UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

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The Effect of Relative Standing on Self-Perceived Health among Europeans Aged 50 or Older

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Abstract

In order to identify determinants of health among individuals older than 50 years, we use panel data from the Survey of Health, Ageing and Retirement in Europe (SHARE) year 2011/2012 and 2014 to estimate the effect of relative standing on self-reported health. Relative standing is defined as the difference between an individual's net worth and the median net worth in his or her reference group. Using panel data enables us to control for unobserved individual heterogeneity which mitigates potential endogeneity issues. The results suggest that the effect of relative standing with respect to net worth is significant and robust across different specifications.

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Contents

List of Figures

List of Tables

1 Introduction

Public and private health care expenditures constitutes a large share of GDP in European countries. Over the years 1980 to 2010 the share of GDP spent on health care increased from 7.1 percent to 10.3 percent on average in the EU member states. The share is expected to increase in the coming decades across all EU member states. One reason for this is the changing age structure of Europeans: people become older and this is likely to further increase health care expenditures (European Commission, 2013). In 2012, Europeans aged above 65 years old accounted for 17.9 percent of the population. This share is expected to reach 28.7 percent in 2080. Also, the share of individuals older than 80 years old is expected to double between the years 2013 and 2080 (Eurostat, 2015). Identifying the determinants of health among 50+ individuals is therefore of importance in order to be able to construct policies to curb or decrease health expenditures.

In this paper we investigate whether relative standing with respect to wealth have an effect on self-perceived health among individuals older than 50 years in Europe, i.e. if relative standing with respect to income is a *determinant* of health among 50+ individuals. We define relative standing as the difference between an individual's net worth and the median net worth of his or her reference group. If relative net worth matters, income distribution play a role for people's self-perceived health and redistributive policies can be a helpful tool.

Previous literature has to a large extent investigated the relationship between relative standing with respect to income and well-being, measured as self-reported happiness, (Luttmer, 2005; Senik, 2005) and the relationship between absolute income and health (Pritchett & Summers, 1996; French, 2011). There is a gap in the literature when it comes to self-perceived health and relative standing, as we define it, that we are hoping to fill. Many studies has established that income has an effect on individual health but the relationship between income inequality and health is yet to be conclusively determined (Subramanian & Kawachi, 2004). The difficulties of reaching conclusive results are partly due to problems of endogeneity that are difficult to approach (Jones & Wildman, 2008; Subramanian & Kawachi, 2004).

In this study, we used cross-country panel data (the SHARE-survey) collected in 2011/2012 and 2014. We found that there is a significant, but small, effect of relative standing with respect to net worth on self-perceived health. Net worth is preffered to income since the sample consist of individuals older than 50 years old. The majority is retired and does not earn a wage. Net worth is therefore a more suitable measure of the respondents' wealth (Allin, Masseria & Mossialos, 2009) since they are assumed to live of savings and floating assets as well as income. The results suggest that an increase in net worth relative to the median net worth of the reference group increases the probability of belonging to the highest three health categories (*Excellent, Very Good* and *Good*). The effect of absolute net worth is also included, the sign is the same as for relative net worth but the magnitude of the marginal effects are slightly larger.

We controlled for individual unobserved heterogeneity employing the panel part of the SHARE-survey. Our findings are robust across different versions of the sample (only individuals with positive net worth, the entire sample and the sample excluding the five percent poorest and five percent richest, respectively) and across different types of specifications (non-linear and linear). We utilized imputed data for non-responses, which may constitute a caveat as to the interpretation of the obtained estimates, since the validity of the data may be adversely affected (Dardanoni, De Luca, Modica & Peracchi, 2015). Anther limitation pertains to the construction of reference groups. The reference groups consist of 'relevant others': individuals or groups of people to whom the respondents compare and are therefore necessary to define when working with relative standing. It is a sensitive matter to decide to whom someone compares and we have therefore relied on previous studies (Clark & Senik, 2010) when constructing the reference groups. If these are misspecified, i.e that the individuals in a reference group do not compare themselves to each other, then the variable of relative standing does not capture what we aim to estimate.

The structure of the rest of the paper is as follows: Section 2 presents an overview of previous studies in this area. Based upon this, the theoretical framework is developed in section 3, which leads to the testable hypotheses in section 4. In section 5, we discuss our key variables and present a summary of the dataset. Section 6 describes the empirical strategy and the results are presented in section 7. Finally, section 8 contains a discussion of the results and the conclusions from this study.

2 Literature Review

Previous research has shown that individuals are sensitive to how well off people in their surroundings are when evaluating their own situation. For example, Solnick and Hemenway (2005) use survey results and find that *"(...) given a constant purchasing power of money, almost half of respondents would prefer to live in a poorer world, earning $200,000 rather than $400,000, if most other people were earning $100,000 rather than $800,000."* (p. 150). Studies performed during the last decade, including Solnick and Hemenway (2005), have analyzed relative standing and consumption, see for example (Carlsson et al., 2009; Falk & Knell, 2004; Frank, 2005; Luttmer, 2005).

Several studies examine the relationship between subjective well-being and relative standing, for example, Bookwalter and Dalenberg,(2010); Johansson-Stenman, Carlsson and Daruvala (2002); Posel and Casale (2011). However, to the best of our knowledge there are no published studies that focus on the relationship between subjective health and relative standing, measured as relative wealth or relative income. Thiel (2014) examines the relationship between self-perceived health and relative standing, measured as relative health. However, instead of wealth he uses the health of others as comparison variable between the reference group and the individual. Thus, the focus of our study – the relationship between the position in the income distribution and self-perceived health – has received little or no attention in the literature.

The empirical approaches that have been employed in previous studies have been either based on experiments or surveys. With regards to survey-based data, Senik (2005) concludes that no consensus regarding the structure of the relationship between relative income and well-being has been reached. Clark, Etilé, Postel-Vinay, Senik and Van der Straeten (2005) discuss issues with heterogeneity in self-reported well-being. Their conclusion is that, even after controlling for fixed effects, the marginal utility of absolute income on well-being is not the same. In other words, the way people transform income to utility is very different both across European countries and individuals. The focus of this paper, however, is on relative net worth and *subjective health* rather than well-being.

Studies in this area depend critically on the definition of relevant comparison groups. Clark and Senik (2010) investigate to whom and how European individuals compare their income to that of others, and conclude that 28 percent of the respondents find comparisons important. Among those who compare their position in some respect to that of others they find that the most frequent income comparisons are made between work colleagues, followed by friends. Comparisons to family members are rare.

Luttmer (2005) uses US panel data in order to examine the effect of relative standing with respect to income on self-reported happiness. His findings suggest that happiness decreases as the income of neighbors increase relative to that of the individual. This result seems to be valid not only for developed countries, but also for developing countries, as suggested by, for instance, Carlsson and Qin (2010) who find that relatively poor individuals care about their relative standing in a similar way that individuals in developed countries do. Their results are corroborated by Alpizar et al. (2005); Solnick, Hong and Hemenway (2007) among others.

There is a large literature concerned with the relationship between health and income. Grossman (1972) laid the foundation for this research area by defining health as part of the individuals stock of human capital. He argues that individuals invest in their health and that health influences the amount of time that the individual can be productive. A higher income could thus allow the individual to invest more in their health by consuming for example health care and prevention.

The issue when examining the relationship between health and income is the problem of reversed causality. Does higher income lead to better health or does better health enable individuals to work more, earning higher income? One solution is to use IV strategies as Pritchett and Summers (1996) have done. They use an IV strategy and are able to conclude in their paper *Wealthier is Healthier* that an increase in income will raise health status. On the other hand, Meer, Miller and Rosen (2003) instrument income using data from the US. Their results are weak, suggesting that the causal relationship between wealth and health is yet to be established. More recent research investigating the effect of relative income on health has very different results and there is no consensus. Results seem to vary across regions and countries (Bechtel, Lordan & Rao, 2012). French (2012) tests if and how health has improved income and if and how income, defined as GDP per capita, has improved health during the last 50 years in OECD countries. He takes on a cross-sectional time-series approach and is able to conclude that the causation goes both ways. Improved health turns out to improve income, but income also improves health.

The existing literature about relative standing, and the relationship between income and health, is extensive. However, the effect of relative standing on health is unclear. Therefore, the objective of this study is to improve knowledge concerning the influence of relative standing on self-perceived health among Europeans older than 50 years old.

3 Theoretical Framework

The impact of income on well-being is widely discussed in the literature. Classical economic theory would suggest that relative income has no impact on well-being, relying on the notion of *homo economicus*. According to Senik (2005) however, little doubt remains that the income of others actually does impact the well-being of the individual. There is no consensus regarding whether the effect is positive or negative. If the relationship is positive this is evidence of altruistic feelings suggested by Becker (1991).

If, on the other hand, the well-being of an individual decreases when the income of others increase, comparison effects would drive the relationship. This latter effect is supported by research performed within other disciplines, such as psychology and sociology. In economics, the notion of comparison effects was developed by Veber (1909) who introduced the theory of conspicuous consumption. Conspicuous consumption is defined as consumption that the individual conducts in order to impress others. In other words, the utility of consumption comes from a psychological effect of displaying economic power and not only from the consumption of the good itself. In an economic setting, this provides support for comparison-based (inter-related) utility functions (Bowles & Park, 2005). Veblen (1909) was the first to introduce the idea that optimal consumption is not only determined subject to the budget of the individual but also subject to the consumption of others. Thus, individual consumption choices are partly determined in relation to the preferences of other individuals. Becker (1974) argues that the idea of "social interaction" got lost in economics. He proposes a model where the utility of an individual depends on social income which he defines as: *"the sum of a person's own income (his earnings, etc.) and the monetary value to him of the relevant characteristics of others, which I call his social environment."* (p.1090).

The most important implication of his model is that the individual maximize social income rather than individual income. If social income is endogenous, interdependence should be incorporated into the utility function of the individual.

3.1 Determinants of Health

Grossman (1972) laid the foundation for explaining the determinants of health. In his Demand for Health model, individuals gain utility from consumption of private goods (C) and good health: $U = U(C, \tau(H))$, where τ is time spent as healthy which is a function of health capital, H. The marginal utility of healthy time is $\frac{\delta(U)}{\delta\tau(H)} > 0$ and $\frac{\delta^2(U)}{\delta\tau(H)^2} < 0$ which indicate that sick individuals derive higher marginal utility from healthy time than those who are less sick (Grossman, 1972).

In a dynamic setting of the Demand for Health Model, age influences the rate at which the stock of health depreciates. With increasing age the depreciation rate increases, making the marginal cost of health capital larger. The marginal cost of health capital increase because for a given level of health, more investments are necessary in order to keep the health stock constant.

When deciding on health investments both consumption and investment benefits of health are taken into account. The investment benefits arise when health influences the amount of healthy time, while the consumption benefits are the utility of being healthy. The cost of investing in health is comprised of time spent on investment and money spent on medical services, such as pharmaceuticals, instead of private goods. For the individuals included in our sample the opportunity cost of time spent (valued according to the human capital method) on investing in health is not very high due to the fact that the majority of the individuals are retired. The budget restriction equalizes the present value of expenditures and the present value of resources. Resources includes initial financial assets and the product of wage rate and working hours. As the majority of respondents in our sample are retired, the second part of the resource-side is rarely present. Instead, initial financial assets play an important role. Thus, as the resource side of the budget constraint increases, ceteris paribus, the amount available for investments in health and consumption of private goods increases. The net effect depends on the marginal utilities derived from time spent in a healthy state and consumption. If the former is higher, absolute wealth would be an important determinant of health. (Grossman, 1972)

As we have discussed in section 2 much research have been focused on this relationship: $h_i = f_I(y_i)$ which is the effect of absolute income on individual health. The Relative-Position Hypothesis, however, stipulates that the health of an individual is affected by social position. In other words: besides the direct effect of income, the relative position in the income distribution also matters (Wagstaff & van Doorslaer, 2000). This would provide support for the notion that income inequality affects health. More formally, the health status of an individual can be described as:

$$h_i = f_I(y_i, R_{i \in N_c}), \tag{1}$$

where h_i is the health status of individual i which is a function of y_i, the individual income and $R_{i \in N_c}$ is the relative rank of the individual in community c (Wagstaff & van Doorslaer, 2000).

Clearly, the major explanatory variable of interest is the relative income variable, $R_{i \in N_c}$. On the other side of the equation is the dependent variable: health status of an individual, (h_i). This variable can be measured in several ways.

3.2 Health Measurement

The amount of health capital held by an individual is only imperfectly observed. Several different empirical methods have been developed and employed. For example health could be measured by EQ-5D, a standardized instrument. Functional measures or self-reported health could also be applicable to measure health outcomes.

Data-aggregation issues notwithstanding, several methodological issues need to be considered when choosing empirical measures for individual health. First, we need to consider where the health measurement comes from. Is it self-reported (subjective) or reported by a third party, such as a physician or nurse (objective)? Zweifel, Breyer and Kifmann (2009) argues that the former is less reliable. Subjective health measures are arguable more difficult to compare than objective health measures. When answering a question such as "How would you say your health is?", the individual may have different reference points (Zweifel et al, 2009). What is good for one individual may be bad for another. However, the access to objective data is restricted due to confidentiality. It also captures only one dimension of health: having a specific symptom or not, while subjective measures capture several dimensions.

Pfarr, Schmid and Schneider (2012) use SHARE data in order to assess what actually determines how individuals report self-rated health. Using a generalized Probit model, the aim was to investigate if there is a gap between reported and actual health. Their findings suggest that there indeed are systematic differences in how people asses their health and how their actual health is. The implication is to be cautious when using subjective data. The authors also note that the timing of measurement is important because health status is assumed to be adaptive (Pfarr et al, 2012). For a respondent, given a certain diagnosis, his or her answer to how he or she feels is likely to be affected by *when* the diagnosis was given. If it was a year ago, the individual has adapted to the new health status and will assess their health given this. If the individual was given the diagnosis yesterday, however, self-reported health is most likely very low since the individual has not yet adapted to the situation. Thus, even though the individuals have the same diagnosis their self-assessed health levels will differ due to adaption.

In this paper, we employ *self-assessed health* as the empirical measure of health. Subjective measures tend to be harder to define and are more complex compared to objective measurements. However, such measures are informative, as have been demonstrated by, for instance, Benjamins, Hummer, Eberstein and Nam (2004), that showed that self-perceived health is a good predictor of mortality. Furthermore, it is likely that objective health to a large extent determines self-perceived health.

4 Hypotheses

Based on the discussion above we formulate the following hypotheses which we aim to test. We are going to focus on the effect of relative standing on self-perceived health and we are going to use differences between individual net worth and median net worth in the reference group as our measure of relative standing, as done by Ferrer-i-Cabonelli (2005). The reference group is constructed based upon gender, country of residence, age and current job situation. In the theory section, we saw that income play a big role in determining health. As we have argued, net worth is a better measure than income for our sample, we therefore have two wealth effects that we are going to test:

1. The relative effect: when the net worth of an individual changes, the relative position with respect to net worth in his or her reference group changes. We expect this to have a positive effect on self-perceived health so if personal net worth increases, ceteris paribus, the reported health status increases and vice versa.

2. The absolute effect: higher net worth increases means available for investments in health, which improves health status. We expect the effect of net worth on self-perceived health to be positive.

4.1 Econometric Model

In order to test the hypotheses, we fit the following model to the data:

$$SPH_{it} = \alpha + \beta nw_{it} + \delta(nw_{refmedian} - nw_{it}) + \mathbf{X}_{it}\phi + u_{it} \tag{2}$$

SPH is the self-reported health measure for individual i and t denotes the two waves included in the data-set. nw_{it} is the net worth of the individual and $\mathbf{X}_{it}$ is a vector of control variables. The main parameter of interest is δ since the difference between the median net worth in a specific reference group and the net worth of the individual is the effect of relative standing as we define it. We expect the effect to be positive, so an increase in net worth relative to the reference group increases the probability of reporting a higher health status. The second parameter of interest is β representing the absolute effect, which we also expect to be positive. The economic model is influenced by the model used by Ferrer-i-Carbonell (2005) and is motivated by the relative-position hypothesis (Wagstaff et al, 2000) as well as the demand for health model by Grossman (1972).

5 Data and Descriptive Statistics

5.1 Survey of Health, Ageing & Retirement in Europe

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a comprehensive cross-country panel database with individual-level information[1]. The aim is to provide micro data on health and socioeconomic status for 50+ people in Europe[a]. It consists of five different waves where the first wave was collected in 2004 and the fifth and latest wave, was collected in 2014. Four out of the five waves are very similar, while the third wave (SHARELIFE) focuses on life histories and retrospective information. The other four waves have similar structures and enables researchers to use panel methods for studying the effects on various socioeconomic outcomes.

In this study we use data from SHARE Wave 5 release 1.0.0, as of March 31st 2015 and SHARE Wave 4 release 1.1.1, as of March 28th 2013. The reason for choosing these two is that they are similar in terms of included countries, questions and imputation methods[2]. Moreover, these waves includes the largest number of observations and is the most recent data. The sample consists of observations from 13 countries[3] out of 15[4]. In the main analysis we only include individuals with positive net worth. The final sample consists of 39,717 individuals in wave 4 and 39,753 individuals in wave 5 summing up to 79,470 observations.

5.2 Variables

5.2.1 Dependent Variable

The variable of interest is self-perceived health (SPH). The exact question in the interview was *"Would you say your health is..."* and the respondent could choose alternatives on a 1-5 scale where *1. Excellent, 2. Very good, 3. Good, 4. Fair* and *5. Poor* (SHARE, 2013b; 2015b). As previously mentioned, there are some issues when using a subjective health measurement. Most notably, reporting heterogeneity across countries, cultures and individuals could be problematic. We do, however, use panel data which enables us to mitigate these problems, at least to some extent. If the heterogeneity in reporting-style

[1]See Börsch-Supan et al., 2013; Börsch-Supan, Hank, & Jürges, 2005 for information regarding the SHARE-project.

[2]The imputation procedure will be presented in section 5.3.1.

[3]Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Denmark, Switzerland, Belgium, Slovenia, Estonia and Czech Republic.

[4]Poland and Israel are dropped because they are not included in both waves.

is time-invariant, it will be controlled for when using data from two waves. Furthermore, the construction of our reference groups only compare those from the same country so direct cross-country comparisons will not be made. We do not have information on timing of health measurements and, hence, cannot take this into account.

5.2.2 Reference Groups

In order to perform this analysis we need to create reference groups for each individual. The reference group consists of individuals to whom the respondent is likely to compare. However, our data does not comprise this type of information.

Based on Clark and Senik (2010), we decided to include the following variables when determining reference groups: *current job situation*, *age*, *sex* and *country of residence*. The job variable is categorized into seven categories: *Unknown*, *Retired*, *Employed or Self-employed*, *Unemployed*, *Permanently Sick or Disabled*, *Homemaker* and *Other*.

Regarding the age categories we have created one group for individuals between and including 0 and 49 years old. The reason for why there are individuals below 50 years old in the sample is probably because some households contain individuals older than 50 as well as younger than 50. In these cases the survey was conducted also on the younger individual. However, the share of the sample belonging to this group is only 1.4 percent. For all individuals who are 50 or older the groups are partitioned into groups covering five years, i.e. one group includes individuals between and including 50 and 54 years old, the next include individuals between and including 55 and 59 years old all the way up to the last group which includes individuals aged between and including 100 and 105 years old. The first group is different from the other groups as it includes almost ten times as many years. The reason for this is that the percent of respondents younger than 50 years old is very small.

Falk and Knell (2004) found that women and men compare differently. Therefore we assume that men are more likely to compare their income with the income of other men and vice versa for women.

The last variable used to allot the respondents into reference groups is *country of residence*. It is reasonable to assume that individuals are more likely to compare themselves to people in their close surroundings. Unfortunately, place of residence is not reported in more detail than country of residence. However, country of residence seems to be an important ground for comparisons since law and regulation differ between countries. This definition of reference groups yields 1,198 different groups comprising between 1 and 963 individuals.

Household net worth is our key variable. It is formally defined as the sum of the values of household financial assets and household real assets minus liabilities. Financial assets comes from seven categories: bank and other transaction accounts, government and corporate bonds, stocks, mutual funds, individual retirement accounts, contractual savings for housing, and life insurance policies. The real assets are residences, own business and vehicles. Finally, liabilities are defined as the sum of debts such as mortgages and other debts on cars, credit cards or towards banks, building societies and other financial institutions (Bonsang, Perelman & Van den Bosch, 2013)

The key variable household net worth takes on positive as well as negative and zero values. Also, the distribution of the variable is skewed. A common way to solve this problem and make the distribution more normal is to take the logarithm of the variable. Unfortunately, the logarithm of negative and zero values does not exist. The variable takes on zero or negative values for 3.3 percent of the sample. This induces a limitation to the analysis. In order to get around this problem in a satisfying way we have decided to use a restricted sample for the main analysis presented below and then conduct robustness checks presented in section 7.2. The restricted sample in the main analysis consists of respondents with a net worth larger than zero, this allows us to correct for the skewed distribution in an adequate way.

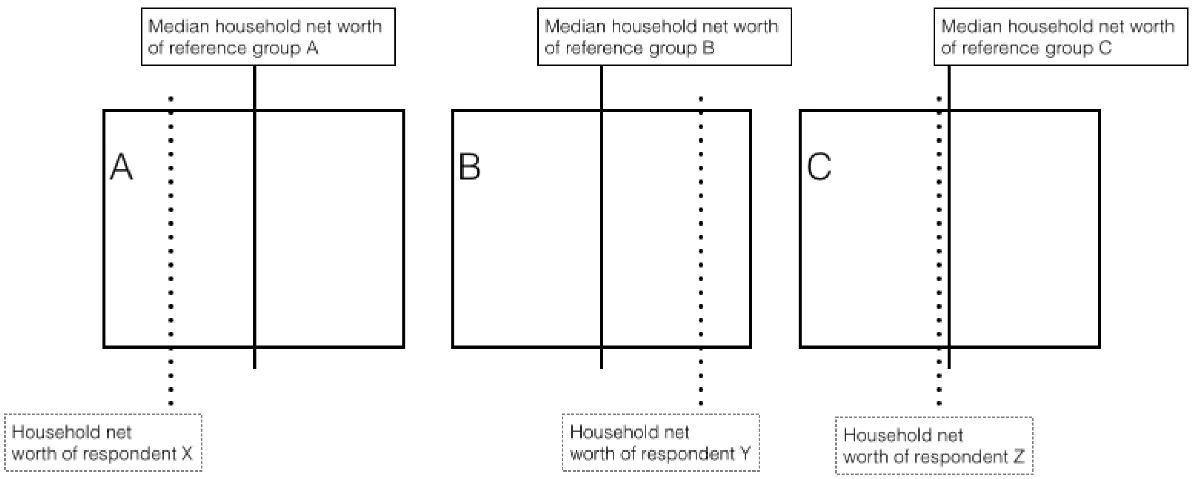
The relative standing with respect to household net worth is defined as *the distance between the reference group's median household net worth and the individual's median household net worth*. We use the median because it is the value in the middle, 50 percent are above and 50 percent are below the median. Figure 1 illustrate the intuition of relative standing with respect to household net worth.

5.2.3 Control Variables

In our specifications, we included a set of control variables in order to control for factors that affects self-perceived health. We control for socio-demographic factors since these are likely to affect health. Gender, age, number of children, household size and marital status are all empirically documented determinants of health (Alem, 2013; Bechtel, Lordan & Rao, 2012; Grossman, 1972; Senik, 2005). We added widow as a socio-dempgraphic control given the age of the respondents (SHARE, 2013; 2015). We included age^2 to control for non-linear effects of age on health status. Furthermore, current job situation and education is expected to affect health, thus we included them in the model. Finally, country dummies are incorporated to control for country fixed effects such as systematic differences in reporting

Figure 1: Relative Standing

The illustrated respondent, X, has a household net worth significantly lower than the median household net worth of his or hers reference group, A. While respondent Y, whom belongs to a different reference group, has a higher household net worth compared to the median of his or hers reference group. Finally, respondent Z has a very similar household net worth compared to his or hers reference group, C.



style or different health care systems.

5.3 Attrition Bias and Non-Responses

The SHARE-survey suffers from attrition creating a sample selection bias which mitigates the validity of the results. The solution would be to use weights (Börsch-Supan et al, 2013), unfortunately calibrating weights are beyond the scope of this study.

Another potential problem is that of non-responses. However, Börsch-Supan et al (2013, p. 60) find that there is not evidence strong enough to confirm non-response bias. But still, the non-responses do constitute a problem as they significantly decrease the sample size, we solve this using imputed data.

5.3.1 Imputed Data

In order to solve the problem of non-responses the missing data has been imputed[5]. The imputation process allows us to keep all observations and therefore exploit also the information in the incomplete observations.(Buuren, 2007) Normally these observations would, by

[5]The imputation has been made by the SHARE project. For a more detailed description than presented here please see (SHARE, 2013; 2015)

default, be dropped by Stata.

The SHARE team has used multiple imputation. This procedure generate a set of imputed values for each missing value, in this case five imputations have been used. For the majority of the variables, the number of missing values is small, in most cases less than five percent of the values are missing. In these cases the SHARE team has adopted univariate imputation methods. For cases where the missing values are more frequent, the SHARE team has adopted the Fully Conditional Specification (FCS) method. (SHARE, 2013; 2015) The FCS method specifies an individual conditional distribution for every variable which makes it more flexible (Buuren, 2007).

In the analysis conducted in this study we have decided to only report the results pertaining to one (arbitrarily chosen) set of imputed values instead of all five. The results are invariant to which one of the five implicats that is chosen.

The rationale behind this decision is that we are able to be more flexible regarding which specifications we use. The largest setback in this decision is that we ignore the variability due to imputation, intuitively: we treat imputed values as true.[6] However, we are able to use one specification with multiple imputation methods. The results are presented in Appendix B.

5.4 Descriptive Statistics

The descriptive statistics are presented in Tables 1-4 below. The tables report the values for the restricted sample only, as discussed in section 4.3.2. In practice, there are 1,295 individuals in wave 4 and 1,259 individuals in wave 5 with a negative or zero household net worth. These respondents will be excluded in the main results in order to make a logarithmic transformation plausible. The final sample used in this estimation consists in total of 73,870 individuals, 36,917 in wave 4 and 36,953 in wave 5. The difference in number of respondents per wave is because some individuals have negative or zero net worth in one wave and positive in the other.

In order to check the robustness of the results, we will run separate regressions for the entire sample to see whether the results are sensitive to this exclusion. These results are presented in Appendix A and described in section 7.2.

The construction of reference groups is based on age, gender, current job situation and country. Showing descriptive statistics for every reference group is too space-consuming since

[6] De Luca, Giuseppe (12th of March 2015) Mail conversation with the authors.

the number of groups is 1,198. The maximum number of respondents in a certain reference group is 963 and the minimum is 1, there are 195 groups with only one individual.

Table 1: Self-Perceived Health

	Wave 4	
SPH	Freq.	Percent
Excellent	2,808	8
Very good	6,638	18
Good	13,500	37
Fair	10,357	28
Poor	3,614	10
Total	36,917	100

	Wave 5	
SPH	Freq.	Percent
Excellent	2,572	7
Very good	6,142	17
Good	13,632	37
Fair	10,556	29
Poor	4,051	11
Total	36,953	100

Table 2: Country

	Wave 4		Wave 5	
Country	Freq.	Percent	Freq.	Percent
Austria	3,800	10	3,802	10
Germany	992	3	1,009	3
Sweden	1,432	4	1,425	4
Netherlands	2,145	6	2,169	6
Spain	2,699	7	2,696	7
Italy	2,471	7	2,473	7
France	3,871	10	3,884	11
Denmark	1,852	5	1,873	5
Switzerland	2,792	8	2,808	8
Belgium	3,856	10	3,855	10
Czechia	3,705	10	3,676	10
Slovenia	1,920	5	1,914	5
Estonia	5,382	15	5,369	15
Total	36,917	100	36,953	100

Table 1 shows the summary statistics of the dependent variable, self-perceived health. There are five categories and the majority of the respondents belongs to the categories *Good* and *Fair*. The largest group is *Good* in both wave 4 and wave 5, consisting of 13,500 and 13,632 individuals respectively. The distributions between the waves are very similar; there is one percent more individuals in the *Poor* category in the fifth wave. Overall, the health status in the fifth wave is slightly worse since approximately one percent of the respondents have reported a lower health category than in wave 4.

Table 2 contains the number of individuals from each countries included in the study per wave. There are 13 countries in the sample. There is very little variation in the number of respondents from each country across the waves. The single largest number of respondents of the respondents comes from Estonia, followed by Czechia, France, Austria and Belgium.

In Table 3, we present both the household net worth measured in Euro (PPP-adjusted to Germany 2005) and the transformed variable: *ln(Net Worth)*. As previously mentioned, the latter variable includes only variables that have a net worth above zero to make logarithmic transformation plausible. The reason for the transformation is that the variable *Net Worth* is skewed. The mean value in wave 4 is €251,668 as can be seen in Table 3. The median, however, is €151,752 which indicates that the distribution of net worth is skewed to the right. The same is true for wave 5; the mean is €248,851 and the median €150,503. The

Table 3: Descriptive Statistics

		ln(Net Worth)	Net Worth	Male	Age
	Mean	11.348	251,668	0.429	65.9
Wave 4	(Std. Dev.)	(2.624)	(417,409)	(0.495)	(10.0)
	No. of obs.	36,917	36,917	36,917	36,917
	Mean	11.409	248,851	0.428	67.9
Wave 5	(Std. Dev.)	(2.352)	(426,256)	(0.495)	(9.96)
	No of obs	36,953	36,953	36,953	36,953
Total no. of observations		73,870	73,870	73,870	73,870

		Married	Children	Widowed	HH Size
	Mean	0.713	2.171	0.139	2.14
Wave 4	(Std. Dev.)	(0.452)	(1.33)	(0.346)	(0.965)
	No of obs	36,917	36,917	36,917	36,917
	Mean	0.693	2.175	0.158	2.14
Wave 5	(Std. Dev)	(0.461)	(1.334)	(0.365)	(0.936)
	No of obs	36,953	36,953	36,953	36,953
Total no. of observations		73,870	73,870	73,870	73,870

variation is very large. The mean of the transformed variable is approximately 11.35 in wave 4 and 11.4 in wave 5. The median is 11.9 in both waves. The latter distribution is close to a normal distribution (as mean and median are more similar) and the variation smaller. Therefore, the natural logarithm of positive household net worth is the variable that we are using for the analysis.

43 percent of the respondents are male and 57 percent are female in both wave 4 and 5. The average age in wave 4 is 65.9 years and 67.9 years in wave 5 with a small variation in both waves. The average size of the household is roughly 2.1 individuals in both waves. In the fourth wave, 71.3 percent are married and 13.9 percent are widows. This changes slightly for the fifth wave: 69.3 percent are married and 15.8 percent are widowed, indicating that some partners have deceased. The number of children is more or less the same; 2.17 children per respondent.

The educational levels of the respondents are classified in compliance with the ISCED classifications provided by UNESCO (2012). The educational categories are *No Education*, *Primary Education*, *Lower Secondary Education*, *Upper Secondary Education* and *Tertiary or Higher Education*. In the fourth wave 41 percent have primary education. The second largest education level is Lower Secondary education. Together, these two groups make up for almost 65 percent of the sample. The variation for both groups is fairly large. No education and Upper Secondary are also common, 15.1 percent and 12.3 percent respectively. Only a very small share of the sample has obtained a Tertiary or Higher level of education.

Table 4: Educational Level and Current Job Situation per Wave

		No Educ.	Primary	Low. Second.	Up. Second.	Tertiary	Master/Higher	
	Mean	0.151	0.410	0.254	0.123	0.054	0.008	
Wave 4	Std. Dev.	(0.358)	(0.492)	(0.435)	(0.329)	(0.226)	(0.089)	
	No. of obs.	36,917	36,917	36,917	36,917	36,917	36,917	
	Mean	0.130	0.421	0.261	0.125	0.055	0.008	
Wave 5	Std. Dev.	(0.336)	(0.494)	(0.439)	(0.330)	(0.228)	(0.090)	
	No. of obs.	36,953	36,953	36,953	36,953	36,953	36953	
Total no. of observations		73,870	73,870	73,870	73,870	73,870	73,870	
		Retired	Self- or Emp.	Unemp.	Disabl.	Home.	Other	Unspec.
	Mean	0.556	0.284	0.029	0.032	0.086	0.010	0.004
Wave 4	Std. Dev.	(0.497)	(0.451)	(0.168)	(0.176)	(0.280)	(0.098)	(0.062)
	No. of obs.	36,917	36,917	36,917	36,917	36,917	36,917	36,917
	Mean	0.610	0.240	0.023	0.031	0.078	0.010	0.008
Wave 5	Std. Dev.	(0.488)	(0.427)	(0.150)	(0.173)	(0.268)	(0.098)	(0.089)
	No. of obs.	36,953	36,953	36,953	36,953	36,953	36,953	36,953
Total no. of observations		73,870	73,870	73,870	73,870	73,870	73,870	73,870

The pattern is similar for the fifth wave, although not exactly the same. This is most likely due to the fact that some individuals are not represented in both waves since the level of education among the respondents is final, they are not likely to be studying anymore.

The current job situation is used when constructing our reference groups and is also used as a control variable. The descriptive statistics reveal that the majority of the individuals are retired. In the fifth wave, the proportion of retired individuals has increased which means that some individuals retired between wave 4 and 5. Approximately 5 percent of the respondents retired between 2013 and 2015. The second largest group is respondents who is either employed or self-employed, 28.4 percent in wave 4 and 24 percent in wave 5 which is consistent with the increase in the retirement group. Only a small share is unemployed or disabled. Homemaker make up the third largest category containing approximately 8 percent of the respondents, with a small decrease between the waves. Finally, the smallest categories are others and unspecified. The unspecified category includes respondents whose answers are missing by design. *Other* are occupations besides those included. These two groups are very small: *Other* is 1 percent and unspecified lies between 0.5 and 1 percent.

6 Empirical Strategy

The empirical methods that we use are based upon models that take the panel structure into account. Due to the ordinal nature of the dependent variable we are going to fit a Pooled

Ordered Probit model. The model basically treats the data as cross-sectional and will serve as a benchmark for the panel-data models. In order to establish a causal relationship, we have to address problems of endogeniety. A potential source of endogeniety is omitted variables, for example individual characteristics that correlates with both self-perceived health and any of the control variables. One advantage of using panel data is that it makes it possible to control for unobserved individual heterogeneity that is time-invariant. An example is *personality* which is likely to affect both sides of the estimate relationship and does not change over time.

Technically, panel data allows us to divide the unobservable error term, u_{it}, into two components: one that is time-invariant, α_i, and one that is time-varying, ϵ_{it}. The panel data models, given the assumptions described in the next section, manages to take care of α_i, which is the time-invariant heterogeneity across the individuals. This mitigate the potential omitted variable bias that arise since we cannot observe all determinants of endogenous regressors. The reference groups may be endogenous if there is self-selection into certain groups, making them choice variables. Ideally, everything that affects which group the individual belongs to would be time-invariant. Some of the variables used as regressors may be endogenous. For instance, current job situation: if the individual *chooses* to retire in order to increase his or her health this would lead to endogeneity problems. We do, however, suspect that this is a small problem given the size of the sample. We assume that most respondents retire at the retirement age.

The first model that we estimate is a Pooled Ordered Probit model. Then, we estimate a Random Effects Ordered Probit model, exploiting the panel structure. In order to test the results, a number of robustness tests are performed and presented in section 7.2.

6.1 Pooled Ordered Probit

The relationship we aim to test is the effect of relative standing on self-perceived health. The dependent variable is categorical but there is a natural ordering among the categories. If we were to use a linear model, we would have to assume that the distance between the different categories were the same when interpreting the coefficients (Verbeek, 2012). We argue that this is unreasonable; for example, the difference between *Good* and *Very Good* is arguable not the same as the difference between *Good* and *Fair*. Moreover, the relationship between relative standing and health may not be linear. As a consequence we are going to apply a non-linear model that takes the natural ordering and non-linearity into account: Ordered Probit. In order to see if the results are sensitive to the particular specification of the model, we have also run a linear model to compare the results. These results are found in the Appendix A and discussed in section 7.2.

The ordered Probit uses a Maximum Likelihood method for estimating the effect of the explanatory variables on the different ordinal categories. An intuitive way to introduce the Probit framework is to describe the latent variable approach.

What we observe from the survey is y_{it} for individual i. What we really want to know, however, is the unobserved latent variable $y*_{it}$ which drives the answer. The relationship we aim to estimate is:

$$y*_{it} = x'_{it}\beta + u_{it}, \tag{3}$$

where $y*_{it}$ is the latent variable and x'_{it} is a vector of explanatory variables. In order to enabling the use of the Probit model, we assume that the error term, u_{it}, is IID standard normal. (Verbeek, 2012)

Let K be a set of outcomes, in this study $K = 5$ corresponding to the different health categories. γ is a set of thresholds ranging from $\gamma_1, \gamma_2....\gamma_{K-1}$. We have four different thresholds in this setting, $\gamma_{K-1} = 4$, that determine what the answer of the respondent is. Thus, we can define the observed variable y_{it} as:

$$\begin{aligned} y_{it} = 1 \quad \text{if} \quad y*_{it} \leq \gamma_1 \\ y_{it} = 2 \quad \text{if} \quad y*_{it} > \gamma_1 \leq \gamma_2 \\ y_{it} = 3 \quad \text{if} \quad y*_{it} > \gamma_2 \leq \gamma_3 \\ y_{it} = 4 \quad \text{if} \quad y*_{it} > \gamma_3 \leq \gamma_4 \\ y_{it} = 5 \quad \text{if} \quad y*_{it} > \gamma_4 \end{aligned} \tag{4}$$

Finally, the probability for one specific outcome, k, is:

$$Pr(y_{it} > k \mid \gamma', x'_{it}, u_{it}) = \Phi(x'_{it}\beta + u_{it} - \gamma_k) \tag{5}$$

The $\Phi(\bullet)$ is the standard normal cumulative distribution function and u_{it} is the error term mentioned above. The Probit will estimate the likelihood that an individual crosses a threshold. The advantage of this model is that we aim to observe the latent variable, attitude towards health. Therefore, we do not have to assume that the health category *Good* is the same for all individuals that have responded *Good*, which we would have had to do in a linear model such as OLS (Moffatt & Daykin, 2002). Ferrer-i-Carbonell and Frijters (2004) argues that the distinction between linear and non-linear is less important compared to the inclusion of controls for individual heterogeneity. In the Pooled Oredred Probit, we do not take the panel structure into account

The Pooled Ordered Probit basically treats the data as cross-sectional thereby ignoring fixed effects. By fitting a Random Effects Ordered Probit, however, we are able to keep the advantages of an Ordered model *and* control for time-invariant heterogeneity.

6.2 Random Effects Ordered Probit

We are worried that the Pooled Ordered Probit provides biased coefficients due to problems of unobserved individual heterogeneity. The Random Effects Ordered Probit model is very similar to the Pooled Ordered Probit presented above, but designed to mitigate the problem unobserved individual heterogeneity. (Verbeek, 2012) An example of unobserved individual heterogeneity that is kept constant over time and affects both wealth and self-perceived health is personality.

In order to adequately estimate a random effects model we must impose an orthogonality condition on the composite error term, $u_{it} = \alpha_i + \epsilon_{it}$. The condition is that $\alpha_i \sim IID(0, \sigma_\alpha^2)$ and $\epsilon_{it} \sim IID(0, \sigma_\epsilon^2)$. The implication of this condition is mainly that the time-invariant part of the error term must be uncorrelated with the explanatory variables, i.e. orthogonal to each other. This is a strong assumption but crucial for the Random Effects Ordered Probit model to produce unbiased estimators. (Verbeek, 2012)

Using the Mundlak adjustment it is possible to relax the orthogonality assumption by including individual time means in the regression. Mundlak (1978) defines the composite error term as follows:

$$u_{it} = \alpha_i + \epsilon_{it}, \tag{6}$$

where he lets

$$\alpha_i = \omega_i + \sum \lambda_j \bar{z}_{ji} \tag{7}$$

In equation (7), the first part, ω_i, is an error term uncorrelated with the explanatory variables, x_{kit}, that are included in the regression. Where k is the number of explanatory variables.

The second part of the error term in equation (7) is correlated with a subset, z_{jit} (where $j \leq k$), of the explanatory variables in the regression. The subset includes variables that vary over time, invariant variables are assumed not to pose any threat to the statistical analysis. We let the correlation between the random unobserved individual heterogeneity and the subset be $\lambda_j \bar{z}_{ji}$ where $\bar{z}_{ji}$ is the individual time mean of z_{jit}. As can be seen in the equation it is assumed that the correlation does not change over time. (Ferrer-i-Carbonell, 2005)

By including the observable individual time means of all time-varying explanatory variables we allow for some correlation between the explanatory variables and the unobserved individual heterogeneity.

7 Results

Table 5: Main Estimation Results: Positive Net Worth

Variable	**Coefficients**		
	(1)	(2)	(3)
Self-perceived Health	Ordered Probit	RE Ordered Probit	RE Ordered Probit
Relative ln(net worth)	-0.066***	-0.091***	-0.092***
ln(net worth)	-0.110***	-0.146***	-0.146***
Socio-demographic controls			
Household size	0.016***	0.023**	0.021**
Male	-0.007	-0.019	-0.018
Widowed	-0.012	-0.046	-0.044
Married	-0.015	-0.063***	-0.061**
Children	-0.003	0.000	0.000
Age	-0.006	-0.019*	-0.021**
Age^2	0.000***	0.000***	0.000***
Job situation controls (Retired omitted)			
Self- or Employed	-0.235***	-0.295***	-0.296***
Unemployed	0.084***	0.136***	0.134***
Disabled	1.019***	1.282***	1.279***
Homemaker	0.078***	0.101***	0.102***
Other	-0.010	-0.085	-0.086
Unspecified	0.139*	0.040	0.032
Education Controls (No Education omitted)			
Primary educ.	-0.067***	-0.070***	-0.074***
Low second educ.	-0.226***	-0.324***	-0.330***
Up second educ.	-0.356***	-0.534***	-0.541***
Tertiary educ.	-0.396***	-0.611***	-0.618***
Master/higher	-0.383***	-0.576***	-0.583***
$Pseudo-R^2$	0.0979	-	-
σ_u^2	-	1.512 (0.029)	1.513 (0.029)
Number of observations	73870	73870	73870
Clustered standard errors	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*
Mundlak adjustment	*No*	*No*	*Yes*

LR test vs. Oprobit regression: $\bar{\chi}_1^2 = 11925.87$ $Prob \geq \bar{\chi}^2 = 0.0000$

Significance levels: $*$: 10% $**$: 5% $***$: 1%

The main estimation results are presented in Table 5. The first column displays the Ordered Probit results, the second displays the Random Effects Ordered Probit results and the third column displays the Random Effects Ordered Probit results with the Mundlak adjustment. The dependent variable for all three specifications is SPH, remember that the definition of the variable is the following: *1. Excellent, 2. Very good, 3. Good, 4. Fair* and *5. Poor* which mean that a negative sign yields a positive interpretation. The sample consist of all individuals with a net worth larger than zero.

Since the specifications are Probit models we are unable to interpret the magnitudes of the coefficients directly, therefore the marginal effects are presented in section 7.1. We can, however, interpret the signs and the statistical significance of the coefficients.

As can be seen in the table, the results differ little between the Ordered Probit in column (1) and the Random Effects Ordered Probit models in columns (2) and (3). The key variable Relative *ln(net worth)* as well as *ln(net worth)* are statistically significant at the one percent level, also the direction of the coefficients are the same for all specifications. When it comes to the control variables there are some changes in the statistical significance, for example *Married* is statistically significant in the Random Effects Ordered Probit models but not in the Ordered Probit. There are similar differences between the models for *Age*, *Unspecified Job Situation* and the *Netherlands*. However, the signs does not change between the models for any of the statistically significant coefficients.

The signs on the coefficients of interest are negative. An increase in net worth relative to the median net worth in the reference group is associated with a decrease in probability of belonging to the highest group. The highest group in our paper is *Poor* health so an increase in relative wealth seem to increase the reported health status. Moreover, the absolute effect of net worth is also negative, the likelihood of reporting a *Poor* health status decreases as absolute net worth increase. Increased age and being married decrease the probability of reporting poor health. With regards to the job situation; working decreases the likelihood of bad health. The other groups however, increase the probability of having poor health as can be seen by their positive coefficients. Finally, education, compared to no education, has a positive effect on reported health status, as the probability of being in the worst health category decreases.

In order to determine what model that best fits the data we can look at the σ_u^2 which is the variance of the random effect, in other words, the unobserved time-invariant individual heterogeneity. The closer σ_u^2 is to zero the more similar the Pooled Ordered Probit is to the Random Effect Ordered Probit. As can be seen in Table 5, the σ_u^2 is 1.512 with a standard error of 0.029. Thus, it seems the variance is significantly different from zero which would favor the Random Effects Ordered Probit model. We formally test the fit of the models using a Likelihood Ratio test. The null hypothesis is that σ_u^2 is unimportant and the models would then fit the data equally well (Alsakka & Ap Gwilym, 2010). The reported likelihood ratio test enables us to reject the null hypothesis at any conventional level of significance. Thus the random effects component is important and therefore the Random Effects Ordered Probit model fits the data better than the Pooled Ordered Probit model.

The test result above indicates that the Random Effects Ordered Probit models do solve problems of unobserved individual heterogeneity which we discussed in section 6.2. Therefore, the estimates in columns (2) and (3) are less biased than those in column (1).

When comparing the two Random Effects Ordered Probit specifications in column (2) and (3) we can see some differences but they are very small. With regards to the statistical significance of the coefficients it is very similar between the models. The signs are, as mentioned above, identical. The only interesting, but still very discrete, difference between (2) and (3) is the small differences in magnitudes for some of the coefficients. The difference indicates that the Mundlak adjustment probably relax at least some of the orthogonality assumption discussed in section 6.2. The above analysis leads us to present the marginal effects of the Ordered Probit model and those of the Random Effects Ordered Probit model with the Mundlak adjustment in section 7.1.

7.1 Marginal Effects

Table 6: Marginal Effects at Means: Positive Net Worth

	Ordered Probit		RE Ordered Probit	
	(1)	(2)	(3)	(4)
Health Status	Relative	Absolute	Relative	Absolute
Excellent	0.0079	0.0132	0.0038	0.0061
Very Good	0.0099	0.0165	0.0137	0.0218
Good	0.0036	0.0061	0.0071	0.0113
Fair	-0.0115	-0.0193	-0.0185	-0.0294
Poor	-0.0099	-0.0165	-0.0061	-0.0097

All effects are significant at 1% level of significance

The marginal effects are presented in Table 6. The effects are at the mean of all control variables, i.e. *everything else is kept constant*. The relative column corresponds to the variable of relative standing and the absolute to the effect of the logarithmic net worth. The 3rd and 4th column are the marginal effects from the Mundlak-adjusted results in Table 5.

The signs are the same from both estimations and the magnitudes are small while the latter is different across the specifications. The difference indicates that there is indeed individual heterogeneity present in column (1) and (2). The effects in column (3) and (4) are from the panel-specification, thus less sensitive to this type of bias as we can control for time-invariant heterogeneity. The marginal effect of the absolute net worth is larger than those from relative net worth. More specifically, a one percent increase in net worth (equal to 0.01 in logarithmic wealth) increases the probability of reporting *Excellent* health by 0.0061 percentage points. With regards to the relative variable; a one percent increase in net worth relative to the reference group (which is constant) increases the likelihood of reporting excellent health by 0.0038 percentage points (Boes & Winkelmann, 2006).

The effect of both relative and absolute wealth is larger for individuals in the *Very good* category. An increase in net worth leads to a 0.0218 percentage points higher probability of reporting very good health and a relative increase corresponds to a 0.0137 percentage points higher probability. The same pattern goes for the category *Good*. The absolute effect is larger than the relative and both are positive. The sign of the coefficient changes when the categories are *Fair* and *Poor*. Here an increase in net worth decreases the probability of reporting these two. This is intuitive; an increase in wealth decreases the probability of reporting fair health by 0.0294 percentage points. An increase relative to the median net worth of the reference group decreases the probability with 0.0185 percentage points. Ultimately, the effect of net worth on belonging to the worst health category, poor, is small and negative (as for belonging in the excellent category).

The pattern of the effects is the same across the columns: the absolute effect is larger (in absolute numbers) than the relative. The relative effect is still significant, however, but the magnitude is very small. This is consistent across both specifications even though the magnitude is somewhat different. As we have argued previously, the latter (RE Ordered Probit) is more reliable because it controls for individual heterogeneity. The robustness of the results will be discussed in section 7.2.

7.2 Robustness Checks

Due to the limitation discussed in section 6 we conduct a number of robustness checks using selected parts of the sample as well as different estimation strategies.

7.2.1 Exclusion of Extreme Values of Net Worth

We are primarily interested in the effects on individuals with non-extreme values of net worth. Therefore, we exclude the five percent most wealthy individuals and the five percent poorest individuals. In this way we are able to investigate how robust the results are to changes in the data set with respect to extreme values of wealth.

In Table 7 the signs and the statistical significance of the coefficients are very similar to the results in Table 5. The marginal effects in Table 8 are larger than the main marginal effects which is not very surprising since a large part of the poorest five percent probably are excluded in the main regression and the wealthiest five percent are less likely to care about their relative standing with respect to net worth since they often are richer than the median of their reference group. Very wealthy individuals might also tend not to react very strong to a one percent change in their wealth.

7.2.2 IHS Transformation

Since the household net worth is less than- or equal to zero in some cases we are unable to take the logarithm of the variable. However, we are able to use the Inverse Hyperbolic Sine (IHS) transformation of the variable to solve for the skewness but also take negative and zero wealth into consideration. Let y_i be the i'th observation of variable y, then the IHS transformation is expressed as follows (StataCorp, 2013):

$$y_{i,IHS} = ln(y_i + \sqrt{y_i^2 + 1}) = sinh^{-1}(y_i) \tag{8}$$

The IHS transformation has advantages, the most obvious being that it is able to handle negative and zero values. Moreover, it is easy to re-transform into the original value due to the uncomplicated transformation function shown in equation (8). Normally, the coefficients must be re-transformed in order to be possible to interpret (Zhang, Fortney, Tilford, & Rost, 2000), however, for small values ($y_{i,IHS} < 1$) the IHS values are approximately the same as the re-transformed values.

The results from the estimation are presented in Table 9 and show signs and statistical significances very similar to those presented in the main regression above. In Table 10 the marginal effects are presented and there are some differences compared to the marginal effects presented in Table 6. However, they are small and largely they support the main results in section 7.

7.2.3 Linear Estimation

We also estimate a linear random effects regression to make sure that the results are independent of how we treat our dependent variable. In Table 11 we find similar results to those presented in Table 5. The signs and the statistical significance are the same for the key variables, which suggest that the results presented in Table 5 are robust across these two types of estimation procedures: Random Effects (GLS) and Random Effects Ordered Probit (Maximum Likelihood). Moreover, this confirms the findings by Ferrer-i-Cabonelli (2004): treating the categorical variable as ordinal or cardinal is of second importance for the results.

8 Discussion of Results and Conclusion

The results presented in section 7 suggest that there is both a relative and an absolute effect of net worth on self-perceived health. The absolute effect is slightly larger than the effect of relative net worth. Our results support the Relative-Position hypothesis; peoples' health is affected by their relative position with respect to the net worth of other individuals in their reference group. The probability of individuals reporting better health when their net worth increase is positive but small. There may be at least two explanations for this finding.

First, our data comprises only 50+ (main) respondents. In the demand-for-health framework the rate at which health deteriorates increases over time (with age) (Grossman, 1972). This means that a given amount of wealth or a given increase in wealth would affect health less for older individuals than the corresponding increase would for a young individual. Thus, the small magnitudes may be due to the age-structure of the sample.

Second, it is possible that the effect of relative standing on health has two components: one negative comparison effect and one positive altruistic effect (Senik, 2005). The modest size of the relative effect found in this paper is not necessarily an indicator of almost no effect. It might be that the counter-effects, comparison and altruism, cancel each other out.

We estimated a positive effect of absolute net worth on health. However, we were not able to determine whether or not this is due to causality between wealth and health, and if so, in what direction. There are theoretical arguments for causality in both directions. In order to determine causality, we would have to use an IV-strategy, instrumenting net worth to solve the problem of reverse causality. This is beyond the scope of this study.

With regards to the hypotheses, we find support for the first hypothesis: relative standing does affect health. The hypothesis is supported so a change in net worth relative to the median net worth of the reference group affects the probability of belonging to a certain health category. However, the effect is small. Similarly, our empirical results provide some support for the second hypothesis: that an increase in absolute net worth increases the likelihood of good health. Also in this case the estimated effects are small.

The determinants of health are important to identify for several reasons. Improving the tools available to policy-makers to curb the massive increase in public expenditures on health in developed countries is among the most pressing current public issues (Zweifel et al, 2009). The more we know about what determines health, the better are the conditions for improving health and containing health expenditures. However, the findings in this paper does not identify relative, nor absolute standing as *crucial* determinants of health among 50+ Europeans.

Our empirical results suffer from some caveats. First, the results were obtained using a construction of reference groups grounded in previous literature (Thiel, 2014; Clark & Senik, 2010). To the extent that these reference groups capture the true comparisons that the individuals do, our results are reliable. In order to improve the reliability of our results we would need direct information about what comparisons the respondents do.

Moreover, the imputed data (see section 5.3.1) for non responses may suffer from various methodological shortcomings. First, the validity of the imputation procedure could be disputed as the imputation model could be incorrectly specified[7].

The second threat with regards to imputed data is that we only use one of five imputation sets. Given the similarity of the results between using only one and using all five imputed sets we regard the validity of our results as solid.

The main purpose of this paper is to test if relative standing has an effect on self-reported health among 50+ Europeans. Panel data from the SHARE data set was used to study this question. We find support for the notion that relative position matters, but the effect is small. The findings are robust across different specifications. The results suggest that relative effects cannot be ignored when designing policies. With regards to causality, it is difficult to establish. As a consequence, more research must be undertaken in this area. One suggestion for future research is to use instruments in order to mitigate the endogeneity concern.

Further suggestions for future researchers is to run separate regressions for smaller samples, for example per country, in order to possibly obtain more clear-cut results. Moreover,

[7] De Luca, Giuseppe (12th of March 2015) Mail conversation with the authors. For more information about the imputation process please see (Dardanoni, De Luca, Modica, & Peracchi, 2015)

using a younger sample for comparisons between the effect of relative standing for young and 50+ individuals would be informative. Finally, it would be interesting to discern between comparison and information effects more explicitly.

Notes

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A Robustness Checks: Tables

A.1 Results: Excluding the Poorest and Richest

Table 7: Estimation Results: Excluding the Tails

Variable	**Coefficients**		
	(1)	(2)	(3)
Self-perceived Health	Ordered Probit	RE Ordered Probit	RE Ordered Probit
Relative ln(hhnet worth)	-0.092***	-0.123***	-0.123***
ln(hh net worth)	-0.170***	-0.225***	-0.226***
Socio-demographic Controls			
Household Size	0.018***	0.028**	0.027***
Male	0.003	-0.012	-0.011
Widowed	-0.004	-0.024	-0.022
Married	0.002	-0.032	-0.030
Children	0.002	0.01	0.001
Age	0.000	-0.009	-0.011
Age^2	0.000***	0.000***	0.000***
Job Situation Controls (Retired omitted)			
Self- or Employed	-0.229***	-0.298***	-0.299***
Unemployed	0.080**	0.122***	0.121***
Disabled	1.083***	1.294***	1.292***
Homemaker	0.086***	0.106***	0.107***
Other	0.005	-0.027	-0.057
Unspecified	0.047	0.078	-0.085***
Education Controls (No Education omitted)			
Primary Educ.	-0.073***	-0.079***	-0.083***
Low Second Educ.	-0.0229***	-0.327***	-0.0332***
Up Second Educ.	-0.344***	-0.517***	-0.522***
Tertiary Educ.	-0.378***	-0.577***	-0.583***
Master/Higher	-0.352***	-0.527***	-0.533***
$Pseudo - R^2$	0.0959	-	-
σ_u^2	-	1.496 (0.0302)	1.4962 (0.0302)
Number of observations	68778	68778	68778
Clustered standard errors	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*
Mundlak adjustment	*No*	*No*	*Yes*

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 8: Marginal Effects at Means: Excluding the Tails

	Ordered Probit		**RE Ordered Probit**	
Health Status	Relative	Absolute	Relative	Absolute
Excellent	0.0107	0.0197	0.0049	0.0089
Very Good	0.0138	0.0254	0.0178	0.0329
Good	0.0058	0.1060	0.0108	0.0197
Fair	-0.0162	-0.0298	-0.0252	-0.0461
Poor	-0.0141	-0.2590	-0.0084	-0.0154

All effects are significant at 1% level of significance

A.2 Results: IHS Transformation

Table 9: Estimation Results: IHS Transformation

Variable	**Coefficients**		
	(1)	(2)	(3)
Self-perceived Health	Ordered Probit	RE Ordered Probit	RE Ordered Probit
Relative IHS net worth	-0.029***	-0.039***	-0.039***
IHS net worth	-0.058***	-0.071***	-0.071***
Socio-demographic controls			
House Hold Size	0.011*	0.015*	0.014*
Male	-0.015	-0.030*	-0.029*
Widowed	-0.013	-0.054*	-0.052*
Married	-0.028*	-0.087***	-0.085***
Children	-0.001	0.003	0.003
Age	-0.008	-0.024**	-0.026**
Age^2	0.000***	0.000***	0.000***
Job situation controls (Retired omitted)			
Self- or Employed	-0.248***	-0.312***	-0.313***
Unemployed	0.105***	0.164***	0.162***
Disabled	1.113***	1.297***	1.295***
Homemaker	0.077***	0.100***	0.101***
Other	-0.013	-0.085	-0.086
Unspecified	0.196***	0.165	0.157
Education controls (No educ. omitted)			
Primary Educ.	-0.068***	-0.074***	-0.078***
Low Second Educ.	-0.230***	-0.333***	-0.339***
Up Second Educ.	-0.365***	-0.553***	-0.559***
Tertiary Educ.	-0.411***	-0.638***	-0.644***
Master/Higher	-0.390***	-0.592***	-0.597***
Clustered Standard Errors	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*
Mundlak adjustment	*No*	*No*	*Yes*

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Table 10: Marginal Effects at Means: IHS Transformation

	Ordered Probit		**RE Ordered Probit**	
Health Status	Relative	Absolute	Relative	Absolute
Excellent	.00341	.00687	.00159	.00293
Very Good	.00426	.00858	.00572	.01053
Good	.00169	.00340	.00321	.00591
Fair	-.00493	-.00994	-.00782	-.01439
Poor	-.00442	-.00891	-.00271	-.00499

All effects are significant at 1% level of significance

A.3 Results: Linear Regression

Table 11: Estimation Results: Random Effects

Variable	**Coefficient**
Self-perceived Health	
Relative ln(net worth)	-0.054***
ln(net worth)	-0.082***
Socio-demographic Controls	
Household Size	0.011**
Male	-0.011
Widowed	-0.027*
Married	-0.035***
Child	0.001
Age	-0.007
Age^2	0.000***
Job situation controls (Retired omitted)	
Self- or Employed	-0.166***
Unemployed	0.075***
Disabled	0.639***
Homemaker	0.057***
Other	-0.051
Unspecified	0.004
Education controls (No educ. omitted)	
Primary Educ.	-0.035**
Low Second Educ.	-0.175***
Up Second Educ.	-0.293***
Tertiary Educ.	-0.340***
Master/Higher	-0.323***
R^2	0.2439
Clustered Standard Errors	Yes
Country fixed effects	Yes
Mundlak adjustment	No

Significance levels: $*$: 10% $**$: 5% $***$: 1%

B Multiple Imputation Results

It is not possible to use **if** commands, or in any other way adjust the sample, with respect to imputed variables in Stata 13 when conducting multiple estimation analysis. Therefore, we are only able to report the regression results from the IHS transformation specification. However, we are able to report the IHS transformation results from the Pooled Ordered Probit, the Random Effects Ordered Probit, the Random Effects Ordered Probit with the Mundlak adjustment and lastly the linear Random Effects model. As can be seen in all below tables the results are very similar to those presented in this thesis and the fact that we have treated imputed values as true does not seem to have had any large implication on the results. Unfortunately, we are unable to present the marginal effects from the Probit estimations below as Stata 13 cannot compute these after multiple imputation estimations.

Table 12: Multiple Imputation Estimation Results: IHS Transformation

Variable	**Coefficients**			
	(1)	(2)	(3)	(4)
Self-perceived Health	Ordered Probit	RE Ordered Probit	RE Ordered Probit	Linear Random Effects
Relative IHS net worth	-0.054***	-0.067***	-0.033***	-0.018**
IHS net worth	-0.025***	-0.033***	-0.070***	-0.035***
Socio-demographic controls				
House Hold Size	0.011*	0.015*	0.014	0.006
Male	-0.015	-0.031*	-0.03*	-0.017*
Widowed	-0.013	-0.054*	-0.052*	-0.030*
Married	-0.028*	-0.087***	-0.085***	-0.047***
Children	-0.001	0.003	0.003	0.002
Age	-0.008	-0.025**	-0.027**	-0.012**
Age^2	0.000***	0.000***	0.000***	0.000***
Job situation controls (Retired omitted)				
Self- or Employed	-0.249***	-0.312***	-0.315***	-0.179***
Unemployed	0.105***	0.165***	0.163***	0.092***
Disabled	1.115***	1.300***	1.297***	0.651***
Homemaker	0.077***	0.100***	0.101***	0.057***
Other	-0.011	-0.085	-0.082	-0.049
Unspecified	0.215***	0.191*	0.184*	0.092*
Education controls (No educ. omitted)				
Primary Educ.	-0.068***	-0.074***	-0.078***	0.039***
Low Second Educ.	-0.229***	-0.333***	-0.339***	-0.184***
Up Second Educ.	-0.365***	-0.553***	-0.559***	-0.307***
Tertiary Educ.	-0.411***	-0.637***	-0.643***	-0.358***
Master/Higher	-0.390***	-0.591***	-0.596***	-0.335***
Clustered Standard Errors	*Yes*	*Yes*	*Yes*	*Yes*
Country fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Mundlak adjustment	*No*	*No*	*Yes*	*Yes*

Significance levels: $*$: 10% $**$: 5% $***$: 1%