A methodological comparison of the empirical assessment of adaptation to disability

Can time heal all wounds?

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Abstract

Chronically disabled patients generally report a higher quality of life in their impaired health state compared to members of the general public when imagining the experience of the same health state. 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 both self-perceived health and life satisfaction in a large longitudinal data set. Moreover, it examines what model specification is best suited to measuring adaptation in panel data.

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 6 waves of data collection. 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 linear fixed effects model are recommended in the literature. I propose a fixed effects ordered logit model because the dependent variable is measured on an ordinal scale and the proposed parameterization of the fixed effects in the ordered probit model is prone to misspecification. In order to assess how different model specifications affect the effect associated with adaptation, I also analyze the fixed effects probit and linear models.

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.

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 model features that appear to affect the measured adaptation process the most are added dynamics in the form of a lagged dependent variable and the assumed measurement scale of the dependent variable with associated estimation methods. The difference in outcome between the analysis with self-perceived health and that with life satisfaction can 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.

Key words: adaptation, disability, self-perceived health, life satisfaction, fixed effects ordered logit

1 Introduction

Chronically disabled patients generally report a higher quality of life in their impaired health state compared to members of the general public when imagining the experience of the same health state (Sackett & Torrance, 1978; Krahn et al., 2003; Peeters & Stiggelbout, 2010). The difference in quality of life measurements between the patient and the public is often attributed to adaptation. The adaptation process is thought to be an evolutionary driven ability that enables us to adjust to new circumstances and thereby increases our chances of survival (Frederick & Loewenstein, 1999). Moreover, several elements - like skill enhancement and goal adjustment - have been identified as potential mechanisms that drive the adaptation process. Although adaptation is generally perceived as a positive phenomenon, not all of these elements are deemed desirable, which complicates the value we attach to adaptation in practice. I will expand on this in the literature review below. When applied to chronic illness or disability, adaptation is characterized as a true change in the patient's subjective health or well-being, with the discrepant quality of life measurements as a result.

While the theoretical construct of hedonic adaptation has been around for centuries[1] and the adaptation phenomenon is widely accepted within the psychology literature (Diener et al., 1999), there have been relatively few quantitative studies aimed at empirically assessing the adaptation process. In general, the study of adaptation assesses the subjective effect of a life event on one's well-being over time while controlling for the objective effect of this event. Even when these measures are perfectly captured by empirical data, modelling these elements is complex in and of itself, having to account for subjective and objective measures obtained from individuals over time.

In practice, additional complications arise that explain the lack of quantitative research to date. First of all, the subjective nature of the response variable might give rise to different interpretations of the corresponding question between different respondents. Moreover, the interpretation might change for an individual respondent over time. Secondly, an unbiased estimation of adaptation requires pre- and post-event levels of the response variable in question that are only available in longitudinal data. However, sufficient longitudinal data, including information on the relevant outcome variables, has only become available relatively recently. Additionally, if the response variable is measured on an ordinal scale (as is the case for the subsequent analysis), then the ordering of the dependent variable can only be accounted for in a nonlinear model for which the regression coefficients cannot be estimated with regular linear estimation techniques. In panel data, the transformations applied in a linear setting to omit the individual specific effects are not feasible, resulting in the incidental parameters problem (Neyman & Scott, 1948), which is still the subject of econometric

[1] The hedonic treadmill theory was formulated by Eysenck (1994), saying that human happiness remains stationary, despite negative set-backs or efforts to advance it. However, the notion of human adaptation was contemplated long before the treadmill theory. For example, the medieval writer St. Augustine is cited in Robert Burton's *The anatomy of melancholy* (1651) stating: "A true saying it is, 'Desire hath no rest;' is infinite in itself, endless; and as one calls it, a perpetual rack, or horse-mill, . . . still going round as in a ring."

research to date (Wooldridge, 2005; Baetschmann, Staub & Winkelmann, 2015).

Moreover, recent studies that have overcome these data and modelling challenges, do not seem to agree on the presence or extent of adaptation in disabled patients (Lucas, 2007; Oswald & Powdthavee, 2008; Cubí-Mollà, Jofre-Bonet and Serra-Sastre, 2016). Thus, more and different research investigating adaptation is necessary. A better understanding of the trajectory over time of subjective health and well-being in a certain health state is not only relevant to researchers in the fields of epidemiology, psychology and health economics, but also to health practitioners and policy makers. For example, adaptation has played a pivotal role in the normative discussion regarding the body of people that should be consulted to obtain quality of life estimates for health states. These health states may in turn inform economic evaluations that are used in the policy regarding allocation of health care resources (Menzel, Dolan, Richardson & Olsen, 2002; Versteegh & Brouwer, 2016).

It is the objective of this thesis to study adaptation to chronic disability. The main research question is whether the time since the onset of chronic disability has a positive effect on the probability of reporting higher life satisfaction and better self-perceived health. I will also examine what model specification is best suited to measuring adaptation, since there appear to be many different specifications proposed in the literature, with hardly any comparison between them. To this end, I analyze adaptation by means of a linear fixed effects model and a fixed effects ordered probit model proposed in the literature, and a fixed effects ordered logit model proposed by me. Additionally, I analyze and discuss potential differences in the adaptation process for life satisfaction and self-perceived health. Both constructs are used in the adaptation literature, but a discussion on the potential differences in adaptation outcome is notably absent in adaptation research to date.

In all of the analyses, the effect of adaptation is assessed through the time an individual has experienced limitations with instrumental activities of daily living (IADL) and the severity of these limitations. These activities include actions like dressing, bathing and eating. This measure was chosen to ensure a universal comparison of disability impact across different health conditions. I aim to establish changes in either life satisfaction or self-perceived health that can be attributed to the adaptation process as a function of time spend with a disability. Note that both of these measures are highly subjective, since the adaptation studied here is operationalized as a change in the respondent's self-evaluation of some well-being measure. I will expand on this issue in the data section. Furthermore, I control for the objective intensity of the underlying impaired health condition. The objective measure is given by the number of limitations with IADL, which is to some extent indicative of the severity of the 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 and employment 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.

The empirical results show that a longer duration is significantly related to a higher probability of being satisfied with life, but not with the probability of reporting a better self-perceived health.

This thesis consists of the following sections. The next section contains a literature review discussing the main empirical findings on adaptation to date and the contribution of this thesis to the existing literature. The third section regards the data set and the fourth section the methodology focusing on three econometric models of interest. Section 5 presents the results, including an investigation regarding the robustness of the findings. The final section provides a conclusion and a discussion on the limitations with suggestions for future research.

2 Literature review

This thesis is concerned with what Frederick and Loewenstein (1999) refer to as *hedonic adaptation*. They describe hedonic adaptation as "a reduction in the affective intensity of favorable and unfavorable circumstances" (1999, p.302). They identify two main functions of adaptation. First of all, adaptation protects the individual by lowering the internal impact of external stimuli. Furthermore, adaptation enhances perception by elevating the signal value produced by departures from the baseline level. A physiological example of this latter function is how we adapt our vision upon entering a dark environment. These two functions are also believed to govern hedonic states (hunger, thirst, pain etc.) leading to hedonic adaptation. Hedonic states are crucial as they alert our attention on pressing needs and avert us from engaging in dangerous activities. Nevertheless, prolonged exposure to a strong hedonic state (stress for example), is believed to have detrimental physiological and psychological effects (Sapolsky, 1999). Hence, the ability to adapt may serve a protective function. Additionally, if an aversive state is persistent, the perception enhancing function of hedonic adaptation might redirect motivation to productive changes in one's situation as opposed to lingering attempts to change the unchangeable.

In the literature, adaptation is often indiscriminately denominated as a response shift. 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). The first component of this definition (a change in internal standards) is identified by Ubel, Peeters and Smith (2010) as scale recalibration, meaning that the interpretation of a subjective response scale changes, but not well-being itself. This is not in accordance with the definition of adaptation I have given above. However, in most quantitative research it is not possible to identify whether an observed change in well-being should be attributed to scale recalibration or adaptation. Therefore, one should be cautious when interpreting empirical results on adaptation. I will return to this issue in the discussion.

The other two components of the response shift definition (a change in values and the conceptualization of quality of life) can be grouped under adaptation. A more precise overview of the mechanisms that are thought to govern the adaptation process is provided by Menzel, Dolan, Richardson and Olsen (2002). They identify eight elements of adaptation. Firstly, through skill enhancement, people may simply acquire greater skills to achieve their goals without adjusting them or the activities required to attain them. Secondly, people may change the activities needed to reach their goals. Additionally, the goals themselves could be adjusted. Also, people might alter their conception of health. This means that a person adopts a different definition of health that is more productive in thinking about their state of health. For example, the humanistic conception of health construes that health should be evaluated in terms of one's ability to adapt to the problems in life, not by the biostatistical nature of the problems themselves (Nordenfelt, 1993). These first four elements were deemed by Menzel et al. to be admirable achievements in the light of the unfortunate circumstances in which they occurred.

The next three elements of adaptation are described as regretful (yet aiding the adaptation) and Versteegh and Brouwer (2016, p.70) point out that they are perception biases rather than an "adjustment of oneself". First of all, cognitive denial of one's functional health leads to a factually mistaken self-evaluation of health. Another cognitive deficiency is the suppressed recognition of full health, meaning that there is no acknowledgment of what it is like to be in full health and what type of possibilities that allows for. Thirdly, people can change their expectations regarding what level of achievement for a certain goal would be acceptable. These lowered expectations appear to be the least desirable out of all elements of adaptation. The last element is heightened stoicism and it is not deemed particularly admirable nor regrettable. Somewhat related to lowering expectations, heightened stoicism states that people come to evaluate their happiness by means of what is achievable. Hence, they realize that not coming as close to reaching their goals as they might have done previously does not have to impede their happiness.

In sum, adaptation might be necessary from an evolutionary or biological standpoint, but it might not altogether be desirable from a psychological point of view. An in depth normative discussion of the adaptation process is beyond the scope of this thesis, since this study focuses on finding empirical evidence for adaptation in longitudinal data, be it desirable or not. However, the normative appraisal of adaptation is of great importance to the practical application of my results and therefore deserves a mention. For further reading see Menzel, Dolan, Richardson and Olsen (2002) and Versteegh and Brouwer (2016).

Even though the theory regarding the adaptation process and the mechanisms governing it are well developed, the empirical evidence regarding adaptation is somewhat lacking. Early studies by Brickman, Coates and Janoff-Bullman (1978), Schulz and Decker (1985), and Tyc (1992) investigating adaptation to impaired health states all find that patient well-being is well above what would have been expected given their circumstances. However, these studies all employ cross-sectional methods. Therefore, the patient's pre-disability level of well-being is not known. Since the life event might not be completely exogenous and well being levels of those affected may already have differed from the public norm before the event has even occurred, testing for adaptation in cross-sectional data can produce biased estimates.

To overcome this problem, recent studies have used panel data in order to examine adaptation. The advantage of panel data is that it enables a prospective design, in which pre-event levels of well-being are known for all participants. One of the simplest examples of one such study design is given by Clark, D'Ambrosio and Ghislandi (2016) who study adaptation to poverty. They use a "within" fixed-effect linear regression, but find no true change in life satisfaction. When it comes to adaptation to disability, the current empirical evidence does not provide unambiguous support for the occurrence or level of adaptation to disability. 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, whilst analyzing the same data sets and outcome. They find a considerable level of adaptation and suggest that the differences in outcome are due to a difference in the respective methodologies, with the multilevel model used by Lucas being technically closer to a random effects model. The random effects assumption states that the individual heterogeneity cannot be correlated with the regressors. This appears to be too unrealistic, considering that the variables under consideration (particularly the socioeconomic covariates) are likely to have an underlying individual determinant. Thus, on the basis of methodology, Oswald and Powdthavee (2008) might have a stronger case for the validity of their results. Finally, Cubí-Mollà, Jofre-Bonet and Serra-Sastre (2016) do find some evidence for adaptation after a relatively long duration of 20 years in self assessed health. They make use of a dynamic fixed effects probit model by utilizing Wooldridge's (2005) approach. Note that the differences in results from the abovementioned studies might be caused by differences in the target population (adaptation could differ per health condition), differences in econometric strategy or the difference in response variable used (life satisfaction or self assessed health). Particularly the last two issues are not addressed in the current literature.

Like the recent studies on adaptation, this thesis also employs panel data as opposed to cross-sectional data. In doing so, the trajectory of adaptation over time can be studied and I can control for individual heterogeneity. This thesis extends the existing literature in that adaptation is analyzed for both self-perceived health and life satisfaction. As was pointed out earlier, very little distinction between the two outcome measures is made in the literature and adaptation results for the two constructs are often discussed interchangeably or grouped together. However, there is a very distinct difference in definition. Self-perceived health is generally considered a domain of life satisfaction, whereas the latter construct may also be affected by spiritual, cultural, economic and political factors (Wilson, Paul & Clearly, 1995). Therefore, it is possible that the adaptation process differs, depending on which construct is used. For example, it may take longer to measure a true change in subjective health, since the impaired health state is likely to be at the forefront of this assessment. On the other hand, in the evaluation of life satisfaction the patient may put more weight on the nonmedical factors that constitute well-being, thereby facilitating a faster change in the reported level of life satisfaction.

Where previous studies focused on the (medical) diagnosis of chronic illness or disability, this thesis uses one or more limitations with instrumental activities of daily living (IADL) within a population of chronic illness as an indicator of disability. In doing so, there is a uniform measure of the severity of the health impairment across different chronic illnesses and disabilities. This allows me to include subjects with varying chronic conditions, while still controlling for the intensity of a condition in terms of the number of IADL limitations.

This thesis also contributes to the state of knowledge about adaptation because my approach differs from some of the approaches in existing adaptation studies - e.g. Cubí-Mollà, Jofre-Bonet and Serra-Sastre (2016) and Oswald and Powdthavee (2008) - in that 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 cause a deterioration of health over time.

A final contribution of this thesis is that it analyzes which model specification is best suited to investigating adaptation, what the corresponding defining features might be and how they affect the effect associated with adaptation. This discussion is crucial, since there appears to be little consensus on the model specification that is most appropriate to measure adaptation, whilst this can have a significant impact on the outcome (as was illustrated with the studies conducted by Lucas (2007) and Oswald and Powdthavee (2008)). I study three types of models. One of the models is based on the methodology used by Cubí-Mollà, Jofre-Bonet and Serra-Sastre (2016). The second model is derived from the study by Clark, D'Ambrosio and Ghislandi (2016). These two papers were chosen because they both propose parsimonious fixed effects models, whose specifications differ in clearly identifiable features. As mentioned previously, I believe the fixed effects assumption is warranted in this and other adaptation studies. Incorporating the strong features of these two models, I propose a third model. This is the 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. An extensive comparison of the three methodologies is provided in the fourth section.

In sum, this thesis aims to add new insights to the investigation of adaptation to disability. I study three possible methodological approaches and discuss the advantages and disadvantages of all model choices involved. Finally, analyses are performed for both life satisfaction and self-perceived health, to shed light on the potential differences in the adaptation process for the two response variables and different model specifications.

3 Data

The following section gives a description of the SHARE data and provides a discussion on the variables relevant to the analysis. The data used for this thesis is obtained from the SHARE (Survey of Health, Ageing and Retirement in Europe) database. It consists of a self-completed survey whose "ultimate goal is to provide high-quality micro-level panel data of economic, social and health factors that accompany and influence aging processes at the individual and societal levels" (Börsch-Supan et al., 2013, p. 993). The subjects are sampled from 18 European countries and Israel, and data has been collected for 6 waves between 2004 and 2015 [2]. The eligibility of the subjects is based on their age. Subjects of fifty years and over at the time of sampling were asked to participate in the SHARE project, whereas their spouse was asked to participate regardless of his or her age (SHARE Release Guide 6.0.0, 2017).

This thesis investigates the onset of disability in relation to life satisfaction and self-perceived health. The dependent life satisfaction measure is obtained by the question: "*On a scale from 0 to 10 where 0 means completely dissatisfied and 10 means completely satisfied, how satisfied are you with your life?*". For the analysis with life satisfaction, only waves 2, 4, 5 and 6 are used. Waves 1 and 3 are excluded because they do not contain information on the relevant outcome variable. The question on self-perceived health is posed in terms of how the respondent would describe their health in general, with categories Poor, Fair, Good, Very good and Excellent. For this analysis, wave 1 does contain the relevant information on the response variable and only wave 3 is excluded.

Note that the subjective nature of the dependent variables introduces additional noise in the outcome measurements, since the interpretation of a question might be different between respondents and alter for the same respondent over time. However, they are absolutely crucial to the upcoming analyses that focus on changes in the self-evaluation of some well-being measure. Alternative measures for the life satisfaction variable are available in the SHARE data set, like the CASP-12 index, which exclusively measures non-health dimensions of quality of life. For the self-perceived health variable, an alternative 5-point scale is provided, with categories going from Very bad to Very good as opposed to Poor to Excellent. However, these measures are either not available for the majority of the waves or do not capture the entire breadth of the concept under consideration.

The number of individuals in the three bottom categories of the life satisfaction variable is too low to yield computationally feasible estimates in some of the subsequent analyses. Therefore, the first three categories of the 11-point scale variable are merged, creating an 8-point scale. The resulting distribution of frequencies per life satisfaction category is displayed in table 1. Clearly, there are still relatively few people in the lowest categories, even after this re-categorization. For the self-perceived health variable the opposite is true. The frequency distribution across the self-perceived health groups can be found in table 2. Here, relatively few subjects fall into the "higher" categories of Very good and Excellent self-perceived health.

Table 3 presents the included variables and descriptive statistics. The main independent variables are the number of limitations with IADL and duration (the time since the onset of the chronic limitations with IADL). The activities included in IADL are dressing, walking across a room, bathing or showering, eating, getting in or out of bed, using the toilet, using a map to figure out how to get around in a strange

[2]DOIs: 10.6103/SHARE.w1.600, 10.6103/SHARE.w2.600, 10.6103/SHARE.w3.600, 10.6103/SHARE.w4.600, 10.6103/SHARE.w5.600, 10.6103/SHARE.w6.600, see Börsch-Supan et al. (2013) for methodological details.

Table 1: Life satisfaction categories with frequency distribution across waves

Life satisfaction	Waves			
	2004/2006(%)	2006/07(%)	2013(%)	2015(%)
1 = Rating scale 0,1,2	0.021	0.019	0.035	0.025
2 = Rating scale 3	0.021	0.020	0.028	0.023
3 = Rating scale 4	0.023	0.029	0.035	0.029
4 = Rating scale 5	0.120	0.144	0.183	0.171
5 = Rating scale 6	0.104	0.097	0.104	0.104
6 = Rating scale 7	0.191	0.166	0.167	0.170
7 = Rating scale 8	0.272	0.273	0.231	0.259
8 = Rating scale 9	0.122	0.107	0.100	0.105
9 = Rating scale 10	0.125	0.145	0.118	0.115

Table 2: 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

place, preparing a hot meal, shopping for groceries, making telephone calls, taking medications, doing work around the house or garden, managing money, leaving the house independently and accessing transportation services and doing personal laundry. For the main analysis, I select individuals that report to have a disability at some point after their first observed wave. Having a chronic disability is operationalized as having one or more limitations with IADL. This means that in their first observed wave, the number of limitations with IADL of the included respondents is 0. The prospective nature of this approach allows me to calculate the duration since the onset of the disability. Moreover, from the moment an individual indicates to have a disability, the disability cannot go away for the entire remainder of their observed waves. Hence, in all waves between the first wave with a disability and the last observed wave, the number of limitations with IADL cannot return to 0. Lastly, from the moment the respondent has one or more limitations with IADL, he or she should also indicate to be chronically ill. The chronic illness may already be indicated in the waves preceding the onset of the limitations, since I study adaptation to disability, and not to a diagnosis per se. These last two criteria ensure the chronic nature of the health limitations. This leaves me with over 13000 observations for the main analyses with life satisfaction and over 15000 for that with self-perceived health.

Since there is no duration measure available in the SHARE data recording the age at onset of the IADL limitations, I construct the duration variable myself. If an individual reports to have a disability in a particular wave, but not in the closest recorded preceding wave, the duration is approximated by the time in years between these two waves divided by two. If the individual has already reported chronic limitations for more than one wave, the full length in years between the current and preceding wave is added to the previously recorded duration. The time in years between two consecutive waves is based on the difference in age of a respondent between those waves. In some of the consecutive analyses, duration is split up in dummy variables. Generally, the dummy categories represent whether there is no disability, whether the onset of the disability is reported within the past 2 years, between 2 and 5.5 years or more than 5.5 years ago. This division is chosen because it corresponds to the number of waves spend with disability. For example, the category for the onset of a chronic disability within the past 2 years includes all the individuals that indicate to have chronic limitations for the first time and excludes those that have had a disability for more than 1 wave or that have no disability at all. Hence, this particular division of the duration variable aids the interpretation in terms of waves as well as years.

Additionally, I control for socioeconomic characteristics. A wide range of socioeconomic variables is available in the SHARE data, including modules on demographics, employment and housing. The choice of covariates is guided by those used in comparable analyses like the study by Clark, D'Ambrosio and Ghislandi (2016) and Cubí-Mollà, Jofre-Boner and Serra-Sastre (2016). The covariates consist of marital status (married or registered partnership, not married), employment status (retired, employed, unemployed, inactive) and number of children. The reference categories for marital status and employment status are being married and being retired respectively[3]. Income is not included, since it is notoriously prone to measurement error and missing values (Moore, Stinson & Welniak, 2000). This decision relies on the fact that the included covariates are believed to be a good proxy for income.

In table 3 it is apparent that by the end of data collection, about half of the observations concern individuals with disabilities (see incidence of disability). An overwhelming majority of the observations concerns individuals with a chronic illness. Note that these descriptive statistics only concern the individuals included in the analysis and hence exclude all subjects that remain healthy over the entire data collection period. This explains the high proportion of chronically ill subjects, in combination with the mature mean age of the sample and the fact that the chronic illness variable also includes minor health impairments like hypertension and high blood pressure. The average number of limitations with IADL is 2.4. This means that on average a chronically disabled individual reports to have between 2 and 3 limitations with instrumental activities of daily living such as dressing and eating. The average duration of having chronic limitations is 2 years. Note that relatively few observations fall into the categories Very good and Excellent for self-perceived health. This could be due to the age group studied in this data set, which is older compared to the general population with a mean age of 72. Furthermore, approximately 41 % is male and 62 % is married. Not surprisingly, the majority of the sample is retired.

[3]Since this particular sample consists of relatively older respondents, education is assumed to be time invariant and not included as a covariate. Education was added as a covariate at an earlier stage of the research process. However, upon closer inspection, the variation over time appeared to be caused by measurement error rather than true changes in education level.

Table 3: Descriptive statistics

Variable	Definition	Label	Mean	Standard deviation
Life satisfaction[1]	1 = Rating scale 0,1,2	Life satisfaction 1	0.026	0.159
	2 = Rating scale 3	Life satisfaction 2	0.023	0.150
	3 = Rating scale 4	Life satisfaction 3	0.030	0.171
	4 = Rating scale 5	Life satisfaction 4	0.159	0.365
	5 = Rating scale 6	Life satisfaction 5	0.102	0.303
	6 = Rating scale 7	Life satisfaction 6	0.171	0.377
	7 = Rating scale 8	Life satisfaction 7	0.256	0.437
	8 = Rating scale 9	Life satisfaction 8	0.107	0.309
	9 = Rating scale 10	Life satisfaction 9	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
Incidence of chronic illness	Incidence of chronic illness	Illness incidence	0.832	0.374
Number of limitations[2]	Number of chronic limitations with IADL	Number of limitations	2.433	2.020
Duration[2]	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
Number of children	Number of children	Number of children	2.276	1.534
Number of observations	15826			
Number of subjects	5341			

[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] Number of limitations and duration are calculated taking only the observations with a chronic disability into account.

4 Methods

This section contains the methods for the analyses of adaptation to disability. The first subsection concerns a theoretical comparison of the three model specifications that are used in this thesis to identify the model specification that is most appropriate for measuring adaptation and provides an overview of the most important modelling choices involved in measuring adaptation. I will explain why I believe ex ante that the ordered logit model proposed by me is superior to the other two models that were derived from the literature. The next three subsections describe the three methodologies used in the empirical comparison of the three specifications. Specifically, section 4.2 discusses the linear fixed effects model, section 4.3 the fixed effects ordered probit model and section 4.4 the fixed effects ordered logit model. The final subsection provides information on the actual analyses that are performed to obtain the results.

4.1 Theoretical comparison of three adaptation models

A perusal of the adaptation literature brings to light the myriad of choices involved in the econometric modelling of the adaptation process. In this thesis, three methodologies are compared in order to investigate what model features are best suited to measuring adaptation to disability. I will first theoretically compare two methods employed in the literature with my proposed model and justify the modelling choices in the latter specification. Subsequently, the econometric strategy is given for each model separately as it is used in the empirical comparison later on.

The first methodology obtained from the literature is provided by Clark, D'Ambrosio and Ghislandi (2016). They study adaptation to poverty by assessing changes in life satisfaction. Hardly any evidence of adaptation to poverty is found. The second empirical strategy is provided by Cubí-Mollà, Jofre-Boner and Serra-Sastre (2016) who study adaptation to a long-standing illness via measuring changes in self-assessed health. Their results support the existence of adaptation, albeit only after a very long duration. The model proposed by me incorporates the strongest elements of the methodologies proposed by Clark, D'Ambrosio and Ghislandi and by Cubí-Mollà, Jofre-Boner and Serra-Sastre.

A schematic overview of the most important features of the three models under consideration can be found in table 4. The model proposed by myself is denoted as "This paper". First of all, note that all model specifications assume fixed effects, meaning that the individual heterogeneous terms might be correlated with the regressors. This particular modelling choice is warranted, since it is highly unlikely that the individual specific effects are uncorrelated with socioeconomic covariates like marital status and employment status.

Secondly, the response variables used in this thesis (life satisfaction and self-perceived health) are measured on an ordinal scale. In a cross-sectional setting, the ordered nature of the outcome variables can be accounted for easily in an ordered probit or logit model specification. However, when these nonlinear models are introduced in panel data, new problems arise. In the linear fixed effects model, the unobserved individual specific heterogeneity can simply be removed by performing a linear transformation. However, there is no linear transformation that removes the individual specific effects in a nonlinear setting and the number of parameters to be estimated remains equal to the number of regressors plus the number of individuals in the panel. Hence, for a fixed number of time periods, even as the number of individuals grows without bound, the number of parameters to be estimated goes to infinity as well. 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 (Greene, 2004).

The three methods discussed here all have distinct ways of modelling the dependent variable and dealing with the incidental parameters problem. First of all, Clark, D'Ambrosio and Ghislandi ignore the discrete ordered nature of the dependent variable and treat it as if it were continuous. In doing so, they return to a linear setting in which they apply within fixed effect regression and effectively remove the individual fixed effects by linear transformation. However, the imposed linearity might be too strict of an assumption. The ordered logit model proposed by me and the ordered probit model of Cubí-Mollà, Jofre-Boner and Serra-Sastre both model the ordered response variable in a nonlinear setting. First of all, Cubí-Mollà, Jofre-Boner and Serra-Sastre deal with the incidental parameters problem by making use of a parameterization of the fixed effects as a function of the means of the regressors following Wooldridge's (2005) approach. Even though their solution is parsimonious and easy to implement, the parameterization is prone to misspecification (Wooldridge, 2005). Hence, I propose a technique based on the principles of the conditional logit estimator. It effectively eliminates the fixed effects by finding a sufficient statistic for the individual heterogeneity in an ordered logit model and yields consistent estimates, without having to parameterize the fixed effects. The estimator in question is described in Baetschmann, Staub, and Winkelmann (2015).

Another modelling choice is featured in the ordered probit model of Cubí-Mollà, Jofre-Boner and Serra-Sastre. They introduce dynamics in the form of a lagged dependent variable, stating that this allows them to control for individual health state dependency, meaning that an individual reports worse or better subjective health by default. This poses an additional problem for the estimation of the parameters, since no information is available on the initial period when the individual data generating process began. This is deemed the initial conditions problem and is dealt with in the parameterization of the fixed effects that also accounts for the incidental parameters problem. Consequently, the parameterization of the fixed effects proposed for the ordered probit specification is a function of the regressors and the first dependent variable observed in the sample. The linear fixed effects model by Clark, D'Ambrosio and Ghislandi and the ordered logit model proposed by me do not include this modelling choice. Whether or not one should include dynamics is expanded upon in the discussion.

Finally, all methods measure adaptation by means of the duration since the onset of the life event. 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. On the other hand, Cubí-Mollà, Jofre-Boner and Serra-Sastre use a continuous duration variable in their analyses. I believe that this continuous form for adaptation is too restrictive, since no research has shown that the effect is in fact linear, and use the dummy specification proposed by Clark, D'Ambrosio and Ghislandi.

In sum, the main features of the three discussed models based on the literature can be found in table 4. The remainder of this thesis is focused on the analysis of adaptation to disability by assessing the effect of duration on both life satisfaction and self-perceived health. This analysis is done for all three models discussed here

Table 4: Model choices of three models measuring adaptation in panel data

	Clark, D'Ambrosio & Ghislandi (2016)	Cubí-Mollà, Jofre-Boner & Serra-Sastre (2016)	This paper
Life event under consideration			
Adaptation to life event	Poverty	Long-standing illness	Disability in subjects with chronic illness
Dependent variable			
Life satisfaction[1]	Yes (11)	No	Yes (9)
Subjective health[1]	No	Yes (4)	Yes (5)
Functional form			
Assumed measurement scale DV	Continuous	Discrete (ordinal)	Discrete (ordinal)
Econometric specification	Linear	Ordered probit	Ordered logit
Lagged dependent variable	No	Yes	No
Duration specification[2]	Dummy variables (6)	Continuous	Dummy variables (3)
Individual specific effects			
Assumed fixed effects	Yes	Yes	Yes
Parameterization of FE	No	Yes	No

Note. DV stands for dependent variable. All of the models considered study adaptation in panel data. Adaptation is measured through the effect of duration since the onset of the studied life event on life satisfaction or subjective health.
[1] The number of categories of the dependent variable, as it is used in the analyses of the authors, are given in parentheses. This is the number that remains after potential merging of categories.
[2] The number of dummy variables added to the regression equation are given in parentheses.

in order to assess what model specification is most appropriate for measuring adaptation to disability in panel data. In order to achieve a fair comparison, I have to adapt some of the original model features of the models by Clark, D'Ambrosio and Ghislandi and by Cubí-Mollà, Jofre-Boner and Serra-Sastre. First of all, all analyses performed will be done for both life satisfaction and self-perceived health, using the same number of categories for both dependent variables across all analyses (9 and 5 respectively). Also, the life event under consideration is always chronic disability. Moreover, the same covariates are used for all analyses. All model characteristics mentioned underneath *Functional form* and *Individual specific effects* in table 4 will remain in place and are the core features that are studied to investigate how different modelling choices affect the adaptation found in the results. From this point on I will refer to the model incorporating the functional form and individual specific effects of Clark, D'Ambrosio and Ghislandi and by Cubí-Mollà as the linear fixed effects model. The model based on the modelling features from Cubí-Mollà, Jofre-Boner and Serra-Sastre's methodology will be referred to as the fixed effects ordered probit model. My own porposed model is denoted as the fixed effects ordered logit model. Next, an in depth discussion devoted to the econometric theory of the three models is provided.

4.2 Linear fixed effects model

First of all, the simplest model is denoted as the linear fixed effects model and is based on the methodology proposed by Clark, D'Ambrosio and Ghislandi (2016) who use it to investigate adaptation to poverty. The regression equation is:

$$Y_{it} = C_{it}'\theta + D_{it}'\delta + IADL_{it}'\gamma + \alpha_i + \varepsilon_{it}, \tag{1}$$

with Y_{it} the self-reported 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. The dummy categories are no limitations, a duration of limitations between 0.1 and 2 years, between 2 and 5.5 years and for more than 5.5 years. The reference category of this dummy variable is a duration of limitations between 0.1 and 2 years, since this allows me to measure whether the other dummies are significantly different with respect to the onset of the limitations, which concurs with the definition of adaptation. Moreover, C_{it} is a vector with the covariates marital status, labour force status and number of children. I expect a negative effect for $IADL_{it}$, but a positive effect for at least one of the dummies contained by D_{it}. The coefficients are estimated by means of ordinary least squares linear fixed effects. Additional statistics can be obtained with the conventional fixed effects calculations.

4.3 Fixed effects ordered probit model

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

A latent response variable is modelled by

$$Y_{it}^* = Y_{i,t-1}\lambda + C_{it}'\theta + D_{it}\delta + IADL_{it}\gamma + \alpha_i + \varepsilon_{it}, \tag{2}$$

where Y_{it}^* and $Y_{i,t-1}$ represent the latent response variable and observed response variable in the period $t-1$. D_{it} measures the continuous duration since the onset of the chronic disability. The remaining regressors are the same as for the linear fixed effects regression. The response variable is again either self-reported health or life satisfaction. Moreover, $IADL_{it}$ represents the number of limitations with IADL. Lastly, some socioeconomic control variables, C_{it}, are included. Here, I expect a negative effect for $IADL_{it}$, but a positive effect for the duration variable D_{it}. For convenience sake, all non-dynamic regressors are collected in the vector $X_{it} = (C_{it}', D_{it}, IADL_{it})'$ with corresponding parameters $\beta = (\theta', \delta, \gamma)$. 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

$$Y_{it} = k \text{ if } \tau_{k-1} < Y_{it}^* < \tau_k \text{ for } k = 1, \dots, K. \tag{3}$$

Here, K is the total number of categories, $\tau_0 = -\infty$ and $\tau_K = \infty$ and $\tau_{k-1} < \tau_k$ for all k. The probability for individual i in period t of reporting a specific Y_{it} category becomes:

$$P(Y_{it}=k) = \Phi(\tau_k - Y_{i,t-1}\lambda - X'_{it}\beta - \alpha_i) - \Phi(\tau_{k-1} - Y_{i,t-1}\lambda - X'_{it}\beta - \alpha_i), \quad (4)$$

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:

$$\alpha_i = \sigma + \phi Y_{i,1} + \mu \bar{X}_i + \varepsilon_i \quad (5)$$

The final equation can be obtained by substituting the results in 5 back into 4 producing:

$$\begin{aligned} P(Y_{it}=k) = \Phi(\tau_k - Y_{i,t-1}\lambda - X'_{it}\beta - \sigma - \phi Y_{i,1} - \mu\bar{X}_i) \\ -\Phi(\tau_{k-1} - Y_{i,t-1}\lambda - X'_{it}\beta - \sigma - \phi Y_{i,1} - \mu\bar{X}_i), \end{aligned} \quad (6)$$

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).

4.4 Fixed effects ordered logit model

Lastly, 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). I consider panel data consisting of $i = 1, \ldots, N$ subjects, where $t = 1, \ldots, T_i$ corresponds to the total number of time periods observed for individual i. The ordered logit specification assumes the existence of a latent response variable according to:

$$Y^*_{it} = C'_{it}\theta + D'_{it}\delta + IADL_{it}\gamma + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T_i. \quad (7)$$

Here, Y^*_{it} is the respondent's latent self-perceived health or life satisfaction, $IADL_{it}$ the number of limitations with IADL, D_{it} a vector with dummy variables capturing the time since the onset of the disability and C_{it} a vector with covariates. I again expect a negative effect for $IADL_{it}$, but a positive effect for at least one of the dummies contained by D_{it}. 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:

$$F(\varepsilon_{it}|X_{it}, \alpha_i) = \frac{exp(\varepsilon_{it})}{1 + exp(\varepsilon_{it})} \equiv \Lambda(\varepsilon_{it}) \quad (8)$$

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

$$Y_{it} = k \quad \text{if } \tau_{ik-1} < Y_{it}^* \leq \tau_{ik}, \quad k = 1, \ldots, K. \tag{9}$$

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

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

$$P(Y_{it} = k | X_{it}, \alpha_i) = \Lambda(\tau_{ik} - X_{it}'\beta - \alpha_i) - \Lambda(\tau_{ik-1} - X_{it}'\beta - \alpha_i). \tag{10}$$

Clearly, (10) does not only depend 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 a fixed number of time periods, 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 $d_i^k = (d_{i1}^k, \ldots, d_{iT_i}^k)' = (j_{i1}, \ldots, j_{iT})' = j_i$, where $j_{it} \in \{0, 1\}$, is given by

$$P_i^k(\beta) = P(d_i^k = j_i | \sum_{t=1}^{T_i} d_{it}^k = g_i) = \frac{exp(j_i' X_i \beta)}{\sum_{j \in B_i} exp(j' X_i \beta)}. \tag{11}$$

Here, the sum of all the outcomes over time, $\sum_{t=1}^{T_i} d_{it}^k = g_i = \sum_{t=1}^{T_i} j_{it}$, is a sufficient statistic for α_i, since the probability in (11) is independent of α_i and the thresholds. The sum in the denominator of (11) concerns the set B_i which consists of all vectors j of length T_i that have as many elements equal to one as the observed vector j_i of individual i:

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

Moreover, X_i is a $T_i \times M$ matrix, with M the number of regressors and row t equal to X_{it}.

The resulting conditional log likelihood is given by

$$LL^k(b) = \sum_{i=1}^{N} log(P_i^k(b)). \tag{12}$$

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 $P(d_{it}^k = 1 | \sum_{t=1}^{T_i} d_{it}^k = T_i) = P(d_{it}^k = 0 | \sum_{t=1}^{T_i} d_{it}^k = 0) = 1$. 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:

$$LL^{BUC}(b) = \sum_{k=2}^{K} LL^{k}(b), \tag{13}$$

where $LL^k(b)$ is defined in (12). 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 (13) 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 $\sqrt{n}(\hat{\beta}^{BUC} - \beta)$):

$$Avar(\hat{\beta}^{BUC}) = \left\{ \sum_{k=2}^{K} E(H_i^k(\beta)) \right\}^{-1} \left[\sum_{k=2}^{K} \sum_{l=2}^{K} E(s_i^k(\beta) s_i^l(\beta)') \right] \left\{ \sum_{k=2}^{K} E(H_i^k(\beta)) \right\}^{-1}. \tag{14}$$

Here, $H_i^k(\beta)$ denote the individual Hessians and $s_i^k(\beta)$ the first-order derivatives of the Chamberlain log likelihood function (12) with respect to β. 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. For this type of interpretation the marginal effects are required. In the subsequent analyses, I use the marginal effect on $P(Y_{it} > k) = 1 - \Lambda(\tau_{ik} - X_{it}'\beta - \alpha_i)$, since the sign of the regression estimate here always concurs with that of the corresponding marginal effects and the interpretation is straightforward. The general formula for the marginal effect of the lth regressor on the probability that a respondent reports an outcome higher than category k is:

$$\frac{\partial P(Y_{it} > k | X_{it}, \alpha_i)}{\partial X_{itl}} = \Lambda_{ik}(1 - \Lambda_{ik})\beta_l, \tag{15}$$

with $\Lambda_{ik} = \Lambda(\tau_{ik} - X'_{it}\beta - \alpha_i)$. Usually, the average of the effects is calculated to aid the interpretation. Unfortunately, average marginal effects for $P(Y_{it} > k)$ cannot be calculated directly, since τ_{ik} and α_i are not estimated by the BUC estimator. However, I will approximate the required probabilities with the sample probabilities:

$$\tilde{\Lambda}_{ik} = \tilde{P}(Y_{it} \leq k) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T_i} 1[Y_{it} \leq k]}{\sum_{i=1}^{N} T_i}. \tag{16}$$

These are computed by summing the number of observations in the categories larger than k and dividing this by the total number of observations.

The standard errors of the marginal effects are approximated by means of the Krinsky and Robb method (1986, 1990). This method is based on the fact that the estimator is consistent and draws $s = 1, \ldots, S$ vectors from a multivariate normal distribution with mean $\hat{\beta}^{BUC}$ and covariance matrix based on the expression in (14). Marginal effects are then calculated according to (15) and (16) for each $\hat{\beta}_s^{BUC}$ separately, resulting in an empirical distribution of the marginal effects $m(\tilde{\Lambda}_{ik}, \hat{\beta}_s^{BUC})$. The standard deviations of the simulated sample of marginal effects $m(\tilde{\Lambda}_{ik}, \hat{\beta}_s^{BUC})$ is an estimate of the standard error of $m(\tilde{\Lambda}_{ik}, \hat{\beta}^{BUC})$. Even though the resulting marginal effects and their standard errors are approximations, I use them to aid the interpretation of the results.

4.5 Analyses

In the next section, results are provided for all three models mentioned above. The motivation for providing this extensive set of results and not limiting myself to the analysis of the ordered logit model is that this allows me to examine how sensitive the adaptation process is to model specification. It will also aid the discussion on what functional form is best suited to measure adaptation.

Moreover, I perform several robustness checks on my own proposed model (the fixed effects ordered logit model) to assess the sensitivity in outcome to small changes in the categorization of the duration dummy categories and the life satisfaction categories. The construction of both of these variables is based on personal preference and practical considerations. The robustness checks provide valuable insight into how robust the results are to slight changes in the categorization.

Generally, in the regressions with life satisfaction, 9% of the observations contain a missing value. In the analysis with self-perceived health, this is equal to 16%. The exceptions to this are the two regressions performed for the ordered probit model, since the first period is removed from the sample to enable the inclusion of the lagged variables and parameterization. Here, 11% of the observations have a missing value for the self-perceived health analysis and 5% of the observations for the analysis with life satisfaction. Multiple imputations are obtained with the R package Amelia, which is suited to impute panel data. I chose for multiple imputations, since this allows me to incorporate the uncertainty introduced by the imputations of the missing values in my final regression estimates. For each analysis, the number of imputed data sets used is set equal to the percentage of missing values present in the observations. If this percentage is smaller than 10, 10 imputations are used. The analyses are performed on each imputed data set separately and the final result is obtained by pooling these results with the Amelia package. In order to do this, the Amelia package makes use of Rubin's (1987) rules for combining several results from multiply imputed data sets.

5 Results

In this section, the results are discussed for the analyses on adaptation to disability for three different model specifications. I examine to what extent the model specification influences the effect of duration since the onset of disability on the response variable and how the effect differs for life satisfaction and self-perceived health. First, the results are presented for the fixed effects ordered logit model (section 5.1). These results are presented first and most elaborately, since this model is supposedly the superior specification of the three and the results from the other two models will be compared to this first set of results. Following are the results for the linear fixed effects model (section 5.2) and fixed effects ordered probit model (section 5.3).

I find that both the results for the linear model and ordered probit model are very similar to those obtained with the ordered logit model. However, in the analysis with self-perceived health the sign of duration is positive, although the effect is not significant in both the linear and ordered probit model. This is opposed to the negative sign found in the ordered logit analysis. The difference between the linear and ordered logit model is caused by the difference in assumed measurement scale of the dependent variable and the associated model specification (ordered logit or linear, see table 4). Upon further investigation, it becomes clear that the difference between the ordered logit and probit specification is due to the dynamics in the probit model. Hence, these are the modelling features that affect a change in adaptation results, although not my conclusions (none of the effects are significant).

The last section investigates the causes for the differences in results and the robustness of the results of the fixed effects ordered logit model when two modelling features are tweaked. The first feature is the number of life satisfaction categories, since they were collided as was described earlier. Two regressions are performed for life satisfaction consisting of 11 and 5 categories. The second feature under investigation is the specification of the duration variable. I analyze how robust the results are to a continuous specification as opposed to the dummy specification used in the main fixed effects ordered logit model. In two additional regressions alternative categorizations of the duration dummy variables are analyzed.

5.1 Results fixed effects ordered logit model

Here, I present the results for the estimation of the fixed effects ordered logit model (see section 4.4). Table 5 presents the regression estimates for both the analysis with life satisfaction and that with self-perceived health.

In the regression with life satisfaction, marital status and number of children have no significant effect on the probability of selecting a certain life satisfaction score. There is a significant effect for the employed with respect to the retired, with the employed respondents being more satisfied with their lives. It is likely that this effect is influenced by the age difference between the groups, considering the majority of the SHARE sample is retired. The estimated coefficient on the number of IADL limitations is significant and negative. This supports the hypothesis that a higher number of limitations is related to a lower life satisfaction. Moreover, there is no significant effect of having no limitations with respect to the first period of experiencing limitations (0.1 to 2 years). Furthermore, the coefficient on more than 5.5 years of IADL limitations is significant and positive. This supports the adaptation hypothesis, meaning that higher levels of life satisfaction are more prevalent among individuals who have lived with disability longer.

In the regression with self-perceived health, employment status is again the only covariate for which a significant effect is found. Employed respondents have a higher self-reported health compared to retired respondents. Particularly in the context of self-perceived health, this is not surprising, since the group consisting of retired respondents is older on average and age is supposedly negatively correlated with (subjective) health. The number of IADL limitations also has a significant negative effect on self-perceived health. Interestingly, there is a significant effect of having no limitations on self-perceived health compared to the first reported period with a disability. The positive sign indicates that individuals with no IADL limitations have a higher self-perceived health than those that have recently experienced the onset of disability. There is no indication of adaptation, with the effect of the subsequent duration dummies of 2 to 5.5 years and more than 5.5 years not being significantly different from that of the first term of 0.1 to 2 years. I can only speculate that there is the possibility of the effect occurring after a longer duration as was found by Cubí-Mollà, Jofre-Bonet and Serra-Sastre (2016). An indication for this could be the fact that the negative coefficients on 2 to 5.5 years and more than 5.5 years are decreasing in absolute size.

Table 6 and 7 present the estimated marginal effects for the regressions with life satisfaction and self-perceived health (see the end of section 4.4 for the estimation of the marginal effects). The marginal 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.

From the table for life satisfaction, it is apparent that a unit increase in the number of IADL limitations, decreases the probability of reporting higher than categories 1, 2, 3, 4, 5, 6, 7 and 8 with approximately 0.4, 0.8, 1.2, 3.1, 3.8, 4.2, 3.0 and 1.9 percentage points. On the other hand, having experienced a chronic disability for over 5.5 years increases the probability of reporting a life satisfaction category higher than 1, 2, 3, 4, 5, 6, 7 and 8 by 1.2, 2.3, 3.6, 8.9, 11, 12.3, 8.8 and 5.4 percentage points respectively. Hence, time since the onset of a disability has a relatively large effect on the probability of reporting a higher life satisfaction compared to the negative effect of the number of limitations.

The marginal effects for the regression with self-perceived health show that the number of IADL limitations decreases the probability of reporting higher than the categories Poor, Fair, Good and Very good by 3.1, 3.5, 1.1 and 0.3 percentage points respectively. Note that the effect is a lot smaller for the categories Good and Very good, which is surprising, since one would expect the negative effect to be particularly pronounced in the categories corresponding to a better health. A possible explanation for this is that the proportion of individuals reporting a self-perceived health that is Very good or Excellent is very small (see table 2), which affects the marginal effects estimation (see the end of section 4.4). Moreover, not having any IADL limitations

Table 5: FE ordered logit regression (7) for life satisfaction and self-perceived health

	Life satisfaction	Self-perceived health
Marital status		
(Ref. Married)		
Not married	-0.281	-0.058
	(0.157)	(0.153)
Employment status		
(Ref. Retired)		
Employed	0.48^{***}	0.731^{***}
	(0.138)	(0.146)
Unemployed	-0.243	0.091
	(0.217)	(0.229)
Inactive	-0.088	-0.102
	(0.101)	(0.1)
Number of children		
Number of children	0.047	-0.031
	(0.039)	(0.028)
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	0.063	0.971^{***}
	(0.114)	(0.193)
2-5.5 years IADL limit.	0.143	-0.043
	(0.076)	(0.08)
$>$ 5.5 years IADL limit.	0.491^{***}	-0.024
	(0.144)	(0.146)
Number of IADL limitations		
Number of IADL limit.	-0.17^{***}	-0.16^{***}
	(0.029)	(0.027)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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 $Y > k$ for life satisfaction

	Life satisfaction								
	Score 1 Very dissatisfied	Score 2	Score 3	Score 4	Score 5	Score 6	Score 7	Score 8	Score 9 Very satisfied
Duration									
(Ref. 0.1-2 years IADL limitations)									
0 years (NO) IADL limit.	0.002	0.003	0.005	0.011	0.014	0.016	0.011	0.007	-
	(0.003)	(0.005)	(0.008)	(0.021)	(0.026)	(0.028)	(0.02)	(0.013)	-
2-5.5 years IADL limit.	0.004	0.007	0.01	0.026	0.032	0.036	0.026	0.016	-
	(0.002)	(0.004)	(0.005)	(0.014)	(0.017)	(0.019)	(0.013)	(0.008)	-
> 5.5 years IADL limit.	0.012***	0.023***	0.036***	0.089***	0.11***	0.123***	0.088***	0.054***	-
	(0.004)	(0.007)	(0.011)	(0.026)	(0.032)	(0.036)	(0.026)	(0.016)	-
Number of IADL limitations									
Number of IADL limit.	−0.004***	−0.008***	−0.012***	−0.031***	−0.038***	−0.042***	−0.03***	−0.019***	-
	(0.001)	(0.001)	(0.002)	(0.005)	(0.006)	(0.007)	(0.005)	(0.003)	-

Note. Ref. stands for reference category. 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 the Krinsky and Robb method. The marginal effects for the socioeconomic covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

with respect to the first period of experiencing those limitations (0.1 to 2 years) increases the likelihood of reporting a category higher than Poor, Fair, Good an Very good with 18.8, 21, 6.6 and 1.6 percentage points.

Table 7: Marginal effects on the probability of reporting $Y > k$ for self-perceived health

	Self-perceived health				
	Poor	Fair	Good	Very good	Excellent
Duration					
(Ref. 0.1-2 years IADL limitations)					
0 years (NO) IADL limit.	0.188***	0.21***	0.066***	0.016***	-
	(0.038)	(0.042)	(0.013)	(0.003)	-
2-5.5 years IADL limit.	−0.008	−0.009	−0.003	−0.001	-
	(0.015)	(0.017)	(0.005)	(0.001)	-
> 5.5 years IADL limit.	−0.005	−0.005	−0.002	0	-
	(0.028)	(0.032)	(0.01)	(0.002)	-
Number of IADL limitations					
Number of IADL limit.	−0.031***	−0.035***	−0.011***	−0.003***	-
	(0.005)	(0.006)	(0.002)	(0)	-

Note. Ref. stands for reference category. 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 the Krinsky and Robb method. The marginal effects for the socioeconomic covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

5.2 Results linear fixed effects model

Table 8 presents the regression estimates for the linear fixed effects model (see section 4.2). For the full table of results including the effects of covariates see appendix A.3. For both the regression with life satisfaction and that with self-perceived health, the number of limitations with IADL has a significant negative effect on the outcome variable. The effect of duration on life satisfaction is comparable to that found in the ordered logit fixed effects regression (see table 5). All time periods following the first period of experiencing a disability (0.1 to 2 years after onset) have a significant positive effect on the outcome variable. Moreover, this effect is increasing, as the estimated effect of a duration longer than 5.5 years is larger than that of a duration of 2 to 5.5 years.

On the other hand, a duration of 2 to 5.5 or more than 5.5 years has no significant effect on self-perceived health, although both coefficients are positive as opposed to the negative coefficients found in the ordered logit analysis (see table 5). A significant difference is found in the self-perceived health score for respondents without any disability compared to those in their first period of the disability onset (0.1 to 2 years). In line with my expectations, subjects without any limitations report a higher self-perceived health compared to those that have experienced limitations for less than 2 years. The difference in sign on the duration coefficients between the linear model and the ordered logit model is due to the assumed measurement scale of the dependent variable and the associated model specification, since this is the only differing feature between the two models. As stated before, I believe that the linear specification is too simplistic and therefore prefer the results obtained with the ordered logit model.

Table 8: Linear FE regression (1) for life satisfaction and self-perceived health

	Life satisfaction	Self-perceived health
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	0.034	0.319^{***}
	(0.043)	(0.017)
2-5.5 years IADL limit.	0.122^{*}	0.019
	(0.055)	(0.023)
$>$ 5.5 years IADL limit.	0.393^{***}	0.051
	(0.107)	(0.043)
Number of IADL limitations		
Number of IADL limit.	-0.176^{***}	-0.082^{***}
	(0.016)	(0.005)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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, and number of children. The reference categories for marital and employment status are married and retired.

5.3 Results fixed effects ordered probit model

The regression estimates for the fixed effects ordered probit model with life satisfaction can be found in table 9. The results for the ordered probit model with self-perceived health are displayed in table 10. This methodology is described in section 4.3. For the full tables of results including the effects of covariates see appendix A.4.

For the analysis with life satisfaction, the reference category for the lagged response variable (Y_{t-1}) and the first observed response variable ($Y_{t,1}$) is the first score on the converted 9-point life satisfaction scale ($Y_{t-1} = 1$ and $Y_{t,1} = 1$). The results suggest that there is state dependence, seeing that the coefficients on the lagged variables are significant and increasing for scores 6 to 9. Additionally, the number of IADL limitations have a significant negative effect on life satisfaction. Disability duration is specified as a continuous variable and is significantly and positively related to life satisfaction in accordance with the previous analyses.

Table 10 presents the results for the probit analysis on self-perceived health. Here, the reference categories for the lagged response variable and the first period are a reported Poor health (Y_{t-1} = Poor and $Y_{t,1}$ = Poor). The lagged response variables are significant and increasing which again suggests state dependence. Moreover, the first observed self-perceived health measures are also significant and increasing, which indicates that the initial self-perceived health affects self-perceived health in the consecutive waves. The coefficient on the number of IADL limitations is negative and

Table 9: FE ordered probit regression (2) for life satisfaction

Coefficients	Life satisfaction	Parameterization of FE	
Lagged dependent variable		**First period dependent variable**	
(Ref. $Y_{t-1} = 1$, Very dissatisfied)		(Ref. $Y_{t,1} = 1$, Very dissatisfied)	
$Y_{T-1} = 2$	0.607	$Y_{t,1} = 2$	−0.039
	(0.665)		(0.882)
$Y_{T-1} = 3$	0.931	$Y_{t,1} = 3$	0.142
	(0.696)		(0.982)
$Y_{T-1} = 4$	1.143	$Y_{t,1} = 4$	0.159
	(0.65)		(0.937)
$Y_{T-1} = 5$	1.245	$Y_{t,1} = 5$	0.251
	(0.665)		(0.951)
$Y_{T-1} = 6$	1.485*	$Y_{t,1} = 6$	0.235
	(0.657)		(0.973)
$Y_{T-1} = 7$	1.711*	$Y_{t,1} = 7$	0.402
	(0.665)		(0.993)
$Y_{T-1} = 8$	1.888**	$Y_{t,1} = 8$	0.569
	(0.679)		(1.002)
$Y_{T-1} = 9$	2.121**	$Y_{t,1} = 9$	0.621
	(0.672)		(1.004)
Duration		**Mean duration**	
Disability duration	0.078*	Mean disability duration	−0.058
	(0.035)		(0.045)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	−0.085**	Mean number of IADL limitations	−0.025
	(0.029)		(0.02)
Thresholds			
Threshold 1	−0.280	Threshold 5	1.384
Threshold 2	0.034	Threshold 6	1.884
Threshold 3	0.298	Threshold 7	2.694*
Threshold 4	1.050	Threshold 8	3.141**
Number of subjects	4556		
Number of observations	8252		

Note. Ref. stands for reference category. 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, and number of children. The reference categories for marital and employment status are married and retired.

significant, which implies that having a disability negatively affects self-perceived health and that more limitations correspond to a lower self-perceived health.

Duration since the onset of the disability has a positive coefficient, as opposed to the negative sign found in the ordered logit model, but no significant effect on self-perceived health. There are three differences in modelling features between the ordered probit and logit models that could explain this difference (see table 4). One possible explanation is that the difference in sign is caused by the continuous specification for duration in the ordered probit model. Another option is that the opposing signs are due to the difference in assumed error distribution (logistic or normal) and the associated estimation methods. However, it seems more likely that the dynamics in the ordered probit model account for this difference in sign, since the lagged dependent variable is also a function of duration. The next section addresses these issues.

Table 10: FE ordered probit regression (2) for self-perceived health

Coefficients	Self-perceived health	Parameterization of FE	
Lagged dependent variable		**First period dependent variable**	
(Ref. Y_{t-1} = Poor)		(Ref. $Y_{t,1}$ = Poor)	
Y_{t-1} = Fair	0.45***	$Y_{t,1}$ = Fair	0.282***
	(0.041)		(0.046)
Y_{t-1} = Good	0.813***	$Y_{t,1}$ = Good	0.549***
	(0.048)		(0.05)
Y_{t-1} = Very good	1.064***	$Y_{t,1}$ = Very good	0.796***
	(0.065)		(0.063)
Y_{t-1} = Excellent	1.051***	$Y_{t,1}$ = Excellent	1.071***
	(0.103)		(0.095)
Duration		**Mean duration**	
Disability duration	0.014	Mean disability duration	−0.037*
	(0.013)		(0.016)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	−0.195***	Mean number of IADL limitations	−0.021
	(0.011)		(0.014)
Thresholds			
Threshold 1	0.062		
Threshold 2	1.439***		
Threshold 3	2.595***		
Threshold 4	3.360***		
Number of subjects	5335		
Number of observations	10 455		

Note. Ref. stands for reference category. 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, and number of children. The reference categories for marital and employment status are married and retired.

5.4 Robustness checks

In this section, I study how robust the results are to small tweaks in the fixed effects ordered logit model specification. This is done to examine to what extent small changes in practical decisions made by me affect the conclusions. The re-categorization of the life satisfaction variable is discussed in subsection 5.4.1 and the re-categorization and continuous measurement scale of the duration variable is presented in subsection 5.4.2. The conclusions based on the results from the ordered logit model remain unaffected by the tweaks in the categorization of the life satisfaction variable and duration variable. Moreover, I will examine what causes the difference in effect in the self-perceived health analyses for the fixed effects ordered probit model compared to the fixed effects ordered logit model (subsection 5.4.3). By doing so, I conclude that the difference in outcome between the ordered probit and logit specifications for the self-perceived health regression is due to the dynamics in the ordered probit model.

5.4.1 Alternative re-categorization of life satisfaction

Table 11 shows the results for the ordered logit model with two alternative categorizations for the life satisfaction variable. Remember that the variable originally is measured on an 11-point scale and that the main analysis makes use of a 9-point scale by grouping the first 3 categories together. This was done to make the analysis computationally feasible in all models under consideration. In table 11, the first column presents the results for which the life satisfaction variable has more categories than in the original analysis. The 10 categories are formed by pooling the first two categories on the 11-point scale. Here, in addition to the coefficient on the dummy variable for more than 5.5 years of IADL limitations, the coefficient on 2 to 5.5 years of IADL limitations is also positive and significant. Hence, these results also support the presence of adaptation. The second column corresponds to an analysis in which life satisfaction is divided into 5 categories. The categories are formed by grouping the first three categories together, putting the scores 3 and 4 into one group, leaving score 5 as a category, grouping scores 6 and 7 together and forming a category out of the highest three scores. The second dummy variable is not significant anymore, but the last one (on more than 5.5 years since the onset of disability) still is. Clearly, these findings show that the additional information gained from leaving the original 11-point scale as much in tact as possible is reflected in the significance of the parameter estimates. Nevertheless, the sign of the effects is the same as in the main analysis. Thus, re-categorization of the life satisfaction categories has no effect on the conclusions drawn compared to those based from the main analysis.

Table 11: FE ordered logit regression (7) with differing number of life satisfaction categories

	Life satisfaction (10 categories)	Life satisfaction (5 categories)
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	-0.125	-0.123
	(0.187)	(0.206)
2-5.5 years IADL limit.	0.152^{*}	0.161
	(0.076)	(0.083)
$>$ 5.5 years IADL limit.	0.48^{***}	0.53^{**}
	(0.145)	(0.164)
Number of IADL limitations		
Number of IADL limit.	-0.182^{***}	-0.202^{***}
	(0.027)	(0.031)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

5.4.2 Alternative re-categorization of duration dummy

Tables 12 and 13 present regression results for the ordered logit model with two alternative ways of partitioning the dummy variables for duration. The first table makes use of 7 duration dummies. Since the dummies do not correspond to the number of waves spend with a chronic disability as in the original division, the effect of duration is somewhat disparate in both the regression with life satisfaction and self-perceived health.

In the regression with life satisfaction, the significant coefficients on 1 to 2 years, 4 to 6 years and more than 7.5 years are all positive, which agrees with the previous findings from the ordered logit model. They seem to increase, although this pattern is not as smooth as it was in the original dummy specification. Again, this is likely caused by the fact that these dummies do not correspond to the number of waves since the onset of the limitations. In the regression with self-perceived health, we now see some negative and significant coefficients on the dummies for 1 to 2 years, 3 to 4 years and 4 to 6 years. The score on self-perceived health appears to be decreasing up until 3-4 years of IADL limitations and increasing again after that.

A similar pattern can be revealed for the analyses in table 13. The dummies for 4 to 6 and more than 8 years of IADl limitations are significant for the regression with life satisfaction. The signs of the coefficient are again positive. The results for the regression with self-perceived health are very similar to those found in the original specification, with only the first dummy for no IADL limitations being positive and significant.

Finally, table 14 shows the results when the dummies for duration are replaced by one continuous variables as in the ordered probit model. The coefficient on disability duration is significant and positive for life satisfaction, which concurs with the results on the dummy variables in the ordered logit model. It is significant and negative in the analysis with self-perceived health. For both analyses, the significance is slightly deceptive, since we know from the previously discussed results that there is only a significant effect for a few of the duration dummies and the effect is thus not present throughout the complete observed period.

Hence, re-categorization of the dummies or a continuous measurement scale of the duration variable does not affect the conclusions that can be drawn compared to the main analysis.

Table 12: FE ordered logit regression (7) with 7 duration dummy categories

	Life satisfaction	Self-perceived health
Duration		
(Ref. 0.1-1 years IADL limitations)		
0 years (NO) IADL limit.	-0.087	0.752^{***}
	(0.159)	(0.228)
1-2 years IADL limit.	0.073	-0.369^{***}
	(0.115)	(0.102)
2-3 years IADL limit.	0.23^{*}	0.093
	(0.093)	(0.101)
3-4 years IADL limit.	-0.183	-0.629^{***}
	(0.162)	(0.16)
4-6 years IADL limit.	0.615^{***}	-0.363^{*}
	(0.17)	(0.169)
6-7.5 years IADL limit.	0.389	-0.389
	(0.275)	(0.254)
$>$ 7.5 years IADL limit.	0.739^{*}	-0.178
	(0.351)	(0.382)
Number of IADL limitations		
Number of IADL limit.	-0.19^{***}	-0.17^{***}
	(0.026)	(0.033)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

Table 13: FE ordered logit regression (7) with 5 duration dummy categories

	Life satisfaction	Self-perceived health
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	0.019	0.855^{***}
	(0.128)	(0.225)
2-4 years IADL limit.	0.084	-0.032
	(0.079)	(0.084)
4-6 years IADL limit.	0.609^{***}	-0.057
	(0.142)	(0.142)
6-8 years IADL limit.	0.34	-0.112
	(0.258)	(0.236)
> 8 years IADL limit.	0.658	0.108
	(0.339)	(0.367)
Number of IADL limitations		
Number of IADL limit.	-0.165^{***}	-0.166^{***}
	(0.031)	(0.026)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

Table 14: FE ordered logit regression (7) for life satisfaction and self-perceived health with continuous duration

	Life satisfaction	Self-perceived health
Duration		
Disability duration	0.056^{*}	-0.123^{*}
	(0.023)	(0.049)
Number of IADL limitations		
Number of IADL limit.	-0.173^{***}	-0.265^{***}
	(0.027)	(0.032)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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. The regression estimates for the covariates are not shown for paucity. The covariates included are marital status, employment status, and number of children. The reference categories for marital and employment status are married and retired.

5.4.3 FE ordered probit versus ordered logit specification

Lastly, the three suggested causes for the difference in sign of the effect of duration between the ordered probit model (see table 10) and the ordered logit model (see table 5) were the duration specification, the assumed distribution of the error term and the associated estimation method and the dynamics in the ordered probit model. The first potential cause can be investigated by looking at table 14. This shows the results when the dummies for duration in the ordered logit model are replaced by one continuous variable as is the case in the ordered probit specification. The coefficient on disability duration is negative in the analysis with self-perceived health, which concurs with the effect found in the ordered logit model with duration dummies. Hence, the positive effect of duration in the probit specification is not a result of the continuous specification for the duration variable.

Another potential cause for the difference in results are the dynamics that are included in the ordered probit model, but not in the ordered logit model. In order to check this, the dynamics are removed from the ordered probit model, resulting in the exact same model features as those used to obtain the results in table 14, with the exception of the assumed distribution of the error terms[4]. The results of this analysis are displayed in table 15. The effect of duration on self-perceived health is negative, which is the same direction as was found for the ordered logit regression. Thus, the dynamics introduced in the ordered probit model change the direction of the effect of disability duration on self-perceived health. I will return to the question on whether or not the dynamics are desirable in this analysis in the discussion.

[4]The error terms in the ordered logit model are assumed to follow a logistic distribution and those in the ordered probit model a normal distribution.

Table 15: FE ordered probit regression (2) for self-perceived health without dynamics

	Self-perceived health		
Coefficients		Parameterization of FE	
Duration		**Mean duration**	
Disability duration	-0.063^{***}	Mean disability duration	-0.023
	(0.012)		(0.016)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	-0.178^{***}	Mean number of IADL limitations	-0.046^{***}
	(0.01)		(0.013)
Thresholds			
Threshold 1	-1.107^{***}		
Threshold 2	0.122^{***}		
Threshold 3	1.140^{***}		
Threshold 4	1.820^{***}		
Number of subjects	5341		
Number of observations	15 802		

Note. Ref. stands for reference category. 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, and number of children. The reference categories for marital and employment status are married and retired.

6 Discussion

This master thesis analyzed adaptation to disability assessed through the effect of time since the onset of disability on both life satisfaction and self-perceived health. The SHARE data was used for the analyses, consisting of individuals aged 50 and over spanning 6 waves. Both life satisfaction and self-perceived health were studied because the literature has made hardly any distinction between the two, even though self-perceived health is generally considered part of the much broader defined construct of life satisfaction, which might affect the adaptation process. Moreover, these analyses were performed for three different model specifications to infer what modelling features should be included to measure adaptation. The three specifications that were studied differed on the following features: the assumed measurement scale of the dependent variable (discrete or continuous), the econometric model (linear fixed effects, fixed effects ordered probit, fixed effects ordered logit), the inclusion of dynamics, the specification of the duration variable (continuous or dummy variables) and the parameterization of the fixed effects.

In the fixed effects ordered logit model, supportive evidence for adaptation in the life satisfaction data was found, but not for self-perceived health. Through several robustness checks it became clear that small tweaks in the categorization of the duration dummy variables or the life satisfaction variable do not alter these conclusions. The difference in sign on the duration dummy coefficients between the ordered logit model and the linear model in the analysis with self-perceived health is caused by the difference in assumed measurement scale of the dependent variable and the associated estimation methods. Here, the linear model presented positive signs, whereas the logit model had negative signs. The ordered logit model assumes a discrete measurement scale which is true to the actual measurement scales of the dependent variables. Therefore, I prefer the results from the ordered logit model over those of the linear model. Moreover, the positive sign on the coefficient for duration in the ordered probit model was also opposite to that found in the ordered logit regression for self-perceived health. Upon further inspection, the empirical results show that the dynamics present in the ordered probit model cause the difference in results. The question of whether or not to include dynamics depends on whether one believes health state or well-being dependency is time invariant. (State dependence is the tendency to report higher or lower values by default.) If this premise is true, there is no need to control for it by means of a lagged dependent variable, since this type of variation is accounted for by the individual specific effects. In my opinion, this is indeed the case in this particular data set. This analysis concerns a relatively old sample who will have had ample time to develop a concept of health and well-being and how that relates to their personal circumstances. As a result, their state dependence is likely to be relatively stable. Of course, one might change his or her conception of health or well-being and thereby the state dependence might shift, but this is one of the attributes of adaptation (see the literature review in section 2) and should therefore be modelled as such. Therefore, no dynamics were added to the ordered logit model.

The obvious discrepancy in adaptation between the analyses with life satisfaction and self-perceived health is probably due to the nature of the dependent variables. It is likely that people take many factors into account when answering a question about life satisfaction, which makes it into a more holistic measure of well-being. Hence, adaptation to disability might occur faster for life satisfaction levels, since nonmedical factors, like social support, facilitate the adaptation process. In contrast, the question on self-reported health presumably focuses people's attention on their health situation, which is not likely to have improved due to its chronic nature. Moreover, the difference in adaptation could be explained by considering one of the eight elements of adaptation defined by Menzel, Dolan, Richardson and Olsen (2002) (see section 2). This element is defined as adopting a different definition of health or well-being that is more productive in thinking about one's state of health or well-being. Self-perceived health may be harder to redefine as a concept, since its original definition is much more narrowly defined compared to that of life satisfaction, which would explain the adaptation in life satisfaction and the lack of adaptation in self-perceived health.

A limitation of this study is that its prospective nature - meaning that the analyses only include individuals whose onset of chronic disability is known - severely limits the duration span I can measure. My maximum duration of experiencing chronic limitations is approximately 9.5 years and only a very small sub-sample is observed for this maximum duration. All methodological differences aside, Cubí-Mollà, Jofre-Bonet, and Serra-Sastre (2016) only found a significant effect of duration after 20 years on subjective health. Thus, the observed period in the SHARE data might simply not be long enough. A longer duration could particularly benefit the analysis with self-perceived health, since the coefficients for all three model specifications seem to be hinting at the presence of adaptation, but none of the found effects are significant. Hence, continuing data collection in the currently available panel data sets like SHARE could benefit future adaptation research.

Furthermore, the SHARE data set is restricted to individuals of age 50 and up. It is possible that the adaptation process of the SHARE subjects differs from that of younger individuals. For example, it is imaginable that younger subjects find it easier to adapt to a chronic disability or disease, since they can more easily change their occupation or enhance their skill set. Thus, the differences in the adaptation process for different age categories is a question for future research. Alternatively, the chronic conditions prevalent in the younger sample might be different to those reported by the older sample and the adaptation process for these subsets of diseases could differ. The study by Cubí-Mollà, Jofre-Bonet, and Serra-Sastre has made a beginning at studying the adaptation process for different health impairments, but more research is needed breaking down the adaptation process for different diseases and disabilities.

Finally, a complicating factor in the study of adaptation is that one cannot verify what mechanisms cause the adaptation or in fact whether the change in well-being or subjective health levels are truly a result of adaptation. An apparent change in life satisfaction or self-perceived health does not necessarily reflect a true change in these constructs. In fact, one might change his or her internal standards, also deemed scale recalibration, leading to a different interpretation of the subjective response scale, but not to a true change in life satisfaction or self-perceived health itself. Empirically, the effects of scale recalibration and adaptation cannot be separated. Depending on the application of the current results, this should be taken into account. For example, measuring nothing but a the true change in self-perceived health or life satisfaction might be relevant to epidemiological applications. Thus, additional qualitative research has to be conducted investigating how subjects interpret certain scales and whether their definitions change over time.

Following are some implications my results have for the theory on adaptation. From the results it became clear that the adaptation process differs for life satisfaction and self-perceived health, with the adaptation for self-perceived health being slower or potentially nonexistent. In future theoretical discussions, this distinction ought to be made. Moreover, the effect of duration on either self-perceived health or life satisfaction was nonlinear and should be treated as such in future discussions. I advise future research to take the ordered nature of the dependent variable into account if it is measured on an ordinal scale by using a fixed effects ordered logit or probit specification. Of these two, I prefer the ordered logit specification, as I explained earlier, but this choice is largely based on the purpose of the study.

In practice, the findings are relevant to epidemiologists, since they provide insight into the trajectory of a patient's subjective health and well-being over the course of the disability. Furthermore, they can be used as empirical evidence for adaptation in the debate whether quality of life estimates should be obtained from patients or members of the general public. However, as was mentioned previously, this thesis cannot conclude on the desirability of the adaptation found here in the context of societal decision making. Thus, the debate on the body of people that should be used to obtain quality of life estimates for health states will likely remain based on the normative evaluation of adaptation and its mechanisms.

In conclusion, this thesis provides evidence for adaptation to disability in life satisfaction, but not in self-perceived health.

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APPENDIX

A.1 Derivatives of the conditional Chamberlain likelihood function

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

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

The individual Hessians for this likelihood function are given by

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

A.2 Marginal effects ordered logit model

Marginal effects on the probability of reporting $Y > k$ for life satisfaction

	Life satisfaction								
	Score 1 Very dissatisfied	Score 2	Score 3	Score 4	Score 5	Score 6	Score 7	Score 8	Score 9 Very satisfied
Marital status									
(Ref. Married)									
Not married	-0.007	-0.013	-0.02	-0.051	-0.063	-0.07	-0.05	-0.031	-
	(0.004)	(0.007)	(0.011)	(0.028)	(0.035)	(0.039)	(0.028)	(0.017)	-
Employment status									
(Ref. Retired)									
Employed	0.012***	0.022***	0.035***	0.087***	0.108***	0.12***	0.086***	0.053***	-
	(0.003)	(0.006)	(0.01)	(0.025)	(0.031)	(0.034)	(0.025)	(0.015)	-
Unemployed	-0.006	-0.011	-0.018	-0.044	-0.054	-0.061	-0.043	-0.027	-
	(0.005)	(0.01)	(0.016)	(0.039)	(0.049)	(0.054)	(0.039)	(0.024)	-
Inactive	-0.002	-0.004	-0.006	-0.016	-0.02	-0.022	-0.016	-0.01	-
Number of children									
Number of children	0.001	0.002	0.003	0.009	0.011	0.012	0.008	0.005	-
	(0.001)	(0.002)	(0.003)	(0.007)	(0.009)	(0.01)	(0.007)	(0.004)	-
Duration									
(Ref. 0.1-2 years IADL limitations)									
0 years (NO) IADL limit.	0.002	0.003	0.005	0.011	0.014	0.016	0.011	0.007	-
	(0.003)	(0.005)	(0.008)	(0.021)	(0.026)	(0.028)	(0.02)	(0.013)	-
2-5.5 years IADL limit.	0.004	0.007	0.01	0.026	0.032	0.036	0.026	0.016	-
	(0.002)	(0.004)	(0.005)	(0.014)	(0.017)	(0.019)	(0.013)	(0.008)	-
$>$ 5.5 years IADL limit.	0.012***	0.023***	0.036***	0.089***	0.11***	0.123***	0.088***	0.054***	-
	(0.004)	(0.007)	(0.011)	(0.026)	(0.032)	(0.036)	(0.026)	(0.016)	-
Number of IADL limitations									
Number of IADL limit.	-0.004***	-0.008***	-0.012***	-0.031***	-0.038***	-0.042***	-0.03***	-0.019***	-
	(0.001)	(0.001)	(0.002)	(0.005)	(0.006)	(0.007)	(0.005)	(0.003)	-

Note. Ref. stands for reference category. 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 the Krinsky and Robb method.

Marginal effects on the probability of reporting $Y > k$ for self-perceived health

	Self-perceived health				
	Poor	Fair	Good	Very good	Excellent
Marital status					
(Ref. Married)					
Not married	-0.011	-0.013	-0.004	-0.001	-
	(0.03)	(0.033)	(0.01)	(0.003)	-
Employment status					
(Ref. Retired)					
Employed	0.142^{***}	0.158^{***}	0.05^{***}	0.012^{***}	-
	(0.028)	(0.031)	(0.01)	(0.002)	-
Unemployed	0.018	0.02	0.006	0.002	-
	(0.044)	(0.05)	(0.016)	(0.004)	-
Inactive	-0.02	-0.022	-0.007	-0.002	-
	(0.019)	(0.022)	(0.007)	(0.002)	-
Number of children					
Number of children	-0.006	-0.007	-0.002	-0.001	-
	(0.005)	(0.006)	(0.002)	(0)	-
Duration					
(Ref. 0.1-2 years IADL limitations)					
0 years (NO) IADL limit.	0.188^{***}	0.21^{***}	0.066^{***}	0.016^{***}	-
	(0.038)	(0.042)	(0.013)	(0.003)	-
2-5.5 years IADL limit.	-0.008	-0.009	-0.003	-0.001	-
	(0.015)	(0.017)	(0.005)	(0.001)	-
$>$ 5.5 years IADL limit.	-0.005	-0.005	-0.002	0	-
	(0.028)	(0.032)	(0.01)	(0.002)	-
Number of IADL limitations					
Number of IADL limit.	-0.031^{***}	-0.035^{***}	-0.011^{***}	-0.003^{***}	-
	(0.005)	(0.006)	(0.002)	(0)	-

Note. Ref. stands for reference category. 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 the Krinsky and Robb method.

A.3 Results linear fixed effects model

Complete linear FE regression (1) for life satisfaction and self-perceived health

	Life satisfaction	Self-perceived health
Marital status		
(Ref. Married)		
Not married	-0.342^{**}	-0.028
	(0.115)	(0.043)
Employment status		
(Ref. Retired)		
Employed	0.299^{**}	0.285^{***}
	(0.097)	(0.039)
Unemployed	-0.196	0.019
	(0.15)	(0.062)
Inactive	-0.096	-0.039
	(0.075)	(0.03)
Number of children		
Number of children	0.042	-0.001
	(0.039)	(0.015)
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	0.034	0.319^{***}
	(0.043)	(0.017)
2-5.5 years IADL limit.	0.122^{*}	0.019
	(0.055)	(0.023)
$>$ 5.5 years IADL limit.	0.393^{***}	0.051
	(0.107)	(0.043)
Number of IADL limitations		
Number of IADL limit.	-0.176^{***}	-0.082^{***}
	(0.016)	(0.005)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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 Results fixed effects ordered probit model

Complete FE ordered probit regression (2) for self-perceived health

Coefficients	Self-perceived health	Parameterization of FE	
Lagged dependent variable		**First period dependent variable**	
(Ref. Y_{t-1} = Poor)		(Ref. $Y_{t,1}$ = Poor)	
Y_{t-1} = Fair	0.45***	$Y_{t,1}$ = Fair	0.282***
	(0.041)		(0.046)
Y_{t-1} = Good	0.813***	$Y_{t,1}$ = Good	0.549***
	(0.048)		(0.05)
Y_{t-1} = Very good	1.064***	$Y_{t,1}$ = Very good	0.796***
	(0.065)		(0.063)
Y_{t-1} = Excellent	1.051***	$Y_{t,1}$ = Excellent	1.071***
	(0.103)		(0.095)
Marital status		**Mean marital status**	
(Ref. Married)		(Ref. Married)	
Not married	0.027	Mean not married	0.039
	(0.104)		(0.106)
Employment status		**Mean employment status**	
(Ref. Retired)		(Ref. Retired)	
Employed	0.153	Mean employed	0.053
	(0.097)		(0.109)
Unemployed	0.024	Mean unemployed	0.025
	(0.162)		(0.187)
Inactive	−0.046	Mean inactive	−0.016
	(0.069)		(0.076)
Number of children		**Mean number of children**	
Number of children	−0.031	Mean number of children	0.03
	(0.039)		(0.04)
Duration		**Mean duration**	
Disability duration	0.014	Mean disability duration	−0.037*
	(0.013)		(0.016)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	−0.195***	Mean number of IADL limitations	−0.021
	(0.011)		(0.014)
Thresholds			
Threshold 1	0.062		
Threshold 2	1.439***		
Threshold 3	2.595***		
Threshold 4	3.360***		
Number of subjects	5335		
Number of observations	10 455		

Note. Ref. stands for reference category. 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 FE ordered probit regression (2) for life satisfaction

	Life satisfaction		
Coefficients		Parameterization of FE	
Lagged dependent variable		**First period dependent variable**	
(Ref. $Y_{t-1} = 1$)		(Ref. $Y_{t,1} = 1$)	
$Y_{T-1} = 2$	0.607	$Y_{t,1} = 2$	−0.039
	(0.665)		(0.882)
$Y_{T-1} = 3$	0.931	$Y_{t,1} = 3$	0.142
	(0.696)		(0.982)
$Y_{T-1} = 4$	1.143	$Y_{t,1} = 4$	0.159
	(0.65)		(0.937)
$Y_{T-1} = 5$	1.245	$Y_{t,1} = 5$	0.251
	(0.665)		(0.951)
$Y_{T-1} = 6$	1.485*	$Y_{t,1} = 6$	0.235
	(0.657)		(0.973)
$Y_{T-1} = 7$	1.711*	$Y_{t,1} = 7$	0.402
	(0.665)		(0.993)
$Y_{T-1} = 8$	1.888**	$Y_{t,1} = 8$	0.569
	(0.679)		(1.002)
$Y_{T-1} = 9$	2.121**	$Y_{t,1} = 9$	0.621
	(0.672)		(1.004)
Marital status		**Mean marital status**	
(Ref. Married)		(Ref. Married)	
Not married	0.015	Mean not married	−0.117
	(0.224)		(0.271)
Employment status		**Mean employment status**	
(Ref. Retired)		(Ref. Retired)	
Employed	−0.018	Mean employed	0.041
	(0.78)		(0.898)
Unemployed	−0.492	Mean unemployed	0.429
	(0.971)		(1.139)
Inactive	−0.066	Mean inactive	0.055
	(0.265)		(0.278)
Number of children		**Mean number of children**	
Number of children	0	Mean number of children	0.026
	(0.078)		(0.062)
Duration		**Mean duration**	
Disability duration	0.078*	Mean disability duration	−0.058
	(0.035)		(0.045)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	−0.085**	Mean number of IADL limitations	−0.025
	(0.029)		(0.02)
Thresholds			
Threshold 1	−0.280	Threshold 5	1.384
Threshold 2	0.034	Threshold 6	1.884
Threshold 3	0.298	Threshold 7	2.694*
Threshold 4	1.050	Threshold 8	3.141**
Number of subjects	4556		
Number of observations	8252		

Note. Ref. stands for reference category. 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.

A.5 Results robustness checks

A.5.1 Alternative re-categorization of life satisfaction

Complete FE ordered logit regression (7) with differing number of life satisfaction categories

	Life satisfaction (10 categories)	Life satisfaction (5 categories)
Marital status		
(Ref. Married)		
Not married	−0.293	−0.278
	(0.16)	(0.173)
Employment status		
(Ref. Retired)		
Employed	0.477***	0.68***
	(0.138)	(0.163)
Unemployed	−0.3	−0.266
	(0.212)	(0.228)
Inactive	−0.099	−0.139
	(0.104)	(0.114)
Number of children		
Number of children	0.047	0.013
	(0.038)	(0.041)
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	−0.125	−0.123
	(0.187)	(0.206)
2-5.5 years IADL limit.	0.152*	0.161
	(0.076)	(0.083)
> 5.5 years IADL limit.	0.48***	0.53**
	(0.145)	(0.164)
Number of IADL limitations		
Number of IADL limit.	−0.182***	−0.202***
	(0.027)	(0.031)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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.

A.5.2 Alternative re-categorization of duration dummies

Complete FE ordered logit regression (7) with 7 duration dummy categories

	Life satisfaction	Self-perceived health
Marital status		
(Ref. Married)		
Not married	-0.251	-0.046
	(0.159)	(0.154)
Employment status		
(Ref. Retired)		
Employed	0.502^{***}	0.741^{***}
	(0.14)	(0.146)
Unemployed	-0.228	0.1
	(0.207)	(0.227)
Inactive	-0.103	-0.087
	(0.101)	(0.104)
Number of children		
Number of children	0.049	-0.029
	(0.038)	(0.029)
Duration		
(Ref. 0.1-1 years IADL limitations)		
0 years (NO) IADL limit.	-0.087	0.752^{***}
	(0.159)	(0.228)
1-2 years IADL limit.	0.073	-0.369^{***}
	(0.115)	(0.102)
2-3 years IADL limit.	0.23^{*}	0.093
	(0.093)	(0.101)
3-4 years IADL limit.	-0.183	-0.629^{***}
	(0.162)	(0.16)
4-6 years IADL limit.	0.615^{***}	-0.363^{*}
	(0.17)	(0.169)
6-7.5 years IADL limit.	0.389	-0.389
	(0.275)	(0.254)
$>$ 7.5 years IADL limit.	0.739^{*}	-0.178
	(0.351)	(0.382)
Number of IADL limitations		
Number of IADL limit.	-0.19^{***}	-0.17^{***}
	(0.026)	(0.033)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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.

Complete FE ordered logit regression (7) with 5 duration dummy categories

	Life satisfaction	Self-perceived health
Marital status		
(Ref. Married)		
Not married	-0.271	-0.053
	(0.159)	(0.152)
Employment status		
(Ref. Retired)		
Employed	0.466^{***}	0.738^{***}
	(0.14)	(0.148)
Unemployed	-0.285	0.097
	(0.214)	(0.23)
Inactive	-0.113	-0.095
	(0.101)	(0.101)
Number of children		
Number of children	0.052	-0.03
	(0.039)	(0.028)
Duration		
(Ref. 0.1-2 years IADL limitations)		
0 years (NO) IADL limit.	0.019	0.855^{***}
	(0.128)	(0.225)
2-4 years IADL limit.	0.084	-0.032
	(0.079)	(0.084)
4-6 years IADL limit.	0.609^{***}	-0.057
	(0.142)	(0.142)
6-8 years IADL limit.	0.34	-0.112
	(0.258)	(0.236)
$>$ 8 years IADL limit.	0.658	0.108
	(0.339)	(0.367)
Number of IADL limitations		
Number of IADL limit.	-0.165^{***}	-0.166^{***}
	(0.031)	(0.026)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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.

Complete FE ordered logit regression (7) for life satisfaction and self-perceived health with continuous duration

	Life satisfaction	Self-perceived health
Marital status		
(Ref. Married)		
Not married	−0.301	−0.122
	(0.16)	(0.16)
Employment status		
(Ref. Retired)		
Employed	0.493***	0.879***
	(0.143)	(0.153)
Unemployed	−0.248	0.22
	(0.212)	(0.23)
Inactive	−0.1	−0.046
	(0.101)	(0.102)
Number of children		
Number of children	0.044	−0.026
	(0.037)	(0.027)
Duration		
Disability duration	0.056*	−0.123*
	(0.023)	(0.049)
Number of IADL limitations		
Number of IADL limit.	−0.173***	−0.265***
	(0.027)	(0.032)
Number of subjects	5259	5341
Number of observations	13 328	15 802

Note. Ref. stands for reference category. 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.

A.5.3 Probit versus logit specifications

Complete FE ordered probit regression (2) for self-perceived health without dynamics

Coefficients	Self-perceived health	Parameterization of FE	
Marital status		**Mean marital status**	
(Ref. Married)		(Ref. Married)	
Not married	−0.121	Mean not married	0.034
	(0.069)		(0.072)
Employment status		**Mean employment status**	
(Ref. Retired)		(Ref. Retired)	
Employed	0.225***	Mean employed	0.077
	(0.061)		(0.072)
Unemployed	−0.009	Mean unemployed	−0.02
	(0.095)		(0.121)
Inactive	−0.102*	Mean inactive	−0.038
	(0.046)		(0.054)
Number of children		**Mean number of children**	
Number of children	−0.024	Mean number of children	0.003
	(0.024)		(0.025)
Duration		**Mean duration**	
Disability duration	−0.063***	Mean disability duration	−0.023
	(0.012)		(0.016)
Number of IADL limitations		**Mean number of IADL limitations**	
Number of IADL limitations	−0.178***	Mean number of IADL limitations	−0.046***
	(0.01)		(0.013)
Thresholds			
Threshold 1	−1.107***		
Threshold 2	0.122***		
Threshold 3	1.140***		
Threshold 4	1.820***		
Number of subjects	5341		
Number of observations	15 802		

Note. Ref. stands for reference category. 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.