Socioeconomic Status and Health:

The different Roles of Subjective and Objective Measures

Hannah Franziska Sowa

Dissertation written under the supervision of Professor Miguel Gouveia

Dissertation submitted in partial fulfilment of requirements for the

MSc in Economics, at CATÓLICA-LISBON School of Business & Economics

January 2024

Socioeconomic Status and Health:
The different Roles of Subjective and Objective Measures

Hannah Franziska Sowa

January 2024

Supervisor: Professor Miguel Gouveia

Abstract

Background: Understanding the complex interplay of self-rated health (SRH) and socioeconomic status (SES) is crucial for uncovering health disparities and for formulating effective policies to address them. It is essential to explore not only objective but also subjective determinants of SRH to allow for a more comprehensive understanding. This paper contributes to the literature by adding valuable empirical evidence on the role of SES and perceived satisfaction ratings for SRH. Thereby, this thesis fills a gap by including a unique set of satisfaction variables, namely perceived income, work, housing as well as overall life satisfaction.

Methodology: This empirical study employs longitudinal data sourced from the German Socio-Economic Panel Wave 37, encompassing a sample of 11,672 individuals spanning the years 2014, 2016, and 2018. To ascertain the influence of a comprehensive range of objective and subjective variables on SRH, ordered response models are estimated. Furthermore, model robustness is tested by estimating an alternative model specification.

*Result*s: In the German context, objective measures of SES alone do not fully capture the main drivers explaining socioeconomic health disparities. The results indicate that work and life satisfaction add significant explanatory power to SRH. Occupational prestige and level of education play a significant role in the likelihood of reporting most SRH categories. The presence of chronic diseases and the reporting of daily difficulties due to health most strongly predict SRH.

Keywords: Self-rated health, Socioeconomic Status, Generalized Ordered Probit Model

Socioeconomic Status and Health:
The different Roles of Subjective and Objective Measures

Hannah Franziska Sowa

January 2024

Supervisor: Professor Miguel Gouveia

Resumo

Contexto: Compreender a complexa interação entre a saúde auto-avaliada (SRH) e o status socioeconômico (SES) é crucial para revelar disparidades de saúde e formular políticas eficazes para abordá-las. É essencial explorar não apenas determinantes objetivos, mas também subjetivos, para permitir uma compreensão mais abrangente dos fatores determinantes da SRH. Este artigo contribui para a literatura ao adicionar evidências empíricas valiosas sobre o papel do SES e das avaliações de satisfação percebida para a SRH. Assim, esta tese preenche uma lacuna ao incluir uma combinação única de variáveis de satisfação, nomeadamente renda percebida, trabalho, habitação, bem como satisfação geral com a vida.

Metodologia: Este estudo empírico utiliza dados longitudinais provenientes do German Socio-Economic Panel Wave 37, abrangendo uma amostra de 11.672 indivíduos nos anos de 2014, 2016 e 2018. Para avaliar a influência de uma ampla gama de variáveis objetivas e subjetivas na SRH, são estimados modelos de resposta ordenada. Além disso, a robustez do modelo é testada por meio da estimação de uma especificação alternativa.

Resultados: No contexto alemão, medidas objetivas de SES por si só não capturam completamente os principais fatores que explicam as disparidades socioeconômicas em saúde. Os resultados indicam que a satisfação no trabalho e na vida adiciona poder explicativo significativo para a SRH. Prestígio ocupacional e nível de educação desempenham um papel significativo na probabilidade de relatar a maioria das categorias de SRH. A presença de doenças crônicas e o relato de dificuldades diárias devido à saúde são os principais preditores da SRH.

Keywords: Saúde auto-avaliada, Estatuto socioeconómico, Modelo Probit ordenado generalizado

Table of Contents

Abbreviations

AIC	Akaike´s Information Criterion
AME	Average Marginal Effect
BIC	Bayesian Information Criterion
BMI	Body Mass Index
CR	Collinearity
CPI	Consumer Price Index
FMM	Finite Mixture Model
FMOPM	Finite-Mixture Ordered Probit Model
GOPM	Generalized Ordered Probit Model
GSOEP	German Socio-Economic Panel
ISCED	International Standard Classification of Education
ISEI	International Socio-Economic Index
LL	Log-Likelihood
LR	Likelihood Ratio
OECD	Organization for Economic Cooperation and Development
OLM	Ordered Logit Model
OPM	Ordered Probit Model
SES	Socio-Economic Status
SRH	Self-rated Health
SWLS	Satisfaction with Life Scale
WHO	World Health Organization

List of Figures

List of Tables

1 Introduction

Is Self-Rated Health (SRH) only truly a matter of objective health? In fact, socioeconomic determinants were commonly found to have a significant impact on health, with individuals from higher socioeconomic backgrounds generally experiencing a better health outcome (Lago et al. (2017); Adler & Rehkopf (2008); Wilkinson (1997)). The main disparities in health are caused by differences in health care, environmental exposure, health behaviour as well as chronic stress associated with low SocioEconomic Status (SES) (Adler & Newman (2002)). It is essential to explore not only objective but also subjective determinants of SRH to allow for a more comprehensive understanding. This paper contributes to the literature by adding valuable empirical evidence on the role of SES and perceived satisfaction ratings for SRH.

SES is a multidimensional construct influenced by a variety of factors. Identifying suitable measures of SES is challenging, and not only from a social policy perspective. It is determined by "occupational position, education, household income, satisfaction with standard of living, and feeling of financial security regarding the future" (Singh-Manoux et al. (2003)). Understanding the complex interplay of these components is crucial for understanding health disparities and formulating effective policies to address them.

SRH is frequently addressed in general population surveys and has been established as a valid and reliable measure of health status (Bombak (2013); Quesnel–Vallée (2007)). The indicator provides a broad evaluation of overall health condition, independent of any illness, with a primary focus on physical and functional aspects of well-being (Idler et al. (1999)). When analyzing the relationship between SRH and SES, it is important to not only consider common objective measures but also subjective proxies. The association between poor health and lower social position is valid for both subjective and objective measures (Macleod et al. (2005); Präg et al. (2016); Hoebel and Lampert (2020)).

Diverse measures, specifications and empirical models have been employed to assess subjective SES. One of the most common ones is the MacArthur Scale of Subjective Social Status which asks individuals to rank themselves on a 10-rung ladder with the highest rung representing the most well-off people and the lowest representing the least (Präg (2020); Kezer and Cemalcilar (2020); Zell et al. (2018); Kim and Park (2015)). Satisfaction data and its relationship with SRH, however, have been less frequently analysed. It can be assumed that objective measures of SES may not necessarily align with an individual's satisfaction with its economic and social situation.

This thesis explores the role of perceived income, work, housing, and overall life satisfaction on SRH to understand to what extent those factors drive socioeconomic health disparities. This is done in conjunction with traditional measures of SES, namely education, income, occupational status, and employment. Furthermore, it is controlled for objective health status. Thereby, this thesis addresses the following research question: How do measures of satisfaction with life circumstances impact SRH and do they add significant explanatory power to the objective indicators of SES?

The empirical analysis is divided into two main parts. First, an Ordered Probit Model (OPM) is estimated as a baseline to understand the relationship between the independent variables and SRH. After testing the OPM´s proportional odds assumption, a more flexible Generalized Ordered Probit Model (GOPM) is estimated. Second, to have a more concrete understanding of the effect of the independent variables on the probability of reporting different health outcomes, the respective Average Marginal Effects (AMEs) of both models are calculated. Furthermore, robustness of the results is tested across genders and across a different model specification.

This thesis contributes to literature in two ways. First, while most previous research primarily relies on cross-sectional studies, this study analyzes large-scale longitudinal data from the German Socio-Economic Panel (GSOEP). To the best of my knowledge, this thesis presents a novel analysis of the GSOEP dataset. It explores a unique combination of SES indicators and their association with SRH. Beyond that, this thesis fills a gap by including a unique set of satisfaction variables, namely perceived income, work, housing as well as overall life satisfaction. This paper contributes to literature by adding valuable empirical evidence on the role of SES and perceived satisfaction ratings for SRH.

The paper is structured in the following manner: Section 2 reviews literature that has investigated the relationship between SRH and objective and subjective SES measures as well as measures of satisfaction, both with cross-sectional and longitudinal survey data. In Section 3 an overview of the dataset, sample selection and descriptive statistics are provided. Section 4 offers an overview of the variables employed in the empirical analysis and their construction. The econometric model and techniques as well as model tests are outlined in Section 5. The empirical results are presented in Section 6 and checked for robustness in Section 7. Limitations and practical relevance of the findings are discussed in Section 8. A Conclusion is drawn in Section 9.

2 Literature Review

2.1 Socioeconomic Status and Self-rated Health

The relationship between SRH and socioeconomic factors is a widely studied topic, not only for economists. Many of them have found a positive association between subjective socioeconomic measures and health outcomes (Cundiff and Matthews (2017); Hoebel and Lampert (2020); Präg et al. (2016); Coustaury et al. (2022); and Zell et al. (2018)). Traditionally, SES has been measured using indicators such as income, education, and occupation.

However, some studies offer distinct perspectives on the importance of subjective and objective socioeconomic dimensions. Macleod et al. (2005) find that both subjective, status-based measures of lower social position and those based on objective material assets are associated with a lower SRH. However, their empirical findings do not strongly support subjective social status as a more significant determinant of health than objective social status; instead, material inequality was identified as the determining factor. Having a father with a manual occupation, low height and lack of car were found to be strong predictors of poor health outcomes. In an age-adjusted analysis, occupation, educational status, residence area and workplace status were strongly associated with SRH. The primary measure used to assess subjective social status was derived from perception of workplace status. The authors conduct a workplace-based study of 5,232 Scottish men who were followed by the researchers for up to 25 years. They aim to assess the association between subjective and objective measures of social position and health outcome. The health outcome is measured by perceived psychological stress, cardiovascular disease risk factors and subsequent objective health. A proportional hazards model was used to compare survival and hospital-free survival between the different social groups.

Research has highlighted the importance of subjective socioeconomic measures, which refer to an individual's perceptions of its economic and social standing, as well as psychological factors for SRH (Meireles et al. (2015); Molarius (2007)). Indeed, some evidence even suggests that subjective SES affects health above objective indicators (Hoebel and Lampert (2020); Senik (2009); Hayo & Seifert (2003)). Präg (2020) supports this finding by analysing longitudinal data from the German General Social Survey between 2004 and 2018. He finds a link between subjective SES and SRH. His paper suggests that subjective SES predicts SRH irrespective of objective family socioeconomic background.

According to Singh-Manoux et al. (2003) subjective social status is a stronger predictor of objective ill-health. Their study was conducted with a cohort of 6,981 male and female office staff aged 35 to 55, employed across 20 Civil Service departments based in London. The authors use the presence of angina, diabetes, respiratory illness, depression, and self-assessed general health as measures of health outcomes. Objective SES is measured by occupation, education, personal income and a household´s income and wealth. Feelings of financial security, satisfaction with standard of living, material deprivation, and general life satisfaction are used as measures of life satisfaction. For the empirical analysis, logistic regression models are employed to test the relationship between subjective SES and health with a total of 16 predictor variables.

Barrett (2003) uses US longitudinal data from 1995 and 1996 to discover that socioeconomic differences in age shape health inequalities and the subjective experience of aging. The author estimates an ordinary least squares regression to analyse a sample of 2,864 people aged between 25 and 74. Poorer peers are found to have a worse prediction of future health than wealthier ones.

Leveraging individual-level data from 29 European countries, Präg et al. (2016) explore cross-national variation of the relationship between subjective SES and SRH by employing a random coefficient and two-step regression models. Subjective SES is measured by the McArthur scale. Their findings indicate that subjective SES is associated with health outcomes, specifically, SRH psychological well-being, across all the countries studied, even after controlling for income, education, and occupational prestige.

Furthermore, objective and subjective measures of SES were found to influence quality of life. Generally, health and socioeconomic measures are both important components of life quality (Fallowfield (2009)). In a longitudinal analysis, Choi et al. (2015) effectively demonstrate this association. The authors show that individuals with low household incomes and low subjective social class had the highest probability of reporting low health-related quality of life. Irrespective of subjective social class, individuals are found to experience a decline in their quality of life as their objective social class decreases. This result is based on data from 12,530 participants aged 18 and older in the Korean Health Panel Survey. A linear mixed model is estimated to analyse the relationship between objective (income and education) and subjective (McArthur scale) social class and health-related quality of life (EuroQol-Visual analogue scale).

2.2 Satisfaction and Self-rated Health

Various satisfaction indicators such as subjective well-being (Boes and Winkelmann, (2006a)), financial satisfaction (Cialani and Mortazavi (2020)) and life satisfaction (Reyes Fernández et al. (2016)) are connected to SES. Previous empirical analyses have utilized satisfaction data to investigate the relationship between socioeconomic standing and SRH outcomes (Frey and Stutzer (2000); Cialani and Mortazavi (2020)).

Cialani and Mortazavi (2020) compare the effects of income satisfaction and objective SES variables on SRH. They find that income satisfaction has a stronger impact on the probability of reporting a higher SRH status compared to objective income measures. The authors use a GOPM to analyse data from the European Health Interview Survey of approximately 16,000 Italian households. Overall, there results suggest that subjective income satisfaction has a more significant effect on SRH than objective income.

Kezer and Cemalcilar (2020) examine the relationship between objective and subjective SES and SRH as well as well-being in a representative sample of Turkish youth. Their findings indicate that both objective and subjective SES are positively associated with overall health, life satisfaction, happiness, and financial satisfaction. A polynomial model is employed to highlight a moderate correlation between objective and subjective SES. The authors suggest that subjective perceptions of economic status are not solely determined by objective markers of SES.

Knoechelmann et al. (2020) find a similar association between income satisfaction, objective income and SRH. The authors use the GSOEP to investigate the effect of income and housing satisfaction on SRH in different life stages. By estimating a fixed effects model separately for men and women, the authors find that a higher satisfaction with housing and income is associated with a better SRH. Cluster-robust standard errors were computed to make statistical results robust to heteroscedasticity.

Psychological implications of subjective dissatisfaction with socioeconomic measures have been found to influence the SRH of survey participants. Low subjective SES can be accompanied by stress and as such influence health outcomes negatively (Präg (2014)). It was found to affect “patterns of violence, disrespect, shame and poor social relations, and depression” (Wilkinson (1999)).

Furthermore, responses to similar objective financial situations were found to differ among individuals (Hayo et al. (2003); Senik (2009)). One of the reasons for that is that perceived

economic and general satisfaction is often influenced by their social environment and past living conditions. In general, measures of subjective satisfaction are expected to encompass not just present conditions but incorporate evaluations of previous socioeconomic, educational, and economic background, as well as their prospects (Singh-Manoux et al. (2003)).

Li and Muennig (2018) did not find a significant effect of low job satisfaction and satisfaction with their overall financial situation on the likelihood to report certain SRH. The authors used multinomial logistic regression models to assess the relationship between satisfaction variables, subjective social class identification and SRH. Subjective assessment of family income relative to average income, satisfaction with one's financial situation as well as job satisfaction were the main measures interest. Furthermore, objective income and education levels are included as measures of objective SES. Their findings are based on US cross-sectional data from the 2014 General Social Survey-National Death Index. Overall, SRH was found to have a strong and significant association with survival time.

Reyes Fernández et al. (2016) found that SRH is negatively associated with depressed mood by studying the relationship between SRH and self-rated economic situation with depressed mood. An interaction analysis revealed that an improved economic satisfaction mitigates the impact of a low self-rated health status on life satisfaction. The longitudinal study is based on a subsample of 1,618 individuals from the Costa Rican Longevity and Healthy Aging Study.

Muhammad and Maurya (2023) investigate if gender-based variations in SRH can be linked to factors such as SES and individual perception of income adequacy. Through descriptive and bivariate analysis, along with a chi-square test, the authors examined the potential significance of associations between explanatory and outcome variables in the study. Utilizing data from the Building a Knowledge Base on Population Ageing in India (BKPAI-2011) dataset, the authors highlight the connection of gender differences in SRH to subjective income status, SES and health-related variables.

Generally, the influence of self-rated perception of life circumstances on SRH is supported by literature. Previous empirical results, however, differ between countries and samples analyzed. The relationship between SRH and socioeconomic satisfaction calls for more empirical evidence.

3 Data

3.1 The German Socio-Economic Panel

For the empirical analyses data from the GSOEP version 37 is used. The GSOEP is an annual household survey that interviews nearly 15,000 households and around 30,000 randomly selected persons every year. The information is collected at the household- and individual level by the German Institute for Economic Research (DIW Berlin). The survey provides personal information for every household member aged 16 and older. The longitudinal survey offers data from the Federal Republic of Germany from 1984 to 2020 and the eastern German states from 1990 to 2020 (DIW Berlin (2023)). The GSOEP dataset encompasses a wide range of variables that can be classified into two categories: "objective" variables, including income, age, gender, education, and employment status, and "subjective" variables, such as life satisfaction, perceptions of fairness, and SRH. The richness of individual characteristics in the dataset allows me to examine both subjective and objective aspects of health and social standing.

The GSOEP dataset has been used in empirical research to investigate socioeconomic factors and their effects on different outcomes. A study by Buechel and Mertens (2004) examined the theory of career mobility using the GSOEP data. While this study focuses on overeducation and wage growth, it provides valuable information on the relationship between education, occupation as well as socioeconomic factors. Like Knoechelmann et al. (2020), Frijters et al. (2005) found evidence of a small significant positive effect of income changes on SRH. The authors used data from the GSOEP between 1984 and 2002 to analyze the causal effects of income changes on the health satisfaction of East and West Germans in the years following reunification. For this, they estimate a fixed-effects ordinal logit model controlling for fixed individual traits such as parental background and a personal discount rate.

Miething (2013) utilizes the GSOEP to study the link between income and social inequality in health and mortality. A discrete-time survival analysis with Cox regression was performed using data from 22,588 individuals aged 25 to 64 between 1995 and 2010. With mortality as a dependent variable, the author subsequently controls for education and employment status as well as for self-rated health. Overall, income satisfaction seems to play a potential role in the causal relationship between income and mortality. Furthermore, Schwarze (2003) estimates equivalence scale elasticity by using income satisfaction data from the GSOEP. He accomplishes this by directly estimating individual panel data on income satisfaction while controlling

for age, age^2, sex, employment status, education, nationality, ethnic characteristics, and time effects. He finds that there is an optimal elasticity at which people feel satisfied with their income. Boes and Winkelmann (2006a) use data from the GSOEP to show that income has only a minor effect on positive subjective well-being while it has a large effect on negative well-being. A total of 9,734 person-year observations of single-person households aged between 25 and 65 from 1984 to 2004 was included. The dependent variable is life satisfaction, and it is controlled for age, age^2, unemployment, and objective health status.

3.2 Sample Construction

This thesis uses longitudinal individual-level survey data from the GSOEP. An unbalanced panel design is utilized, as not all participants are observed an equal number of times. The estimation only includes respondents who were surveyed at least twice.

Generally, there is a bidirectional causality between SES and health measures. Poor health can result in diminished productivity and limited employment opportunities, potentially exerting negative impacts on income and occupational standing. Both SRH and work limitations were identified to correlate with workability (Dwyer and Mitchell (1998); Ford et al. (2011)). Higher income, education, and occupational status have been associated with greater access to health-improving resources, such as quality healthcare, nutritious food, and safer living conditions (Marmot et al. (2012); Ross & Mirowsky (2010); Mirowsky (2017)). This could lead to biased and inconsistent estimates of the relationship between socioeconomic indicators and health. To account for this bidirectional causality, a longitudinal study design is employed to explore the relationship between the predictor variables and SRH over time.

The empirical analysis focuses exclusively on individuals aged 25 to 65, as this range typically represents the working-age population. The restricted age range targets individuals who have completed education and whose household income and employment status are likely a valid measure of their SES. The analysis thereby achieves a more homogenous sample, reducing potential variability introduced by extreme age differences.

3.3 Descriptive Statistics

Table 1 provides an overview of the sample characteristics for the independent variables used in the empirical analysis. The sample consists of 29,817 observations, it includes slightly more females with 51.8% and only 48.2% of participants who identify as male. The mean age of the

sample is 46 years. The observations include 11,672 individuals from 8,629 households for the years 2014, 2016, and 2018. The scope of my long-term trend analysis is constrained by data availability, primarily due to non-response data and the exclusion of certain survey questions in specific years. Observations with non-response items and missing data were excluded from the empirical analysis.

The ISEI score which is based on income, education, and occupation and has a mean of 48.70. 6.88% of the sample is educated at the lower secondary level or less, while the majority of 45.86% has an upper secondary level of education, and 36.47% of individuals have completed the first and second stages of tertiary education. Most of the survey participants are employed with an employment level of 98.62%. The mean equivalent household income after taxes that is earned or received amounts to 26,731 Euros annually.

The mean satisfaction with its household's income is 7 out of 10 which indicates that most survey participants are content with their earnings. The mean work satisfaction is 7 and the mean housing satisfaction is 8. The mean score for overall life satisfaction within the sample is approximately 7.5, indicating a notably high level.

Moreover, the majority exhibit indications of a good objective health status. Only 6% of the sample report some kind of disability and one-third of individuals' health is affected by a chronic disease. In the age group of 25-35 only a 22 percent report a chronic disease while for the age group 56 to 65 44 percent suffer from at least one chronic disease. 34.56% of the sample visited a doctor only between zero and four times in the previous year while 24.37% visited once a month or more. According to their BMI, over half of the survey participants are either overweight, 36.36% or obese, 20.36%.

Figure 1: Proportion of Individuals with a Disability (in %)

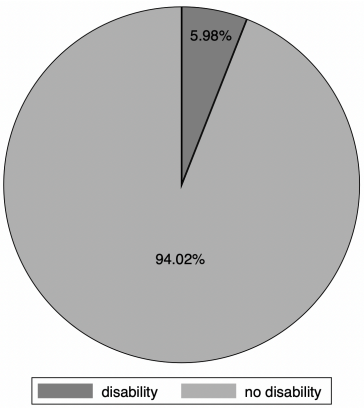
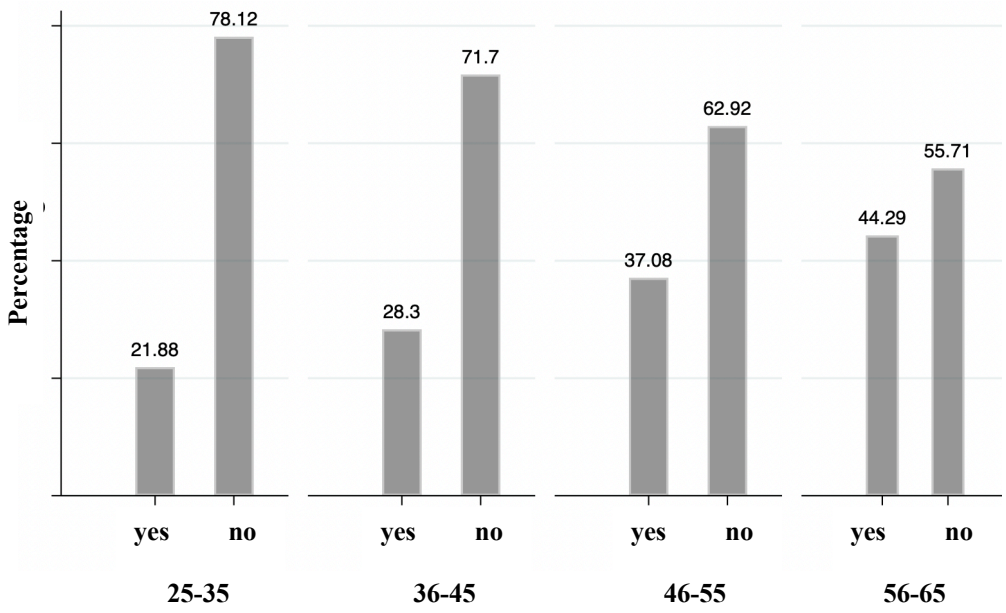


Table 1: Overview Sample Characteristics (N= 29,817)

Variable	*Category*	*Value*
gender	male	48.20 %
	female	51.80%
age	mean	45.89
	standard deviation	9.54
employment	employed	98.62%
	not employed	1.38%
equivalent income	mean	26,730.76 Euro
	standard deviation	21,087.81 Euro
disability	disabled	5.98%
	not disabled	94.02%
ISEI score	mean	48.70
	standard deviation	21.31
chronic disease	yes	33.43%
	no	66.57%
ISCED	primary	0.95%
	lower secondary	5.93%
	(upper) secondary	45.86%
	post-secondary non-tertiary	10.79%
	1. and 2. stage of tertiary	36.47%
difficulties daily	yes	30.46%
	no	69.54 %
hospital nights	mean	0.09
	standard deviation	0.28
doctor visits	mean	2.31
	standard deviation	1.18
BMI	underweight	1.20%
	normal	43.32%

	overweight	36.59%
	obese	18.89%

Figure 2: Distribution of Presence of Chronic Diseases by Age Group (in %)



4 Methodology

4.1 Self-rated Health

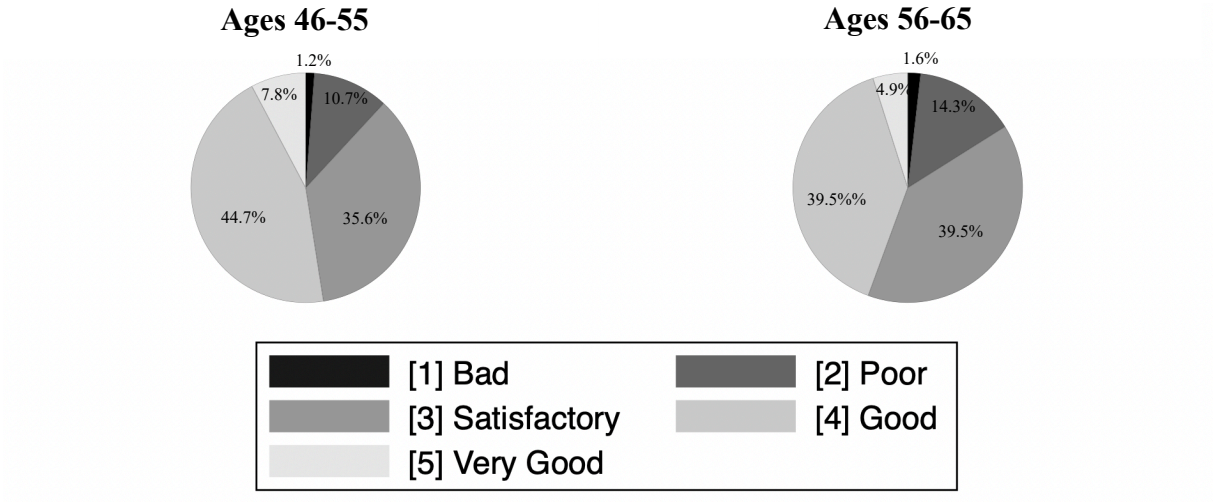
This thesis aims to examine the relationship between the outcome variable SRH and different objective SES and subjective satisfaction measures. Consistent with prior research, the GSOEP measures the SRH variable by the question 'How would you describe your current state of health?'. Ordered response options are given on a five-point scale ranging from '[1] Bad', '[2] Poor', '[3] Satisfactory', '[4] Good' to '[5] Very Good'.

SRH may not always align with an individual's objective health status. SRH may capture perceived aspects of health that are not captured by objective health measures. It enables the participants to weigh and rank various dimensions of their health. SRH thereby captures an individual's subjective perspective on overall health and well-being. However, an assessment bias due to misreporting or subjectivity of individuals can be assumed to affect SRH observations (Kerkhofs et al. (1995); Layes et al. (2012); Greene et al. (2015)). An individual's response can be influenced by personal bias due to different reference points, inter alia, because of age (Barrett (2003); McFadden et al. (2008)), cultural background (Bombak (2013)) or gender (Muhammad & Maurya (2023)).

Nevertheless, it is a well-established measure of health. I assume the true health status to be a latent and unobservable variable.

Pie charts depicting the differences in the distribution of health responses by age are presented in Figure 3. The percentage of good or very good SRH decreases steadily with age. In the youngest age cohort 69.5% report very good or good SRH. Among individuals aged 56 to 65 this percentage is approximately 44.4%.

Figure 3: Pie Chart of SRH by Age Cohort (in %)



Out of a total of the 29,817 observations, the respective percentages for each response are 9.8% for '[5]', 46.65% for '[4]', 32.05% for '[3]', 10.3% for '[2]', and 1.2% for '[1]'. It can be observed that most of the frequency distribution is concentrated in the upper three rating categories. Since there are relative few observations of '[1] Bad', I group categories '[1]' and '[2]' into one category for the empirical analysis. Thus, to avoid sparse data, I use a modified four-point scale of SRH in the estimation. Thus, SRH is considered on a four-point scale ranging from '[1] Poor or Bad' to '[4] Very Good'.

The mean SRH is 2.46 with a 95% confidence that the true average SRH rating lies between 2.45 and 2.47 in our sample. Overall, the mean SRH rating is very similar between the three considered survey years (see Table 2).

Table 2: SRH Mean Statistics by Survey Year

	Observations	*Mean*	*Std. err.*	*[95% conf. interval]*	
Sample	29,817	2.5476	.8209	2.45475	2.47405
2014	9,111	2.5652	.8118	2.54858	2.58192
2016	11,098	2.5409	.8273	2.525604	2.55639
2020	9,608	2.5384	.8217	2.521972	2.55484

4.2 Objective Health Measures

As previously stated, one objective of this thesis is to study the effect of different satisfaction variables on SRH. To do so, I need to control for the objective health. It is approximated based

on six exogenous health indicators. namely presence of chronic conditions, disability status, number of annual doctor visits in the previous year, a difficulty of daily tasks scoring and Body Mass Index (BMI). All six health indicators are included as independent variables in the empirical analysis.

First, the number of chronic diseases is derived from the response to 'Have you ever been diagnosed by a doctor with one or more of the following conditions?'. Survey participants have the option to choose from a list of multiple chronic conditions using a multiple-choice format. A dummy variable is generated based on the responses provided. The binary variable takes value 1 if the individual has at least one preexisting chronic health condition and 0 otherwise.

Second, generate the binary variable hospital nights that classifies the continuous number of overnight-hospital-stays in the previous year into two categories. The generated categorial variable ranges from '[0] hospital night does not apply' to '[1] hospital night applies'.

The disability status is a binary variable that is 1 if the individual is disabled and 0 otherwise. The assessment of the difficulty of daily tasks includes the binary variables 'difficulty/ needing help getting in/out bed', 'Have trouble climbing stairs', and 'dressing difficult alone'. A binary response variable for the difficulty of daily tasks is created that takes values between 0 (= no difficulties) and 1 (= some difficulties apply).

BMI is included as an ordered independent variable on a four-point scale. BMI is calculated as '(body weight)/ (body height in meters)^2'. The resulting index is classified, according to World Health Organization (WHO) recommendations, into an ordered variable that ranges from '[4] $\geq$ 30 Obese', '[3] 25.0 $\leq$ 30 Overweight', '[2] 18.5-<25 Normal' to '[1] <18.5 Underweight'. Although the measure has deficiencies as it, inter alia, does not consider factors like muscle mass, age, or distribution of fat, it is an important indicator for the identification of obesity or overweight (Himes (2009)). As such it is often included in SRH studies as an independent variable (Bombak (2013)). Prior results on the significance of overweight for SRH differ between countries. Cullinan and Gillespie (2016) found that being overweight has a negligible impact on SRH by studying a sample of Irish parents and their children. Marques-Vidal et al. (2012) discovered an increasing correlation between obesity and poor SRH in Switzerland, yet no such association was observed in Portugal.

4.3 Objective Socioeconomic Status Measures

I control for the effects of several objective socioeconomic characteristics and their influence on SRH. In the literature, objective SES is usually measured with income, education, and employment levels (Cialani and Mortazavi (2020)). To measure objective SES, I rely on four indicators which are included as independent variables in the empirical analysis.

The first measure is an individual's equivalent household income. I equivalize household post-government income using the modified Organization for Economic Cooperation and Development (OECD) scale to account for variations in the makeup of households. The scale sets a single adult to be 1.0, each additional adult to be 0.5 and each child in the household to be 0.3 (Schwarze (2003)). Furthermore, the annual Consumer Price Index (CPI) is used to create the deflated equivalent household income. This is done to account for inflation and maintain the purchasing power of the household income over time. To incorporate the concept of relative income position, I compute five quintiles of the deflated equivalent household income for each calendar year. Average SRH in the sample increases by income quintile. In the 1st quintile average SRH is 2.45, 2.48 in the 2nd, 2.51 in the 3rd, 2.58 in the 4th and 2.64 in the 5th.

Second, the level of education is classified according to the ISCED. In contrast to income, education can be assumed to be a more consistent indicator of lifelong SES as it is less influenced by the reverse causality effect of poor health leading to a decline in SES. The ISCED classifies the highest attained degree from '[1] primary education', '[2] lower secondary education', '[3] upper secondary education', '[4] post-secondary non-tertiary education' to '[5] first and second stage of tertiary education'. For my analysis, individuals who are in school are omitted. Due to the very small proportion of people with '[1] primary education', I merge the first two categories into one. Consequently, the ISCED variable used in the empirical estimation has a 4-point ordered scale. The measure should be regarded as an approximation of educational status, as it does not account for variations in the quality of education nor captures the different levels of post-secondary education. Like gender, the ISCED variable is treated as time-invariant.

Third, the employment status is included as a determinant of objective SES. For the statistical analysis it is measured on a binary scale whereby '[1] employed' and '[0] not employed'.

The fourth indicator used is occupational prestige. For this, the International Socio-Economic Index of Occupational Status (ISEI) is used as a standardized measure. The index is constructed based on the current occupation's ISCO-08 code using a Stata ado called "derive scores" developed by Daniel Bela and Knut Wenzig (paneldata.org). The score is provided by the GSOEP,

and the respective datasets are merged and added. The ISEI score ranges from 10 to 90 and "is coded based on required educational qualifications and the expected income" (Miyamoto and Wicht (2020)). It was developed by Ganzeboom (2010) and has since been used in various studies to measure SES. The index is used, along with other measures, to assess socioeconomic status in the Programme for International Student Assessment (PISA) study (Avvisati (2020)). Hovanec et al. (2018) measure SES using the ISEI and the European Socio-economic Classification. The authors investigate the relationship between SES and lung cancer using an unconditional logistic regression. Präg et al. (2016) measure objective SES with an individual's ISEI score, the International Standard Classification of Education (ISCED) to distinguish educational status and equivalent household income. For the empirical analysis, I divide the ISEI score into five quintiles to enhance the interpretability of marginal effects. Hence, the study involves the categorization into five quantiles based on the varying levels of occupational prestige they hold. In the empirical analysis, I use and ordinal approach and model them as a set of n-1 dummy variables. Same applies for the modeling of income quintiles and ISCED. Thus, the coefficients can be interpreted in terms of ordinal ranking and how they affect SRH in relation to a reference level.

Individuals who did not provide information about employment, educational or income status were omitted. The same applies for occupational prestige. Furthermore, year dummies for the years 2014 and 2016 are created to account for period effects.

4.4 Self-rated Satisfaction

Objective measures of SES may not fully reflect personal perception of economic and social deprivation. Previous studies have indicated that subjective measures can play an influential role in assessing perceived health compared to objective ones (Senik (2009); Hayo & Seifert (2003)). Four indicators are considered for a more comprehensive understanding of their role for SRH. These include satisfaction with household income, satisfaction with occupation, satisfaction with housing and general current life satisfaction.

The variables satisfaction with income, occupation and housing are measured by the question 'How satisfied are you currently with the following areas of your life? (Please answer by using the following scale, in which 1 means completely dissatisfied, and 10 means completely satisfied.)' on an ordinal 10-point scale. Satisfaction with its income can be described as "the discrepancy between desired income and received income, and the extent to which the received income complies with expectations and aspirations compared to idealized others and prior

income histories" (Miething (2013)). Thus, it likely includes a socioeconomic comparison with peers and surroundings.

The degree of perceived housing satisfaction serves as an indicator of quality of housing, living conditions and neighborhood environment. The indicator thus can be utilized as a proxy for aspects of SES. Among other factors, the presence of lower perceived neighborhood safety has been found to be associated with poorer health (Warr et al. (2009)).

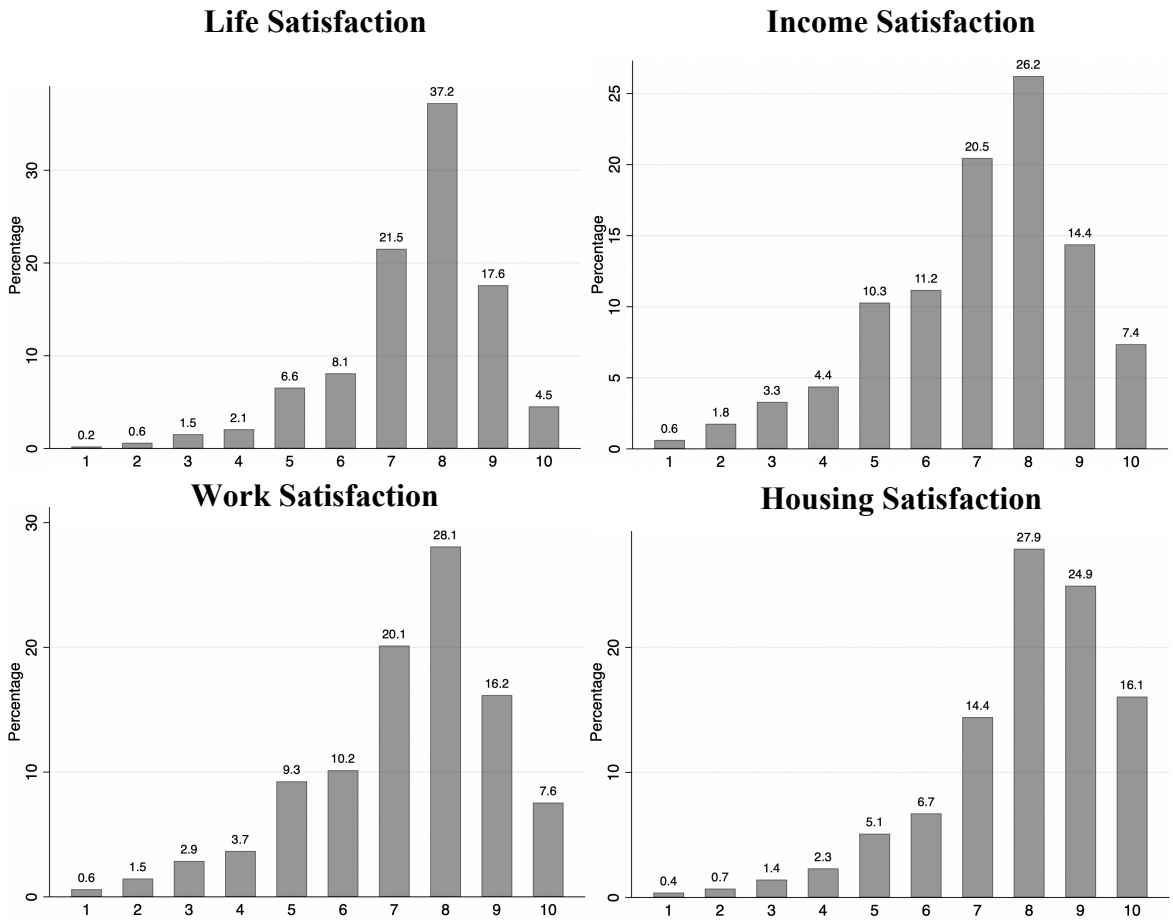
Work satisfaction was linked to overall well-being, mental health, and stress levels. While it was found to have a strong association with mental health, it was found to correlate moderately with physical conditions (Faragher et al. (2005)).

The GSOEP measures life satisfaction on an 11-point scale by the question 'How satisfied are you presently, all things considered, with your life?'. Answers range from '[0] completely dissatisfied' to '[10] completely satisfied'. The Satisfaction with Life Scale (SWLS) is commonly used to assess the subjective quality of life among individuals with significant health issues and has demonstrated its reliability and validity (Pavot & Diener (2008)). The score can capture how individuals weigh their overall life circumstances and aspects of life including economic and health conditions (Diener et. al. (2013)). Diener and Chan (2011) found that life satisfaction scores predict health and longevity. For the empirical analysis I group answers '[0]' with '[1]' due to small number of observations (N = 32). Consequently, I consider life satisfaction on a 10-point scale.

Since all subjective measures listed inherently depend on an individual's perception, these variables, much like SRH, can be influenced by personal bias and external factors.

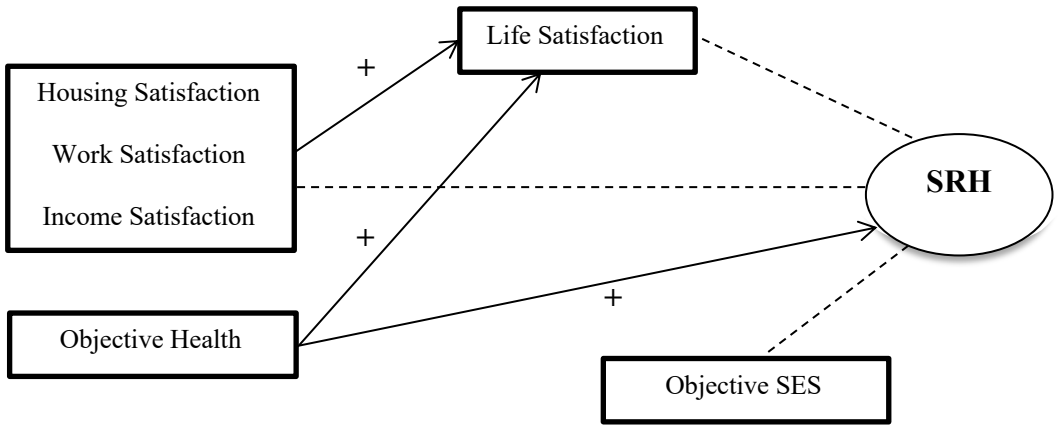
Housing, work and income satisfaction can be assumed to have a positive influence on the overall life satisfaction (Figure 5). The same applies for objective health. An individuum with no chronical diseases can be assumed to be more likely to report better SRH. It is plausible that there is a direct positive relationship between objective and subjective health.

Figure 4: Distribution of Satisfaction Ratings (in %)



Note: x-axis shows satisfaction rating from 1 to 10 and y-axis shows percentage share of the respective rating on in the analyzed sample (N=29,817)

Figure 5: Assumed Direction of Effect between independent variables and SRH



5 Econometric Model

5.1 Ordered Response Models

Ordered response models are regression models used to analyze ordinal dependent variables by assuming a continuous latent variable that underlies the observed ordinal categories. SRH status, which is the outcome variable in this study, is an ordinal variable since answers are provided in four distinct ordered categories, i.e., $y \in \{1,2,3,4\}$. As such the SRH measure does not have a continuous measurement scale. The latent health status of the respondent, y^*, is assumed to underly the observed SRH.

By employing an ordered response model, I can assess how changes in both perceived satisfaction and objective SES relate to shifts in the likelihood of moving from one SRH category to another. The model estimates cut-off points α that separate the latent variable into different categories. Those categories determine the probabilities of observing each of them. Thereby, the cut-off points represent the unobserved thresholds at which SRH transitions from one category to another.

In addition to the Ordered Logit Model (OLM), the OPM is part of a broader family of ordered response models. The choice between OPM and OLM depends on the assumptions of the underlying distribution of the error terms in the data. While the OLM assumes y^* follows a logistic distribution, the OPM supposes the underlying latent variable follows a standard normal distribution. Both models provide similar empirical results. The OPM is widely used to analyze satisfaction and health status in survey data (Cullinan & Gillespie (2016); Cialani & Mortazavi (2020)). In this thesis, I stick to common literature and estimate an OPM. OPMs were compared to OLM estimates and only insignificant differences in the results could be observed.

This thesis aims to determine how satisfaction with life circumstances, measured as satisfaction with its household's income, work, housing and general life satisfaction, influence SRH. To study this relationship, I employ an OPM. In the estimation age, age^2 (to allow for a non-linear relationship between SRH and age), gender, BMI, doctor visits, nights spent in hospital, disability status, presence of one or more chronic diseases, daily difficulties, ISEI quintile, employment status, ISCED level, deflated equivalent income quantile and t-1-year dummies, D_{t-1}, are included as independent variables to explain the SRH outcome. Furthermore, satisfaction with household income, satisfaction with work and housing as well as general life satisfaction are included as independent variables. I estimate the following model:

$SRH_{i,t}^* = \beta_1\, age_{i,t} + \beta_2\, age_{i,t}^2 + \beta_3\, female_i + \beta_4\, BMI_{i,t} + \beta_5\, doctor\_visits_{i,t} + \beta_6\, hospital\_nights_{i,t} + \beta_7\, disability\_status_{i,t} + \beta_8\, chronic\_\ diseases_{i,t} + \beta_9\, daily\_difficulties_{i,t} + \beta_{10}\, q2\_ISEI\_quintile_{i,t} + \beta_{11}\, q3\_ISEI\_quintile_{i,t} + \beta_{12}\, q4\_ISEI\_quintile_{i,t} + \beta_{13}\, q5\_ISEI\_quintile_{i,t} + \beta_{14}\, employment_{i,t} + \beta_{15}\, q2\_ISCED_i + \beta_{16}\, q3\_ISCED_i + \beta_{17}\, q4\_ISCED_i + \beta_{18}\, q2\_income\_quantile_{i,t} + \beta_{19}\, q3\_income\_quantile_{i,t} + \beta_{20}\, q4\_income\_quantile_{i,t} + \beta_{21}\, q5\_income\_quantile_{i,t} + \beta_{22}\, income\_satisfaction_{i,t} + \beta_{23}\, satisfaction\_work_{i,t} + \beta_{24}\, satisfaction\_housing_{i,t} + \beta_{25}\, satisfaction\_life_{i,t} + D_{t-1} + \varepsilon_i$ (1)

First, I estimate a standard OPM and subsequently compare its model fit to that of the GOPM.

5.1.1 Standard Ordered Probit Model

The starting point of the OPM is an index model with a single unobservable latent variable y_i^* where β is a $k \times 1$ vector of parameters, x_i a vector of independent variables and the error term ε_i is $\varepsilon|x \sim N(0,1)$; i.e., $E[\varepsilon_i] = 0$ and $Var[\varepsilon_i] = 1$:

$y_i^* = x_i'\beta + \varepsilon_i$ *i = 1, 2, …, N individuals* (2)

The cut-off points for the 4-alternative ordered model are defined by $y_i = j$ if $\alpha_j < y_i^* \leq \alpha_{j+1}$, whereby j= 1, ..., 4, i.e., equal to the number of SRH ordered categories.

To ensure well-defined probabilities, $\alpha_{j+1} > \alpha_j$, $\forall j$, and $\alpha_j = \infty$ such that $F(\infty) = 1$ and $\alpha_j = -\infty$ such that $F(-\infty) = 0$ are required (Boes and Winkelmann (2006b)). F is assumed to be the cumulative density function of the standard normal distribution. Those are estimated together with the βs. The unobserved continuous health status y* is assumed to quantify its rating using discrete scale ranging from 1 to 4 relative to the cut points. It can be interpreted as the underlying propensity to report a certain SRH status. It is assumed that the categories of SRH can be observed as (Güneri et al. (2022)):

$$y_i = \begin{cases} \text{'[1]Poor or Bad'} & y^* \leq 0, \\ \text{'[2]Satisfactory'} & 0 < y^* \leq \alpha_1 \\ \text{'[3]Good'} & \alpha_1 < y^* \leq \alpha_2 \\ \text{'[4] Very Good'} & \alpha_2 < y^* \end{cases}$$

The sign of the regression parameters β provides an immediate interpretation, indicating whether the latent variable y* increases or decreases with changes in the regressor.

The estimates can be obtained consistently via the maximum likelihood method. Thereby, the log-likelihood (LL) function plays a crucial role in the estimation of the model. The LL function is used to estimate the model's parameters based on the observed data. The goal in estimating

the OPM is to find the set of parameter values (β) that maximizes the log-likelihood function LL(β) (Cameron and Trivedi (2005)):

$$\text{Log L } (\alpha, \beta) = \sum_{i=1}^{N} 1\,[y_i = 0] \log [\Phi\,(\alpha_1 - x'_i\beta)] + 1[y_i = 1] \log [\Phi\,(\alpha_2 - x'_i\beta) - \Phi\,(\alpha_1 - x'_i\beta)] +$$

$$+ \ldots + 1[y_i = J] \log [1 - \Phi\,(\alpha_J - x'_J\beta)] \qquad (3)$$

As the thesis focuses on the effect of the variables on the probabilities of observing a certain SRH status, the main parameters of interest are the AMEs which are calculated for each variable. The marginal effects indicate how a small change in a predictor variable impacts the distribution of the outcome variable (Boes and Winkelmann (2006b)). In the standard OPM marginal effects are the same for all individuals in the sample.

Hence in this thesis, the marginal effects represent the change in the probability of being in a higher SRH category, i.e., reporting a better SRH, to a one-unit change in the predictor variable, holding all other variables constant. For marginal effects in the probabilities, one must take the first order derivative with respect to x_k (Cameron and Trivedi (2005)):

$$\frac{\partial Pr[y_i = 0]}{xk} = -\beta_k\,\Phi\,(\alpha_1 - x'_i\beta)$$

$$\frac{\partial Pr[y_i = J]}{xk} = \beta_k\,\Phi\,(\alpha_J - x'_i\beta)$$

$$\frac{\partial Pr[y_i = j]}{xk} = \beta_k\,[\Phi\,(\alpha_{j-1} - x'_i\beta) - \Phi\,(\alpha_j - x'_i\beta)] \qquad (4)$$

However, standard OPMs have important restrictive limitations (Boes and Winkelmann (2006b); Greene and Hensher (2010); Johnston et al. (2020)). First, the relative marginal probability effects are constant across individuals and the outcome distribution. That is because the distributional assumption does not account for additional individual heterogeneity between individual realizations. Furthermore, the sign of the marginal probability effects undergoes only a single change between the smallest and largest ordered outcome which is a consequence of the standard normal distribution´s bell-shaped density function (Boes and Winkelmann (2006b)).

Moreover, the standard OPM is limited by the single index and constant threshold assumption. The OPM assumes that β is the same for all four categories of SRH. That implies that as the independent variable increases, the cumulative distribution shifts either to the right or left,

without altering the slope of the distribution (Schneider et al. (2012)). Consequently, the ratio of the explanatory variables marginal effects on probabilities of reporting a certain SRH is constant.

5.1.2 Generalized Ordered Probit Model

A more generalized approach is the estimation of a GOPM which relaxes the assumption of a standard normal distribution for the error term (Boes and Winkelmann (2006b); Williams (2006); Greene and Hensher (2010); Cialani and Mortazavi (2020); Johnston et al. (2020)). It provides an alternative estimation method if the parallel slope assumption is not met. Contrary to the standard OPM, the GOPM allows variation in indices across outcomes (Greene and Hensher (2010)). The threshold parameters are unique to each individual and are contingent upon the covariates (Schneider et al. (2012)):

$$\alpha_{ij} = \tilde{\alpha}_j + x_i'\gamma_j \qquad j = 1, \ldots, 4 \qquad (5)$$

The influence parameter of covariates on the cut-off points α_j is illustrated by γ_j and α_j is a constant term (Schneider et al. (2012)). The generalized specification can reduce distributional misspecification and, in that case, leads to more efficient estimators (Johnston et al. (2020)).

5.2 Model Tests

To decide on whether the generalized specification is preferable for the dataset of this thesis, I test the OPM´s restrictive assumption of parallelism. The following null hypothesis is used to assess whether the β coefficients of the independent variables are equal for each category (Güneri et al. (2022)):

$$H_0 = \beta_{1j} = \beta_{2j} = \ldots = \beta_{(K-1)\,j} = \beta \qquad j = 1, \ldots, 4 \qquad (6)$$

Following Cialani and Mortazavi (2020), the null hypothesis assumes that coefficients of the independent variables are the same for each category of respondent variable, i.e., the standard OPM offers a better fit. To examine whether the difference in log-likelihood between the OPM and GOPM is statistically significant, I perform a LR test:

$$(LR = 2(LL_{\text{unrestricted}} - LL_{\text{restricted}})) \qquad (7)$$

The test can be used to contrast the goodness of fit of an unrestricted model with a special or limiting version (Johnston et al. (2020)). If the parallelism assumption is not satisfied,

interpretations of the OPM results will be inaccurate. Thus, the GOPM is used instead of standard OPM to find correct marginal effects.

Regardless of statistical reasons, it is rational to assume that the "thresholds people apply when assign their health status are likely to vary" (Cialani and Mortazavi (2020)). This intuition suggests a preferred application of the GOPM over the standard OPM. To decide on the model fit I employ standard criteria of model performance to compare the model fit of the OPM and GOPM.

For this, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values are determined. The BIC and AIC are frequently used to examine the model fit of non-nested models. The BIC is calculated as:

$$BIC = k \log(n) - 2\,LL \tag{8}$$

whereby n is the sample size and k the number of independent variables (Johnston et al. (2020)):

The AIC, which was proposed by Akaike in 1973, is calculated as (Güneri et al. (2022)):

$$AIC = -2 \log (LL) + 2k \tag{9}$$

Generally, lower AIC or BIC values indicate a better model fit.

Furthermore, the Pseudo-R^2 test statistics are estimated for both models and compared. Generally, a higher R^2 indicates a better model fit.

Moreover, for OLM a Brant statistic can be calculated in Stata (see TableA1 in the Appendix). This is however not the case for an OPM. When estimating my model as an OLM, the significant test statistic of the Brant test provides evidence that the parallel regression assumption has been violated. Thus, the relationship between each outcome category and the predictors are not parallel. This suggests the application of a more generalized model for the OLM case.

All empirical analyses and data preparations were carried out using Stata BE 17. I fit the standard OPM by using the oprobit command in Stata. For the estimation of the GOPM, I employ Stata's goprobit command.

6 Results

6.1 Estimation OPM and GOPM

First, the restrictive assumptions of the standard OPM are tested. The standard criteria of model performance favor the GOPM over the OPM. For the standard OPM, I find a value of 57,516.72 for the AIC and 57,765.8 for the BIC. For the GOPM, lower values are estimated for both criteria, namely 57,056.31 for the AIC and 57,753.74 for the BIC. Following those criteria, the GOPM is an improvement in model fit compared to the standard OPM.

Furthermore, the OPM has a Pseudo-R^2 test statistic value of 0.1949 (=1-(-28,729.98)/ (-35,684.54)) which can be useful for model selection. The Pseudo-R2 test statistic has a value of 0.202 (=1-(-28,444.15)/ (-35,684.542)) for the GOPM. This value is higher than for the standard OPM which suggests a higher explanatory value of the variation in the GOPM.

Table A1 in the Appendix shows the estimated OPM regression output. The upper section provides the values of the log-likelihood (5) for each stage of the iterative process. Those can be used to calculate the LR test statistic of 13,909.12 (= 2(35,684.542- 28,729.98)) that is provided by Stata. Because of the number of independent variables, the statistic is distributed as a χ^2 with 27 degrees of freedom. Overall, the p-value below the test statistic demonstrates a strong significance. The LR test statistic of the GOPM is equal to 14,480.78 (= 2(35,684.54- 28,444.15)). Although the change in LL between the two models appears small (= 284.21), the LR test suggests a statistically significant improvement.

Table 3: Model Validity Tests and Goodness of Fit Indicators

	OPM	*GOPM*
AIC	57,516.72	57,056.31
BIC	57,765.8	57,753.74
Pseudo-R^2	0.1949	0.202
LL (null)	-35,684.54	-35,684.54
LL (model)	-28,729.98	-28,444.15
LR	13,909.12	14,480.78

Table A2 shows the estimated coefficients and their associated standard errors, z statistics, p-values, and confidence intervals for the standard OPM. Most of the βs are highly significant with each of the coefficients βs being statistically significant at a 1% significance level. This

does not apply to the year dummy of 2014 and female, employment, housing satisfaction and income quintile. Standard errors are quite small. The latent variable y* is estimated to increase with a rise in ISEI score, no presence of a chronic disease, no disability, the level of education and all satisfaction variables. These statistical associations of SES indicators are consistent with existing research on the social determinants of health. An increase in objective health outcome is found to increase SRH. As expected, a ceteris paribus increase in the propensity to report a worse SRH with rising age can be observed. Estimates for the cut off points α_1, α_2 and α_3 are provided.

Table 4 shows the estimated coefficients for the GOPM. Column 'GOP_1' represents the effect of the independent variables on the cutoff point between the lowest category and the next category in SRH. Column 'GOP_2' shows the effect for the cutoff point between the second and the third category and column 'GOP_3' between the third and the fourth category.

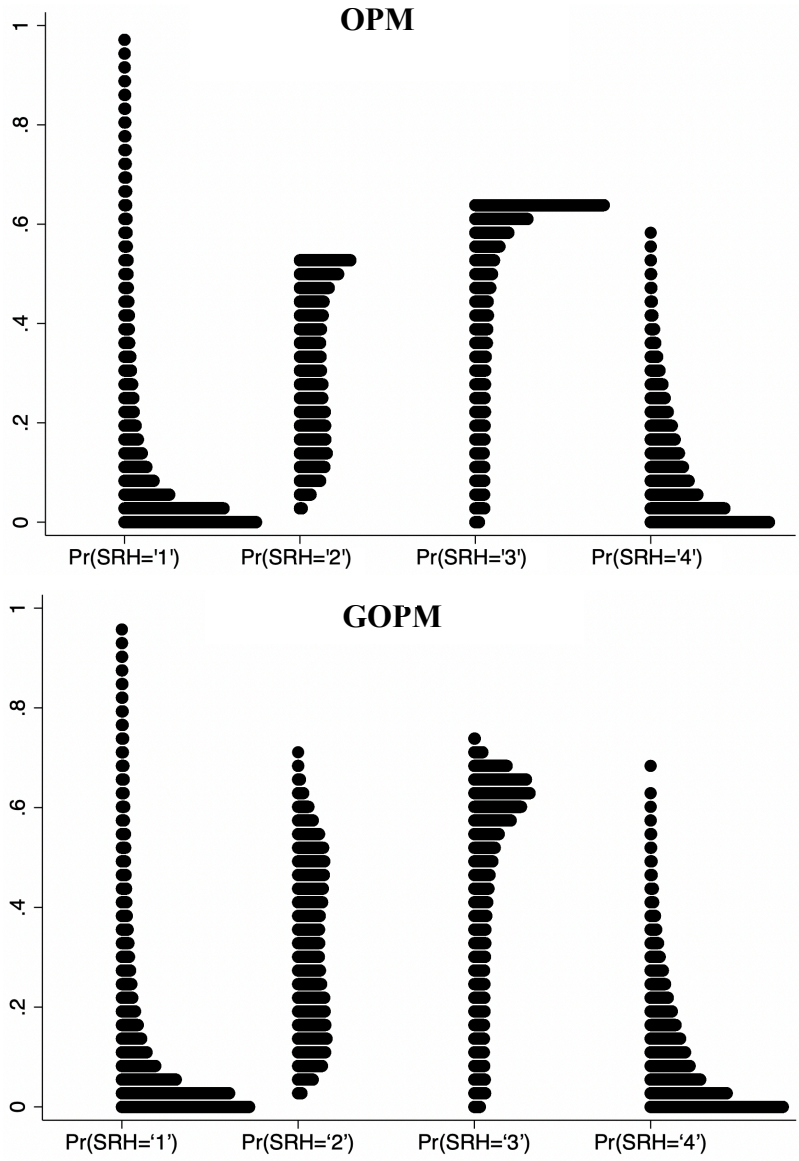
Negative coefficients, i.e., doctor visits or BMI, suggest that an increase in these independent variables makes it more likely for the latent variable to move to a lower category, i.e., report worse SRH. The estimated positive coefficients, i.e., income, work, and life satisfaction, suggest the opposite. Significance and coefficients differ between 'GOP_1', 'GOP_2' and 'GOP_3'.

Table 4: Estimated Coefficients based on GOPM and OPM (N=29,817)

	GOP_1	*GOP_2*	*GOP_3*	*OPM*
Age	-.0069(.0107)	**-.0247***(.0077)**	**-.0311***(.0102)**	**-.0331***(.0061)**
Age²	.0001(.0001)	**.0001*(.0001)**	.0002(.0001)	**.003***(.0001)**
Female	-.0145(.0233)	.0141(.0173)	**.0488*(.0236)**	.0193(.0138)
BMI	**-.0447***(.0146)**	**-.0926***(.0113)**	**-.1836***(.0170)**	**-.1007***(.009)**
Hospital nights	**-.1852***(.0339)**	**-.1926***(.0302)**	-.0638(.0491)	**-.1715***(.0239)**
Doctor visits	**-.2914***(.0102)**	**-.2043***(.0074)**	**-.1418***(.0111)**	**-.2117***(.0061)**
Disability	**-.1821***(.038)**	**-.1612***(.0388)**	**-.1378(.0881)**	**-.1581***(.0295)**
Chronic disease	**-.4897***(.0239)**	**-.5405***(.0184)**	**-.4907***(.0327)**	**-.5155***(.0154)**
Daily difficulty	**-.5864***(.0243)**	**-.661***(.0191)**	**-.6333***(.0397)**	**-.6172***(.0161)**
Employment	-.0436(.0946)	.0394(.0718)	.0839(.1001)	.0353(.0571)
ISEI				
D2_ISEI	**.1245***(.0363)**	**.0481*(.0278)**	-.0528(.0415)	**.0394*(.0223)**
D3_ISEI	**.1495***(.0379)**	**.1113***(.0286)**	**-.0967**(.0418)**	**.0618***(.0229)**
D4_ISEI	**.1034***(.0388)**	**.1145***(.0296)**	.0373(.0425)	**.0902***(.0237)**
D5_ISEI	**.0911**(.0449)**	**.1438***(.0331)**	.0703(.0456)	**.1204***(.0264)**
ISCED				
D2_ISCED	**.1408***(.0449)**	.0526(.0358)	-.0403(.0519)	**.0589**(.0286)**
D3_ISCED	**.1551***(.0555)**	**.1291***(.0428)**	.0758(.0603)	**.1314***(.0342)**
D4_ISCED	**.1732***(.0508)**	**.1665***(.0397)**	**.1039*(.0567)**	**.1617***(.0317)**
Income	.			
D2_ Income qu.	**.0661*(.0349)**	-.0168 (.0267)	-.0521(.0381)	-.0062(.0213)
D3_ Income qu.	**.0979***(.0270)**	.0019(.0277)	-.0628(.0393)	.0100(.0222)
D4_ Income qu.	**.0631*(.0392)**	.0322 (.0292)	-.0574(.0408)	.0206(.0233)
D5_ Income qu.	**.0751*(.0433)**	.0527(.0321)	.0053(.0433)	**.0532**(.0255)**
Income sat.	.0108(.0071)	.0066(.0056)	**.0367***(.0083)**	**.0143***(.0044)**
Work sat.	**.0631***(.0063)**	**.0825***(.0051)**	**.0657***(.0078)**	**.0715***(.0041)**
Housing sat.	-.0039(.0069)	**.0176***(.0055)**	.0657(.0079)	.0067(.0041)
Life satisfaction	**.2072***(.0082)**	**.236***(.007)**	**.255***(.0113)**	**.2285***(.0054)**

Note: Rounded to fourth decimal point; Standard error in brackets; * p < 0.1, ** p < 0.05, ***p < 0.01

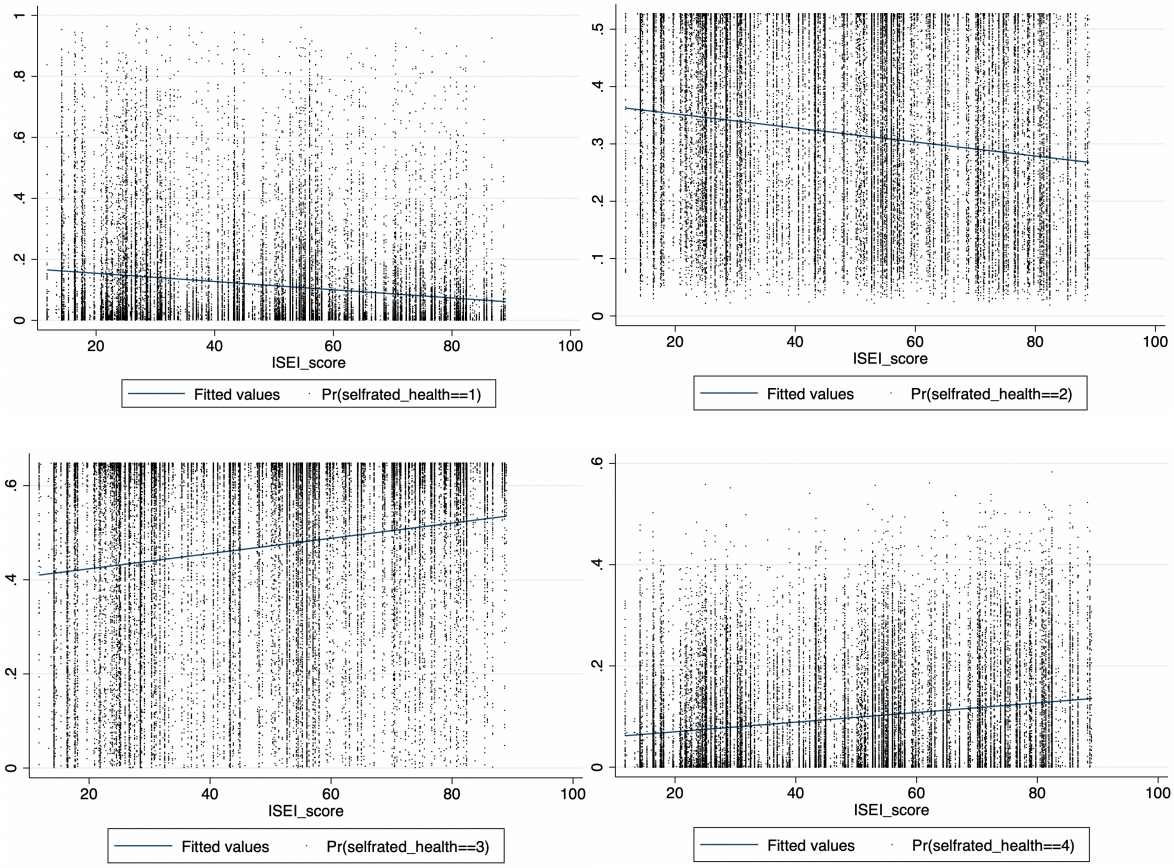
Figure 6: Graph of Estimated Probabilities for OPM and GOPM



Note: Y axis shows probability from 0 to 1.

Figure 6 shows the predicted probabilities for each SRH outcome in the OPM and in the GOPM. It provides two important insights about variation in the distribution of predicted probabilities between the two estimation methods: It differs particularly for a SRH of '[2] Satisfactory' and '[3] Good'. The probability distribution is quite similar for SRH of '[4] Very Good' and '[1] Poor or Bad'. The dots at the extreme ends (close to 0 or 1) indicate a high confidence in predicting the corresponding SRH category.

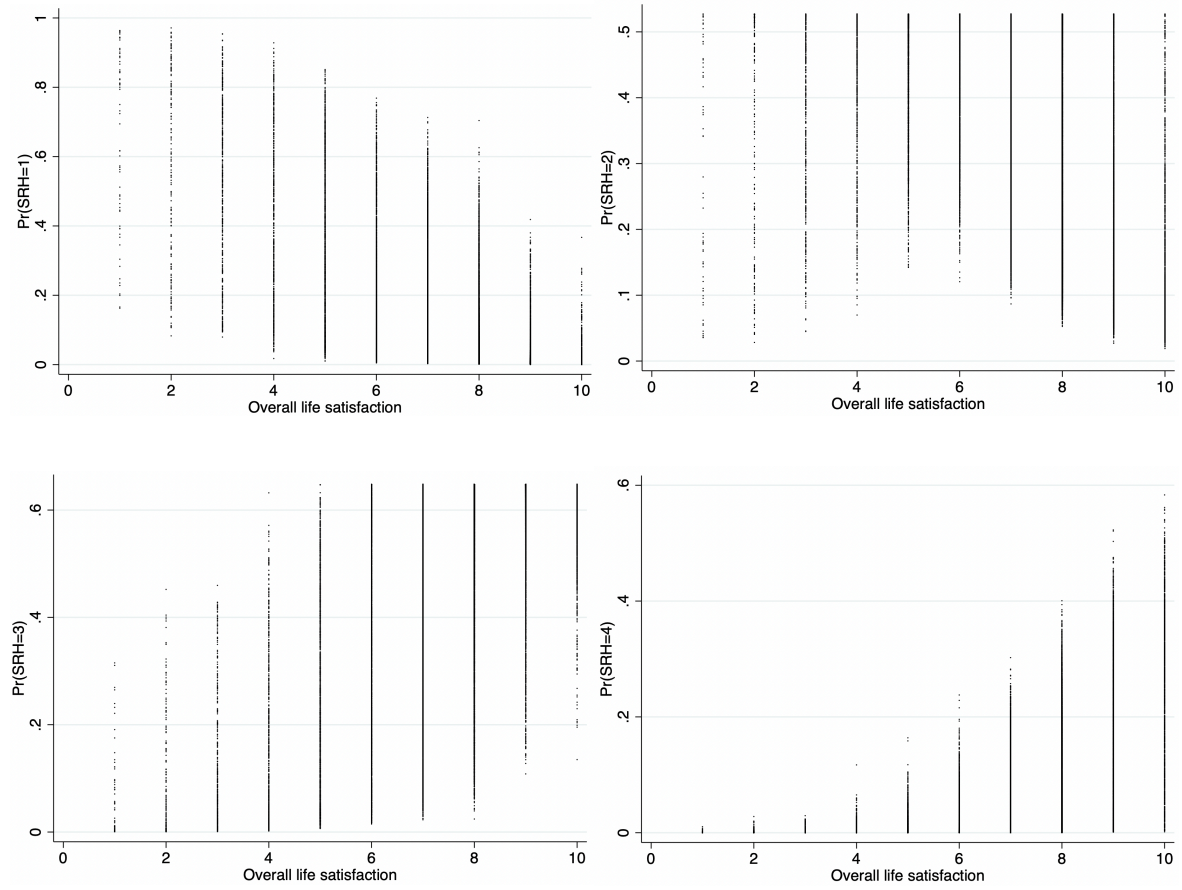
Figure 7: Scatter Plot with Linear Fit Line for Estimated Probabilities of SRH Ratings and ISEI Score (based on GOPM estimation)



The distribution of predicted SRH probabilities in relation to ISEI score presented in Figure 7. On the x-axis the ISEI score, ranging from 10 to 90, is depicted while the y-axis shows the predicted probabilities under the GOPM, spanning from 0 to 1. Are there any discernible patterns or trends? One can observe that with higher levels of occupational prestige, the frequency of having a high likelihood to report '[1] Poor or Bad' or '[2] Satisfactory' SRH decreases. On the contrary, there is a higher frequency of predicted probability corresponding to a '[4] Very Good' or '[3] Good' SRH for higher ISEI scores. That means in the fifth quintile of ISEI score, considerably more individuals have a higher predicted probability to report high SRH outcomes than a lower SRH outcome. Furthermore, higher predicted probabilities are reported for the middle categories satisfactory and good SRH compared to the more extreme SRH outcomes.

Figure 8: Scatterplot of Life Satisfaction Rating and Predicted Probability of SRH

(based on GOPM estimation)



A similar relationship can be observed between overall life satisfaction ratings and the predicted probabilities of reporting a certain SRH (see Figure 8). The concentration of predicted probabilities for higher overall life satisfaction ratings (>8) is higher for '[4] Very Good' SRH, while the equivalent concentration is low for '[1] Poor or Bad' SRH.

Figure A1 in the Appendix depicts the relationship between income satisfaction ratings and the predicted probabilities. Especially for predicted '[4] Very Good' SRH outcomes, the concentration of high-income satisfaction is considerably higher while the opposite is true for '[1] Poor or Bad' SRH ratings. This trend is less pronounced in the two middle SRH levels. Those trends are indicators for objective SES measures and dissatisfaction influencing the probability of reporting a certain SRH.

6.2 Marginal Effects

Aside from sign and significance, it is difficult to get a concrete sense of how large the observed effects are based on the coefficients provided above. To understand the effect of independent variables on the probability of reporting SRH, the respective marginal effects are calculated (see Table 5 and Table 6).

6.2.1 OPM

Based on the standard OPM, Table 5 provides the AMEs for each response of SRH. The AMEs indicate the change in the probability of SRH being in a particular ordered category due to a one-unit change in the predictor. Most AMEs are highly significant at a 1% level.

There is no statistically significant difference between genders in the survey. Age is found to have a significant effect on SRH with an increase in age by one year reducing the likelihood of reporting the two highest SRH by on average 0.5 percentage points and increasing the likelihood of a '[2] Satisfactory' or '[1] Poor or Bad' by 0.5 percentage points.

Income has a significant effect on the probability of rating a certain SRH outcome in the highest income quintile compared to the lowest. On average, being in the 5th income quintile compared to the 1st is associated with an 0.7 percentage point decrease in the likelihood of reporting '[1] Poor or Bad' SRH and 0.8 percentage point increase in reporting '[4] Very Good' SRH.

Interestingly, subjective income satisfaction is found to have a significant AME of reporting a certain SRH outcome in all four rating categories. However, the AMEs are quite small. On average, one is 0.2 percentage points more likely to report very good health, or 0.2 percentage points more likely to report good health, if their income satisfaction rating increases by one unit. Reporting a lower SRH of '[1] Poor or Bad' is 0.2 percentage points less likely with a one unit increase in income satisfaction.

ISCED score and ISEI quintiles are observed to have a significant influence in all four SRH categories. A higher ISCED score and ISEI quintile are on average associated with an increase in the likelihood of reporting '[3] Good' and '[4] Very Good' SRH and a decrease in the probability of reporting one of the two lowest SRH categories.

Among the subjective indicators, life satisfaction has the highest AMEs. On average individuals are 3.3 percentage points more likely to report very good SRH, or 3.4 percentage points more likely to report '[3] Good' health, if their life satisfaction rating increases by one unit. They are 3.1 percentage points less likely to report bad or poor health and 3.6 percentage points less

likely to report satisfactory health. The direction of influence is the same for work satisfaction. However, the AMEs of work satisfaction are smaller at 1 percentage points. The AMEs of housing satisfaction are insignificant.

As expected, objective health criteria are observed to exert a substantial impact on the likelihood of reporting a specific SRH. All the calculated AMEs for these criteria hold statistical significance. Thereby, the presence of chronic diseases and the reporting of daily difficulties are found to exert the greatest influence on the probabilities of reporting specific health outcomes. On average, a chronic disease decreases the probability to report very good SRH by 7.4 percentage and increases 7 percentage points for bad or poor health. On average, people with daily difficulties are 8.8 percentage points less likely to report very good health, and 8.4 percentage points more likely to report bad or poor health. Individuals with a disability are 2.3 percentage points less likely to report very good and 2.4 percentage points less likely to report good health compared to individuals without disability. On average, disabled individuals are 2.1 percentage points more likely to report poor or bad health. The same direction of effects applies to the covariates doctor visits and hospital nights. The AMEs for BMI are found to be significant. On average, the likelihood to report very good SRH decreases by 1 percentage point if their BMI increases by one category. Likewise, individuals are on average more likely to report one of the two lowest SRH categories if BMI increases by one category.

Table 5: Estimated Marginal Effects based on OPM Estimation

	SRH = 1	*SRH = 2*	*SRH = 3*	*SRH = 4*
Age	**.0045***(.0008)**	**.0052***(.001)**	**-.005***(.0009)**	**-.0047***(.0009)**
Age²	**-.0000***(.0000)**	**-.0000***(.0000)**	**.0000***(.0000)**	**.0000***(.0000)**
Female	-.0028(.0018)	-.0032(.0021)	.003(.002)	.003(.002)
BMI	**.0137***(.0012)**	**.0158***(.0114)**	**-.0151***(.0014)**	**-.0144***(.0013)**
Hospital nights	**.0233***(.0032)**	**.0269***(.0037)**	**-.0257***(.0036)**	**-.0245***(.0034)**
Doctor visits	**.0287***(.0009)**	**.0332***(.001)**	**-.0317***(.001)**	**-.0302***(.0009)**
Disability	**.0214***(.004)**	**.0248***(.0047)**	**-.0237***(.0044)**	**-.0226***(.0042)**
Chronic disease	**.07***(.0022)**	**.0809***(.0024)**	**-.0772***(.0024)**	**-.0735***(.0024)**
Daily difficulty	**.0837***(.0023)**	**.0968***(.0025)**	**-.0924***(.0024)**	**-.0881***(.0025)**
Employment	-.0034(.0077)	-.0039(.0089)	.0037(.0085)	.0035(.0081)
ISEI				
D2_ISEI	**-.0053*(.0030)**	**-.0062*(.0035)**	**.0059*(.0033)**	**.0056*(.0032)**
D3_ISEI	**-.0084***(.0031)**	**-.0097***(.0036)**	**.0093***(.0034)**	**.0088***(.0033)**
D4_ISEI	**-.0122***(.0032)**	**-.0141***(.0037)**	**.0135***(.0035)**	**.0129***(.0034)**
D5_ISEI	**-.0163***(.0036)**	**-.0189***(.0041)**	**.0180***(.004)**	**.0172***(.0038)**
ISCED				.
D2_ISCED	**-.008**(.0039)**	**-.0092**(.0045)**	**.0088**(.0043)**	**.0084**(.0041)**
D3_ISCED	**-.0178***(.0046)**	**-.0206***(.0054)**	**.0197***(.0051)**	**.0187***(.0049)**
D4_ISCED	**-.0219***(.0043)**	**-.0254***(.005)**	**.0242***(.0048)**	**.0231***(.0045)**
Income				
D2_ Income qu.	.0008(.0035)	.0009(.0033)	-.0009(.0032)	-.0009(.0030)
D3_ Income qu.	-.0014(.0030)	-.0016(.0035)	.0015(.0033)	.0014(.0032)
D4_ Income qu.	-.0028(.0032)	-.0032(.0037)	.0031(.0035)	.0029(.0033)
D5_ Income qu.	**-.0072**(.0034)**	**-.0083**(.004)**	**.008**(.0038)**	**.0076**(.0036)**
Income sat.	**-.0019***(.0006)**	**-.0022***(.0007)**	**.0021***(.0007)**	**.002***(.0006)**
Work sat.	**-.0097***(.0006)**	**-.0112***(.0006)**	**.0107***(.0006)**	**.0102***(.0006)**
Housing sat.	-.0009(.0006)	-.0011(.0007)	.001(.0007)	.001(.0006)
Life satisfaction	**-.031***(.0008)**	**-.0358***(.0009)**	**.0342***(.0009)**	**.0326***(.0009)**
2014	-.0033(.0023)	-.0038(.0026)	.0036(.0025)	.0035(.0024)
2016	**.0065***(.0021)**	**.0075***(.0025)**	**-.0071***(.0024)**	**-.0068***(.0023)**

Note: Rounded to fourth decimal point; Standard error in brackets; * p < 0.1, ** p < 0.05, ***p < 0.01

6.2.2 GOPM

Table 6 reports the AMEs based on the GOPM estimation. The significance of the independent variable differs between GOPM and OPM. Furthermore, the significance of some explanatory variables differs between the four SRH categories. Based on the OPM, AMEs of age are significant for every SRH rating category (see Table 5). In the context of the GOPM, however, age is observed to have a statistically significant impact solely on the probability of assigning a '[4] Very Good' rating. An increase in age by one year reduces the likelihood of reporting '[4] Very Good' on average by 0.5 percentage point. Furthermore, an individual's gender is found to have a significant effect on the probability of reporting '[4] Very Good' SRH. On average, being male makes it 0.6 percentage more likely to report very good health.

For the year dummies, the AMEs indicate the change in probability of the SRH being a particular rating due to the change from the year 2018 to the specified year. 2016, compared to 2018, is associated with a predicted decrease of 0.7 in the probability of moving from one SRH category to the next higher category for poor or bad SRH. For 2014 the respective decrease is estimated to be 1 percentage point. For the remain SRH categories, the AMEs for the years 2014 and 2016 in comparison to 2018 are not statistically significant.

6.2.2.1 Effect Objective Health Status

As in the OPM estimation, objective health criteria have a substantial impact on the likelihood of reporting a specific SRH based on a GOPM estimation. However, contrary to the OPM estimation, not all the calculated AMEs for these criteria hold statistical significance. The effect of disability status and the number of hospital nights in the previous year on the likelihood of reporting '[4] Very Good' health was found insignificant. The same applies for BMI and the likelihood of reporting '[3] Good' SRH. On average, individuals are 2.6 percentage points less likely to report '[4] Very Good', and 2.1 percentage points more likely to report '[2] Satisfactory' health, if their BMI increases by one category.

Just like based on the OPM estimation, the presence of chronic diseases and the reporting of daily difficulties have the greatest influence on the probabilities of reporting specific health outcomes. On average, people with a chronic disease are 8.5 percentage points less likely than to say their health is '[3] Good' compared to individuals without, and 8.7 percentage points more likely to report '[2] Satisfactory' health.

If daily difficulties are reported it is 8.9 percentage points less likely to report very good health, and 8.2 percentage points more likely to report bad or poor health. Individuals with a disability are 2.6 percentage points less likely to report good and 2.5 percentage points more likely to report poor or bad SRH as well as 2.1 percentage points more likely to report satisfactory health.

The same direction of effects applies to the variable doctor visits. On average, the probability of reporting very good health decreases by 2.0 percentage points or 3.8 percentage points for good SRH, if doctor visits increase by one unit. Reporting a lower SRH of poor or bad is on average 4.1 percentage points more likely.

If overnight- hospital-stays apply, the likelihood of reporting poor or bad SRH increases on average 2.6 percentage points and 2.9 percentage points to report satisfactory SRH. Individuals are on average 0.9 percentage points less likely to report very good and 4.6 percentage points less likely to report good SRH.

6.2.2.2 Effect Objective SES

Although the results show indications of health disparities based on SES, the observed effects are quite small. Certain measures, such as employment status, even exhibit no significance in the empirical results which is consistent with the OPM results. Among the objective SES measures the AMEs significance varies among the four SRH ratings.

While income was found significant only for quintile 5 compared to quintile 1 based on the OPM estimation, a significant effect is found for poor or bad SRH in all quintiles based on the GOPM estimation. Being in the 5th income quintile compared to the 1st decreases the likelihood of reporting poor or bad SRH on average by 1 percentage point. Being in the 3rd income quintile compared to the 1st quintile increases the probability of reporting good health on average by 1.7 percentage points. Health disparities between income quintiles seem to be especially relevant for the lowest SRH.

Higher levels of occupational prestige, measured by the ISEI score, significantly influence the probability of rating a certain SRH status in most quintiles. On average, individuals in the highest ISEI quintile are 1.3 percentage points less likely to report '[1] Poor or Bad' SRH and 2.8 percentage points less likely to report '[2] Satisfactory' SRH compared to individuals in the lowest ISEI quintile. Those individuals are on average 3.3 percentage points more likely to report '[3] Good' SRH compared to participants in the lowest quintile. On average, being in the

3rd ISEI quintile compared to the 1st, increases the likelihood of reporting '[3] Good' SRH by 4.6 percentage points.

In line with previous findings, a higher educational status is associated with a better SRH outcome. Compared to the AMEs based on the OPM, the effect of ISCED is found less significant for the likelihood of reporting '[4] Very Good' health under the GOPM. Reporting '[1] Poor or Bad' becomes 2.4 percentage points less likely with '[4] First and Second Stage of Tertiary Education' as compared to '[1] Primary Education or Lower Secondary Education'. The same applies to the reporting of '[2] Satisfactory' health. Individuals who completed the '[4] First and Second Stage of Tertiary Education' are on average 3.3 percentage points more likely to report good SRH compared to those with only '[1] Primary Education or Lower Secondary Education'. Likewise, they are on average 1.5 percentage points more likely to '[4] Very Good' SRH compared to individuals who only completed primary education. Individuals with a higher educational status can be assumed to have a higher health literacy which influences their SRH. Furthermore, education is linked to health-promoting behavior such as healthy diet and regular exercise (Reisi et al. (2014)).

6.2.2.3 Effect Satisfaction Ratings

Considering the estimated AMEs of the subjective satisfaction variables, significance varies between OPM and GOPM. The results suggest that housing satisfaction does not have a significant impact on the probability of a SRH rating of '[1] Poor or Bad' and '[4] Very Good'. It has however found to be highly significant for the probability of reporting '[2] Satisfactory' and '[3] Good' SRH. On average, the probability of reporting satisfactory health increases 0.5 percentage point and the probability of rating satisfactory health decreases by the same percentage, if the subjective housing satisfaction increases by one unit.

Income satisfaction is found to not have a significant impact on the probability of reporting '[1] Poor or Bad' and '[2] Satisfactory' health. The individual perception of income only significantly influences the probability of rating the highest SRH category. If income satisfaction increases by one unit, people are on average 0.5 percentage points more likely to report '[4] Very Good' SRH. In contrast, income satisfaction was found to have a significant effect on the probability of rating each SRH outcome based on the OPM. Hence, an individual with an income satisfaction of 10 is on average 4.5 percentage points more likely to report '[4] Very Good' SRH, compared to an individual who with an extreme income dissatisfaction, i.e., income satisfaction reporting of 1.

Just like based on the OPM, The AMEs of work satisfaction are significant for all SRH categories. On average, a one unit increase in work satisfaction increases the probability of rating '[4] Very Good' SRH by 0.9 percentage points and '[3] Good' SRH by 1.5 percentage points. The likelihood of reporting '[1] Poor or Bad' or '[2] Satisfactory' health decreases by 0.9 and 1.5 percentage points. Thereby, an individual with maximum work satisfaction is on average 8.1 percentage points more likely to report '[4] Very Good' SRH, or 13.5 percentage points to report '[3] Good' SRH, compared to an individual with minimal work satisfaction.

Among the satisfaction ratings, life satisfaction is found to have the strongest influence on the likelihood of rating a certain SRH status. An increase in life satisfaction by one unit, is on average associated with an increase in the probability of rating '[4] Very Good' SRH by 3.4 percentage points, '[3] Good' SRH by 3.1 percentage points. Thus, people with maximal life satisfaction are on average 30.6 percentage points to report '[4] Very Good' SRH compared to individuals with minimal life satisfaction. The probability of rating '[1] Poor or Bad' or '[2] Satisfactory' decreases on average by 2.9 or 3.9 percentage points.

Overall, the results indicate that subjective satisfaction variables, particularly work and life satisfaction, have a strong influence on the probability of rating certain SRH. The AMEs of objective SES measures are overall small, with most remaining below 1 percentage point. Occupational prestige and level of education do play a significant role for the likelihood of reporting most SRH categories. In sum, this highlights the multifaceted dynamics between perceived socioeconomic well-being and objective SES measures, underscoring the differential influence of subjective factors on SRH.

Table 6: Estimated Marginal Effects based on GOPM Estimation

	SRH = 1	*SRH = 2*	*SRH = 3*	*SRH = 4*
Age	.001(.0015)	**.0063***(.0023)**	-.0027(.0024)	**-.0044***(.0014)**
Female	.0015(.0033)	-.0066(.0051)	-.0028(.0054)	**.0069**(.0033)**
BMI	**.0062***(.002)**	**.0205***(.0033)**	**-.0006(.0036)**	**-.0259***(.0024)**
Hospital nights	**.0258***(.0047)**	**.0293***(.0087)**	**-.0462***(.0101)**	-.0087(.007)
Doctor visits	**.0405***(.0014)**	**.018***(.0021)**	**-.0384***(.0024)**	**-.0201***(.0016)**
Disability	**.0254***(.0053)**	**.0212**(.0109)**	**-.0264*(.0154)**	-.0199(.0125)
Chronic disease	**.0681***(.0033)**	**.0867***(.0052)**	**-.0852***(.0063)**	**-.0696***(.0046)**
Daily difficulty	**.0817***(.0033)**	**.1078***(.0053)**	**-.1***(.007)**	**-.0893***(.0056)**
Employment	.0061(.0132)	-.0132(.0214)	-.0016(.0229)	.0094(.0142)
ISEI				
D2_ISEI	**-.0173***(.0051)**	.0036(.0083)	**.0212**(.009)**	.0074(.0059)
D3_ISEI	**-.0208***(.0053)**	-.0111(.0085)	**.0455***(.0092)**	**.0136**(.0059)**
D4_ISEI	**-.0144***(.0054)**	**-.0184**(.0087)**	**.0275***(.0095)**	.0053(.006)
D5_ISEI	**-.0127**(.0063)**	**-.0284***(.0098)**	**.0313***(.0105)**	.0099(.0064)
ISCED				
D2_ISCED	**-.0196***(.0062)**	.0045(.0105)	**.0208*(.0114)**	-.0057(.0073)
D3_ISCED	**-.0216***(.0077)**	-.0154(.0126)	**.0263**(.0136)**	.0107(.0085)
D4_ISCED	**-.0241***(.0071)**	**-.0236**(.0117)**	**.033***(.0126)**	**.0147*(.008)**
Income				
D2_ Income qu.	**-.0092*(.0048)**	**.014*(.0079)**	.0025 (.006)	-.0073(.0054)
D3_ Income qu.	**-.0136***(.0051)**	.0131(.0083)	.0094 (.0089)	-.0088(.0056)
D4_ Income qu.	**-.0088*(.0055)**	-.0004(.0087)	**.0173**(.0093)**	-.0081(.0058)
D5_ Income qu.	**-.0105*(.0060)**	-.0046(.0096)	.0143 (.0101)	.0007(.0061)
Income sat.	-.0013(.001)	-.0008(.0017)	-.0031(.0018)	**.0052***(.0012)**
Work sat.	**-.0088***(.0009)**	**-.0148***(.0015)**	**.0145***(.0017)**	**.0091***(.0011)**
Housing sat.	.0004 (.001)	**-.0056***(.0016)**	**.0047***(.0018)**	**.0003(.0011)**
Life satisfaction	**-.0289***(.0011)**	**-.0388***(.002)**	**.0316***(.0023)**	**.0364***(.0016)**
2014	**-.0095**(.004)**	.0021(.0063)	.0094(.0066)	-.0020(.004)
2016	**.0065*(.0037)**	.0076(.0059)	-.008(.0063)	-.0062(.0039)

Note: Rounded to fourth decimal point; Standard error in brackets; * p < 0.1, ** p < 0.05, ***p < 0.01

Figure 9: Graph Average Marginal Effects of Life Satisfaction on SRH (95% Confidence Interval)

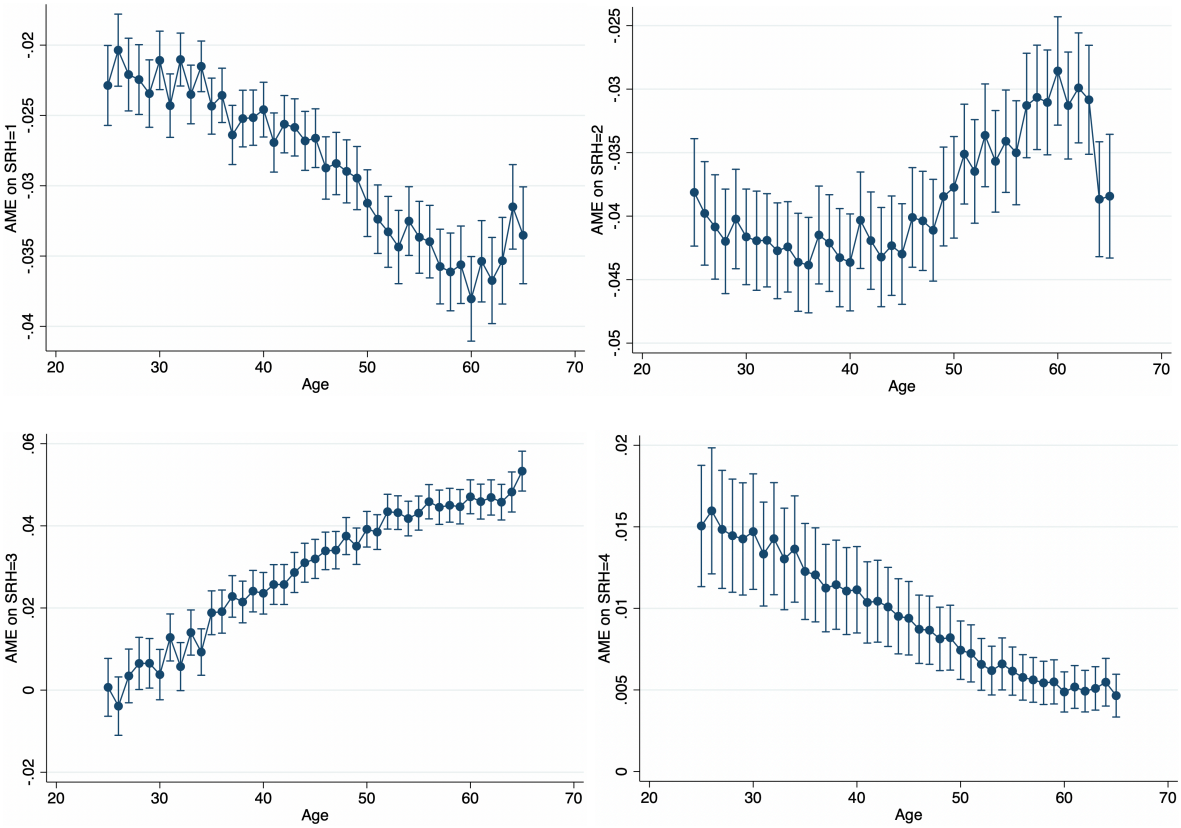


Figure 10 shows the AMEs of life satisfaction by age in the four SRH categories. Each point represents the estimated AME of life satisfaction by age. The AMEs are highly significant (<1%) at all ages for all SRH outcomes except for reporting good health at ages 25, 26, 27 and 30. It can be observed that an increase in life satisfaction influences the likelihood of reporting very good SRH stronger in younger cohorts. The opposite trend can be observed for the likelihood of reporting poor or bad health: The AMEs have a stronger influence on the older half of the sample. On average, a one unit increase in life satisfaction decreases the probability of reporting poor or bad SRH by 3.8 percentage points for 60-year-olds and by 2.3 percentage points for 25-year-olds. The AMEs of good SRH follow a similar trend. With an increase in age, the AMEs increase. The age trend of the AMEs for work satisfaction is presented in Figure A2. The satisfaction variable´s AMEs show a similar trend as life satisfaction. On average, the probability of rating very good health increases by 1.5 percentage points for 25-year-olds if work satisfaction increases by one unit and by only 0.5 percentage points. For satisfactory SRH the age trend is less linear than for other SRH categories. It can be observed that for very good SRH the 95% confidence interval is wider for younger age cohorts compared to older ones. This suggests a greater uncertainty in the estimated AMEs for younger participants.

7 Robustness Analysis

In this section, I assess the stability and reliability of the above results by analyzing the AME´s robustness. As seen, both OPM and GOPM show similar direction of effects and AMEs. Relative consistent results between the OPM and GOPM are a first indication of robustness.

First, I evaluate men and woman separately to see if the independent variable´s AMEs differ between genders. Table A3 with respective results can be found in the Appendix. For a '[4] Very Good' SRH outcome, the differences in AMEs are around or smaller than 0.01 percentage points. The same applies for the other SRH categories. Thus, the results appear to be robust to changes in gender.

Second, I calculate the correlation matrix for the variables in the model to check for the presence of collinearity in the model. High correlation coefficients with a value close to 1 or -1 between two variables could indicate a collinearity problem. Overall, Table A4 does not show any signs of collinearity between the variables (see Appendix). Life satisfaction and SRH are the two variables with the highest collinearity of 0.410. Same applies for life satisfaction and housing satisfaction (CR=0.428), work satisfaction (CR=0.411) and income satisfaction (CR=0.349). As depicted in Figure 6, this relationship is not surprising as all those variables were assumed to influence life satisfaction. Housing satisfaction is found to be correlated with income satisfaction by 0.409. Intuitively, this relationship makes sense as the quality of housing often depends on an individual´s income.

Third, I examine the model under a different specification. For this I estimate a Finite Mixture Model (FMM) OPM to control for unobserved heterogeneity among survey participants. Opposed to commonly used fixed- or random-effects model, the FMM does not impose common slopes for all individuals, i.e., not all share the same marginal effects and characteristics (Llorca et. al (2019)). As FMMs require heterogeneity in the data, they are popular when analyzing skewed or asymmetrical data.

FMMs are probabilistic models that combine multiple density function in the data. The observed SRH responses are assumed to originate from g distinct classes (f_1, f_2, ..., f_g) in proportions represented by probabilities π_1, π_2, ..., π_g (StataCorp. (2017)). A g-component finite mixture model has density (StataCorp. (2017)):

$$f(y) = \sum_{i=1}^{g} \pi_i f_i(y|\, x'\beta_i) \qquad \text{with} \quad 0 \leq \pi_i \leq 1; \sum \pi_i = 1 \tag{10}$$

As the set of available explanatory variables might not fully explain the SRH rating, this can introduce unobserved heterogeneity and a potential bias.

A finite mixture model for ordered data, is an extension of the GOPM and OPM (Everitt and Merette (1990); Uebersax (1999); Boes and Winkelmann (2006b)). The observed individuals are assumed to consist of distinct latent classes, whereby the distributional assumption of the standard model and implied homogeneity are relaxed (Boes and Winkelmann (2006b)). For each class a set of parameters is estimated, and individuals are assigned to a specific class based on their likelihood of being a member (Lanza et al. (2013)).

Thus, in the FMOPM the number of obtained probits equals the number of classes. For this, different groups of survey participants are assumed based on their responses and characteristics. Both represent distinct segments of survey participants who exhibit different patterns of SRH and its associated factors. The individual heterogeneity between survey participants is inherently unobservable. In the first step the latent class probabilities are estimated. The second step estimates a OPM within each latent class using specified count variables and other predictors. Thus, in the employed FMOPM, the number of obtained probits equals the number of classes identified (Llorca et al. (2020)).

The estimated FMOPM uses the goodness of fit to allocate the individuals to the classes. Results indicate a similar statistical associations of SES indicators and objective health measures as found with the OPM and FFM estimation. An increase in objective health outcome is found to increase the SRH score, i.e., improve one's SRH (see Appendix Table A5). AMEs for objective health status are all highly significant and similar (≈ 1 percent point deviation) to the AMEs estimated based on GOPM (see Table A6). Employment is insignificant based on the FMOPM. Income quintiles are found significant for '[1] Low or Poor' for all SRH except for the 2nd quintile. Based on GOPM AMEs were found significant for poor or bad SRH in all quintiles. ISEI quintile and ISCED have similar AMEs with deviations <1 percent point. Income satisfaction influences the likelihood of rating all four SRH categories under the FMOPM. This is an interesting finding which suggests that income satisfaction might indeed have a significant effect on SRH. AMEs for work and life satisfaction are like the ones under the GOPM estimation. However, housing satisfaction is significant for all except poor or bad SRH under the GOPM and only for satisfactory and very good SRH under the FMOPM.

In sum, the FMOPM specification suggests overall robustness for objective health and SES variables. However, indications for income satisfaction and income quintiles to be sensitive to the initial modeling choices are found.

8 Limitations

As any empirical analysis, my analysis has some limitations that need to be pointed out. Health is a multi-layered construct and as such difficult to measure. People are heterogenous and influenced by subjectivity which affects their understanding and rating of what is good or bad health. The model aimed to account for the reverse causality of health-influencing satisfaction variables by analyzing longitudinal data. The results are based on high-quality survey data from the GSOEP.

However, effects due to the endogeneity of the relationship between SES and health might not be fully entangled as, i.e., genetic health components remain unobserved. Furthermore, health risk factors such as consumption of alcohol and drugs as well as smoking behavior are not included in the analysis. No biographic information about parental background and upbringing of the survey participants are available. Moreover, sample selection and the high number of non-response items might have biased the results. The GSOEP does not offer much information on individual health affecting behaviors. Aspects such as the physical activity as well as eating habits would offer additional explanatory value.

In addition, the findings may not be applicable to other countries. Cultural factors can influence response patterns and the role of subjectivity. Moreover, public health systems differ between countries. This might lead to objective SES such as income play a more important role for SRH in countries with weaker social security systems than Germany.

Moreover, some degree of collinearity was observed in the data between life satisfaction and other satisfaction measures. It is plausible that income, housing, and work satisfaction are correlated with unobserved characteristics that make individuals similarly sensitive to subjective perception of their health. Furthermore, it can be assumed that there is a reverse causality between life satisfaction and SRH.

9 Conclusion

This thesis improves the understanding of the relationship between SRH, objective health and SES, as well as subjective measures of satisfaction by analyzing German survey data from 2014, 2016 and 2018. The results indicate that measures of satisfaction with life circumstances impact SRH. Exhibiting low job or life satisfaction increases the likelihood of reporting worse health outcomes. Exhibiting a higher dissatisfaction with of parts of SES, makes it generally more likely to report low SRH, i.e., experience a more adverse health outcome. The potential psychological effect of feelings of financial security on SRH was found significant. However, the robustness check suggests that this might be sensitive to the choice of model. The objective SES measures show some indications of health disparities based on, i.e., education, occupational prestige, and income quintile in some SRH categories, the observed effects are quite small. The strong effect of objective health status on SRH was confirmed. Overall, the thesis highlights the importance of not only considering objective measures of socioeconomic standing but also subjective well-being and satisfaction measures when analysing SRH outcomes.

Empirical evidence on the relationship between SES, satisfaction with socioeconomic life circumstances, and SRH is important for at least two reasons. First, it provides a more comprehensive understanding of health disparities. Incorporating measures as satisfaction with income, work, and life, allows for a more nuanced examination of how perception of SES influences health. This can help researchers to anticipate health issues in specific groups and to facilitate early interventions and preventive measures. Second, empirical evidence can raise more awareness about the social determinants of SRH and support social policy decision making. Social policy interventions could shift their focus on promoting mental and emotional health to improve life satisfaction. Work satisfaction was previously found to have a strong association with mental health (Faragher et al. (2005)). Addressing work satisfaction could impact overall well-being positively and contribute to a healthier population. This could include measures such a stress reduction or more workplace flexibility. Interestingly, there is a threshold effect for income satisfaction which was found to only have significant effects on reporting very good SRH. Future research could investigate a longitudinal study spanning a longer time frame. Investigate how the relationships between the independent variables and SRH evolve over different periods is of interest.

Furthermore, causal inference methods, such as instrumental variable analysis or propensity score matching, could be applied to strengthen the evidence for causal relationships between the independent variables and SRH.

References

Adler, N. E., & Newman, K. (2002). Socioeconomic disparities in health: pathways and policies. Health affairs, 21(2), 60-76.

Adler, N.E., & Rehkopf. D.H. (2008). US disparities in health: descriptions, causes, and mechanisms. Annu Rev Public Health, 29:235–52.

Avvisati, F. (2020). The measure of socio-economic status in PISA: A review and some suggested improvements. Large-Scale Assessments in Education, 8(1), 1-37.

Barrett, A. E. (2003). Socioeconomic status and age identity: The role of dimensions of health in the subjective construction of age. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 58(2), S101-S109.

Boes, S., & Winkelmann, R. (2006a). The effect of income on positive and negative subjective well-being (No. 0605). Working paper.

Boes, S., & Winkelmann, R. (2006b). Ordered response models. Allgemeines Statistisches Archiv, 90, 167-181.

Bombak, A. E. (2013). Self-rated health and public health: a critical perspective. Frontiers in public health, 1, 15.

Buechel, F., & Mertens, A. (2004). Overeducation, undereducation, and the theory of career mobility. Applied economics, 36(8), 803-816.

Johnston, C., McDonald, J., & Quist, K. (2020). A generalized ordered Probit model. Communications in Statistics-Theory and Methods, 49(7), 1712-1729.

Cameron, A. C., & Trivedi, P. K. (2005). Microeconometrics: methods and applications. Cambridge university press.

Choi, Y., Kim, J. H., & Park, E. C. (2015). The effect of subjective and objective social class on health-related quality of life: new paradigm using longitudinal analysis. Health and quality of life outcomes, 13(1), 1-11.

Cialani, C., & Mortazavi, R. (2020). The effect of objective income and perceived economic resources on self-rated health. International journal for equity in health, 19, 1-12.

Coustaury, C., Jeannot, E., Moreau, A., Nietge, C., Maharani, A., Richards, L., & Präg, P. (2022). Subjective Socioeconomic Status and Self-Rated Health in the English Longitudinal Study of Aging. A Fixed-Effects Analysis. SocArXiv doi, 10.

Cullinan, J., & Gillespie, P. (2016). Does Overweight and Obesity Impact on Self-Rated Health? Evidence Using Instrumental Variables Ordered Probit Models. Health economics, 25(10), 1341-1348.

Cundiff, J. M., & Matthews, K. A. (2017). Is subjective social status a unique correlate of physical health? A meta-analysis. Health Psychology, 36(12), 1109.

Diener, E., & Chan, M. Y. (2011). Happy people live longer: Subjective well-being contributes to health and longevity. Applied Psychology: Health and Well-Being, 3, 1–43.

Diener, E., Inglehart, R., & Tay, L. (2013). Theory and validity of life satisfaction scales. Social indicators research, 112, 497-527.

DIW Berlin (2023). Research Infrastructure 'Socio-Economic Panel (SOEP)'. Available at: https://www.diw.de/en/diw_01.c.615551.en/research_infrastructure__socio-economic_panel__soep.html (Last accessed: 31.07.2023)

Dwyer, D. S., & Mitchell, O. S. (1999). Health problems as determinants of retirement: Are self-rated measures endogenous?. Journal of health economics, 18(2), 173-193.

Everitt, B. S., & Merette, C. (1990). The clustering of mixed-mode data: a comparison of possible approaches. Journal of Applied Statistics, 17(3), 283-297.

Fallowfield, L. (2009). What is quality of life. Health Economics, 1(8), 1–8.

Faragher, E. B., Cass, M., & Cooper, C. L. (2005). The relationship between job satisfaction and health: a meta-analysis. Occupational and environmental medicine, 62(2), 105-112.

Ford, M. T., Cerasoli, C. P., Higgins, J. A., & Decesare, A. L. (2011). Relationships between psychological, physical, and behavioural health and work performance: A review and meta-analysis. Work & Stress, 25(3), 185-204.

Frey, B. S. &A. Stutzer (2000): Maximizing Happiness?, German Economic Review, (1), 145-167.

Frijters, P., Haisken-DeNew, J. P., & Shields, M. A. (2005). The causal effect of income on health: Evidence from German reunification. Journal of health economics, 24(5), 997-1017.

Ganzeboom, H. B. (2010). A new International Socio-Economic Index (ISEI) of occupational status for the International Standard Classification of Occupation 2008 (ISCO-08) constructed with data from the ISSP 2002–2007. In annual conference of international social survey programme, Lisbon (Vol. 1).

Güneri, Ö. İ., Durmuş, B., & İncekırık, A. (2022). Ordered Choice Models: Ordinal Logit and Ordinal Probit. JIS, 6(2).

Greene, W.H., & Hensher, D.A. (2010). Modeling ordered choices: a primer. Cambridge University Press.

Hayo, B., & Seifert, W. (2003). Subjective economic well-being in Eastern Europe. Journal of economic psychology, 24(3), 329-348.

Himes, J. H. (2009). Challenges of accurately measuring and using BMI and other indicators of obesity in children. Pediatrics, 124(Supplement_1), s3-s22.

Hoebel, J., & Lampert, T. (2020). Subjective social status and health: Multidisciplinary explanations and methodological challenges. Journal of Health Psychology, 25(2), 173-185.

Hovanec, J., Siemiatycki, J., Conway, D. I., Olsson, A., Stücker, I., Guida, F., ... & Behrens, T. (2018). Lung cancer and socioeconomic status in a pooled analysis of case-control studies. PloS one, 13(2), e0192999.

Idler, E. L., Hudson, S. V., & Leventhal, H. (1999). The meanings of self-ratings of health: A qualitative and quantitative approach. Research on aging, 21(3), 458-476.

Jeffrey, J., Klomhaus, A., Enenbach, M., Lester, P., & Krishna, R. (2020). Self-report rating scales to guide measurement-based care in child and adolescent psychiatry. Child and Adolescent Psychiatric Clinics, 29(4), 601-629.

Johnston, C., McDonald, J., & Quist, K. (2020). A generalized ordered Probit model. Communications in Statistics-Theory and Methods, 49(7), 1712-1729.

Kezer, M., & Cemalcilar, Z. (2020). A comprehensive investigation of associations of objective and subjective socioeconomic status with perceived health and subjective well-being. International Review of Social Psychology, 33(1), 1-11.

Knoechelmann, A., Seifert, N., Guenther, S., Moor, I., & Richter, M. (2020). Income and housing satisfaction and their association with self-rated health in different life stages. A fixed effects analysis using a German panel study. BMJ open, 10(6), e034294.

Lanza, S. T., & Rhoades, B. L. (2013). Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. Prevention science, 14(2), 157-168.

Layes, A., Asada, Y., & Kephart, G. (2012). Whiners and deniers–What does self-rated health measure?.Social science & medicine, 75(1), 1-9.

Lampert, T., Kroll, L., Müters, S., & Stolzenberg, H. (2013). Measurement of socioeconomic status in the German Health Interview and Examination Survey for Adults (DEGS1). Bundesgesundheitsblatt-Gesundheitsforschung-Gesundheitsschutz, 56, 631-636.

Lechner, M. (2009). Long-run labour market and health effects of individual sports activities. Journal of health economics, 28(4), 839-854.

Li, S., Zhang, Q., & Muennig, P. (2018). Subjective assessments of income and social class on health and survival: An enigma. SSM-population Health, 6, 295-300.

Lindeboom, M., & van Doorslaer, E. (2004). Cut-point shift and index shift in self-reported health. Journal of Health Economics, 23(6), 1083–1099.

Macleod, J., Smith, G. D., Metcalfe, C., & Hart, C. (2005). Is subjective social status a more important determinant of health than objective social status? Evidence from a prospective observational study of Scottish men. Social science & medicine, 61(9), 1916-1929.

Marmot, M., Allen, J., Bell, R., Bloomer, E., & Goldblatt, P. (2012). WHO European review of social determinants of health and the health divide. The Lancet, 380(9846), 1011-1029.

Marques-Vidal P, Ravasco P, Paccaud F. (2012). Differing trends in the association between obesity and self-reported health in Portugal and Switzerland. Data from national health surveys 1992–2007. BMC Public Health 12: 588.

McFadden, E., Luben, R., Bingham, S., Wareham, N., Kinmonth, A. L., & Khaw, K. T. (2008). Social inequalities in self-rated health by age: Cross-sectional study of 22 457 middle-aged men and women. BMC public health, 8(1), 1-8.

Meireles, A. L., Xavier, C. C., de Souza Andrade, A. C., Proietti, F. A., & Caiaffa, W. T. (2015). Self-rated health among urban adolescents: the roles of age, gender, and their associated factors. PLoS One, 10(7), e0132254.

Meisters, R., Putrik, P., Westra, D., Bosma, H., Ruwaard, D., & Jansen, M. (2023). Two sides of the same coin? Absolute income and perceived income inadequacy as social determinants of health. International Journal for Equity in Health, 22(1), 128.

Miething, A. (2013). A matter of perception: Exploring the role of income satisfaction in the income–mortality relationship in German survey data 1995–2010. Social Science & Medicine, 99, 72-79.

Mirowsky, J. (2017). Education, social status, and health. Routledge.

Miyamoto, A., & Wicht, A. (2020). Developmental trajectories of the socioeconomic status of occupational aspirations during adolescence. Journal of Adolescence, 84, 26-35.

Molarius, A., Berglund, K., Eriksson, C., Lambe, M., Nordström, E., Eriksson, H. G., & Feldman, I. (2007). Socioeconomic conditions, lifestyle factors, and self-rated health among men and women in Sweden. The European Journal of Public Health, 17(2), 125-133.

Moro-Egido, A. L., Navarro, M., & Sánchez, A. (2022). Changes in subjective well-being over time: Economic and social resources do matter. Journal of Happiness Studies, 23(5), 2009-2038.

Muhammad, T., & Maurya, P. (2023). Gender differences in the association between perceived income sufficiency and self-rated health among older adults: A population-based study in India. Journal of Women & Aging, 35(2), 168-182.

Neubert, M., Süssenbach, P., Rief, W., & Euteneuer, F. (2019). Unemployment and mental health in the German population: the role of subjective social status. Psychology research and behavior management, 557-564.

Lago, S., Cantarero, D., Rivera, B., Pascual, M., Blázquez-Fernández, C., Casal, B., & Reyes, F. (2018). Socioeconomic status, health inequalities and non-communicable diseases: a systematic review. Journal of Public Health, 26, 1-14.

Pavot, W., & Diener, E. (2008). The satisfaction with life scale and the emerging construct of life satisfaction. The journal of positive psychology, 3(2), 137-152.

Präg, P., Mills, M. C., & Wittek, R. (2016). Subjective socioeconomic status and health in cross-national comparison. Social Science & Medicine, 149, 84-92.

Präg, P. (2020). Subjective socio-economic status predicts self-rated health irrespective of objective family socio-economic background. Scandinavian Journal of Public Health, 48(7), 707-714.

Quesnel–Vallée, A. (2007). Self-rated health: caught in the crossfire of the quest for 'true' health? International Journal of Epidemiology, 36(6), 1161-1164.

Reisi, M., Javadzade, S. H., Heydarabadi, A. B., Mostafavi, F., Tavassoli, E., & Sharifirad, G. (2014). The relationship between functional health literacy and health promoting behaviors among older adults. Journal of education and health promotion, 3.

Reyes Fernández, B., Rosero-Bixby, L., & Koivumaa-Honkanen, H. (2016). Effects of self-rated health and self-rated economic situation on depressed mood via life satisfaction among older adults in Costa Rica. Journal of aging and health, 28(2), 225-243.

Ross, C. E., & Mirowsky, J. (2010). Why education is the key to socioeconomic differentials in health. Handbook of medical sociology, 6, 33-51.

Schneider, U., Pfarr, C., Schneider, B. S., & Ulrich, V. (2012). I feel good! Gender differences and reporting heterogeneity in self-assessed health. The European Journal of Health Economics, 13, 251-265.

Schröder, C., König, J., Fedorets, A., Goebel, J., Grabka, M. M., Lüthen, H., ... & Liebig, S. (2020). The economic research potentials of the German Socio-Economic Panel study. German Economic Review, 21(3), 335-371.

Schwarze, J. (2003). Using panel data on income satisfaction to estimate equivalence scale elasticity. Review of Income and Wealth, 49(3), 359-372.

Senik, C. (2009). Direct evidence on income comparisons and their welfare effects. Journal of Economic Behavior & Organization, 72(1), 408-424.

Singh-Manoux, A., Adler, N. E., & Marmot, M. G. (2003). Subjective social status: its determinants and its association with measures of ill-health in the Whitehall II study. Social science & medicine, 56(6), 1321-1333.

Skopek, J., & Munz, M. (2016). Life-Course Data and the Longitudinal Classification of Education. In Methodological Issues of Longitudinal Surveys: The Example of the National Educational Panel Study (pp. 669-690). Wiesbaden: Springer Fachmedien Wiesbaden.

StataCorp, L. L. C. (2017). STATA finite mixture models reference manual. StataCorp LLC: College Station, TX, USA.

Uebersax, J. S. (1999). Probit latent class analysis with dichotomous or ordered category measures: Conditional independence/dependence models. Applied Psychological Measurement, 23(4), 283-297.

Warr, D., Feldman, P., Tacticos, T., & Kelaher, M. (2009). Sources of stress in impoverished neighbourhoods: insights into links between neighbourhood environments and health. Australian and New Zealand journal of public health, 33(1), 25-33.

Wilkinson, R. G. (1999). Health, hierarchy, and social anxiety. Annals of the New York Academy of sciences, 896(1), 48-63.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. The Stata Journal, 6(1), 58-82.

Zell, E., Strickhouser, J. E., & Krizan, Z. (2018). Subjective social status and health: A meta-analysis of community and society ladders. Health Psychology, 37(10), 979.

Appendix

Figure A1: Boxplot of ISEI Score

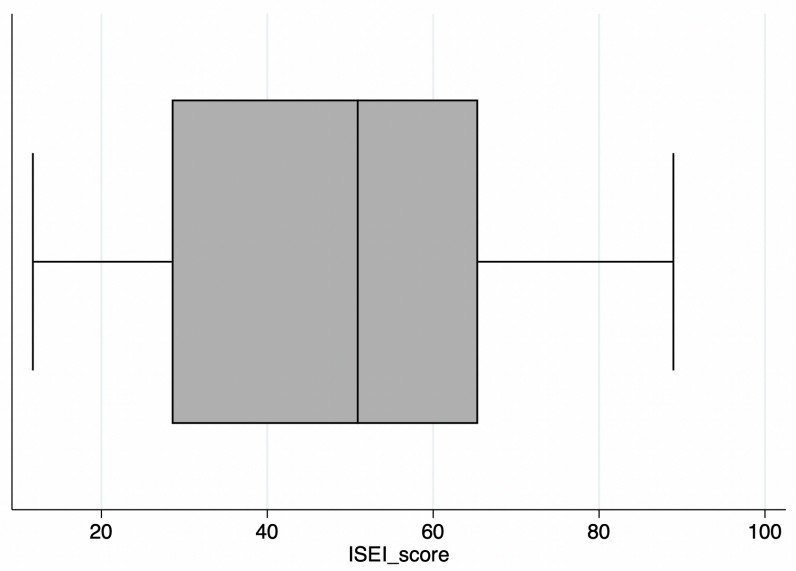
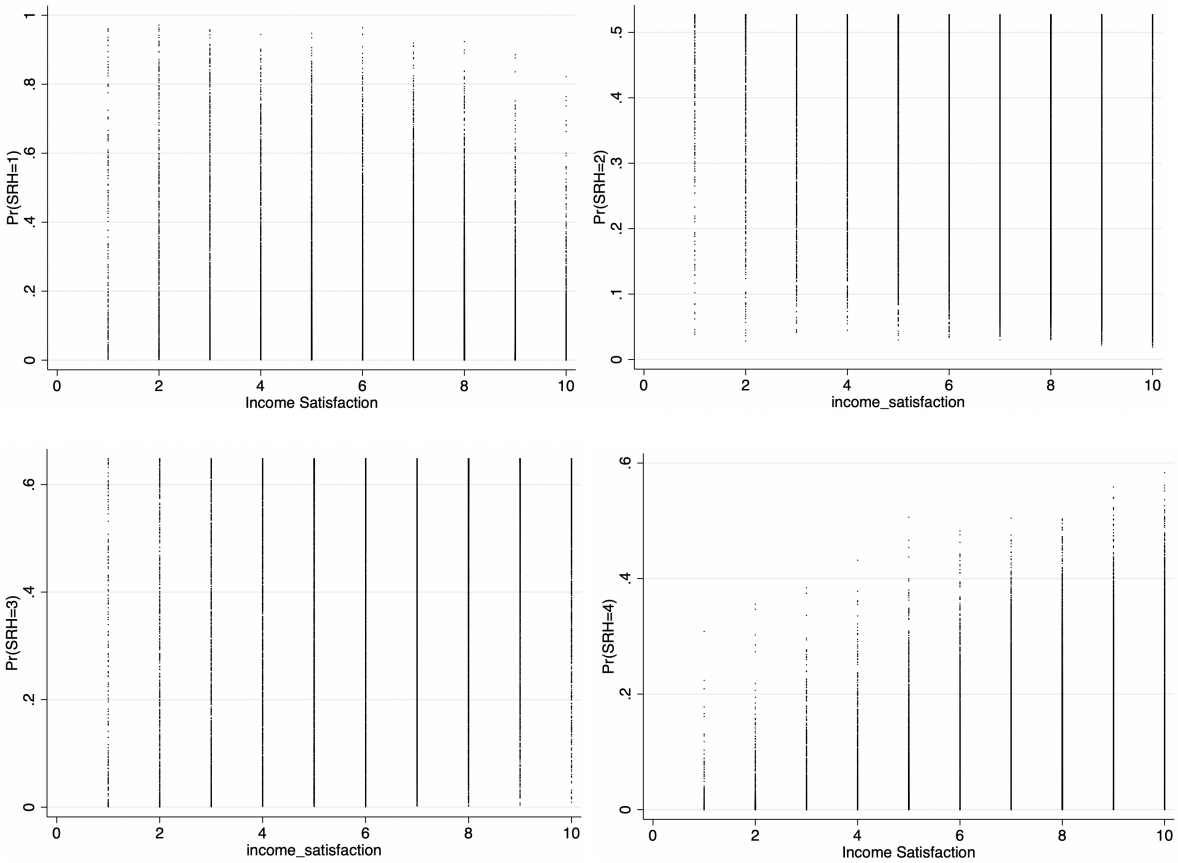


Figure A2: Scatterplot of Income Satisfaction and Predicted Probability of SRH (Based on GOPM Estimation)



Note: For predicted '[4] Very Good' SRH outcomes, the concentration of high-income satisfaction is considerably higher while the opposite is true for '[1] Poor or Bad' SRH ratings. This trend is less pronounced in the two middle SRH levels. Those trends are indicators for objective SES measures and subjective dissatisfaction influencing the probability of reporting a certain SRH.

Figure A3: Average Marginal Effects of Work Satisfaction on SRH by Age

(with 95% Confidence Interval)

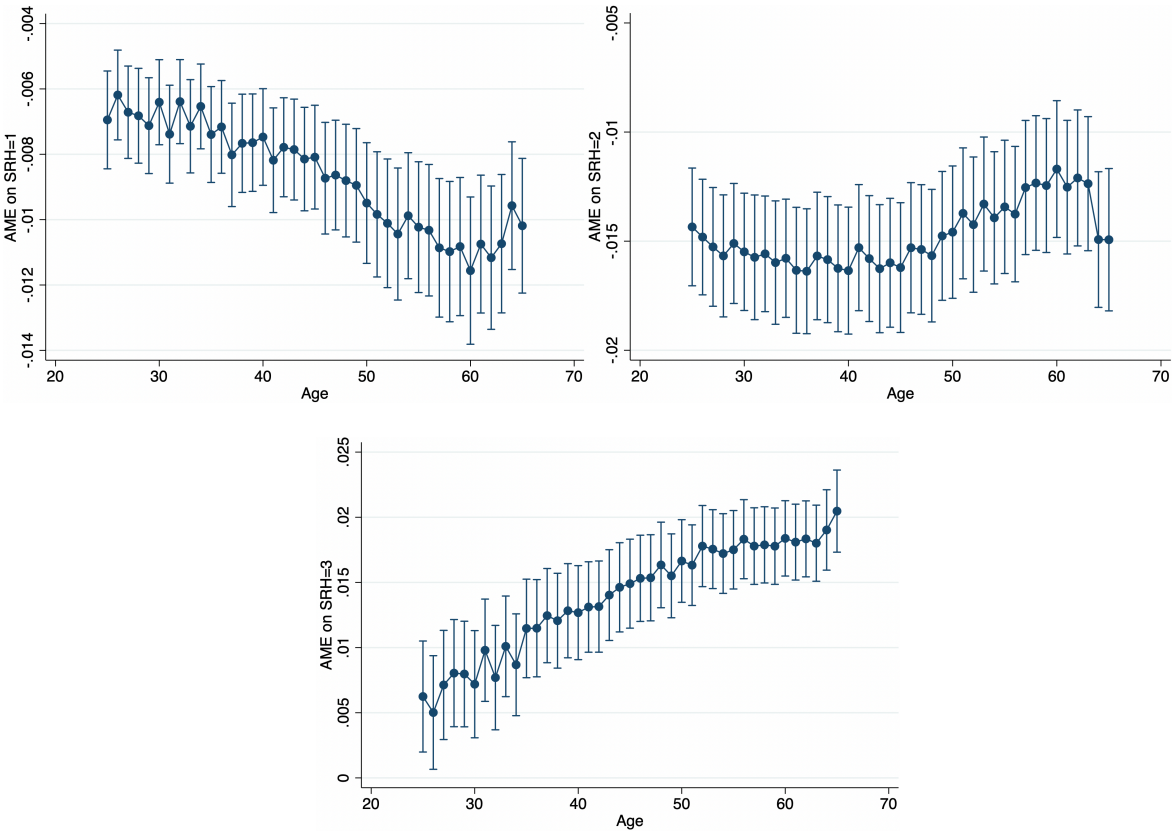


Table A1: Brant Test of Parallel Regression Assumption

(Based on OLM Estimation)

	chi2	p>chi2	df
All	**511.24**	**0.000**	**38**
age	**3.64**	**0.162**	**2**
age2	**0.63**	**0.731**	**2**
female	**0.59**	**0.744**	**2**
BMI	**48.08**	**0.000**	**2**
hospitalnights	**4.71**	**0.095**	**2**
visits_doctor	**121.63**	**0.000**	**2**
presence_disability	**0.35**	**0.839**	**2**
presence_chronic_disease	**0.82**	**0.663**	**2**
difficulty_daily	**6.45**	**0.040**	**2**
employment	**1.18**	**0.554**	**2**
ISEI_quintile	**3.61**	**0.165**	**2**
ISCED	**6.39**	**0.041**	**2**
income_quintile	**1.56**	**0.459**	**2**
income_satisfaction	**8.23**	**0.016**	**2**
satisfaction_work	**2.87**	**0.239**	**2**
satisfaction_housing	**11.23**	**0.004**	**2**
life_satisfaction	**57.52**	**0.000**	**2**
year_dummy2014	**4.27**	**0.118**	**2**
year_dummy2016	**0.09**	**0.956**	**2**

Note: The significant test statistic provides evidence that the parallel regression assumption has been violated. Thus, the relationship between each outcome categories and the predictors is not parallel. This suggests the application of a more genialized model.

Table A2: Coefficient Output based on OPM Estimation in Stata

```
Iteration 0:   log likelihood = -35684.542
Iteration 1:   log likelihood =  -28794.97
Iteration 2:   log likelihood = -28730.135
Iteration 3:   log likelihood =  -28729.98
Iteration 4:   log likelihood =  -28729.98

Ordered probit regression                       Number of obs =   29,817
                                                LR chi2(27)   = 13909.12
                                                Prob > chi2   =   0.0000
Log likelihood = -28729.98                      Pseudo R2     =   0.1949
```

selfrated_health	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	-.0325785	.0060728	-5.36	0.000	-.044481	-.0206761
age2	.0002398	.0000668	3.59	0.000	.0001089	.0003707
female	.0205908	.0138044	1.49	0.136	-.0064653	.0476468
BMI	-.1003177	.0090343	-11.10	0.000	-.1180246	-.0826109
hospitalnights	-.1713482	.0238988	-7.17	0.000	-.218189	-.1245075
visits_doctor	-.2119237	.0060921	-34.79	0.000	-.2238641	-.1999833
presence_disability	-.1567921	.0295594	-5.30	0.000	-.2147274	-.0988568
presence_chronic_disease	-.5153067	.0153918	-33.48	0.000	-.5454741	-.4851393
difficulty_daily	-.6172906	.0160598	-38.44	0.000	-.6487673	-.5858139
employment	.0265298	.0569706	0.47	0.641	-.0851305	.1381901
q2_ISEI_quintile	.0381466	.0222758	1.71	0.087	-.0055131	.0818062
q3_ISEI_quintile	.057846	.0228655	2.53	0.011	.0130305	.1026616
q4_ISEI_quintile	.0855249	.0236889	3.61	0.000	.0390956	.1319543
q5_ISEI_quintile	.1147399	.0264702	4.33	0.000	.0628592	.1666206
q2_ISCED	.0549594	.0285484	1.93	0.054	-.0009945	.1109133
q3_ISCED	.1270726	.0342041	3.72	0.000	.0600337	.1941114
q4_ISCED	.1565691	.0316896	4.94	0.000	.0944587	.2186795
q2_income_quintile	-.0062122	.0212807	-0.29	0.770	-.0479216	.0354971
q3_income_quintile	.0100495	.0221577	0.45	0.650	-.0333788	.0534777
q4_income_quintile	.0205622	.023294	0.88	0.377	-.0250932	.0662176
q5_income_quintile	.0532186	.0254702	2.09	0.037	.0032978	.1031393
income_satisfaction	.0129979	.0044362	2.93	0.003	.0043032	.0216927
satisfaction_work	.071787	.0040589	17.69	0.000	.0638318	.0797423
satisfaction_housing	.0066047	.0043374	1.52	0.128	-.0018965	.0151059
life_satisfaction	.228561	.0054	42.33	0.000	.2179773	.2391448
year_dummy2014	.0259481	.0166937	1.55	0.120	-.006771	.0586673
year_dummy2016	-.0456598	.01581	-2.89	0.004	-.0766468	-.0146728
/cut1	-1.133239	.1549841			-1.437003	-.8294762
/cut2	.3025152	.1549468			-.001175	.6062053
/cut3	2.164365	.1551434			1.86029	2.46844

Table A3: Differences in Average Marginal Effects between Genders

(based on GOPM estimation)

	SRH= 1	*SRH = 2*	*SRH= 3*	*SRH= 4*
age				
female	.0009(.0014)	.0064***(.0022)	-.0023(.0024)	-.0049***(.0014)
male	.0010(.0016)	.0062***(.0023)	-.0024(.0024)	-.0048***(.0014)
BMI				
female	.0056***(.0019)	.0210***(.0033)	-.0004(.0037)	-.0263***(.0024)
male	.0067***(.0022)	.0200***(.0034)	-.0008(.0037)	-.0259***(.0024)
hospital nights				
female	.0235***(.0043)	.0316***(.0085)	-.0463***(.01)	-.0087(.007)
male	.028***(.0051)	.0273***(.0088)	-.0466***(.01)	-.0087(.0069)
doctor visits				
female	.0369***(.0014)	.0215***(.0021)	-.0382***(.0024)	-.0202***(.0016)
male	.0438***(.0016)	.0147***(.0023)	-.0386***(.0024)	-.0199***(.0016)
disability				
female	.0229***(.0048)	.0234**(.0108)	-.0262*(.0155)	-.0201(.0126)
male	.0272***(.0057)	.0192*(.0111)	-.0266*(.0154)	-.0198(.0124)
chronic disease				
female	.0621***(.0031)	.0926***(.0051)	-.0845***(.0064)	-.0701***(.0047)
male	.0738***(.0036)	.0813***(.0053)	-.0859***(.0063)	-.0692***(.0046)
difficulty_daily				
female	.0743***(.0032)	.1148***(.0053)	-.0992***(.0072)	-.0899***(.0058)
male	.0882***(.0037)	.1013***(.0054)	-.1008***(.0071)	-.0887***(.0057)
employment				
female	.0049(.0120)	-.0127(.021)	-.0016(.0229)	.0095(.0143)
male	.0058(.0143)	-.0137(.0218)	-.0015(.0229)	.0094(.0141)
ISEI				
D2 female	-.0053(.0013)	-.0054(.0022)	.0056 (.0051)	.0051 (.0047)
D3 female	-.0151***(.0046)	-.0152***(.0047)	.0159***(.0048)	.0145***(.0044)
D4 female	-.0187***(.0047)	-.0189***(.0048)	.0196***(.0050)	.0179***(.0045)
D5 female	-.0223***(.0056)	-.0225***(.0057)	.0234***(.0059)	.0213***(.0054)
D2 male	-.0040(.0037)	-.005 (.0049)	.0048(.0043)	.0047(.0049)
D3 male	.0002(.0041)	.0003(.0051)	-.0003(.0048)	-.0003(.0049)
D4 male	-.0042(.0043)	-.0056(.0058)	.0049(.0052)	.0049(.0050)
D5 male	-.0092**(.0045)	-.0123**(.0061)	.0107**(.0052)	.0108**(.0053)
ISCED level				
D2 female	-.0133**(.0059)	-.0135***(.0059)	.0140**(.0062)	.0127**(.0057)
D3 female	-.0201***(.0068)	-.0203***(.0069)	.0211***(.0073)	.0193***(.0066)

D4 female	-.0237***(.0065)	-.024***(.0065)	.024***(.0069)	.0228***(.0063)
D2 male	-.0012 (.0050)	-.0016 (.0067)	.0014 (.0058)	.0014 (.0058)
D3 male	-.0149**(.0062)	-.0200**(.0083)	.0174**(.0072)	.0174**(.0073)
D4 male	-.0188***(.0055)	-.0252***(.0030)	.0220***(.0032)	.0221***(.002)
income quantiles				
D2 female	-.0101**(.0042)	-.0103(.0043)	.0106**(.0045)	0097*(.0041)
D3 female	-.0061(.0044)	.0062(.0045)	-.0064(.0046)	-.0058(.0042)
D4 female	-.0009(.0047)	-.0009(.0047)	.001(.005)	.0009(.0045)
D5 female	-.0074(.0051)	-.0074(.0052)	.0078(.0054)	.0071(.0049)
D2 male	-.0090**(.0038)	-.0120**(.0052)	.0105**(.0045)	.0105**(.0045)
D3 male	-.0093**(.0040)	-.0125**(.0054)	.0109**(.0047)	.0109**(.0047)
D4 male	-.0058(.0041)	-.0077(.0056)	.0067(.0048)	.0068(.0049)
D5 male	-.0082*(.0045)	-.0110*(.0061)	.0096*(.0053)	.0097*(.0053)
income satisfaction				
female	-.0012(.0009)	-.0009(.0016)	-.0031*(.0018)	.0052***(.0012)
male	-.0013*** (0.011)	-.0007(.0017)	-.0031*(.0018)	.0052***(.0012)
satisfaction work				
female	-.008***(.0008)	-.0156***(.0015)	.0144***(.0017)	.0092***(.0011)
male	-.0095***(.001)	-.0141***(.0015)	.0146***(.0017)	.0090***(.0011)
satisfaction housing				
female	.0003(.0009)	-.0054***(.0016)	.0049***(.0018)	.0001(.0011)
male	.0004(.001)	-.0054***(.0017)	.0049***(.0018)	.0001(.0011)
life satisfaction				
female	-.0264***(.0011)	-.0412***(.002)	.0309***(.0024)	.0366***(.0017)
male	-.0313***(.0012)	-.0364***(.0020)	.0315***(.0023)	.0361***(.0016)
year 2014				
female	-.0086**(.0036)	.0013(.0062)	.0094(.0066)	-.002(.0041)
male	-.01026**(.0043)	.0029(.0064)	.0094(.0066)	-.002(.0040)
year 2016				
female	.06*(.0034)	.0082(.0058)	-.0079(.0063)	-.0061(.0039)
male	.007*(.0040)	.0071(.0060)	-.0081(.0063)	-.0061(.0038)

*Note: (N=29,817; * p < 0.1, ** p < 0.05, ***p < 0.01)*

Table A4: Correlation Matrix of Dependent and Independent Variables in the Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) SRH	1.00																	
(2) age	-0.19	1.00																
(3) age2	-0.18	0.99	1.00															
(4) female	-0.03	-0.00	-0.00	1.00														
(5) BMI	-0.10	0.10	0.10	-0.18	1.00													
(6) hospital nights	-0.13	0.04	0.037	0.02	0.05	1.00												
(7) visits doctor	-0.34	0.08	0.086	0.14	0.06	0.16	1.00											
(8) presence disability	-0.19	0.144	0.149	-0.02	0.06	0.11	0.18	1.00										
(9) chronic disease	-0.37	0.16	0.16	0.06	0.12	0.12	0.31	0.24	1.00									
(10) difficulty daily	-0.41	0.19	0.20	0.07	0.25	0.10	0.20	0.18	0.27	1.00								
(11) employment	0.01	0.060	0.057	-0.03	-0.00	-0.04	-0.01	-0.03	-0.01	-0.01	1.00							
(12) ISEI quintile	0.12	-0.01	-0.01	0.022	-0.11	-0.03	0.022	-0.03	-0.03	-0.11	0.03	1.00						
(13) ISCED	0.12	0.026	0.026	-0.04	-0.12	-0.03	0.001	-0.05	-0.04	-0.11	0.022	0.57	1.00					
(14) income quintile	0.08	0.181	0.181	-0.04	-0.06	-0.03	0.039	-0.01	-0.02	-0.07	0.09	0.45	0.37	1.00				
(15) income satisfaction	0.24	0.002	0.001	-0.00	-0.08	-0.05	-0.05	-0.06	-0.09	-0.17	0.04	0.23	0.19	0.40	1.00			
(16) satisfaction work	0.29	-0.05	-0.05	0.006	-0.05	-0.05	-0.13	-0.06	-0.12	-0.16	0.008	0.05	0.03	0.04	0.36	1.00		
(17) satisfaction housing	0.17	0.073	0.071	0.006	-0.04	-0.03	-0.03	-0.02	-0.06	-0.11	0.03	0.08	0.07	0.19	0.41	0.25	1.00	
(18) satisfaction life	0.41	-0.08	-0.08	-0.00	-0.07	-0.06	-0.14	-0.11	-0.17	-0.23	0.01	0.09	0.08	0.13	0.43	0.41	0.35	1.00

Note: All values rounded to the second decimal point (N=29,817)

Table A5: Finite Mixture Ordered Probit Estimation

1. Class

	Coefficient	*Std.err.*	*z*	*P>|z|*
age	-.097	0.030	-3.09	0.002
age2	.001	0.000	1.84	0.065
female	.0377	0.066	0.55	0.583
BMI	-.3277	0.050	-6.54	0.000
hospital nights	-.2253	0.137	-1.63	0.103
doctor visits	.0179	0.034	-0.52	0.600
disability	-.2291	0.151	-1.49	0.036
chronic disease	-.5768	0.077	-7.33	0.000
difficulty_daily	-.7592	0.083	-9.24	0.000
employment	.5325	0.301	1.73	0.184
ISEI quintile				
D2_ISEI	.1135	.1234	0.92	0.358
D3_ISEI	.0538	.1204	0.45	0.655
D4_ISEI	.1748	.1239	1.41	0.159
D5_ISEI	.3101	.1322	2.35	0.019
ISCED				
D2_ISCED	.1031	.2037	0.51	0.613
D3_ISCED	.2791	.2246	1.24	0.214
D4_ISCED	.3438	.2161	1.59	0.112
Income quintile				
D2_ Income qu.	.1350	.1084	1.25	0.213
D3_ Income qu.	.4094	.1218	3.36	0.001
D4_ Income qu.	.1558	.1131	1.38	0.169
D5_ Income qu.	.2036	.1243	1.64	0.101
Income satisfaction	.0088	.0253	0.35	0.726
Satisfaction work	.0581	.0257	2.26	0.024

Satisfaction housing	.0562	.0298	1.89	0.052
Life satisfaction	.9298	.0873	10.64	0.000
year 2014	-.0644	.0844	-0.76	0.445
year 2016	-.0610	.0776	-0.79	0.432

cut1	-.2260	.8068
cut2	4.3601	.9295
cut3	6.4913	.9874

2. Class

	Coefficient	*Std.err.*	*z*	*P>|z|*
age	-.097	.030	-1.67	0.095
age2	.001	.0000	1.14	0.252
female	.024	0.066	0.53	0.594
BMI	-.326	0.050	-3.86	0.000
hospital nights	-.236	0.137	-4.69	0.000
doctor visits	.021	0.034	-24.99	0. 000
disability	-.223	0.151	-4.25	0. 000
chronic disease	-.579	0.077	-23.02	0.000
difficulty_daily	-.745	0.083	-9.020	0.000
employment	-.0937	0.301	-1.00	0.315
ISEI quintile				
D2_ISEI	.0229	.0370	0.62	0.537
D3_ISEI	.0726	.0375	1.94	0.053
D4_ISEI	.0730	.0389	1.87	0.061
D5_ISEI	.0734	.0432	1.70	0.089
ISCED				
D2_ISCED	.0472	.0538	0.88	0.381
D3_ISCED	.0967	.0621	1.56	0.120
D4_ISCED	.1246	.0584	2.13	0.033

Income quintile				
D2_ Income qu.	.0318	.0338	0.94	0.347
D3_ Income qu.	.1211	.0360	3.36	0.001
D4_ Income qu.	.0736	.0370	1.99	0.047
D5_ Income qu.	.1244	.0411	3.03	0.002
Income satisfaction	.010	0.025	1.93	0.053
Satisfaction work	.051	0.025	11.33	0.000
Satisfaction housing	.053	0.029	-0.75	0.452
Life satisfaction	.928	0.088	11.53	0.000
year 2014	-.048	0.082	2.06	0.039
year 2016	-.049	0.076	-1.71	0.087

cut1	-1.3651	.2604
cut2	-.1898	.2594
cut3	1.8186	.2616

Table A6: AMEs Finite Mixture Ordered Probit Estimation

		Delta-method dy/dx	std. err.	z	P>|z|	[95% conf.	interval]
age							
	_predict						
	1	.0025821	.0010731	2.41	0.016	.0004788	.0046854
	2	.0060691	.0011888	5.11	0.000	.0037392	.0083991
	3	-.0036794	.0009991	-3.68	0.000	-.0056377	-.0017212
	4	-.0049718	.0009429	-5.27	0.000	-.0068199	-.0031237
age2							
	_predict						
	1	-.0000187	.0000117	-1.60	0.111	-.0000416	4.27e-06
	2	-.0000409	.0000132	-3.11	0.002	-.0000667	-.0000151
	3	.0000258	.0000109	2.37	0.018	4.46e-06	.0000472
	4	.0000337	.0000104	3.23	0.001	.0000133	.0000542
female							
	_predict						
	1	-.0016585	.0024037	-0.69	0.490	-.0063696	.0030526
	2	-.0029337	.0027624	-1.06	0.288	-.008348	.0024805
	3	.0021155	.0022324	0.95	0.343	-.0022599	.0064909
	4	.0024767	.002184	1.13	0.257	-.0018038	.0067573
BMI							
	_predict						
	1	.0088892	.0015636	5.69	0.000	.0058247	.0119538
	2	.0211824	.0018351	11.54	0.000	.0175856	.0247792
	3	-.0127411	.0015117	-8.43	0.000	-.015704	-.0097782
	4	-.0173305	.0014639	-11.84	0.000	-.0201998	-.0144612
hospitalnights							
	_predict						
	1	.0234331	.0041761	5.61	0.000	.015248	.0316182
	2	.0280639	.0053437	5.25	0.000	.0175905	.0385373
	3	-.0264498	.0038593	-6.85	0.000	-.034014	-.0188857
	4	-.0250472	.0041497	-6.04	0.000	-.0331804	-.0169139
visits_doctor							
	_predict						
	1	.0339784	.0010883	31.22	0.000	.0318455	.0361114
	2	.0257075	.0013409	19.17	0.000	.0230794	.0283356
	3	-.034502	.0013136	-26.26	0.000	-.0370766	-.0319273
	4	-.025184	.0011575	-21.76	0.000	-.0274527	-.0229153
presence_disability							
	_predict						
	1	.0239779	.0048496	4.94	0.000	.0144728	.033483
	2	.0286544	.0065352	4.38	0.000	.0158457	.0414631
	3	-.0270488	.0047244	-5.73	0.000	-.0363085	-.0177891
	4	-.0255834	.0051652	-4.95	0.000	-.035707	-.0154598
presence_chronic_disease							
	_predict						
	1	.0695626	.0025821	26.94	0.000	.0645018	.0746235
	2	.0793065	.0031064	25.53	0.000	.0732181	.0853949
	3	-.0774894	.0025768	-30.07	0.000	-.0825398	-.0724389
	4	-.0713797	.002665	-26.78	0.000	-.0766031	-.0661564
difficulty_daily							
	_predict						
	1	.0830028	.0026275	31.59	0.000	.077853	.0881526
	2	.0977184	.0032736	29.85	0.000	.0913022	.1041345
	3	-.0932549	.0026582	-35.08	0.000	-.0984649	-.0880448
	4	-.0874663	.0029023	-30.14	0.000	-.0931547	-.081778

employment						
_predict						
1	.0075114	.0099779	0.75	0.452	-.012045	.0270678
2	-.0173034	.0119116	-1.45	0.146	-.0406498	.0060429
3	-.0017204	.0092361	-0.19	0.852	-.0198228	.016382
4	.0115125	.0093101	1.24	0.216	-.006735	.0297599
q2_ISEI_quintile						
_predict						
1	-.003454	.0039283	-0.88	0.379	-.0111533	.0042452
2	-.0076274	.0047705	-1.60	0.110	-.0169775	.0017226
3	.0047957	.0035946	1.33	0.182	-.0022496	.011841
4	.0062857	.0037032	1.70	0.090	-.0009724	.0135439
q3_ISEI_quintile						
_predict						
1	-.0089223	.0040025	-2.23	0.026	-.0167671	-.0010776
2	-.0092952	.0047451	-1.96	0.050	-.0185955	5.08e-06
3	.0097137	.003695	2.63	0.009	.0024717	.0169558
4	.0085038	.0037195	2.29	0.022	.0012138	.0157939
q4_ISEI_quintile						
_predict						
1	-.009783	.0041623	-2.35	0.019	-.017941	-.0016251
2	-.0152285	.0048584	-3.13	0.002	-.0247507	-.0057063
3	.011945	.0038365	3.11	0.002	.0044255	.0194645
4	.0130666	.0038152	3.42	0.001	.005589	.0205442
q5_ISEI_quintile						
_predict						
1	-.0107323	.0046463	-2.31	0.021	-.0198389	-.0016258
2	-.0218531	.005245	-4.17	0.000	-.0321332	-.0115731
3	.0144267	.0043155	3.34	0.001	.0059685	.0228848
4	.0181588	.0041534	4.37	0.000	.0100183	.0262994
q2_ISCED						
_predict						
1	-.0062567	.0054648	-1.14	0.252	-.0169676	.0044541
2	-.0093642	.0072483	-1.29	0.196	-.0235707	.0048423
3	.007543	.0046461	1.62	0.104	-.0015632	.0166492
4	.0080779	.0053556	1.51	0.131	-.0024189	.0185747
q3_ISCED						
_predict						
1	-.0132692	.0064057	-2.07	0.038	-.0258241	-.0007143
2	-.0224843	.0081074	-2.77	0.006	-.0383744	-.0065941
3	.0166716	.0055759	2.99	0.003	.0057431	.0276001
4	.0190819	.0060732	3.14	0.002	.0071787	.0309851
q4_ISCED						
_predict						
1	-.0169939	.005975	-2.84	0.004	-.0287047	-.0052831
2	-.0282013	.0077278	-3.65	0.000	-.0433474	-.0130552
3	.0211986	.005155	4.11	0.000	.011095	.0313022
4	.0239966	.0057507	4.17	0.000	.0127254	.0352678
q2_income_quintile						
_predict						
1	-.0028561	.0036454	-0.78	0.433	-.0100011	.0042888
2	.0036484	.0043634	0.84	0.403	-.0049036	.0122005
3	.0014073	.0034229	0.41	0.681	-.0053014	.008116
4	.0021996	.0034486	0.64	0.524	-.0089589	.0045596
q3_income_quintile						
_predict						
1	-.0115699	.0038575	-3.00	0.003	-.0191303	-.0040094
2	.0087885	.0045728	1.92	0.055	-.0001741	.017751
3	.0072404	.0036782	1.97	0.049	.0000313	.0144496
4	.004459	.0036038	1.24	0.216	-.0115223	.0026042

q4_income_quintile						
_predict						
1	-.0076509	.0040108	-1.91	0.056	-.0155119	.0002101
2	.0008124	.0046011	0.18	0.860	-.0082057	.0098304
3	.0060726	.0037859	1.60	0.109	-.0013476	.0134928
4	.000766	.0036787	0.21	0.835	-.0064441	.007976
q5_income_quintile						
_predict						
1	-.013325	.0044338	-3.01	0.003	-.0220152	-.0046348
2	-.0015295	.0049737	-0.31	0.758	-.0112778	.0082188
3	.0113327	.0041841	2.71	0.007	.0031321	.0195334
4	.0035217	.0039921	0.88	0.378	-.0043026	.0113461
income_satisfaction						
_predict						
1	-.0017613	.0007868	-2.24	0.025	-.0033033	-.0002192
2	-.0017588	.0009724	-1.81	0.070	-.0036648	.0001471
3	.0018979	.0007133	2.66	0.008	.0005	.0032959
4	.0016222	.0007472	2.17	0.030	.0001578	.0030866
satisfaction_work						
_predict						
1	-.0100071	.0007442	-13.45	0.000	-.0114657	-.0085485
2	-.0103264	.0009515	-10.85	0.000	-.0121914	-.0084615
3	.0108693	.000687	15.82	0.000	.0095227	.0122159
4	.0094642	.0007428	12.74	0.000	.0080085	.01092
satisfaction_housing						
_predict						
1	.000328	.0008166	0.40	0.688	-.0012725	.0019284
2	-.0021897	.001039	-2.11	0.035	-.004226	-.0001533
3	.0002934	.0007078	0.41	0.678	-.0010939	.0016807
4	.0015683	.0007671	2.04	0.041	.0000647	.0030719
life_satisfaction						
_predict						
1	-.0216047	.0009789	-22.07	0.000	-.0235233	-.0196862
2	-.0572762	.0017699	-32.36	0.000	-.0607452	-.0538072
3	.0324553	.0014969	21.68	0.000	.0295213	.0353892
4	.0464256	.0013219	35.12	0.000	.0438347	.0490165
year_dummy2014						
_predict						
1	-.0061901	.0029417	-2.10	0.035	-.0119558	-.0004244
2	-.0020206	.0032904	-0.61	0.539	-.0084698	.0044285
3	.0056013	.0027313	2.05	0.040	.000248	.0109545
4	.0026095	.002601	1.00	0.316	-.0024883	.0077073
year_dummy2016						
_predict						
1	.0055741	.0027557	2.02	0.043	.0001729	.0109752
2	.0069999	.0031108	2.25	0.024	.0009028	.013097
3	-.006375	.0025637	-2.49	0.013	-.0113997	-.0013502
4	-.006199	.0024717	-2.51	0.012	-.0110434	-.0013546