated directly, since they require estimates of τ_{ik} and α_i. However, I will estimate these by replacing the required probabilities with the sample probabilities. These are computed by summing the number of observations in the categories larger than k and dividing this by the total number of observations. Even though the resulting marginal effects are approximations, they still aid the general interpretation of the results.

2.2 The OLS and probit models

In addition to the fixed effects ordered logit model, I have also analyzed adaptation to chronic disability by following the proposed model specifications of Clark, D'Ambrosio and Ghislandi (2016) and Cubí-Mollà, Jofre-Boner and Serra-Sastre (2016). In light of the previous comparison of these three models, I will examine whether the discussed differences in modelling strategies affect the results. Next, the econometric foundation of these two supplementary models is outlined shortly.

2.2.1 Fixed effects OLS model

The fixed effects OLS model is featured in the study by Clark, D'Ambrosio and Ghislandi (2016) who use it to investigate adaptation to poverty. The regression equation is:

$$Y_{it} = C_{it}'\theta + D_{it}'\delta + IADL_{it}'\gamma + \alpha_i + \varepsilon_{it}, \tag{9}$$

with Y_{it} the self-reported health or life satisfaction, C_{it} a vector with covariates, D_{it} a vector with dummy variables capturing the time since onset of the chronic disability and $IADL_{it}$ the number of limitations with IADL. The coefficients can be estimated by means of ordinary least squares linear fixed effects. Additional statistics can be derived with the standard fixed effects calculations.

2.2.2 Fixed effects ordered probit model

The second model is based on the ordered fixed effects probit model put forward by Cubí-Mollà, Jofre-Boner and Serra-Sastre (2016) to examine adaptation to a long-standing illness.

Similar to the logit specification, a latent response variable is modelled by

$$Y_{it}^{*} = Y_{i,t-1}\lambda + C_{it}'\theta + D_{it}\delta + IADL_{it}\gamma + I_{it}\nu + \alpha_i + \varepsilon_{it}, \tag{10}$$

where Y_{it}^{*} and $Y_{i,t-1}$ represent the latent response variable and observed response variable in the period $t-1$. The response variable is again either self-reported health or life satisfaction. Moreover, I_{it} stands for incidence, corresponding to individuals having one or more limitations with instrumental activities of daily living (IADL) and $IADL_{it}$ represents the number of limitations with IADL. D_{it} measures the duration since the onset of the chronic disability. Lastly, some sociodemographic control variables, C_{it}, are included. For convenience sake, all exogenous regressors are collected in the vector $X_{it} = (C_{it}', D_{it}, IADL_{it}, I_{it})'$ with corresponding parameters $\beta = (\theta', \delta, \gamma, \nu)$. Here, α_i is the individual specific fixed effect and ε_{it} is assumed to follow a standard normal distribution.

The observed outcome Y_{it} is related to the latent response variable Y_{it}^{*} by

$$Y_{it} = k \text{ if } \tau_{k-1} < Y_{it}^{*} < \tau_k \text{ for } k = 1, \ldots, K. \tag{11}$$

Here, K is the total number of categories and $\tau_0 = -\infty$ and $\tau_K = \infty$. The probability for individual i in period t of reporting a specific Y_{it} category becomes:

$$P(Y_{it} = k) = \Phi(\tau_k - Y_{i,t-1}\lambda - X_{it}'\beta - \alpha_i) - \Phi(\tau_{k-1} - Y_{i,t-1}\lambda - X_{it}'\beta - \alpha_i), \tag{12}$$

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

The incidental parameters problem caused by the fixed effects and the initial condition problem as a result of the introduced dynamics are dealt with by using Wooldridge's (2005) approach, which suggests the parameterization of the fixed effects α_i as a function of the first observed outcome in the sample and the average of the exogenous variables:

$$\alpha_i = \sigma + \phi Y_{i,1} + \mu \bar{X}_i + \varepsilon_i \tag{13}$$

The final equation can be obtained by substituting the results in equation 13 back into equation 12 producing:

$$\begin{aligned} P(Y_{it} = k) = {} & \Phi(\tau_k - Y_{i,t-1}\lambda - X_{it}'\beta - \sigma - \phi Y_{i,1} - \mu \bar{X}_i) \\ & -\Phi(\tau_{k-1} - Y_{i,t-1}\lambda - X_{it}'\beta - \sigma - \phi Y_{i,1} - \mu \bar{X}_i), \end{aligned} \tag{14}$$

The likelihood function obtained with these probabilities can be optimized by means of the maximum likelihood estimator. The standard errors can be obtained by the usual information matrix equality (taking the inverse of the Hessian that is calculated with respect to the likelihood function).

3 Results

3.1 Data

Table 2 presents the distribution of respondents across the life satisfaction categories for the four different waves.
Table 3 presents the distribution of respondents across the self-perceived health categories for the five different waves.
Table 4 presents the descriptive statistics.

Table 2: Life satisfaction categories with frequency distribution across waves

Life satisfaction	Waves			
	2006/07(%)	2008/09(%)	2013(%)	2015(%)
1 = Rating scale 1,2,3	0.042	0.038	0.063	0.048
2 = Rating scale 4	0.023	0.029	0.035	0.029
3 = Rating scale 5	0.120	0.144	0.183	0.171
4 = Rating scale 6	0.104	0.097	0.104	0.104
5 = Rating scale 7	0.191	0.166	0.167	0.170
6 = Rating scale 8	0.272	0.273	0.231	0.259
7 = Rating scale 9	0.122	0.107	0.100	0.105
8 = Rating scale 10	0.125	0.145	0.118	0.115

Table 3: Self-perceived health categories with frequency distribution across waves

Self-perceived	Waves				
health	2004/06(%)	2006/07(%)	2008/09(%)	2013(%)	2015(%)
1 = Poor	0.093	0.208	0.255	0.291	0.354
2 = Fair	0.351	0.385	0.434	0.428	0.455
3 = Good	0.403	0.297	0.241	0.222	0.159
4 = Very good	0.110	0.080	0.055	0.049	0.026
5 = Excellent	0.044	0.029	0.016	0.011	0.006

Table 4: Descriptive statistics

Variable	Definition	Label	Mean	Standard deviation
Life satisfaction[1]	1 = Rating scale 1,2,3	Life satisfaction 1	0.049	0.216
	2 = Rating scale 4	Life satisfaction 2	0.030	0.171
	3 = Rating scale 5	Life satisfaction 3	0.159	0.365
	4 = Rating scale 6	Life satisfaction 4	0.102	0.303
	5 = Rating scale 7	Life satisfaction 5	0.171	0.377
	6 = Rating scale 8	Life satisfaction 6	0.256	0.437
	7 = Rating scale 9	Life satisfaction 7	0.107	0.309
	8 = Rating scale 10	Life satisfaction 8	0.126	0.332
Self-perceived health	1 = Poor	Poor	0.263	0.440
	2 = Fair	Fair	0.421	0.494
	3 = Good	Good	0.243	0.429
	4 = Very good	Very good	0.056	0.230
	5 = Excellent	Excellent	0.017	0.130
Incidence of disability	Incidence of any number of chronic limitations with IADL	Disability incidence	0.451	0.498
Number of limitations	Number of chronic limitations with IADL	Number of limitations	1.097	1.818
Duration	Duration of chronic disability	Disability duration	2.000	1.653
Gender	1 = Male	Male	0.413	0.492
Age	Age	Age	72.108	10.388
Martial status	1 = Married/ Registered partnership	Married/ Registered partnership	0.618	0.486
Employment	1 = Retired	Retired	0.712	0.453
	2 = Employed	Employed	0.087	0.283
	3 = Unemployed	Unemployed	0.023	0.149
	4 = Inactive	Inactive	0.178	0.383
Education[2]	1 =< high school	< high school	0.544	0.498
	2 = High school	High school	0.210	0.407
	3 = > high school	> high school	0.246	0.431
Number of children	Number of children	Number of children	2.276	1.534

[1] Life satisfaction is measured on a scale from 1 to 11 where 1 means completely dissatisfied and 11 means completely satisfied. The first three rating scale categories were merged in order to fill the first category enough for estimation purposes.
[2] Education is measured by transforming the years of education in terms of high school duration.

3.2 Results fixed effects ordered logit model

Table 5 presents the regression estimates for the fixed effects ordered logit model.
Table 6 presents the estimated marginal effects for the regression with life satisfaction. The effects represent the size of the effect of a marginal increase in a regressor on the probability of falling into a category higher than k.
Table 7 presents the estimated marginal effects for the regression with self-perceived health.

Table 5: FE ordered logit regression

Variable (Reference category)	Life satisfaction	Self-perceived health
Not married	-0.254	-0.048
(Married)	(0.157)	(0.152)
Retired	-0.443***	-0.725***
(Employed)	(0.133)	(0.146)
Unemployed	-0.705**	-0.662**
(Employed)	(0.235)	(0.228)
Inactive	-0.555***	-0.824***
(Employed)	(0.142)	(0.148)
Educ $<$ high school	0.167	0.231
(High school)	(0.182)	(0.127)
Educ $>$ high school	0.174	-0.010
(High school)	(0.180)	(0.122)
Number of children	0.046	-0.029
	(0.038)	(0.027)
0 years IADL limit.	0.028	0.929***
(0-2 years IADL limit.)	(0.118)	(0.204)
2-5.5 years IADL limit.	0.141	-0.044
(0-2 years IADL limit.)	(0.075)	(0.080)
$>$ 5.5 years IADL limit.	0.474***	-0.026
(0-2 years IADL limit.)	(0.144)	(0.146)
Number of IADL limit.	-0.157***	-0.163***
	(0.029)	(0.027)
Number of subjects	5259	5341
Number of observations	13328	15802

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. Standard errors are obtained by means of a cluster robust variance estimation.

Table 6: Marginal effects on the probability of reporting Y>k

	Life satisfaction						
Variable (Reference category)	Score 1	Score 2	Score 3	Score 4	Score 5	Score 6	Score 7
0 years IADL limit. (0-2 years IADL limit.)	-0.001	-0.001	-0.003	-0.004	-0.004	-0.003	-0.002
2-5.5 years IADL limit. (0-2 years IADL limit.)	0.007	0.010	0.026	0.032	0.036	0.026	0.016
$>$ 5.5 years IADL limit. (0-2 years IADL limit.)	0.023	0.035	0.088	0.109	0.122	0.087	0.054
Number of IADL limit.	-0.008	-0.013	-0.032	-0.039	-0.044	-0.031	-0.019

Note. The marginal effects for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

Table 7: Marginal effects on the probability of reporting Y>k

	Self-perceived health			
Variable (Reference category)	Poor	Fair	Good	Very good
0 years IADL limit. (0-2 years IADL limit.)	0.173	0.193	0.061	0.015
2-5.5 years IADL limit. (0-2 years IADL limit.)	-0.008	-0.009	-0.003	-0.001
$>$ 5.5 years IADL limit. (0-2 years IADL limit.)	-0.005	-0.006	-0.002	-0.000
Number of IADL limit.	-0.033	-0.036	-0.011	-0.003

Note. The marginal effects for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

3.3 Results OLS and probit models

3.3.1 Results fixed effects OLS model

Table 8 presents the regression estimates for the fixed effects linear OLS model. For the full table of results including the effects of covariates see appendix A.3.

Table 8: FE linear least squares

Variable (Reference category)	Life satisfaction	Self-perceived health
0 years (NO) IADL limit.	0.041	0.319***
(0-2 years IADL limit.)	(0.042)	(0.017)
2-5.5 years IADL limit.	0.114*	0.019
(0-2 years IADL limitations)	(0.053)	(0.024)
$>$ 5.5 years IADL limit.	0.363***	0.049
(0-2 years IADL limitations)	(0.103)	(0.043)
Number of IADL limit.	-0.164***	-0.082***
	(0.015)	(0.005)
Number of subjects	5259	5341
Number of observations	13328	15802

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

3.3.2 Results fixed effects ordered probit model

Table 9 presents the regression estimates for the fixed effects ordered probit model. For the full table of results including the effects of covariates see appendix A.4.

Table 9: Ordered probit model life satisfaction

Life satisfaction		Self-perceived health	
Variable (Reference category)	Coefficients	Variable (Reference category)	Coefficients
$Y_{t-1} = 2$	0.693	$Y_{t-1} =$ Fair	0.589***
($Y_{t-1} = 1$)	(0.36)	($Y_{t-1} =$ Poor)	(0.068)
$Y_{t-1} = 3$	0.852*	$Y_{t-1} =$ Good	0.970***
($Y_{t-1} = 1$)	(0.415)	($Y_{t-1} =$ Poor)	(0.098)
$Y_{t-1} = 4$	0.932*	$Y_{t-1} =$ Very good	1.241***
($Y_{t-1} = 1$)	(0.422)	($Y_{t-1} =$ Poor)	(0.145)
$Y_{t-1} = 5$	1.162**	$Y_{t-1} =$ Excellent	1.330***
($Y_{t-1} = 1$)	(0.385)	($Y_{t-1} =$ Poor)	(0.346)
$Y_{t-1} = 6$	1.380***		
($Y_{t-1} = 1$)	(0.354)		
$Y_{t-1} = 7$	1.549***		
($Y_{t-1} = 1$)	(0.336)		
$Y_{t-1} = 8$	1.748***		
($Y_{t-1} = 1$)	(0.373)		
$Y_{t,1} = 2$	0.720	$Y_{t,1} =$ Fair	0.258
($Y_{t,1} = 1$)	(0.448)	($Y_{t,1} =$ Poor)	(0.144)
$Y_{t,1} = 3$	0.728	$Y_{t,1} =$ Good	0.508**
($Y_{t,1} = 1$)	(0.490)	($Y_{t,1} =$ Poor)	(0.173)
$Y_{t,1} = 4$	0.888*	$Y_{t,1} =$ Very good	0.713**
($Y_{t,1} = 1$)	(0.432)	($Y_{t,1} =$ Poor)	(0.227)
$Y_{t,1} = 5$	0.861*	$Y_{t,1} =$ Excellent	1.050**
($Y_{t,1} = 1$)	(0.435)	($Y_{t,1} =$ Poor)	(0.380)
$Y_{t,1} = 6$	1.061*		
($Y_{t,1} = 1$)	(0.461)		
$Y_{t,1} = 7$	1.226**		
($Y_{t,1} = 1$)	(0.445)		
$Y_{t,1} = 8$	1.248*		
($Y_{t,1} = 1$)	(0.506)		
Disability duration	0.100**	Disability duration	0.042*
	(0.031)		(0.018)
Incidence disability	-0.127	Incidence disability	-0.455***
	(0.121)		(0.042)
Number of IADL limitations	-0.061*	Number of IADL limitations	-0.121***
	(0.024)		(0.019)
Threshold 1	0.946	Threshold 1	0.040
Threshold 2	1.215	Threshold 2	1.468
Threshold 3	2.006	Threshold 3	2.683
Threshold 4	2.344	Threshold 4	3.504
Threshold 5	2.841		
Threshold 6	3.658		
Threshold 7	4.133		
Number of subjects	4556	Number of subjects	5335
Number of observations	8252	Number of observations	10455

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. Standard errors are obtained via the inverse of the negative hessian calculated with a maximum likelihood approach at the optimized estimates. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

3.4 Robustness checks

The first two columns of table 10 present the regression estimates for the fixed effects ordered logit model applied to individuals whose limitations with IADL stay constant over their entire observed period.
The second two columns of table 10 present the regression estimates for the fixed effects ordered logit model applied to individuals whose limitations with IADL increase over their observed period.
Table 11 presents the regression estimates for the fixed effects ordered logit model where duration is continuous as opposed to divided into dummy variables.
Table 12 presents the regression estimates for the fixed effects ordered logit model applied to individuals who are observed for at least three waves.

Table 10: FE ordered logit regression different subgroups

	Constant IADL limit.		Increasing IADL limit.	
Variable (Reference category)	Life satisfaction	Self-perceived health	Life satisfaction	Self-perceived health
0 years IADL limit.	-0.126	0.828***	0.694***	1.470***
(0-2 years IADL limit.)	(0.196)	(0.220)	(0.186)	(0.186)
2-5.5 years IADL limit.	0.176	-0.087	0.692***	-0.209
(0-2 years IADL limit.)	(0.124)	(0.131)	(0.195)	(0.227)
$>$ 5.5 years IADL limit.	0.651	-0.297	0.782*	-0.629
(0-2 years IADL limit.)	(0.332)	(0.310)	(0.337)	(0.355)
Number of IADL limit.	-0.163***	-0.191***	-0.221***	-0.090
	(0.041)	(0.041)	(0.052)	(0.058)
Number of subjects	4322	4398	442	444
Number of observations	10493	12262	1270	1654

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

Table 11: FE ordered logit regression continuous duration

Variable (Reference category)	Life satisfaction	Self-perceived health
Disability duration	0.053*	-0.129*
	(0.024)	(0.053)
Number of IADL limit.	-0.170***	-0.267***
	(0.021)	(0.028)
Number of subjects	5259	5341
Number of observations	13328	15802

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

Table 12: FE ordered logit regression including individuals with limitations in at least 3 waves

Variable (Reference category)	Life satisfaction	Self-perceived health
0 years (NO) IADL limit.	-0.214	1.279***
(0-2 years IADL limit.)	(0.224)	(0.205)
2-5.5 years IADL limit.	-0.043	-0.325
(0-2 years IADL limitations)	(0.171)	(0.170)
> 5.5 years IADL limit.	0.512**	-0.183
(0-2 years IADL limitations)	(0.188)	(0.182)
Number of IADL limit.	-0.246***	-0.149*
	(0.059)	(0.058)
Number of subjects	323	324
Number of observations	1142	1487

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, education and number of children. The reference categories are married, employed and high school education.

4 Discussion

4.1 Summary

Supportive evidence for adaptation in the life satisfaction data was found, but not in self-perceived health.

4.2 Limitations

It is possible that the effect of adaptation to chronic disability in self-perceived health can only be found after a longer duration than that measured here. The difference might also be explained by the contextualization of the response variables, where the question on self-perceived health is more focused on health limitations and the question on life satisfaction on general well-being.

4.3 Implicication theory

4.4 Implications practice

4.5 conclusions

REFERENCES

Baetschmann, G., Staub, K.E. & Winkelmann, R. (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society, A, 178(3),* 685-703.

Brickman, P., Coates, D. & Janoff-Bulman, R. (1978). Lottery winners and accident victims: Is happiness relative? *Journal of Personality and Social Psychology, 36*, 917–927.

Clark, A.E., D'Ambrosio, C. & Ghislandi, S. (2016). Adaptation to poverty in long-run panel data. *Review of Economics and Statistics, 98(3),* 591-600.

Cubí-Mollà, P., Jofre-Bonet, M. & Serra-Sastre, V. (2016). Adaptation to health states: Sick yet better off? *Health Economics,* 1-18.

Frederick, S. & Loewenstein, G. (1999). *Hedonic adaptation.* In: Diener, E., Schwarz, N. & Kahneman, D. (Eds.), Hedonic Psychology: Scientific Approaches to Enjoyment, Suffering, and Well-Being. Russell Sage Foundation, New York, pp. 302–329.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *Econometrics Journal, Vol 7(1)*, 98-119.

Krahn, M., Ritvo, P., Irvine, J., Tomlinson, G., Bremmer, K.E., Bezjak, A., Trachtenberg, J. & Naglie, G. (2003). Patient and community preferences for outcomes in prostate cancer: Implications for clinical policy. *Medical Care, 41(1),* 153-164.

Lucas, R.E. (2007). Long-term disability is associated with lasting changes in subjective well-being: Evidence from two nationally representative longitudinal studies. *Journal of Personality and Social Psychology, 92,* 717–730.

Menzel, P., Dolan, P., Richardson, J. & Olsen, J.A. (2002). The role of adaptation to disability and disease in health state valuation: A preliminary normative analysis. *Social Science & Medicine, 55,* 2149-2158.

Neyman, J. & Scott E.L. (1948). Consistent Estimates Based on Partially Consistent Observations. *Econometrica, 16(1),* 1-32.

Oswald, A.J. & Powdthavee, N. (2008). Does happiness adapt? A longitudinal study of disability with implications for economists and judges. *Journal of Public Economics, 92,* 1061-1077.

Peeters, Y. & Stiggelbout, A.M. (2010). Health state valuations of patients and the general public analytically compared: A meta-analytical comparison of patient and population health state utilities. *Value in Health, 13(2),* 306-309.

Sackett, D.L. & Torrance, G.W. (1978). The utility of different health states as perceived by the general public. *Journal of Chronic Diseases, 32(11),* 697-704.

Schulz, R. & Decker, S. (1985). Long-term adjustment to physical disability: The role of social support, perceived control, and self-blame. *Journal of Personality and Social Psychology, 48(5),* 1162-1172.

Sprangers, M.A.G. & Schwartz, C.E. (1999). Integrating response shift into health-related quality of life research: A theoretical model. *Social Science & Medicine 48,* 1507-1515.

Tyc, V. L. (1992). Psychosocial adaptation of children and adolescents with limb deficiencies: A review. *Clinical Psychology Review, 2,* 275-91.

Versteegh, M.M. & Brouwer, W.B.F. (2016). Patient and general public preferences for health states: A call to reconsider current guidelines. *Social Science & Medicine, 165,* 66-74.

Wooldridge, J.M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics, 20,* 39-54.

Zorginstituut Nederland. (2016). Bijlage 2 in Richtlijn voor het uitvoeren van economische evaluaties in de gezondheidszorg. Zorginstituut Nederland, Diemen, The Netherlands.

APPENDIX

A.1

The first order derivatives of the conditional likelihood function for the Chamberlain estimator are as follows:

$$s_i^k = \frac{\partial log(P_i^k(b))}{\partial b} = x_i' \left\{ d_i^k - \sum_{j \in B_i} j \frac{exp(j' x_i b)}{\sum_{l \in B_i} exp(l' x_i b)} \right\}.$$

The individual Hessians for this likelihood function are given by

$$H_i^k(b) = \frac{\partial^2 log(P_i^k(b))}{\partial b \partial b'} = - \sum_{j \in B_i} \frac{exp(j' x_i b)}{\sum_{l \in B_i} exp(l' x_i b)} \times$$

$$\left(x_i' j - \sum_{m \in B_i} \frac{exp(m' x_i b)}{\sum_{l \in B_i} exp(l' x_i b} m' x_i \right) \left(x_i' j - \sum_{m \in B_i} \frac{exp(m' x_i b)}{\sum_{l \in B_i} exp(l' x_i b} m' x_i \right)'.$$

A.2

Table 13: Marginal effects on the probability of reporting Y>k

Variable (Reference category)	Life satisfaction Score 1	Score 2	Score 3	Score 4	Score 5	Score 6	Score 7
Not married (Married)	-0.012	-0.018	-0.046	-0.056	-0.063	-0.045	-0.028
Retired (Employed)	-0.022	-0.034	-0.086	-0.106	-0.118	-0.084	-0.052
Unemployed (Employed)	-0.034	-0.053	-0.131	-0.162	-0.181	-0.129	-0.080
Inactive (Employed)	-0.026	-0.041	-0.101	-0.125	-0.139	-0.100	-0.061
Educ < high school (High school)	0.007	0.012	0.029	0.036	0.040	0.029	0.018
Educ > high school (High school)	0.009	0.015	0.036	0.045	0.050	0.036	0.022
Number of children	0.002	0.003	0.008	0.010	0.011	0.008	0.005
0 years IADL limit. (0-2 years IADL limit.)	-0.001	-0.001	-0.003	-0.004	-0.004	-0.003	-0.002
2-5.5 years IADL limit. (0-2 years IADL limit.)	0.007	0.010	0.026	0.032	0.036	0.026	0.016
> 5.5 years IADL limit. (0-2 years IADL limit.)	0.023	0.035	0.088	0.109	0.122	0.087	0.054
Number of IADL limit.	-0.008	-0.013	-0.032	-0.039	-0.044	-0.031	-0.019

Marginal effects on the probability of reporting Y>k

Variable (Reference category)	Self-perceived health Poor	Fair	Good	Very good
Not married (Married)	-0.009	-0.010	-0.003	-0.001
Retired (Employed)	-0.142	-0.158	-0.050	-0.012
Unemployed (Employed)	-0.125	-0.139	-0.044	-0.011
Inactive (Employed)	-0.158	-0.176	-0.055	-0.014
Educ < high school (High school)	0.044	0.049	0.015	0.004
Educ > high school (High school)	-0.000	-0.000	-0.000	-0.000
Number of children	-0.007	-0.008	-0.002	-0.001
0 years IADL limit. (0-2 years IADL limit.)	0.173	0.193	0.061	0.015
2-5.5 years IADL limit. (0-2 years IADL limit.)	-0.008	-0.009	-0.003	-0.001
> 5.5 years IADL limit. (0-2 years IADL limit.)	-0.005	-0.006	-0.002	-0.000
Number of IADL limit.	-0.033	-0.036	-0.011	-0.003

A.3

Complete ordinary least squares linear fixed effects regression on both life satisfaction and self-perceived health

	Reference category	Life satisfaction	Self-perceived health
Not married	Married	-0.026*	-0.030
		(0.111)	(0.044)
Retired	Employed	-0.299**	-0.286***
		(0.094)	(0.039)
Unemployed	Employed	-0.468**	-0.267***
		(0.157)	(0.065)
Inactive	Employed	-0.387***	-0.326***
		(0.103)	(0.042)
Educ < high school	High school	0.114	0.062
		(0.122)	(0.046)
Educ > high school	High school	0.148	0.004
		(0.123)	(0.043)
Number of children		0.038	-0.001
		(0.038)	(0.015)
0 years (NO) IADL limitations	0-2 years IADL limitations	0.041	0.319***
		(0.042)	(0.017)
2-5.5 years IADL limitations	0-2 years IADL limitations	0.114*	0.019
		(0.053)	(0.024)
> 5.5 years IADL limitations	0-2 years IADL limitations	0.363***	0.049
		(0.103)	(0.043)
Number of IADL limitations		-0.164***	-0.082***
		(0.015)	(0.005)
Number of subjects		5259	5341
Number of observations		13328	15802

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses.

A.4

Complete fixed effects ordered probit regression on self-perceived health.

	Self-perceived health			
	Reference category	Coefficients	Parameterization of FE	
Y_{t-1} = Fair	Y_{t-1} = Poor	0.589***	$Y_{t,1}$	0.258
		(0.068)		(0.144)
Y_{t-1} = Good	Y_{t-1} = Poor	0.970***	$Y_{t,1}$	0.508**
		(0.098)		(0.173)
Y_{t-1} = Very good	Y_{t-1} = Poor	1.241***	$Y_{t,1}$	0.713**
		(0.145)		(0.227)
Y_{t-1} = Excellent	Y_{t-1} = Poor	1.330***	$Y_{t,1}$	1.050**
		(0.346)		(0.380)
Not married	Married	0.070	Mean	0.018
		(0.118)		(0.123)
Retired	Employed	-0.026	Mean	0.055
		(0.116)		(0.227)
Unemployed	Employed	0.074	Mean	0.017
		(0.186)		(0.326)
Inactive	Employed	-0.065	Mean	0.014
		(0.120)		(0.231)
Educ < high school	High school	0.081	Mean	-0.065
		(0.106)		(0.120)
Educ > high school	High school	-0.009	Mean	-0.092
		(0.096)		(0.118)
Number of children		-0.015	Mean	0.038
		(0.040)		(0.041)
Disability duration		0.042*	Mean	-0.030
		(0.018)		(0.024)
Incidence disability		-0.455***	Mean	0.115
		(0.042)		(0.121)
Number of IADL limitations		-0.121***	Mean	-0.049
		(0.019)		(0.017)
Threshold 1		0.040		
Threshold 2		1.468		
Threshold 3		2.683		
Threshold 4		3.504		
Number of subjects		5335		
Number of observations		10455		

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. Standard errors are obtained via the inverse of the negative hessian calculated with a maximum likelihood approach at the optimized estimates.

Complete fixed effects ordered probit regression on life satisfaction.

	Life satisfaction			
	Reference category	Coefficients	Parameterization of FE	
$Y_{t-1} = 2$	$Y_{t-1} = 1$	0.693	$Y_{t,1}$	0.720
		(0.362)		(0.448)
$Y_{t-1} = 3$	$Y_{t-1} = 1$	0.852*	$Y_{t,1}$	0.728
		(0.415)		(0.490)
$Y_{t-1} = 4$	$Y_{t-1} = 1$	0.932*	$Y_{t,1}$	0.888*
		(0.422)		(0.432)
$Y_{t-1} = 5$	$Y_{t-1} = 1$	1.162**	$Y_{t,1}$	0.861*
		(0.385)		(0.435)
$Y_{t-1} = 6$	$Y_{t-1} = 1$	1.380***	$Y_{t,1}$	1.061*
		(0.354)		(0.461)
$Y_{t-1} = 7$	$Y_{t-1} = 1$	1.549***	$Y_{t,1}$	1.226**
		(0.336)		(0.445)
$Y_{t-1} = 8$	$Y_{t-1} = 1$	1.748***	$Y_{t,1}$	1.248*
		(0.373)		(0.506)
Not married	Married	-0.120	Mean	0.040
		(0.201)		(0.194)
Retired	Employed	-0.484	Mean	0.957
		(1.081)		(1.081)
Unemployed	Employed	-0.818	Mean	1.377
		(2.250)		(2.546)
Inactive	Employed	-0.509	Mean	0.918
		(1.078)		(1.133)
Educ < high school	High school	-0.152	Mean	0.277*
		(0.151)		(0.134)
Educ > high school	High school	-0.019	Mean	0.236
		(0.292)		(0.347)
Number of children		0.049	Mean	0.002
		(0.079)		(0.089)
Disability duration		0.100**	Mean	-0.071
		(0.031)		(0.045)
Incidence disability		-0.127	Mean	0.235
		(0.121)		(0.372)
Number of IADL limitations		-0.061*	Mean	-0.071
		(0.024)		(0.045)
Threshold 1		0.946		
Threshold 2		1.215		
Threshold 3		2.006		
Threshold 4		2.344		
Threshold 5		2.841		
Threshold 6		3.658		
Threshold 7		4.133		
Number of subjects		4556		
Number of observations		8252		

Note. The significant codes are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$. Standard errors are reported underneath the regression estimates within parentheses. Standard errors are obtained via the inverse of the negative hessian calculated with a maximum likelihood approach at the optimized estimates.