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Adaptation in life satisfaction and self-assessed health to disability - Evidence from the UK

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ABSTRACT

Experiencing deteriorating health has implications for your quality of life. The theory of adaptation suggests that with time spend living in a health state individuals can adapt, resulting in observed quality of life levels to revert or stagnate despite persistently decreased health. Adaptation has implications for the use of subjective quality of life indicators when quantifying the impact of health changes or the benefits from new medical technologies. As both the impact from ill health and the benefit from new interventions might be disease- or subgroup-specific adaptation further raises ethical concerns but empirical evidence on its existence, magnitude, and heterogeneity remains inconclusive. This paper uses a general population sample of 9,543 individuals that participate in the UK Understanding Society survey and experience the onset of a long-standing illness or disability to provide evidence on these questions. Using ordered-response fixed effects models we explore longitudinal changes in self-assessed health and life satisfaction around the onset of disability. Our results indicate that disability onset is associated with large decreases in subjective health and well-being. Over time this initial decrease in subjective quality of life indicators attenuates, especially in life satisfaction and to a lesser extent for self-assessed health. While the relative difference in adaptation across these two measures remains persistent, we find that across demographic and severity groups the initial impact of disability onset and adaptation differs considerably in its magnitude. These results have important implications for studies aiming to quantify the impact of health conditions on quality of life outcomes, especially when using observational datasets.

1. Introduction

Adaptation to ill health refers to the phenomenon that individuals over time adjust to a deterioration in their health (Frederick and Loewenstein, 1999). Adaptation may lead to an increase in reported levels of quality of life, ceteris paribus, even if the health status has not improved. This may be observed when measuring quality of life using self-assessed health or multi-item health state evaluations (Groot, 2000), but also when using broader subjective well-being measures, which are increasingly seen as a relevant maximand for heath and public policy (Benjamin et al., 2019; Frijters et al., 2020; Loewenstein and Ubel, 2008; Peasgood et al., 2019). This has consequences for the use of subjective quality of life measures in health economic evaluations and health policy. For instance, the fact that economic evaluations often use members of the general public rather than patients as the source for health state valuations was importantly inspired by evidence of adaptation (Brazier et al., 2018; Frederick and Loewenstein, 1999; Versteegh and Brouwer, 2016) and the need to protect patients from the negative consequences of adaptation in allocation decisions (Cohen, 1993; Menzel et al., 2002). After all, if adaptation leads to higher reported subjective health or well-being, the potential gains from health and social care interventions become smaller.

While there is theoretical motivation for the importance of adaptation in the context of subjective quality of life measures as maximands in health economics and health policy the empirical findings regarding its existence and magnitude are not always conclusive. Since Brickman et al. (1978) first documented patterns consistent with adaptation among paraplegics, several studies have explored the dynamic impact of ill health on self-reported well-being and health outcomes. Most of these studies have explored adaptation using longitudinal panel surveys,

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allowing for the observation of individuals transitioning from good into ill health, and the application of panel fixed-effects approaches. Lucas (2007) and Powdthavee (2009) found conflicting evidence for adaptation to the onset of self-reported disability using the same German panel data. More recently Ta (2019) considered the differential impact of mental versus physical disability on life satisfaction conditional on an initial loss in life-satisfaction with evidence suggesting adaptation to be specific to the nature of health changes and the considered subgroup. Binder and Coad (2013), McNamee and Mendolia (2014), Cubí-Mollá et al. (2017) and Baji and Bíró (2018) on the other hand focused on the onset of specific conditions e.g., hypertension or diabetes, and report various levels of adaptation depending on the data, approach and definition of ill health considered. Most recently, de Hond et al. (2019) and Bussière et al. (2021) explored adaptation using the same pan-European panel survey of older individuals but come to somewhat diverging conclusions based on different empirical strategies. Both report adaptation with respect to life satisfaction but the results by Bussière et al. (2021) suggest these findings to be sensitive to the choice of subjective wellbeing measures considered.

This study explores adaptation to ill health using a sample of 9,543 individuals transitioning into living with a long-standing illness or disability participating in waves 1–10 of the UK longitudinal survey Understanding Society (University of Essex, Institute for Social and Economic Research, 2022). Following de Hond et al. (2019), we consider adaptation in life satisfaction and self-assessed health. Life satisfaction is an interesting outcome due to its characteristics as an easy-to-measure conceptualisation of subjective well-being with high policy relevance (Frijters et al., 2020). It encompasses various quality of life dimensions (de Hond et al., 2019) and is highly predictive of individuals' decision making (Kaiser and Oswald, 2022), making it an attractive and relevant experienced utility measure (Dolan and Metcalfe, 2012). It has also received considerable attention in health policy and economics (see e.g., Dolan and Kahneman (2008) or Peasgood et al. (2019)). A growing literature for example has used well-being valuation methods to provide estimates for the monetary equivalent value of health changes to inform health economic decision making, ranging from specific conditions (Howley, 2017; Ólafsdóttir et al., 2020) to generic health changes equivalent with the loss of one quality-adjusted life year (Himmler et al., 2021; Huang et al., 2018). Especially in this context adaptation in subjective well-being is a relevant concern as such methods rely on the trading-off between the relative impact of health and income changes on life-satisfaction to estimate monetary equivalents.

Exploring adaptation on self-assessed health on the other hand is motivated twofold. Firstly, past studies suggest that adaptation in broader well-being measures is driven by adaptation in subjective health perceptions and the related satisfaction-domain (Powdthavee, 2009). Cross-sectional evidence suggests that also with respect to specific health state evaluations adaptation exists (Groot, 2000; Jonker et al., 2017). Evidence from studies using panel data on the other hand provide a mixed picture with some finding adaptation to occur to a limited degree (Baji and Bíró, 2018; de Hond et al., 2019) while others find no adaptation in self-perceived health or only to occur over decades (Cubí-Mollá et al., 2017). Secondly, while less relevant for this study there is a strong link between economic or health-related decisions and health perceptions, ranging from risky and preventive health behaviors (see e.g. Arni et al. (2021); Spitzer and Shaikh (2022)) to decisions on retirement and saving (see e.g., Gan et al. (2015); Schünemann et al. (2017); Spaenjers and Spira (2015)). Adaptation in self-perceived health could indicate a misalignment between objectively experience health changes and the subjective perception of these with potential implications for individual decision making on health.

This study contributes to the literature on adaptation in three ways. Firstly, we study adaptation using a different definition of transitioning into ill health, namely; the onset of a long-standing illness or disability, changes to the short-form 12-item health questionnaire (SF12) mental and physical component scores (Ware et al., 1995), and different levels of functional limitations. This allows us to explore the extent to which adaptation depends on the definition of health and whether it is limited to mild conditions or also observed after more substantial health changes. Secondly, next to de Hond et al. (2019) and Cubí-Mollá et al. (2017) we are only the third study to explore adaptation using (fixed effects) ordered response models. As most studies on adaptation primarily considered life satisfaction or happiness as the main outcome of interest, common practice has been to follow Ferrer-i Carbonell and Frijters (2004) by assuming life satisfaction to be a cardinal measure allowing for regular linear (fixed effects) models to be estimated. An attractive property of such approaches is the ability to directly interpret linear coefficients but recently the appropriateness of such methods to analyse ordinal quality of life data has been debated (see e.g., Kaiser and Vendrik (2019) or Bond and Lang (2019)). However, ordered response models can be applied using fixed effects designs to obtain policy relevant insights not only into the mean changes on an assumed linear scale but along the distribution of ordered outcomes (Chen et al., 2022). Lastly, we explore this topic using the Understanding Society dataset, an annually conducted general population survey. Much of the recent work on adaptation has focused on using surveys among specific populations, such as older individuals (Baji and Bíró, 2018; Bussière et al., 2021; de Hond et al., 2019) or younger cohort studies (Cubí-Mollá et al., 2017). Using a general population survey, we can explore adaptation among a broader range of subgroups.

Table 1
Duration table.

	Time to Onset in Years										
	≤-5	−4	−3	−2	−1	0	1	2	3	4	≥ 5
Total	5,813	3,168	4,277	5,869	9,235	9,235	4,750	3,402	2,381	1,708	2,715
Sex											
Male	2,514	1,374	1,874	2,599	4,040	4,040	2,090	1,497	1,046	749	1,188
Female	3,299	1,794	2,403	3,270	5,195	5,195	2,660	1,905	1,335	959	1,527
Onset Age											
<55	3,199	1,833	2,476	3,440	5,393	5,393	2,532	1,726	1,171	817	1,217
≥55	2,614	1,335	1,801	2,429	3,842	3,842	2,218	1,676	1,210	891	1,498
Observations											52,553
Individuals											9,543

Source: Own calculations based on USoc Waves 2009–2020.

Table 2
Summary statistics.

	Analysis Sample (pre LSI onset)		Never LSI Sample	
	Mean	Std. Dv.	Mean	Std. Dv.
Outcomes				
Life Satisfaction	5.29	1.4	5.4	1.35
Self-Assessed Health	3.68	0.88	3.95	0.82
Health Status and Age				
SF12: Mental Component Score	50.12	9.24	50.75	8.5
SF12: Physical Component Score	52.88	7.55	55.02	5.79
Health Limits Typical Activities	0.15	0.36	0.08	0.28
Age in years	48.04	17.23	39.90	15.8
Socio-Economic Controls				
Employed	0.54	0.50	0.61	0.49
Self-Employed	0.08	0.27	0.09	0.28
Unemployed	0.04	0.2	0.04	0.20
Retired	0.22	0.41	0.09	0.29
Working full-time	0.46	0.50	0.54	0.50
Equivalised household income	1,713.42	1,407.76	1,875.22	2,995.41
Living in urban area	0.74	0.44	0.76	0.43
Highest Education: Primary/other/none)	0.10	0.30	0.06	0.23
Highest Education: Secondary	0.52	0.50	0.52	0.50
Highest Education: Tertiary	0.38	0.49	0.43	0.49
Single	0.19	0.39	0.29	0.45
Married/Partnership	0.68	0.47	0.64	0.48
Widowed	0.05	0.22	0.02	0.13
Separated/Divorced	0.08	0.27	0.05	0.23
Children living in Household	0.34	0.47	0.43	0.50
Observations	28,362		117,608	
Individuals	9,543		23,395	

Source: Own calculations based on USoc Waves 2009–2020.

2. Data

2.1. Data selection and definitions

We use data from the United Kingdom Household Longitudinal Study, also known as Understanding Society (USoc). USoc is an annual panel survey covering a representative sample of the adult UK population and is the direct successor to the British Household Panel Survey. Data collection started in 2009 with approximately 50,000 respondents across 30,000 households. USoc applies an overlapping panel design in which each wave is collected over a 24-month period while individuals are interviewed each year. We use the first ten waves of USoc which surveyed individuals between 2009 and 2020 with surveying for wave 10 being completed in the first quarter of 2020.

Our main outcomes of interest are two annually collected subjective quality of life measures, subjective well-being, and self-assessed health. Subjective well-being is measured using a life satisfaction question asking respondents *"how satisfied are you with your life overall?"*. Individuals respond by indicating on a 7-point scale ranging from 1 (*"completely dissatisfied"*) to 7 (*"completely satisfied"*). Self-assessed health is measured by asking individuals to complete the sentence *"in general would you say your health is … "* with one of five categories ranging from *"poor"* to *"excellent"*. To identify individuals transitioning from good into ill health we use the question *"do you have any long-standing physical or mental impairment, illness, or disability?"*. The survey text defines *"long-standing"* as *"anything that has troubled you over a period of at least 12 months or is likely to trouble you for a period of at least 12 months"*. We use this question to identify those individuals that are observed in good health, not reporting such a long-standing illness or disability (LSI), and a state of ill health, where an LSI is reported for multiple years. We therefore select individuals for the analysis sample based on the observed response pattern across their individual participation waves.

We condition the sample on those respondents providing at least two consecutively observed waves as this is the basic condition for both states to be observable. Secondly, if an individual reports an LSI in the first observed wave we exclude this participant from the analysis as we cannot observe the transition between health states. Likewise, we exclude individuals who never report an LSI, or report an erratic pattern such as multiple spells of periods with and without an LSI. If an individual drops out temporarily due to non-response, we further require this individual to provide at least two consecutive observations on each side of the non-response gap, only allow for one such gap to occur over the available participation waves, and for the length of this gap to be a single wave only. In the case where an individual drops out for one wave but then enters the panel again, now reporting a long-standing illness, we assume that the illness onset coincided with the missing wave to calculate the long-standing illness duration. In case an individual reports multiple spells of long-standing illness or disability with a single wave with no LSI in-between, we treat these spells as a period of repeated reporting of ill health indicating a longer-term health change that we consider as a singular spell. For all subsequent results, we have explored whether this choice alters impacts our results, but this decision was found to have no discernible impact. In case an individual stops consistently reporting an LSI, the observations following the LSI spell are removed.

Apart from conditioning on a sample of individuals observed to have transitioned into a state of ill health, we also condition on the availability of control variables at each observed period. These variables were household income, employment status, educational attainment, marital status, and the presence of children in the household. After imposing all of the aforementioned conditions we are left with a sample of 9,543 unique individuals providing 52,553 individual-year observations. The average respondent is observed for six periods equally split between good (no LSI reported) and ill health (LSI reported). Individuals are therefore observed in periods before an LSI is reported ($t < 0$) and

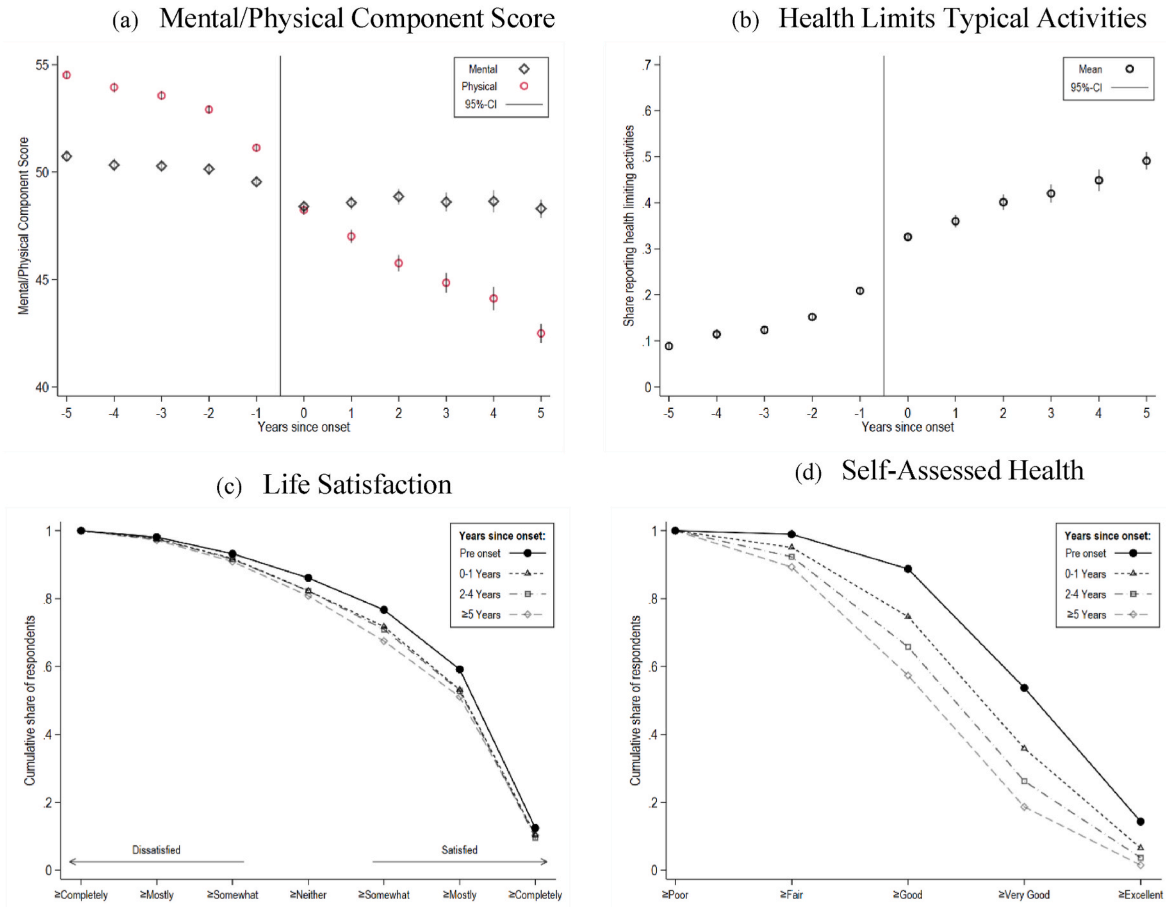


Fig. 1. Subjective and Objective Health and Well-being Outcomes around the LSI Onset
Source: Own calculations based on USoc Waves 2009–2020. *Note:* Panel (a) depicts the average mental and physical component scores by time to LSI-onset, panel (b) depicts the share of individuals reporting to be limited by their health to conduct typical activities. Bars indicate 95-% confidence intervals. The solid vertical line indicates the time point between the last wave directly before a first-reported LSI and the first wave with a reported LSI. Panel (c) depicts the distribution of life satisfaction categories by relative time since LSI-onset and panel (d) depicts the same for self-assessed health. The pre-onset group contains responses from the two years preceding before LSI-onset.

after transitioning into worse health ($t \geq 0$). While we are in principle able to observe individuals living with an LSI for up to nine years, the group living with an LSI for six or more years has a small number of individuals observed and are therefore grouped together ($t \geq 5$). Table 1 provides an overview of the number of individuals observed at the different relative time-points to LSI onset for the full sample and by gender and age.

Individuals responding to the LSI question in the affirmative are further asked to indicate whether the reported LSI results in "*substantial difficulties*" in any or multiple of 11 "*areas of life*". Table A1.2 in the appendix provides a breakdown of our analysis sample with respect to the dimensions affected and the number of limitations reported. While most respondents (54.49%) do not report the LSI onset to be associated with any dimension to be *"substantially limited"*, those respondents that do report such a limitation do so largely in areas of physical mobility and functioning. In our baseline analyses we do not consider this information but when turning towards the role of severity of health changes we do consider this information alongside other indicators to quantify health changes within our sample.

2.2. Summary statistics

Table 2 provides the summary statistics for the analysis sample alongside the sample of excluded individuals never reporting to have any LSI to illustrate the differences between these groups already before LSI-onset. Note that for the LSI group reported means and standard deviations correspond to the waves prior to onset. The analysis sample was considerably older than the never-LSI sample, with 48 years of age compared to 40. Given this age difference we also observe the analysis sample to be already less healthy before the onset of any LSI across measures of health and well-being. We observe slightly lower life satisfaction and considerably lower self-assessed health levels among respondents in the analysis sample. This is also reflected in the multi-dimensional health measures from the SF12. The SF12 component scores, ranging from 0 (worst) to 100 (best) with a mean of 50 and standard deviation of 10 (Ware et al., 1995), are slightly lower in the mental health dimension and 2 points lower (20% of the standard deviation) for physical health. This is also reflected in the almost twice as large proportion of individuals reporting their health to limit daily activities. With respect to other characteristics, differences are in line with the observed age-difference. The analysis sample contains more retired individuals and has a lower average equivalised income (this measure follows Hagenaars et al. (1994) by calculating a weighted income per capita measure for each household with the first adult receiving a weight of 1, subsequent adults and children above 13 a weight of 0.5 and other children a weight of 0.3), while also educational attainment is lower, likely reflecting birth-cohort differences.

Table 3
Baseline results.

	Life Satisfaction		Self-Assessed Health	
LSI Duration				
Onset	−0.213***	(0.031)	−0.937***	(0.031)
Year 1	−0.230***	(0.046)	−1.031***	(0.046)
Year 2	−0.181***	(0.052)	−0.884***	(0.051)
Year 3	−0.103	(0.065)	−0.798***	(0.061)
Year 4	−0.109	(0.075)	−0.660***	(0.074)
Year ≥5	−0.112	(0.083)	−0.508***	(0.081)
Control Variables				
Self-employed (*Ref: Employed*)	0.052	(0.078)	−0.005	(0.068)
Unemployed	−0.242***	(0.067)	0.104	(0.066)
Retired	0.414***	(0.080)	0.052	(0.074)
Working full-time	0.179***	(0.048)	0.223***	(0.047)
log(Equivalised Income)	0.062**	(0.021)	0.028	(0.022)
Living in urban area	−0.099	(0.112)	0.179	(0.104)
Education: Secondary (*Ref: Primary/other*)	−0.242	(0.228)	0.318	(0.222)
Education: Tertiary	−0.445	(0.249)	0.319	(0.248)
Married/Partnership (*Ref: Unmarried*)	0.151	(0.084)	−0.014	(0.095)
Widowed	−0.182	(0.169)	−0.035	(0.178)
Separated/Divorced	−0.183	(0.115)	−0.019	(0.124)
Number of Children in HH	0.035	(0.057)	−0.011	(0.060)
Year Dummies	Yes		Yes	
Region Dummies	Yes		Yes	
Observations	52,553		52,553	
Individuals	9,543		9,543	

Note: * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All analyses use cluster-robust standard errors at the individual level.
Source: Own calculations based on USoc Waves 2009–2020.

3. Methods

In the empirical literature on the determinants of subjective well-being it is common practice to use life satisfaction as a subjective well-being measure assume cardinality despite its categorical nature (Ferrer-i Carbonell and Frijters, 2004). This is attractive as it allows for the application of fixed-effects ordinary least squares models instead of non-linear models for categorical data. This comes with two benefits. Firstly, regression coefficients and effect sizes are easier to interpret due to the linear scale of the dependent variable. Secondly, time-invariant (un)observed factors are absorbed within the individual fixed-effects, already accounting for a large share of confounding variation and allowing for a causal interpretation of estimated coefficients if only this source of variation is of concern. The fixed linear scale also allows for a comparison of effect sizes across models. In non-linear ordered response models, the underlying scale varies across models prohibiting the direct comparisons based on regression coefficients alone.

Past studies of adaptation to ill health and disability have relied on the cardinality assumption, e.g., Oswald and Powdthavee (2008) or Powdthavee (2009). Most of these studies focused on well-being constructs measured using an implied continuous scale such as *"complete dissatisfaction"* to *"complete satisfaction"*. Our empirical strategy is in line with previous work by Cubí-Mollá et al. (2017) and de Hond et al. (2019) who explore the existence of adaptation in self-assessed health and subjective well-being alongside each other by using an ordered logit (fixed-effects) model. Modelling individuals' life satisfaction and self-assessed health using a non-linear ordered response model has multiple benefits. As illustrated by Dickerson et al. (2014), Baetschmann et al. (2015) and Muris (2017) the reliance on linear models for the analysis of categorical data can lead to inconsistent and biased effect estimates. Furthermore, there has been an ongoing debate around how to analyse ordered response quality of life data. The discussion has mostly focused on the question of how such data can be analysed and under what conditions the estimated relationships offer relevant and valid insights (see e.g., Bond and Lang (2019), Kaiser and Vendrik (2019) and Chen et al. (2022) for discussions). In this context ordered response models relying on a dichotomisation to allow for a fixed-effects panel data based approach, such as the estimator proposed by Baetschmann et al. (2015), have been recommended to provide a practical alternative to linear models (Chen et al., 2022). In linear models coefficients indicate point changes but for categorical variables these point changes are often uninformative as the underlying linear scale is only assumed while individuals respond by selecting distinct, discrete levels. Non-linear ordered response models take this into account and allow for estimating the change in response probabilities across the observed life satisfaction and self-assessed health distributions.

To do so we apply the *"blow-up-and-cluster"* (BUC) estimator developed by Baetschmann et al. (2015) and implemented in Baetschmann et al. (2020). Following Baetschmann et al. (2015), assume an individual's subjective well-being and self-assessed health and its determinants can be expressed by the following equation:

$$y^*_{it} = \sum_{j=0}^{5} \gamma_j \, LSI^j_{it} + \sum_{l=1}^{L} \beta_l x^l_{it} + \alpha_i + \varepsilon_{it} \text{with } i = 1, \dots, N \text{ and } t = 1, \dots, T$$

where y^*_{it} is the latent life satisfaction or self-assessed health of a given individual i at time point t. The dummy variables LSI^j_{it} capture the time an individual has spent living with an LSI, ranging from $j = 0$ periods (onset) to $j \geq 5$ years of consecutive LSI reporting. Lastly x^l_{it} represents the L time-varying control variables, α_i, the individual fixed-effect and ε_{it} the remaining error term.

The observed self-assessed health and life satisfaction values y_{it} are related to the laten variable y^*_{it} based on an observation rule;

$$y_{it} = k \text{ if } \tau_{ik} < y^*_{it} \leq \tau_{ik+1} \text{ with } k = 1, \dots, K$$

with individual response thresholds τ_i increasing in K ($\tau_{ik} < y^*_{it} \leq \tau_{ik+1} \forall k$) and $\tau_{i0} = -\infty$ and $\tau_{iK+1} = \infty$. Further, the individual error terms ε_{it} are assumed to be independent and identically distributed with a logistic cumulative distribution function depending on the individual fixed-effect α_i and a vector of control variables X_{it} which contains the L control variables and the J dummies for LSI duration:

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

The probability of observing a specific outcome k for individual i at time t is then given by

$$\Pr(y_{it} = k|X_{it}, \alpha_i) = \Lambda(\tau_{ik+1} - \beta X_{it} - \alpha_i) - \Lambda(\tau_{ik} - \beta X_{it} - \alpha_i)$$

And thereby depends on the vector of estimated coefficients β of the individual control variables X_{it}, the individual fixed-effect α_i, and the individual-specific thresholds τ_{ik} and τ_{ik+1}. However, because for a given observed response only $\tau_{ik} - \alpha_i = \alpha_{ik}$ is identified this results in an identification problem in empirical contexts with large N and small T, the so-called incidental parameter problem (Lancaster, 2000) leads to inconsistently estimated α_{ik}. The estimator proposed by Baetschmann et al. (2015) solves this issue by collapsing the observed outcomes y_{it} into a set of K binary variables d^k_{it} with $d^k_{it} = 1$ if $y_{it} \geq k$ and then using conditional maximum likelihood estimations for binary outcomes and clustering standard errors on the individual level. This procedure lends the estimator its name (Baetschmann et al., 2015).

4. Results

4.1. Descriptive results

Before considering the results of the ordered response fixed-effects models we provide some descriptive evidence on adaptation. Fig. 1 presents information on the health state of the respondents in our analysis sample and their subjective outcome measures around LSI-onset.

Fig. 1 illustrates a couple of key properties of our analysis sample. The onset of an LSI is associated with a decrease in physical health (see Fig. 1 panels (a) and (b)). This decrease is already manifested in the period directly preceding the LSI-onset, on the left-hand side of the solid line, while physical health deteriorates further over time. Overall, the onset of an LSI is associated with the largest year-to-year deterioration. For both life satisfaction (panel (c)) and self-assessed health (panel (d)), LSI-onset is associate with an increase in the share of individuals reporting lower levels of these measures. However, for life-satisfaction, there is little difference between the distribution of responses in the first two years of living with an LSI and those living with an LSI for longer periods. For self-assessed health, the distributions indicate that with longer LSI duration individuals more often report lower health. Nonetheless, the cumulative distributions also indicate that the initial negative association is largest in the first two years and that additional years of living with an LSI reporting are associated with smaller decreases despite a continuous deterioration in physical health.

4.2. Baseline analysis

We further explore the patterns shown in Fig. 1 using the fixed-effects ordered logit approach by Baetschmann et al. (2015). Table 3 presents our baseline results, for these we include the coefficients for our control variables in the results table, but for all subsequent results tables in the Appendix we instead follow the recommendation to focus only on the parameters of interest (Hünermund and Louw, 2020), in our context the time-dummies for LSI-duration. Doing so cautions against the direct interpretation of the conditional coefficients of control variables included in our analysis to avoid the so-called Table 2 Fallacy (Westreich and Greenland, 2013).

Compared to the reference category, living without an LSI, LSI-onset is associated with a decrease in both life-satisfaction and self-assessed health, as can be seen from the negative coefficients. With increasing time spend living with an LSI the strength of the negative association decreases. For life-satisfaction, the size of coefficients is roughly halved and insignificant for those living with an LSI for three years and more. For self-assessed health, the coefficient size decreases more slowly while the coefficients remain significant. Both of these patterns would be consistent with individuals adapting over time to living with an LSI and trending towards pre-onset response levels. Although for self-assessed health this adaptation is only partial as the estimated coefficients remain negative and highly significant.

In ordered response models coefficient size provides limited information. While one can infer the initial differences in life satisfaction and self-assessed health to attenuate after LSI-onset, it is not possible to infer whether these changes are of similar magnitude or response probabilities are changed. To ease interpretation, we follow Baetschmann et al. (2020), by calculating the marginal effect on the average response probability with results depicted in Fig. 2 for life satisfaction panel (a) and self-assessed health panel (b). The vertical y-axis indicates the change in the average response probability in percentage points with 0.05 indicating an increase of 5 percentage points. The horizontal x-axis shows the response categories for each outcome from lowest (left) to highest (right). Within response categories for each year spent living with an LSI the changes in the average response probabilities are plotted from onset (hollow dot, left) to five years and above (filled out triangle, right). Bars indicate 95-% confidence intervals. By construction, the sum of all changes must be zero as relative response probabilities simply shift along the underlying distribution with categories always summing up to one.

Fig. 2 illustrates a general characteristic of our results. Life satisfaction and self-assessed health have a skewed distribution with most respondents reporting the highest two categories before LSI-onset (see Table A1.1). This is reflected in the estimated response probability changes (Fig. 2). Living with an LSI decreases the likelihood to respond in the categories (completely or mostly satisfied with one's life and very good or excellent health) while it increases the probability to respond in the remaining. Over time, these initial changes become smaller with average response probabilities trending towards levels observed before the onset for both measures, although at differential rates. For life satisfaction, the likelihood of responding with either of the highest categories drops by 5.3 percentage points. Given that about 59.2% of respondents reported these levels of life satisfaction before onset (see Table A1.1) a decrease of around 9%. Among those living with an LSI for five or more years, this change in probability decreases to only −2.8 percentage points (4.6%) and becomes insignificant. For self-assessed health the picture is similar, but effect sizes are larger. Individuals are about 23 percentage points less likely to report very good or excellent health at the onset of an LSI, corresponding to a 43% reduction within the response group given the pre-onset share of 54% in these categories (see Table A1.1). Five years after onset, the difference persists but decreases to only 12.6 percentage points (23%). For all subsequently presented results the response shares before onset of an LSI used to calculate relative changes listed in brackets can be found in Appendix Table A1.1.

4.3. Results by subgroups

To explore whether our results differ by subgroups, we divide our sample into male and female respondents. Fig. 3 depicts the estimated changes in the marginal response probabilities for males (black/solid) and females (grey/dashed) for both outcomes (see Table A2.1 for coefficient estimates). With respect to life satisfaction, LSI-onset is associated with a comparable decrease in the probability of responding in the highest two categories for both genders. For men the decrease is 4.8 percentage points (8.1%) and for women it is 5.7 percentage points (9.6%). However, for men already after two years there is no longer a significant difference. For women, differences become insignificant after four years. With respect to self-assessed health the estimated changes in response probabilities are near identical across both groups.

To explore whether the observed pattern of adaptation differs by age at onset, we divide our sample into two groups, those aged below 55 at LSI-onset and those older. This age threshold aligns with previous studies using datasets on older individuals aged 55 and older (Baji and Bíró, 2018; Bussière et al., 2021; de Hond et al., 2019). Fig. 4 depicts the estimated changes in the response probabilities for individuals aged below 55 (black/solid) and those aged 55 and above (grey/dashed) for each outcome measure (see Table A2.2 for coefficient estimates). For life satisfaction, we observe a clear difference between age groups. For younger individuals the onset of an LSI is associated with a stronger decrease in the likelihood of reporting high levels of life satisfaction. The onset is associated with a decrease of 7 percentage points (13.6%) while for older individuals this is only 2.2 percentage points (3.1%) and insignificant. For younger individuals, the initial changes in the average response probability decrease in size with time spent living with an LSI and become insignificant after three years. The point estimates for the average response probability changes for the lower life satisfaction categories are consistently higher for the younger age group than for the older respondents. Unlike for life satisfaction, we observe little difference between age groups for self-assessed health.

4.4. Severity of health changes and subjective well-being

To explore whether adaptation is also observed across the intensity distribution with respect to health changes, we divide individuals into low and high severity groups based on observed differences in the SF12 component scores by computing the within-person difference between mental and physical health scores before and after LSI-onset. For the

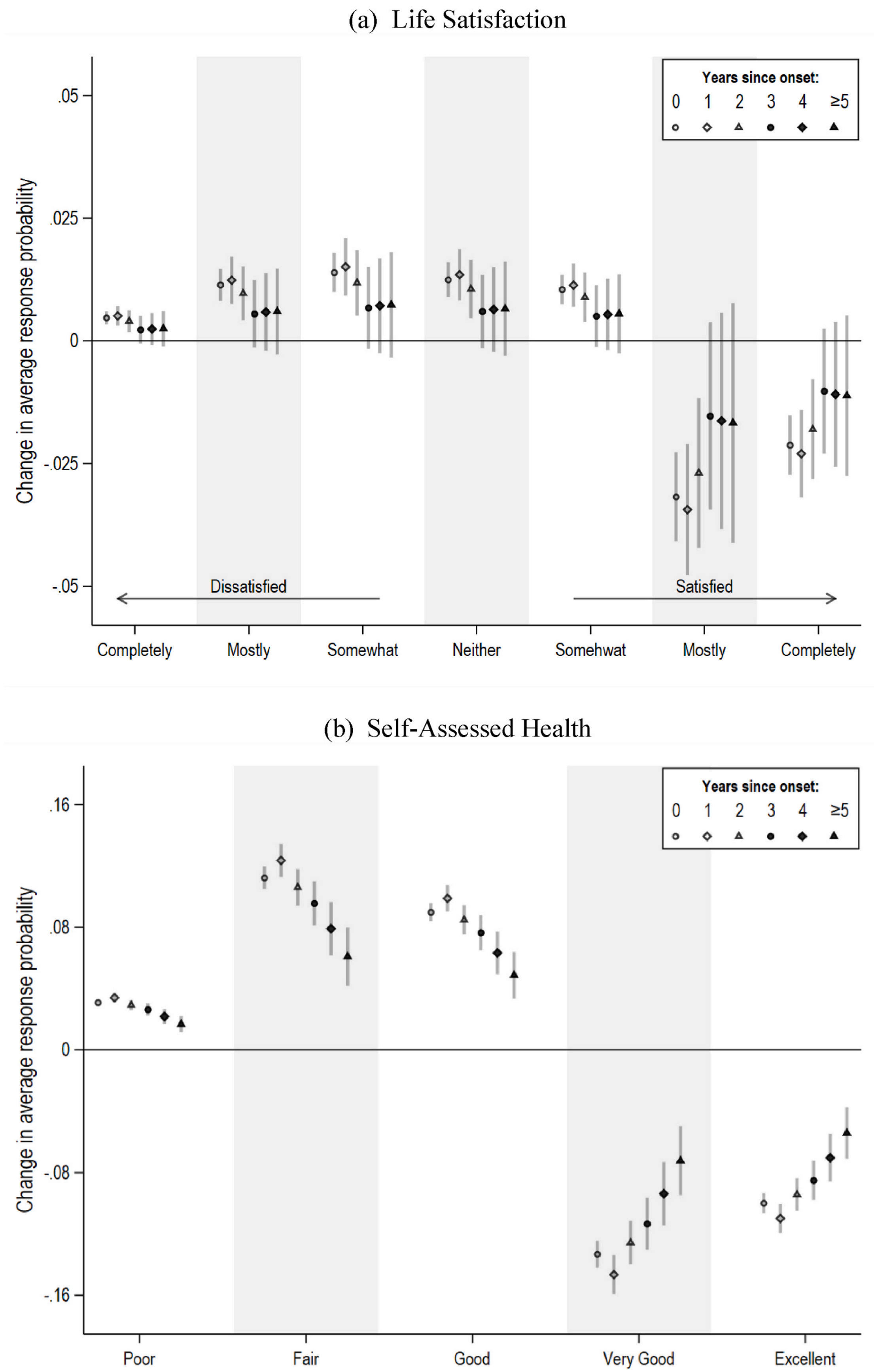
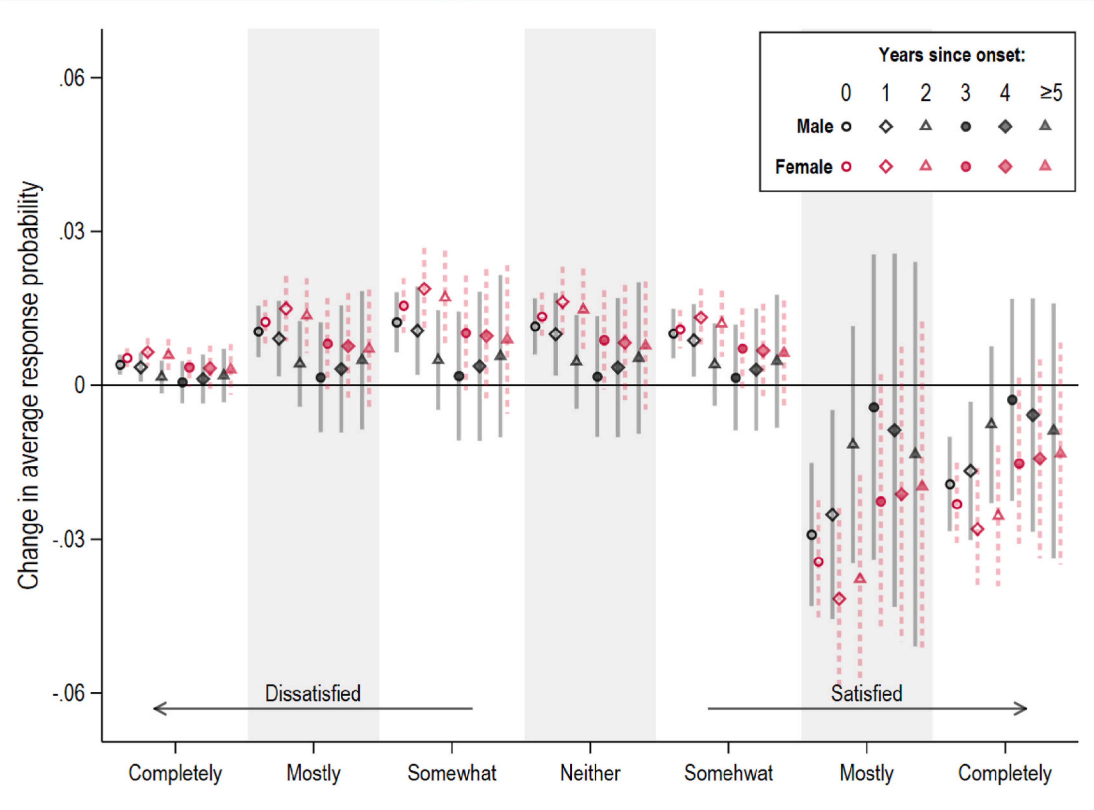


Fig. 2. Marginal Effects by Outcome Variable - Full Sample
Source: Own calculations based on USoc Waves 2009–2020. *Note:* Bars indicate 95-% confidence intervals.

(c) Life Satisfaction



(d) Self-Assessed Health

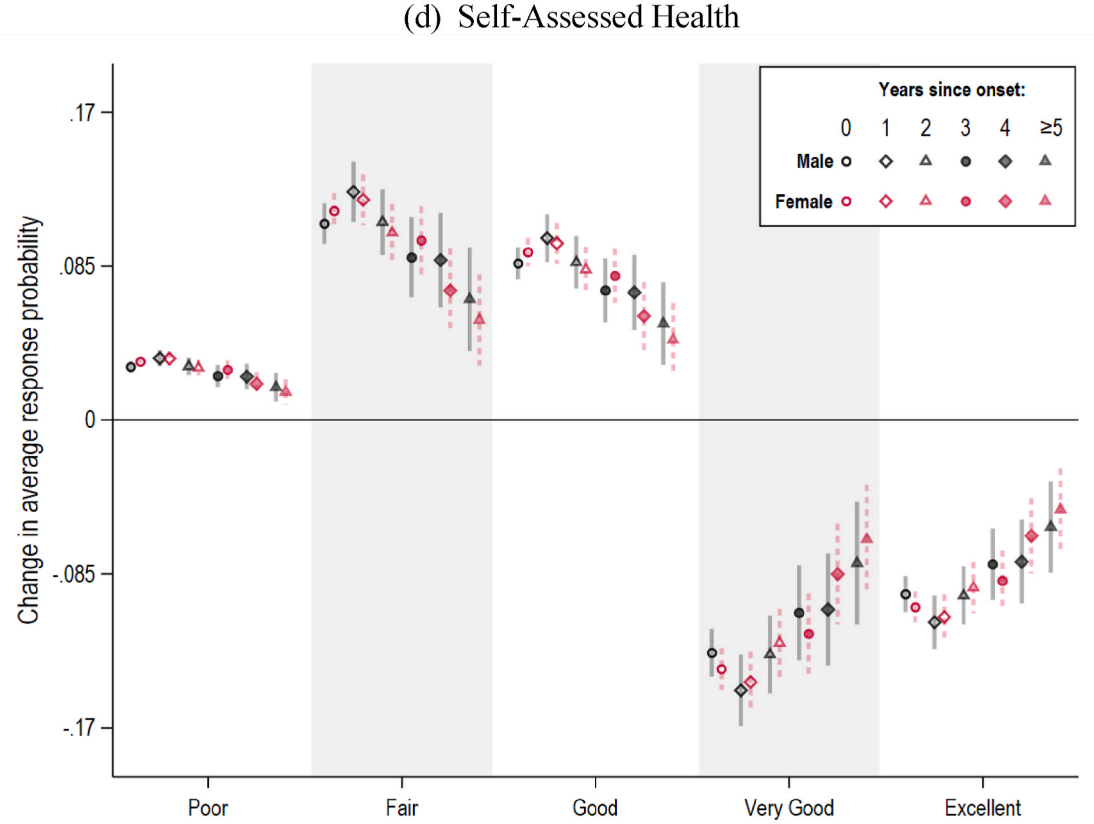


Fig. 3. Marginal Effects by Outcome Variable - Male vs Female Respondents
Source: Own calculations based on USoc Waves 2009–2020. *Note:* Bars indicate 95-% confidence intervals.

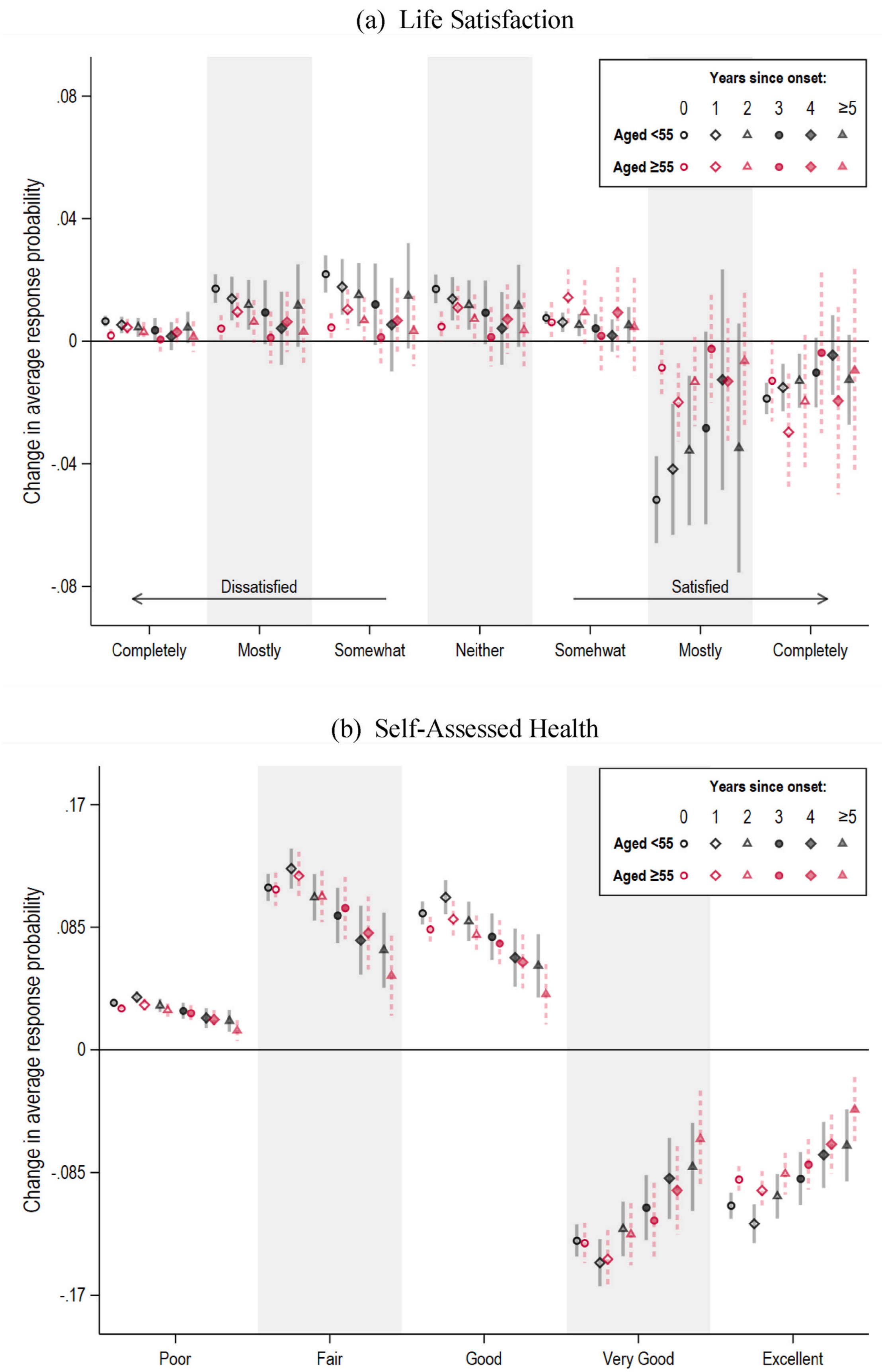


Fig. 4. Marginal Effects by Outcome Variable - Younger vs Older Respondents
Source: Own calculations based on USoc Waves 2009–2020. *Note:* Bars indicate 95-% confidence intervals.

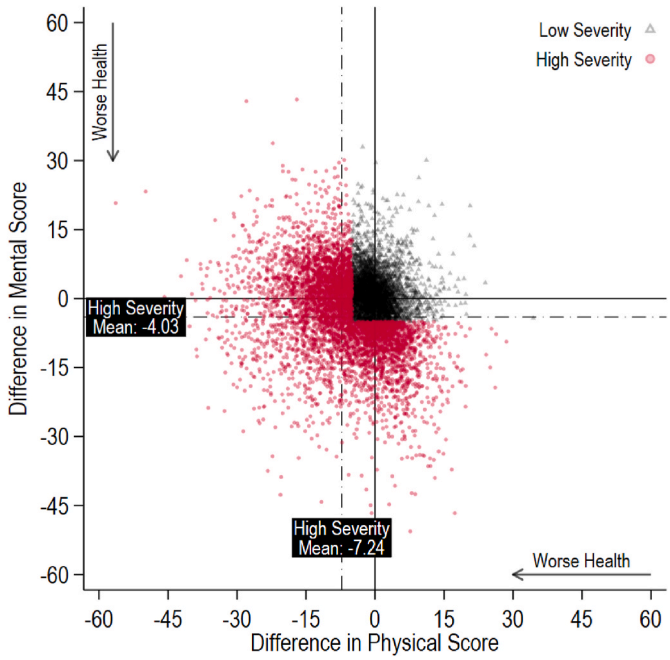


Fig. 5. Individual-Level Difference in Mean Mental/Physical Component Scores
Source: Own calculations based on USoc Waves 2009–2020. *Note:* The difference is calculated by subtracting the individual-level post-onset mean of each score from the pre-onset mean.

average person in the sample, the onset is associated with a deterioration in both dimensions, but for a considerable number of individuals the scores change only marginally. This is in line with the fact that only 54.49% of our analysis sample report a substantial limitation (see Table A1.2) and somewhat expected given the fuzzy definition of a long-standing illness in the survey as a mental or physical impairment, disability, or illness. We chose as our primary measure of severity the SF12 component score-changes as they provide a more granular measure of health changes. However, in the robustness checks we also consider alternative definitions of severity.

We categorize individuals into a high severity of health change group (black dots) if they report a difference of at least 5 points, or half a standard deviation, in either health dimension. For individuals in this high severity group (54% percent of the sample) changes are observed in both health dimensions, with the mean mental score dropping by 4 and the physical score by 7 points. The remaining respondents are included in the low severity group (transparent grey triangles). Fig. 5 plots the individual-level differences for our analysis sample with mental health differences on the y-axis and physical health differences on the x-axis. Lower values indicate that after onset of an LSI the respective dimension score decreased.

This approach is used for exploring adaptation in life satisfaction but cannot be used for exploring adaptation in self-assessed health as mental and physical scores are based on all twelve items of the SF12 which include self-assessed health. Fig. 6 depicts the estimated changes in the average response probability for life satisfaction comparing the low severity (black/solid) with the high severity group (grey/dashed) for both outcome measures (see Table A2.3 for coefficient estimates).

There is a clear relationship between the health change severity and the associated changes in response patterns. A more severe change in physical and/or mental health status is associated with a larger decrease in the predicted likelihood of reporting higher levels of life-satisfaction. In the high severity group, the initial onset is associated with a large decrease in the likelihood of reporting higher levels of life satisfaction. Individuals are 10.4 percentage points (18.6%) less likely to report to be completely or mostly satisfied with their lives. With increasing time spent living with an LSI, this initial difference decreases and becomes

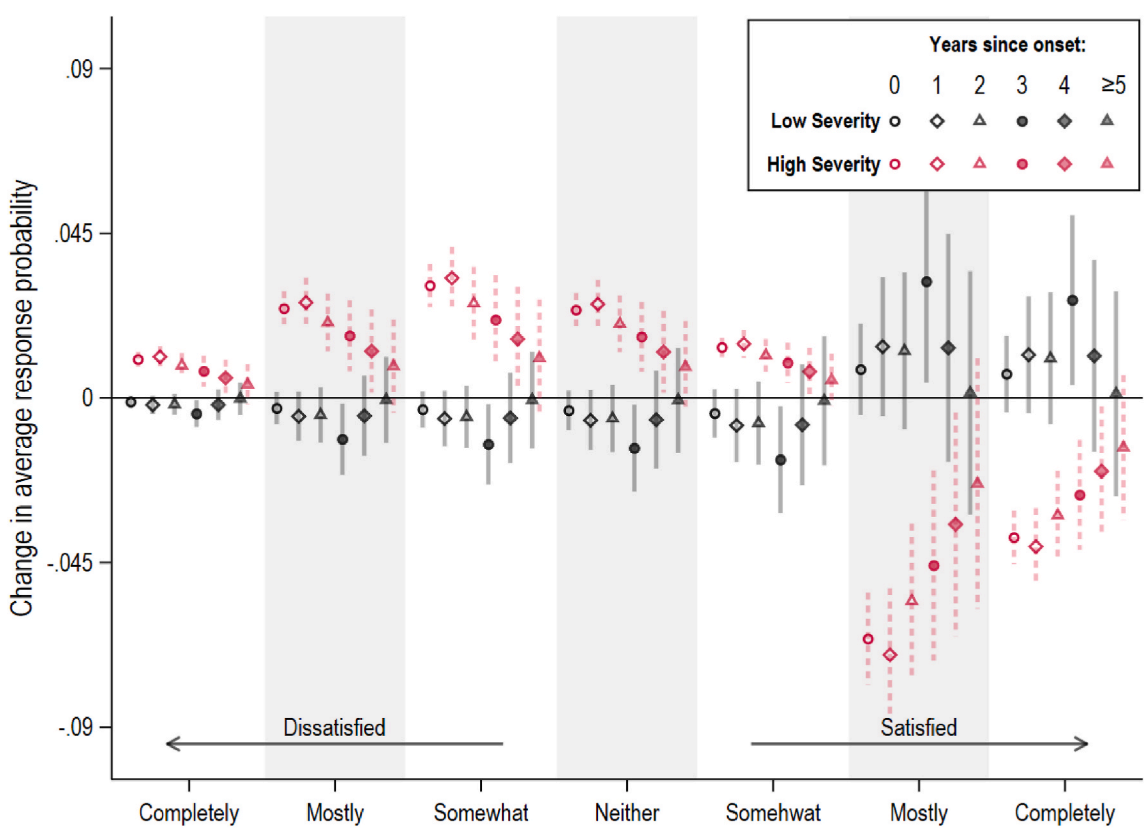


Fig. 6. Marginal Effects on Life Satisfaction by Severity
Source: Own calculations based on USoc Waves 2009–2020. *Note:* Bars indicate 95-% confidence intervals.

insignificant for the five years and above LSI-duration group. No significant changes in the average predicted response probability were observed in relation to the onset of an LSI of low severity.

5. Robustness checks

In the analyses so far, we follow recommendations by Frijters, Haisken-DeNew, and Shields (2004) only including year-dummies in combination with individual fixed-effects to capture ageing. This assumes ageing to have a homogeneous effect on our outcomes of interest across respondents. To explore whether this might be too restrictive we instead include cohort-year interaction terms to allow the effect of ageing to vary flexibly across 10-year birth cohorts. Appendix Figure A3.1 depicts the resulting marginal effects (see Table A3.1 for detailed results) comparing our baseline specification to the flexible specification allowing for age-specific effects. The results are nearly identical, confirming previously reported results by de Hond et al. (2019).

Further, to explore whether we observe patterns consistent with adaptation when changing the definitions of low and high severity groups we use a drop of at least 10 points (one standard deviation) in either the mental or physical health score as the cut-off. The results are depicted in Appendix Figure A3.2 (detailed results are in Table A3.2). The estimated changes in response probabilities are larger with this higher cut-off, but the overall picture is similar, showing that health changes of lower severity are associated with smaller changes in reported well-being. In a second step we consider severity levels defined by the number of areas of life dimensions reported to be substantially limited due to the LSI onset. This specification also allows us to explore differences in adaptation in self-assessed health between individuals reporting more severe health changes. Appendix Figure A3.3 and Table A3.3 compare our results for individuals in our sample reporting no dimension to be affected against those reporting at least one affected dimension. While more severe changes are associated with more pronounced changes in the response categories for both measures the overall pattern suggesting adaptation remains. A related concern follows from our reliance on the LSI question to identify transition into ill health, which is vague with respect to the severity of the underlying illness or disability and the onset-timing. As an alternative approach we use an item of the SF12 health questionnaire encoding whether respondents' health limits their daily activities. Please not that this results in an expanded dataset of different individuals as we now take the SF12-based limitation question and individuals' response patterns as the departure point to construct a dataset as done based on the LSI question. If a limitation is reported individuals indicate its severity as low (*"limited a little"*) or high (*"limited a lot''*). Appendix Figure A3.4 and Table A3.4 depict the results of this alternative definition and suggest that adaptation occurs also when considering health changes associated with an actual functional limitation. As Appendix Figure A3.4 and Table A3.4 show, the pattern for self-assessed health is highly similar to the pattern for life satisfaction. For both the observed patterns indicate that over time response probabilities trend towards their pre-onset levels while the severity of limitations does strongly correlate with the initial decrease.

A last concern relates to the role of disease duration, severity, and survey attrition. Individuals suffering from a severe health shock might be more likely to drop out of the panel over time. If so, we would more observe individuals reporting an LSI at the lower end of the severity distribution, to which they may more easily adapt. To explore whether this is indeed the case, we repeat our baseline analysis on a separate sample of individuals that can be observed for at least four years after reporting an LSI. Appendix Figure A3.5 and Table A3.5 compare the results from the baseline sample to the sample with limited attrition for both outcomes. With respect to life satisfaction, the observed results are highly comparable although it seems that the response probabilities in the group with limited attrition return to levels before onset of the LSI more distinctly. For self-assessed health, the picture is less clear as we observe a higher decrease in the probability of reporting excellent health among the group with limited attrition, while also observing a smaller increase in the likelihood to report good health. On the other hand, we observe a slightly larger decrease in the probability of reporting their health to be very good and a larger increase in the likelihood to report fair or even poor health. However, as we still observe a pattern of attenuating changes across response categories over time, we see little conclusive evidence that the results found by our main analysis are driven by selective attrition alone.

6. Discussion

The propensity to adapt to deteriorating health is a desirable manifestation of psychological resilience at the individual level but may have undesirable implications in the context of health economic evaluations. If adaptation occurs, should it be considered when healthcare resources are allocated? What are the consequences of doing so when adaptation varies across types of conditions and subgroups? As increasingly outcome measures on subjective well-being and health are used to quantify the impact of ill health on individuals' quality of life the possibility of adaptation remains a concern, but empirical evidence is inconclusive. This study uses a general population survey from the UK and fixed effects ordered response models to explore whether and how people adapt to ill health. To do so we use the onset of a long-standing illness or disability in combination with data from SF12 health questionnaires to explore the extent of adaptation across in the domains of life satisfaction and self-assessed health.

Our analyses using life satisfaction as outcome of interest provide evidence that adaptation in well-being measures is substantial and occurs already after a short period. The onset of a long-standing illness or disability decreases the likelihood to report higher levels of life satisfaction considerably, but as time progresses individuals revert towards their levels of life satisfaction before onset after three years, that is, they adapt to persisting ill health. Further, we find evidence that the observed patterns differ across subgroups. Men adapt slightly quicker than women and for individuals younger than 55 at onset the impact of ill health is larger, and adaptation takes longer than for older individuals. Lastly, even in the case of more severe health changes and functional limitations we find adaptation to occur but taking a longer period.

When considering the impact of long-standing illness or disability on self-assessed health our results indicate a reverting trend towards pre-onset levels of self-assessed health before the onset of a long-standing illness but no full adaptation. The onset of ill health results in a large decrease in the likelihood of reporting high levels of subjective health. This effect persists even after five years but the magnitude of these differences decreases. The indicates that while individuals adapt to ill health, it is not sufficient to offset the full impact over time. Interestingly, we do not observe significant differences in adaptation across subgroups.

Overall, our results confirm findings from de Hond et al. (2019) in a sample of individuals aged 55 and older. In addition, our results across specifications are supportive of Powdthavee (2009) and suggest that adaptation in life satisfaction coincides with adaptation in self-assessed health. However, we are also able to provide some complementary perspectives. Adaptation in life satisfaction differs considerably by age while this is not the case for self-assessed health. This could indicate that as individuals age the importance of health for well-being diminishes (Bussière et al., 2021; Frijters, 2000) or that older individuals are more resilient to such shocks (Etilé et al., 2021), potentially because deteriorating health is more expected and accepted, and more common among these age-groups. Our results by gender provide a similar picture with respect to differences being mainly observed when considering life satisfaction but not self-assessed health as the outcome of interest, although the differences between groups are less pronounced than in case of the age-groups.

The results of this study therefore provide useful insights to policy-makers and researchers interested in measuring health-related quality of life changes using subjective outcome measures. Exploring these effects, including the role of adaptation, requires routinely collecting data on disease onset and duration as well as measures of outcomes relevant to individuals and appropriate for policy evaluation. This is especially relevant for studies relying on empirical approaches that exploit the availability of longitudinal data. For example, an increasing literature has applied well-being valuation approaches to explore the monetary equivalent of specific health conditions (see for example recently by Howley (2017) or Ólafsdóttir et al. (2020)) or summary measures such as quality-adjusted life years (Himmler et al., 2021; Huang et al., 2018). Adaptation decreases the monetary value of health obtained from such studies. Considering the possibility of adaptation should therefore be taken into consideration when interpreting their results, for example in health economic evaluations.

6.1. Limitations and future research

Our study has several limitations. We use an ordered response model for life satisfaction and self-assessed health, which differs from most previous studies on the topic of adaptation that use an ordinary least squares fixed-effects design. While our approach provides additional insights it does not alter the underlying assumptions. For a causal interpretation of our results the time-invariant unobservable differences captured by the fixed-effects approach need to be the only source of unobserved confounding. Assuming that the onset of an LSI is exogenous conditional on such characteristics is more credible than without addressing time-invariant unobservable differences, but it remains a strong assumption. Further, in our analyses we rely on a broad classification of ill health using LSI-onset and reported functional limitations while we consider different definitions of periods of ill health based on other measures. This approach has the benefit of relying on individuals that report an ongoing change to their health as opposed to a diagnosis of a specific disease of which the impact on patients' lives is not always consistent over time (de Hond et al., 2019). This is also consistent with the emphasis in the health economic evaluation literature, which predominantly considers measures such as the EQ-5D, to quantify the burden from diseases, given their impact on different dimensions of health-related quality of life irrespective of the specific diagnosis. At the same time, the underlying health issues or diseases causing reported health changes to remain unobserved but could be interesting with respect to the heterogeneous impact of different diseases (Binder and Coad, 2013; Graham et al., 2011). It further raises the questions on the role of health events as sources of information shaping perceived health (Nielsen, 2016) and health behaviors (see recently Gaggero et al. (2022) or Verdun (2022)). Previous studies such as Cubí-Mollá et al. (2017) and Baji and Bíró (2018) have tried to explore jointly whether specific diagnoses underlying the reported LSI result in different patterns of adaptation. However, while general population surveys as used in this study allow for groups of individuals to be observed the number of individuals transitioning into specific conditions is limited. Lastly, we have to rely overall on self-reported information and cannot use objective health measures. Further, while the USoc surveys cover an extensive set of topics they provide only limited information on what type of medical care individuals use. Therefore, we cannot distinguish whether the observed adaptation pattern could partially be explained by recovery, treatment success or the use of (medical) devices that help individuals to function and participate in activities of daily life despite functional limitations. This is an important caveat deserving emphasis because it indicates that the degree to which the adaptation commonly found in empirical studies for certain health changes may in part be a natural occurrence as patients receive treatment or manage their symptoms. This raises important questions on how adaptation should be considered in the context of health economic evaluations, given the ethical dilemmas this implies (Brazier et al., 2018).

The limitations of this study do provide guidance on future research directions. One way to address many of the discussed concerns would be to combine survey data with administrative data that would allow researchers to rule out or at least quantify any bias resulting from unobserved information. Such data could for example be used to determine whether individuals generally participating in such surveys and suffering from a specific disease are overall representative of the general patient population they belong to. Detailed information on hospital admissions and past or future healthcare use would also allow researchers to cross-validate the self-reported information. Such information would also allow a relaxation of the main identifying assumption. While a causal interpretation requires us to assume the health shock (LSI-onset) to be exogenous administrative records would allow one to employ a different identification strategy. Instead of relying on the shock itself to be exogenous one could exploit the exogenous timing of certain health shocks, such as heart attacks or strokes (Fadlon and Nielsen, 2019), to compare individuals that have suffered from such a shock to those that will suffer from it soon. Such an approach might also allow for a more direct disentangling of the different effects a diagnosis might have on subjective well-being and health outcomes. Focusing on the onset of conditions that have strong implications for individuals past and future health would allow to identify whether observed changes are driven by realised health changes i.e., the loss of certain functionalities, as opposed to the information gain resulting from a diagnosis.

7. Conclusion

In summary, our study provides new evidence on individuals' propensity to adapt to health across measures of subjective health and well-being. We observe adaptation to occur in both domains while broader subjective well-being measures such as life satisfaction seem to be more strongly affected by this phenomenon. Our results also indicate that adaptation is not limited to only the mildest health shocks and that it varies across certain subgroups such as gender and age. While from the individual's perspective adaptation is desirable, it poses problems for the application of subjective outcome measures in health economic evaluations. Adaptation should therefore remain a concern for researchers aiming to complement domain specific, objective quality of life measures with broader subjective outcome measures. While the contemporary impact of ill health is captured by such measures, adaptation can be significant even in the case of severe health shocks that lead to functional limitations. As such adaptation remains an obstacle in research practice, and the benefits of using subjective outcome measures should be weighed against the drawbacks resulting from adaptation when applied in practice.

Data availability

This article uses data of the UK Longitudinal Household Study, also referred to as *Understanding Society*.This data is made available via the UK Data Service and can be accessed free of charge for scientific and non-commercial uses after registering with the UK Data Service. For further details on the access procedure please consult the latest access information on the website of *Understanding Society*(https://www.understandingsociety.ac.uk/). This article used the individual-wave files for waves 1-10 of the 17th release edition of *Understanding Society*. A replication package for this article can be found on the Open Science Framework (https://osf.io/q7fx9/). This replication package includes all Stata dofiles used to obtain the presented results alongside those needed to construct the dataset underlying all analyses from the raw *Understanding Society* release files for waves 1-10.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2023.115996.

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