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„The Link between Wealth and Mortality

-

A Survey Analysis“

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Abstract (English)

This master thesis examines the link between wealth and mortality by evaluating data from two waves of the Survey on Health, Ageing and Retirement in Europe (SHARE). Particular care in the evaluation is taken on two known problems: Firstly, the possible sample selection bias in surveys and secondly, the presumable endogeneity of the wealth measure in the regression. To control for the first, a bivariate probit model is employed that directly models selection in the second and last wave of the analysis, while the second problem is primarily dealt with an instrumental variables strategy that uses respondents' received inheritances as an instrument for change of wealth. Obtained results are in line with previous research and indicate that higher wealth is associated with reduced mortality. Further evidence suggests a causal wealth-induced effect on respondent's self-rated health status that is on an equal level to common health determinants age and education.

Abstract (German)

Diese Masterarbeit untersucht den Zusammenhang zwischen Vermögen und Sterblichkeit durch Auswertung zweier Umfragewellen des Survey on Health, Ageing and Retirement in Europe (SHARE). Besonderes Augenmerk in der Untersuchung liegt bei zwei bekannten Problemen: Erstens, die mögliche Stichprobenverzerrung in Umfragen und zweitens, die wahrscheinliche Endogenität von Vermögen in der Regression. Um ersteres Problem zu kontrollieren wird ein bivariates Probit-Modell geschätzt, welches die Selektion in der zweiten und letzten Welle direkt modelliert, während das zweite Problem vor allem mittels einer Instrumentalvariablenschätzung behandelt wird, welche erhaltene Erbschaften der Umfrageteilnehmer als Instrument für ihre Vermögensveränderung nutzt. Die erhaltenen Resultate stehen im Einklang mit früheren Studien und zeigen, dass höheres Vermögen mit geringerer Sterblichkeit einhergeht. Zusätzlich gibt es Hinweise auf ein kausalen Effekt von Vermögen auf die selbst eingeschätzte Gesundheit der Teilnehmer, welcher in seiner Höhe ebenbürtig mit den bekannten Einflussfaktoren Alter und Bildung ist.

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List of Abbreviations

AHEAD	Asset and Health Dynamics of the Oldest-Old
BRS	British Retirement Survey
EU	European Union
EUR	Euro
HRS	Health and Retirement Study
ICD	International Classification of Diseases
ISCED	International Standard Classification of Education
IV	Instrumental variable
mn	Million
NUTS	Nomenclature des unites territoriales statistiques
OLS	Ordinary Least Squares
pp	Percentage points
PSID	Panel Study of Income Dynamics
SES	Socio-economic status
SHARE	Survey of Health, Ageing and Retirement in Europe

1. Introduction

This master thesis shall examine whether differences in individual's socio-economic status (SES) cause inequalities of mortality. Not until recently, the topic of inequality got unprecedented worldwide attention after Thomas Piketty had published his book "Wealth in the twenty-first century" in 2014 where he claims that the prevailing wealth inequalities are caused by the dominant capitalist society and could ultimately lead to a destruction of the basic democratic order (Piketty & Goldhammer, 2014). The book that was originally published in French in 2013 and the accompanying data source that was made publicly accessible triggered lively debates in politics, the media and within the scientific community. The apparent widening of inequalities, possible strategies for a more even income and wealth distribution as well as the consequences of rising inequality inspired many authors and policy makers to seek for adequate measures and reactions to the current situation.

One aspect of inequalities in income and wealth per se, namely that wealth and income levels go hand in hand with life expectancy, did not make it to the broad public debate although there is an abundance of studies documenting that socio-economic status matters for mortality. If it is indeed the case that financial disadvantages pave the way for a short and unhealthy life, then it reasonable that the elimination of inequalities has upmost priority over fears of economic slumps that are brought in the evaluation of potential measures to reduce inequalities. As a result, the motivation for this thesis is grounded in the question whether a causal link running from SES to mortality can be established. Evidence for such a link could fortify the calls for an even distribution of income and wealth and could ultimately lead to political action that ensures equal living standards. The chosen data allowed the examination of this link with income and wealth data, but for several reasons wealth was chosen over income as the basic measure of SES (see Section 3.4. for details).

In the next section of this thesis, the available literature on the relationship between wealth and mortality is reviewed, followed by a description of the data utilized in the analysis, and the estimation issues that arise from the nature of the data. The major part of the thesis is dedicated to two separate models. The first model seeks to directly explain mortality of the SHARE respondents by applying a bivariate probit approach to model sample selection between two waves of the survey. The second model examines respondents' health transitions between the two waves with an instrumental variables (IV) approach to deal with the possible endogeneity of the key explanatory variable wealth. Both estimation issues, sample selection and endogeneity, are further discussed in Section 4 and require a certain econometrical treatment to allow for a meaningful analysis of the connection between wealth and mortality.

2. Literature review

There is an innumerable amount of studies on the relationship between socio-economic status and mortality or more broadly between socio-economic status and health. Here, an overview of some studies dealing with this topic with an extra focus on causality is provided.

The general finding in the literature is that higher levels of SES are associated with better health and higher life expectancy. As noted by Goldman (2001) in a review of the relevant literature, there are many studies dating back as far as the 1800s and across several research areas including sociology, economics, demography, epidemiology, biology, and medicine that identified differentials in health and life expectancy by SES. With few exceptions, these differentials have been found across time, place, gender, and age and moreover for several health indicators (self-rated health, certain illnesses and diseases, mortality, and psychological well-being) as well as for alternative indicators of SES (income, wealth, education, occupation, degree of social integration, and marital status).

The first part of the empirical examination in this thesis is based on a paper by Attanasio and Emmerson (2003), who fit a sample selection model to data from two waves of the British Retirement Survey (BRS) from 1988/1989 and 1994 to quantify the relationship between wealth and health outcomes. Their analysis shows that an ascend in the wealth distribution from the 40th to the 60th percentile, either measured in levels or as wealth rankings, increases the chances of survival between 1.0 and 1.9 percentage points (pp) for a 65-year-old men. For women, the effect lies between 1.1 and 1.3pp depending on the measure of wealth used in the model. To limit the potential endogeneity of the wealth variables, initial health status has been entered in the regressions, but no strong stance for a causal relationship between wealth and mortality is taken by the authors.

Similar results using BRS data is found by Benzeval and Judge (2001) who study the dynamics of income and health and give a review of literature that goes beyond static cross-sectional studies. The results confirm those of previous studies and suggest a causal effect running from income to health outcomes. For instance, individuals in the lowest quintile of the income distribution are 2.4 times as likely to assess their health status as poor and 1.5 times as likely to report above-average health problems as those in the top quintile. They conclude that the income level and its change are both significant determinants of health and that income reductions seem more important for individual's health than increases.

While most researches acknowledge the fact that SES might be reversely caused by health or that SES and health outcomes might be simultaneously determined, few studies aspire to overcome this issue in an econometrical way. As noted in Meer, Miller and Rosen (2003), one careful attempt was performed by Ettner (1996), who uses data from three different surveys to assess the structural impact of income on several health measures. The results from Ettner's IV strategy that uses the state unemployment rate, individual's work experience, parents' education and spousal characteristics as instruments for income, indicate that the income effect on health variables is underestimated when exogeneity is assumed. Depending on the validity of the instruments, increases of income are expected to have a causal effect on respondent's mental and physical health and alcohol consumption.

In this respect, Adams, Hurd, McFadden, Merrill and Ribeiro (2003) fail to find a causal link running from SES to health innovations and mortality in their analysis of the Asset and Health Dynamics of the Oldest-Old (AHEAD) study. After performing Granger-causality inspired tests on the panel, they conclude that there is no evidence that SES triggers mortality differentials. In the same way, Meer et al. (2003) reject causation running from wealth to self-reported health status in an IV framework that uses information on respondents' received inheritances for the change of wealth. The data source for their instrumental variables approach is the Panel Study of Income Dynamics (PSID). Further evidence for the absence of a causal link comes from Ahammer, Horvath and Winter-Ebmer (2016), who find no income effect on worker's death rates after instrumenting actual wages with time-invariant and firm-specific wage components in an assessment of Austrian social security data.

To conclude, the presented studies suggest the absence of a causal effect running from wealth to health outcomes. With the available means and data, this shall be tested with data from two waves of SHARE. The empirical analysis in this thesis is predominantly following the paths laid out by Attanasio and Emmerson (2003), who carried out a neat assessment of the BRS, and those of Meer et al. (2003), who performed an IV strategy with data from the PSID. Wealth is used as the basic SES measure in this analysis due to it being in some aspects superior over income data (see Section 3.4. for details). Dependent variables explained with that measure are respondent's mortality between two waves of SHARE in a bivariate probit setup and the development of self-rated health status between the two waves with the means of an IV probit framework. The rest of the thesis is organized as follows: In Section 3 the data source, the obtained sample, and the variables entering the regressions are presented and the two most crucial estimation issues are discussed in Section 4. In Sections 5 and 6 the models for the analysis and subsequent results are explained. Section 7 concludes followed by the references in Section 8 and Appendices A to D.

3. Data description

This thesis is based on data from SHARE, which is a harmonized panel survey conducted in 20 European countries and Israel. Up until now, over 293,000 interviews of 123,000 individuals were collected during six waves of the project between 2004 and 2015 (SHARE Dates & Facts, n.d.). The target group for the survey are individuals at the age of 50 and above, whereby current partners living in the same household as the selected individuals were also interviewed regardless of their age. Five of the six SHARE waves aimed on gathering information on current living circumstances of the respondents, while the third wave (SHARELIFE) targeted retrospective life histories. The available individual data covers the following areas: physical and psychological health, socio-economic status, demographics, expectations as well as family and social background and support (SHARE FAQ, n.d.). Appendix A gives a summary of the different questionnaire modules in the six SHARE waves. Since not all 21 countries participated in each wave of SHARE and because single waves were not conducted during the same time horizon across countries, an overview of single country's participations and the respective timing of the interviews is also provided in the appendix.

3.1. Data collection

The data collection process in SHARE rests upon computer-assisted personal interviews, where interviewers carry out face-to-face interviews and use a computer with an installed interviewing software that guides through the survey. This does not apply to drop-off and vignettes questionnaires, which are conducted via paper and pencil, and end-of-life interviews that can be carried out via computer-assisted telephone interviews as well (SHARE FAQ, n.d.).

3.2. Sampling design

The basic requirement for the finite sample of Europeans aged 50 and above is to produce a probability sample that allows proper inference and is representative for the target population. To achieve that, the choice of the sampling design in SHARE is ideally an attempt to balance estimators in terms of bias and efficiency and the costs of conducting a survey. Due to country-specific circumstances and constraints, mostly related to the prevailing administrational structure and the availability and accuracy of data, the sampling procedures in SHARE vary between participating countries and can be classified into three different categories: "1. (stratified) simple random sampling from national population registers 2. multi-stage sampling using regional/local population registers and 3. single or multi-stage sampling using telephone directories followed by screening in the field" (Börsch-Supan & Jürges, 2005, p. 32). Consequently, the survey exhibits a more or less complex sampling design depending on the participating country, which should be considered in the statistical analysis to yield correct point estimates and standard errors (O´Donnell et al., 2008).

3.3. Sample description

For the following analysis, data from the second and fourth wave of SHARE is used. The interviews for the second wave were primarily conducted in 2006/07 and those for the fourth wave were carried out in 2011 for most countries (see Appendix A). The choice of these two waves was based on the high number of respondents with complete interviews in both waves. In total, the second wave provides data on 37,183 individuals, but the final sample for the bivariate probit approach in Section 5 is reduced to 20,599 single observations. This reduction is mainly a result of Greece, Ireland and Israel not taking part in the fourth wave and this work's focus on main respondents of the survey only (meaning that solely the main respondent of a household remains in the sample to eliminate one possible source of attrition bias). Furthermore, individuals below the age of 50 are excluded from the sample, but this only applies to few observations. Table 1 lists the number of observations by country and gender. The sample entails a slight overweight of female respondents (54.6%) with the most observations stemming from Belgium followed by France, Sweden and Italy. Relatively few observations are available from Austria and Switzerland, together accounting for less than 10% of the whole sample.

Country	Male	Percent	Female	Percent	Total	Percent
Austria	374	4.0	516	4.6	890	4.3
Belgium	1,084	11.6	1,079	9.6	2,163	10.5
Czech Republic	681	7.3	1,173	10.4	1,854	9.0
Denmark	882	9.4	873	7.8	1,755	8.5
France	897	9.6	1,145	10.2	2,042	9.9
Germany	820	8.8	900	8.0	1,720	8.3
Italy	883	9.4	1,028	9.1	1,911	9.3
Netherlands	869	9.3	975	8.7	1,844	9.0
Poland	743	7.9	1,013	9.0	1,756	8.5
Spain	655	7.0	932	8.3	1,587	7.7
Sweden	955	10.2	1,041	9.3	1,996	9.7
Switzerland	508	5.4	573	5.1	1,081	5.2
Total	9,351	100	11,248	100	20,599	100

Note: Columns may not sum to 100 due to rounding

Table 1: SHARE participation by country and gender

Table 2 describes what happened to the 20,599 respondents between the second and fourth wave.[1] Overall, 68.6% of the respondents in wave 2 survived until wave 4 and 6.4% are known to have died between the two waves. 25.0% of the respondents dropped out of the sample for unknown reasons. The comparison of death and attrition rates by gender shows that a higher percentage of men died, while women are more likely to drop out from the sample. A higher percentage of men dying than

[1] Note that the time between interviews in the second and fourth wave of SHARE varies between 3.3 and 5.4 years for the individuals in the sample.

women is the expected observation given the lower life expectancy of men, but the admittedly small differences in attrition rates between men and women (25.3% vs. 24.7%) could indicate the importance of controlling for sample attrition bias in the sample, which is discussed in Section 4.

	Men	Women	All	No. of Obs.
Those who survive	68.3	68.9	68.6	14,134
Those who die	7.1	5.8	6.4	1,311
Those who attrit from the sample	24.7	25.3	25.0	5,154

Note: Columns may not sum to 100 due to rounding

Table 2: What happened to the sample between waves 2 and 4?

3.4. Variables in the regressions

Some variables for this analysis stem from imputations that were either carried out by hot-deck method, which was essentially used for socio-demographic variables such as age, gender and education, or the fully conditional specification method, predominantly used for monetary variables in SHARE. See SHARE Release Guide 6.0.0 (2017) on how these two methods were applied. SHARE provides five imputations of the missing values, which allows users to consider the additional variability caused by the imputation procedure. Since there is no reason to prefer one of the five imputed values to the others, the five values for each missing value were summed and averaged for this analysis (SHARE FAQ, n.d.).

The estimation procedures in this thesis rely heavily on imputed data in order to maintain a sufficiently large sample size. The variables used in the analysis are briefly explained below and reference is made whenever imputations for a certain variable were taken into account. Summary statistics of the variables in both models are provided in Appendix C and D.

3.4.1. Wealth measure

The key variable of interest in this analysis is wealth. Unfortunately, individual wealth data is difficult to gather in surveys, since respondents are often not able or willing to provide detailed information on their wealth holdings. To limit the potentially high number of missing data on financial variables, the respondents in SHARE were asked a sequence of unfolding-brackets questions after not responding initially. In these questions, the respondents had to answer whether the amount is larger than, smaller than or about equal to three predefined country-specific thresholds. The collected information under this procedure allowed the researchers in charge to obtain either rough point estimates or estimates for the original missing amounts in a certain interval. For the first, the missing amounts were imputed using the selected thresholds in the unfolding-brackets questions, while for the second, the available information was combined with further information from logical constraints and percentiles of the country distribution for a certain indicator (SHARE Release Guide 6.0.0, 2017).

The coverscreen module of wave 2 contains the imputed information on household net worth, which is the sum of household member's real and financial assets minus liabilities and is used as the wealth indicator in this work. To make couples and singles comparable, the value of household net worth is divided by 0.61 for singles, which is a common equivalence factor proposed by McClements (1977) and was similarly applied by Attanasio and Emmerson (2003). The measure is then adjusted for purchasing power to guarantee comparability across the sample consisting of observations from twelve European countries and capped at EUR 1.5mn such that extreme values do not to bias the results. Only 1.4% of the respondents in the sample have a net worth higher than EUR 1.5mn.[2]

In contrast to current income, the usage of household net worth as the key variable to explain life expectancy is more tempting, as individuals, especially retirees, may be very wealthy but can have low income at the same time. In that respect, Feinstein (1993) argues that wealth is a superior measure of economic capacity. Further noted by Feinstein is that wealth is less likely affected by reverse causality than income, "primarily because wealth accumulates over time and hence is less affected by a single episode of sickness" (p.284). Wealth as a measure of economic resources is, however, not exempt from deficiencies as severe health shocks could cause a decline of wealth or because the interplay between wealth and health could still be determined by third factors such as genetics or childhood environment (Meer et al., 2003).

Another issue regarding individual wealth holdings over the lifespan relates to the Life Cycle Hypothesis developed by Modigliani (1986). According to the hypothesis, wealth and savings typically exhibit a hump shape over the life cycle, as individuals accumulate wealth up to retirement and then dissave until death. The implication is that the amount of wealth at a certain time point crucially depends on individual's age and employment status. This is indeed observable in the sample at hand. In Figure 1 the result of a locally weighted regression of the wealth indicator household net worth on respondent's age is plotted. The graph exhibits the characteristic hump shape as proposed by Modigliani (1986) and indicates that the individuals in the sample start dissaving in their late 50ies. This finding is reasonable given OECD data on the effective retirement age for the year 2006 when the second wave of SHARE was predominantly conducted. The data shows that the effective retirement age spans from 58.5 to 64.7 years for men and between 57.9 and 63.9 years for women in the twelve countries in the sample (OECD, 2017).

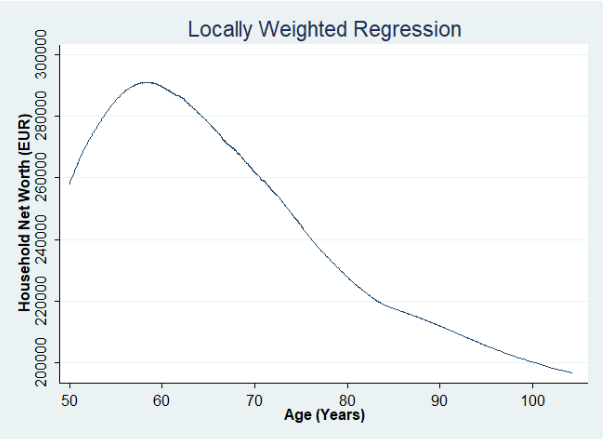

Figure 1: Wealth accumulation and decumulation by respondent's age

[2] Note that there is only one individual per household, as the analysis is based on main respondents in the survey. A spouse or partner living in the same household as the main respondent is not included in the sample.

To consider the issue of changing wealth over respondent's lifetime in the analysis, wealth rankings within four age groups (50-59, 60-69, 70-79 and 80+ years of age) are calculated and used as explanatory variables in separate regressions next to specifications with wealth in levels. The respective wealth ranks are normalized, i.e. divided by the number of individuals in the age group. This is a way of accounting for the wealth accumulation and decumulation per age and introduces additional nonlinearities to the model. Here it should be noted, that a model specification where wealth ranks become more important than wealth levels does not by all means imply that ranks are the better predictors for health outcomes. The ranks could capture some complex nonlinearities in the relationship between wealth and health outcomes, which are not accounted for in the level specification (Attanasio & Emmerson, 2003).

Figure 2 below shows the distribution of wealth in several intervals for singles and couples. Almost half of all singles in the sample have wealth amounting to less than EUR 100,000, while only a bit more than a third of all couples are in the same situation. Compared to singles, a significantly higher share of couples have a wealth level between EUR 100,000 and 500,000, while the distribution in the upper wealth classes above EUR 500,000 is very similar among singles and couples.

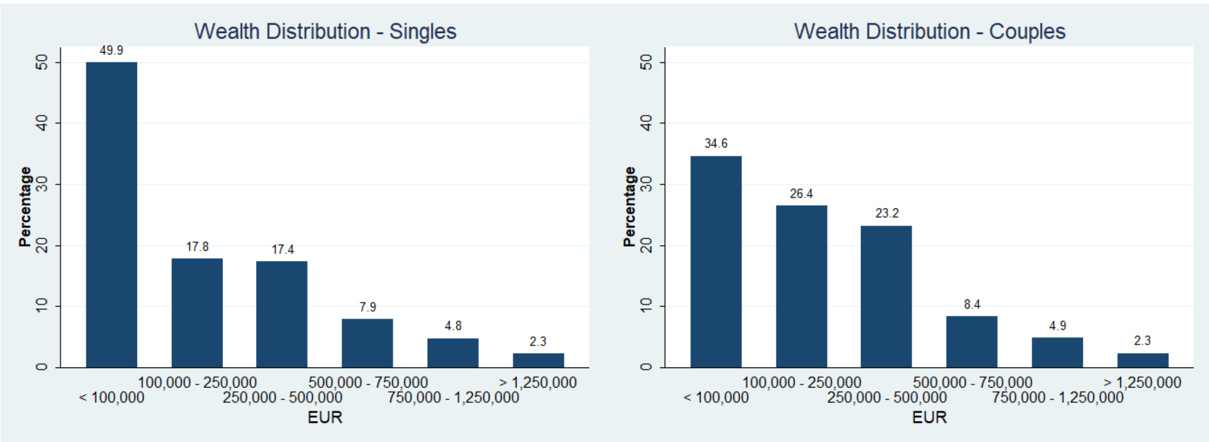

Figure 2: Distribution of wealth for singles and couples

3.4.2. Health status

Next to wealth, respondent's health status is a main factor in the analysis. The imputations module in wave 2 of SHARE contains several variables related to respondent's health, which provide information on the following aspects: diseases, mobility limitations, eyesight and hearing ability, body mass, habits (smoking, drinking), physical activity, communication, cognitive skills, grip strength, depression and health care. To construct a health score for each respondent, the weight of these different variables as indicators of respondent's general health status is assessed and added together. A relatively high weight is assigned to the variables related to diseases, limitations and body mass, while variables such as those related to communication and cognitive skills carry a low weight. The sum of the weighted variables is then allocated to a number between 1 and 5 whereby 1 refers to a very good health status and 5 to a very poor health status. See Appendix B for the allocation formula of the health score.

In addition to the health score, a variable on respondent's self-perceived health is included in the analysis to incorporate more information on individual's health status in the model. The ordinal variable ranges from 1 to 5 with 1 as excellent, 2 as very good, 3 as good, 4 as fair and 5 as poor self-perceived health status. Unsurprisingly, respondent's self-perceived health status is highly correlated with the calculated health score from above. The correlation coefficient amounts to 0.49 and is significant at the 1% level.

Table 3 summarizes the mean values of the calculated health score and self-reported health status by age group and gender. The table shows that both indicators increase with age and that they are higher for women in every age group. The apparent gender health gap is also documented by Eurostat (2016). The data from Eurostat reveals that women are less likely to rate their health as very good or good and are more likely to report experiencing physical pain as well as long-lasting health problems. A further finding is that the gender health gap increases with age, which can also be seen in the SHARE data.

Age group	Health score (1-5)		Self-perceived health (1-5)	
	Men	Women	Men	Women
50-59	1.16	1.22	2.79	2.93
60-69	1.20	1.26	2.97	3.12
70-79	1.35	1.54	3.28	3.52
80+	1.66	1.91	3.53	3.69
Total	1.26	1.39	3.03	3.21

Table 3: Mean values of health score and self-perceived health by age group and gender

3.4.3. Other variables

Among the additional variables entering the model next to measures of respondents' wealth and health is a dummy variable indicating whether the person is sharing the household with a partner. The consideration of the dummy in the regressions results from debates in the scientific community, whether marital status has a positive influence on health and life expectancy. See Robards, Evandrou, Falkingham and Vlachantoni (2012) for the relevant literature and a brief discussion of the issue.

Another variable in the model relates to the educational attainment of respondents. The information on education is included in the imputations module of wave 2 and is based on the International Standard Classification of Education (ISCED) in the version of 1997, which classifies educational attainment into seven different levels (UNESCO, 2006). This information is included in the model via three dummy variables that correspond to high school completion (ISCED levels 2 or 3) as well as post-secondary (level 4) and tertiary education (levels 5 or 6).

Since observations from twelve different countries constitute the sample, regional dummies are included in the regressions to account for local differences in mortality risk. SHARE provides the geographic codes from the NUTS-classification of the EU in the generated housing modules, but not every NUTS level is available in each country data set and the module exhibits a high number of missing NUTS codes. Therefore, this information cannot be used for this analysis and the author decided to include two dummy variables, one for the Southern European states Spain and Italy and the other for previous member states of the Warsaw Pact Poland and Czech Republic. In comparison to a specification with separate dummies for all countries in the sample, the model specification with only two regional dummies is less complex and not inferior.

4. Estimation issues

Two estimation issues are particularly severe in the current assessment of the wealth-health relationship. The first relates to sample attrition that potentially yields biased results as respondent's dropping out of the sample represents a loss of valuable information for the analysis of mortality. The second issue directly relates to the wealth measure that is probably endogenous and as such prevents a causal inference on the relationship between wealth and health. Both issues are discussed below in further detail.

4.1. Sample attrition

The higher drop-out rate for women (see Table 2) could imply that their observed death rate of 5.8% is more biased downwards as compared to the one for men with 7.1%. That is, because one can reasonably assume that poor health causes higher attrition rates, since, for instance, no interviews were conducted for target respondents staying in a hospital during the SHARE interviews. This example underlines that sample attrition might pose serious problems in assessing the main aim of this thesis, namely evaluating the impact of socio-economic status on mortality. When the same factors (e.g. selected respondents staying in hospital during interviews) influence both, attrition and mortality, misleading results are obtained if attrition is assumed to occur randomly at the same time. To avoid this, a not entirely standard approach is pursued in this thesis, which models attrition directly and yields prudent estimates for the effect of SES on mortality.

Table 4 summarizes the mortality rates of men and women in the sample implied by different assumptions on the occurrence of attrition and compares the rates to reference values. Under the assumption that attrition is random and not correlated with mortality, the expected death rates in the sample are 8.8% for men and 7.3% for women. These values are considerably above the observable mortality rates of 7.1% and 5.8%, but below reference rates, which were calculated from Austrian life tables under the assumptions of same age distribution as in the sample and a time span of four years (Statistik Austria, 2017). These findings suggest that attrition in the sample at hand cannot be assumed to occur randomly for two reasons: 1. Mortality rates are significantly above observable rates if random attrition is assumed 2. Obtained mortality rates under random attrition still reside below conservative reference values. Therefore, and despite that the researchers in charge of SHARE attempt to mitigate the potential bias arising from sample attrition by dedicating extra effort into re-interviewing respondents and providing calibrated weights (SHARE FAQ, n.d.), it is evident that there exist distinct factors, which influence attrition and consequently mortality in the sample at hand. In conclusion, sample attrition needs to be modelled to yield solid estimates of the impact of socio-economic status on mortality. The model that is used for this purpose and has similarly been applied by Attanasio & Emmerson (2003) is presented in Section 5.

	Men	Women	All
Waves 2-4 assuming:			
All those who attrit survive	7.1	5.8	6.4
Attrition occurs randomly	8.8	7.3	8.0
All those who attrit die	31.7	31.1	31.4
Expected deaths from life tables	10.2	8.0	8.9

Note: Expected deaths calculated from 2010/12 life tables from Statistik Austria

Table 4: Mortality rates with different assumptions on attrition

The next table (Table 5) provides a deeper look on attrition and mortality by dividing the sample in four different age groups. The table shows that attrition rates are decreasing between the first and third age group, most likely reflecting the higher mobility of younger cohorts (Attanasio & Emmerson, 2003). Between the third and fourth age group the rates increase considerably for both sexes most probably due to the poorer health status and the much higher mortality risk for individuals at the age of 80 and above. Regarding deceased respondents, the table indicates that mortality rates are unsurprisingly higher for higher age groups. Compared to expected mortality rates obtained from Austrian life tables, the observed rates in the sample are much lower, again emphasizing the apparent downward bias of the observed figures due to attrition as explained above.

	SHARE waves 2-4				Austrian life tables	
	Attrit		Deceased		Expected deaths	
Age group	Men	Women	Men	Women	Men	Women
50-59	27.1	26.0	1.7	0.9	2.9	1.4
60-69	22.6	24.0	4.6	2.8	6.5	3.2
70-79	22.1	24.1	10.2	7.2	14.7	9.4
80+	28.6	28.7	27.7	23.1	39.0	33.6
Total	24.7	25.3	7.1	5.8	10.2	8.0

Note: Expected deaths calculated from 2010/12 life tables from Statistik Austria

Table 5: Attrition and mortality by age group

4.2. Endogeneity

The second major estimation issue for assessing the link between wealth and mortality next to sample attrition is the presumable endogeneity of the wealth variable. Endogenous explanatory variables are a result of the variables being correlated to the error term in the regression equation, which is most likely caused by either reverse causality or measurement error in the current analysis (Wooldridge, 2002).

Reverse causality refers to a situation where it is plausible for causation to run in both directions. On the one hand one can securely assume that high wealth enables individuals to afford extraordinary medical treatments, which in turn prolong their life expectancy. In addition, more affluent people can afford a healthier lifestyle and experience place-related health benefits, such as less exposure to noise and pollution as well as higher quality of local services and social networks (Woolf, et al., 2015). On the other hand, however, one can easily think of situations where either wealth accumulation is impeded by poor wealth or where wealth is used up to remedy poor health as argued by Smith (1999). Further, individuals with a shorter lifespan might use up their wealth faster than individuals with a higher life expectancy. Due to this plausible reciprocal relationship between wealth and mortality, economists are generally cautious about assigning a causal interpretation to the observed correlations and stress the possibility of reverse causality (Attanasio & Emmerson, 2003).

To deal with reverse causation, estimates of the wealth effect on mortality are calculated by conditioning on the initial health status of SHARE respondents. This means that the health status assessed during wave 2, which was conducted in the years 2006/07 for all countries in the sample, is used as a control variable in the regressions. This approach is unison with the one pursued by Attanasio and Emmerson (2003), who use health data from the first wave of the BRS as a control factor for reverse causality. Critical readers might argue at this point that the approach cannot completely rule out the prevalence of reverse causality, since respondents' health could, for instance, already have prohibited a regular wealth accumulation in earlier life stages. Information on respondent's health before the second wave of SHARE could be included in the analysis to further limit the possibility of reverse causation, as health data gathered in 2004/05 during the first wave of SHARE as well as information on childhood health surveyed during the third wave (SHARELIFE) is available. Especially the data on health conditions during respondents' childhood would be valuable in such a context, as individual's health in later-life is partly determined in-utero and during childhood as reviewed by Gluckman, Hanson, Copper and Thornburg (2008) and Lumey, Stein and Susser (2011). Unfortunately, the available health data from the first and third wave of SHARE suffers either from lots of missing values or has few observations in common with the final sample of 20,599 individuals from the second wave. This prevents a solid analysis with a sufficiently large sample size and consequently, the data is not considered in the regressions at the expense of possible reverse causation.

The first approach followed in this thesis after Attanasio and Emmerson (2003), however, serves the purpose of describing the sample and giving an insight of the wealth-induced impact on mortality while accounting for sample attrition via a non-standard model. The second instrumental variables approach after Meer et al. (2003) in Section 6 aspires to overcome issues related to reverse causality and to test for a causal effect of wealth on mortality. A further advantage of the IV approach is that it controls for a second potential source of endogeneity, namely the errors-in-variables problem. Measurement errors causing the wealth measure to be endogenous cannot be ruled out in this work, since the information on respondent's wealth levels was obtained via imputations in SHARE.

5. Probit model with sample selection

The above discussion of sample attrition highlighted that attrition between waves 2 and 4 of SHARE does not occur randomly. To control for the selection in the survey, an econometric specification is needed that models the retention of individuals in the sample. Such a specification was used by van den Ven and van Praag (1981) in their assessment of Dutch survey data on insurances, who built upon the work of Heckman (1979) and developed a bivariate probit model that takes sample selection into account. Following this model framework, a simple probit model is assumed to determine survival of respondents between the second and fourth wave of SHARE and another simple probit model is assumed to explain selection in the sample. Formally the model can be written in the following way:

There exists a regression relationship,

$$y_i^{survive} = 1\ [x_i\beta + u_i > 0]$$

where the binary dependent variable $y_i^{survive}$ indicates whether individual i stays alive between the second and fourth wave. However, this variable is only observed if another binary dependent variable y_i^{select} is equal to one, meaning that individual i is still in the sample in wave 4 and formally written as:

$$y_i^{select} = 1\ [\ z_i\gamma + v_i > 0]$$

with

$$u \sim N(0,1)$$
$$v \sim N(0,1)$$
$$corr(u,v) = \rho$$

When $\rho \neq 0$, Heckman has shown that coefficient estimates from a non-random sample are biased, which would be the case if only the first survival equation is considered (Van de Ven & Van Praag, 1981). For such situations, statistical packages provide models that take the selection process into consideration to yield consistent and asymptotically efficient estimates for all parameters (StataCorp, 2013). The estimation of the parameters β and γ, as well as the correlation coefficient ρ is done by the method of maximum likelihood. According to Van de Ven and Van Praag (1981), the likelihood function for this model specification is given by:

$$L = \Pi_{i=not\ selected}\Phi(-\gamma'z)\Pi_{i=selected,alive}\Theta(\gamma'z,\beta'x,\rho)\Pi_{i=selected,dead}\Psi(\gamma'z,-\beta'x,\rho)$$

where Φ, Ψ and Θ are transformations of the univariate and bivariate normal distribution. x and z are vectors of observable variables and β and γ are coefficient vectors.

5.1. Identification

If the selection equation contains exactly the same set of variables as the survival equation, then the model can only be identified via functional form and the coefficient estimates have no structural interpretation. Non-parametric identification of above model requires that at least one additional variable is included in the selection equation that explains attrition but does not determine survival (Attanasio & Emmerson, 2003; StataCorp, 2013). For this purpose, the ability of SHARE country teams in interviewing the respondents during the second wave is proxied by the percentage of complete responses on the value of respondent's residence and subsequently added to the selection equation. The residence value is mostly the main component of household net worth in the sample and therefore a crucial factor in determining individual's socio-economic status. The percentage of complete responses for the value relate to sample attrition in the following two ways: 1. A high share of complete responses reflects a country team's ability to obtain information on monetary variables and gives an indication on how many complete observations can be expected from the country in future survey waves. 2. Respondents' willingness to disclose financial information is a sign of their attitude towards the whole survey and therefore provides an indication on the chance of responding in subsequent waves.

To incorporate the information on complete responses, a categorical variable ranging from 1 to 4 and roughly corresponding to the quartiles of the observed percentages of complete responses is created and included in the regressions. Next to this categorical variable, other model specifications with two different variables for identification, one including respondent's general willingness to answer from the interviewer observations module of the second wave and the other including the number of re-sampled respondents between waves 1 and 2, were tested. The categorical variable related to the quartiles of the observed percentages has proven to perform better in comparison to the other two possible identifying variables, and other quantiles of the percentages or the linear indicator on complete responses.

5.2. Results

In this section, the results obtained from the probit model on mortality with sample selection are presented. In all regressions, the stratified sampling of the SHARE survey was taken into account, while sampling weights were not applied since the selection process between waves 2 and 4 is directly modeled. Both, selection and survival equations, are estimated separately for men and women to allow for different coefficient estimates by gender. As discussed above, the key variable of interest is wealth, which is considered in two functional forms. The first specification includes wealth in levels (PPP-adjusted and equalized between couples and singles) whereas the second specification includes individual's wealth ranking within four age groups. As a result, the outcome of four different regressions is presented below in Tables 6 and 7 to account for gender differences and the two functional forms of wealth.

Several model specifications for the bivariate probit model have been tested, which allow for flexible effects for wealth, age and health score. For wealth in levels and age, different polynomials were included and finally, a specification with quadratic polynomials was chosen. Respondent's health status was tested simply as the sum of weighted health scores, but the sum translated into five categories from very good to very poor health yielded a better fitting model. Additionally, to age, wealth and health score, respondent's self-perceived health status, education as well as their place of residence and partners living in the same household are controlled for. In Tables 6 and 7 the plain coefficient estimates from the bivariate probit model are presented instead of marginal effects on the outcome probabilities. This is because single numbers for marginal effects evaluated at certain values of the covariates (e.g. at the means) neglect much of the individual level variability, as the marginal effects in non-linear models are intertwined and differ with every level of themselves and that of other variables (Cameron & Trivedi, 2010). To give the reader an idea of the effect that the covariates exert on the dependent variable in the bivariate probit model, reference to predictive margins of the outcome or to marginal effects of the covariates evaluated at representative values is made whenever relevant and informative. For summary statistics of the variables in the regressions, it is again referred to Appendix C.

5.2.1. Selection equation

The regression output in Table 6 indicates that attrition is not random, since age, region and wealth are statistically significant determinants of the probability whether a respondent from wave 2 stays in the sample or is known have died in wave 4. The coefficient estimate for the regular age term has a positive sign, while the quadratic polynomial of age exhibits a negative sign. The estimates are significant at the 1% level for all four different model specifications. An evaluation of the marginal effects at representative values of age indicates that that the probability for individuals being re-interviewed in wave 4 increases up to the age of 70-75 and decreases thereafter, which is as expected, given that observed attrition rates in the sample are highest for the highest age group as already shown in Table 5.

The assumption that unhealthier individuals are more likely to drop out between the second and fourth wave cannot be validated as respondent's health conditions have, surprisingly, no significant effect on the attrition probability. Further, no significant impact of education and sharing the household with a partner can be identified. The regional dummies indicate that respondents from the Czech Republic and Poland were less likely to be re-interviewed in wave 4, while there is a higher probability of Spanish and Italian residents being re-interviewed. These regional effects, which are significant at the 1% level for all specifications, were estimated despite that the percentages of complete answers on the value of residence are very close between the country teams of Italy and Poland and between Spain and Czech Republic.

	Men		Women	
	Types of wealth			
	Level	Rank	Level	Rank
Constant	-2.3499***	-2.5148***	-1.5861***	-1.6567***
	(0.5923)	(0.5921)	(0.5052)	(0.5054)
Age	0.0883***	0.0923***	0.0703***	0.0718***
	(0.0177)	(0.0176)	(0.0148)	(0.0147)
Age²	-0.0006***	-0.0007***	-0.0005***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Health score				
2 - Good	-0.0562	-0.0550	-0.0280	-0.0272
	(0.0446)	(0.0447)	(0.0386)	(0.0386)
3 - Fair	-0.1080	-0.1014	0.0184	0.0212
	(0.0824)	(0.0824)	(0.0593)	(0.0593)
4 - Poor	0.1937	0.2007	-0.0021	0.0016
	(0.1540)	(0.1544)	(0.0945)	(0.0946)
5 - Very Poor	0.0356	0.0472	-0.0584	-0.0569
	(0.3040)	(0.3039)	(0.2144)	(0.2144)
Self-perceived health				
2 - Very good	-0.0683	-0.0689	0.0636	0.0621
	(0.0569)	(0.0569)	(0.0581)	(0.0581)
3 - Good	-0.0587	-0.0557	-0.0043	-0.0049
	(0.0526)	(0.0525)	(0.0536)	(0.0535)
4 - Fair	-0.0695	-0.0653	0.0022	0.0027
	(0.0577)	(0.0576)	(0.0571)	(0.0570)
5 - Poor	-0.0140	-0.0101	-0.0772	-0.0759
	(0.0747)	(0.0747)	(0.0694)	(0.0694)
Couple	0.0334	0.0307	-0.0134	-0.0173
	(0.0347)	(0.0347)	(0.0289)	(0.0289)
High-school degree	-0.0127	-0.0124	-0.0383	-0.0386
	(0.0401)	(0.0400)	(0.0337)	(0.0337)
Some college degree	0.0792	0.0805	0.0675	0.0657
	(0.0881)	(0.0880)	(0.0811)	(0.0811)
College degree	0.0244	0.0240	0.0577	0.0562
	(0.0481)	(0.0479)	(0.0471)	(0.0470)
Regional Dummy CZ/PL	-0.1558***	-0.1527***	-0.2295***	-0.2254***
	(0.0460)	(0.0461)	(0.0391)	(0.0391)
Regional Dummy IT/ES	0.3063***	0.3043***	0.1841***	0.1810***
	(0.0466)	(0.0466)	(0.0420)	(0.0421)
Wealth	0.0808***	0.3639***	0.0394***	0.2057***
	(0.0133)	(0.0565)	(0.0124)	(0.0498)
Wealth²	-0.0048***		-0.0020**	
	(0.0010)		(0.0010)	
Complete answers				
2 - Second quartile	-0.3813***	-0.3845***	-0.2621***	-0.2630***
	(0.0423)	(0.0423)	(0.0411)	(0.0414)
3 - Third quartile	-0.0887**	-0.0874**	-0.1108***	-0.1104***
	(0.0390)	(0.0390)	(0.0356)	(0.0356)
4 - Fourth quartile	0.1672***	0.1647***	0.0855*	0.0854*
	(0.0463)	(0.0463)	(0.0507)	(0.0513)
Log Pseudolikelihood	-6,594.8	-6,594.1	-7,818.2	-7,817.4
Observations	9,351	9,351	11,248	11,248
Joint F-test on wealth	20.71		7.45	
coefficients (P-value)	0.00%		0.06%	
Joint F-test on complete answers	50.12	50.26	27.2	27.31
coefficients (P-value)	0.00%	0.00%	0.00%	0.00%

Note: Dependent variable coded 0 (not selected) and 1 (selected). Statistically significant coefficients are indicated by *,** and *** for 10, 5 and 1 percent confidence levels, respectively. Standard errors in parentheses calculated taking stratified sampling into account.

Table 6: Bivariate probit, selection equation

The coefficient estimates for the identification variable itself vary in significance between 1% and 10% and are jointly significant at the 1% level, which shows that the identification is well achieved. The signs of the coefficients are however unexpected, as the re-sampling probability for observations in the second and third quartile of the variable range are significantly lower as compared to the lowest quartile. A possible explanation for this anomaly is that country teams with an initially low share of complete responses in wave 2 put more effort into the interviews in wave 4 to raise the share. For the purpose of this work, however, the statistical significance of the identification variable is most important, which indicates that the identification condition is fulfilled.

With respect to wealth, Table 6 shows that there is a significant effect in all model specifications ($P<0.01$), according to which respondent's probability of staying in the sample increases with wealth. This finding is very interesting given the main objective of this thesis and reaffirms the choice of an appropriate model to control for sample selection bias. The fact that wealthy individuals are more likely to stay in the sample than poor people has a crucial impact on the interpretation of the health-wealth connection, especially since no significant health effects could be identified in the selection equation.

5.2.2. Survival equation

Table 7 below presents the output of the survival equation in the bivariate probit model. The age coefficients are significant at the 1% level in all four model specifications. The average predictions at several age levels in Figure 3 show that the decrease of survival probabilities accelerates with age. 60-year-old men (women) have a chance of surviving of 89.0% (94.7%), while the chances are significantly lower for 70-year-olds with 82.6% (90.2%) and even lower for men (women) at the age of 80 with 68.6% (78.6%). Note that these predictions were obtained from the two model specifications for men and women with wealth in levels, the same calculation for the rank specifications yields very similar results.

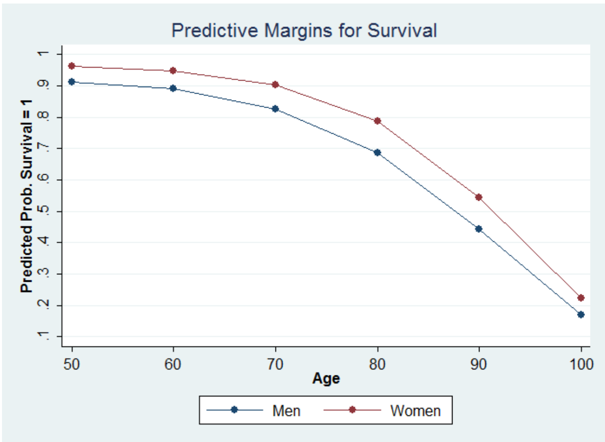

Figure 3: Predictive margins for survival by age and gender

The estimated coefficients for the health score variable are significant at the 1% level in all specifications. However, the variable's influence on survival is quite different between men and women. For men, the five categories of the health score have a relatively consistent effect on the survival probabilities that decrease with every higher category of the health score. The response of women's survival chances to changes in the health score is generally less pronounced compared to that of men and the differentiation between the categories of the score, especially between categories 2 and 3 as well as between 4 and 5, is much smaller. Apparently, there are other variables in the model that explain survival of women better or the construction of the health score categories is more suitable to differentiate between men's health states.

	Men		Women	
	Types of wealth			
	Level	Rank	Level	Rank
Constant	-0.3201	-0.4471	-0.0732	-0.1210
	(1.0103)	(1.0158)	(1.0749)	(1.0912)
Age	0.0870***	0.0894***	0.0894***	0.0899***
	(0.0270)	(0.0271)	(0.0268)	(0.0270)
Age²	-0.0009***	-0.0009***	-0.0010***	-0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Health score				
2 - Good	-0.2997***	-0.2965***	-0.2825***	-0.2821***
	(0.0585)	(0.0585)	(0.0645)	(0.0647)
3 - Fair	-0.5737***	-0.5673***	-0.3487***	-0.3443***
	(0.0953)	(0.0955)	(0.0868)	(0.0874)
4 - Poor	-0.8455***	-0.8387***	-0.7392***	-0.7340***
	(0.1656)	(0.1660)	(0.1291)	(0.1299)
5 - Very Poor	-1.1303***	-1.1141***	-0.7731***	-0.7762***
	(0.3300)	(0.3324)	(0.2730)	(0.2726)
Self-perceived health				
2 - Very good	-0.3015***	-0.3008***	0.0061	-0.0021
	(0.1133)	(0.1133)	(0.1397)	(0.1398)
3 - Good	-0.3489***	-0.3457***	-0.1092	-0.1185
	(0.1040)	(0.1040)	(0.1236)	(0.1236)
4 - Fair	-0.6330***	-0.6288***	-0.2338*	-0.2408*
	(0.1106)	(0.1107)	(0.1279)	(0.1278)
5 - Poor	-0.7937***	-0.7887***	-0.4902***	-0.4959***
	(0.1282)	(0.1285)	(0.1419)	(0.1422)
Couple	0.0948*	0.0881*	0.1281**	0.1130**
	(0.0485)	(0.0482)	(0.0539)	(0.0541)
High-school degree	0.0051	0.0042	0.0033	0.0057
	(0.0529)	(0.0529)	(0.0563)	(0.0566)
Some college degree	0.0562	0.0570	-0.0894	-0.0831
	(0.1311)	(0.1309)	(0.1385)	(0.1377)
College degree	0.0730	0.0699	0.0574	0.0586
	(0.0676)	(0.0673)	(0.0871)	(0.0870)
Regional Dummy CZ/PL	-0.1868***	-0.1694**	-0.2242***	-0.2126***
	(0.0667)	(0.0671)	(0.0741)	(0.0751)
Regional Dummy IT/ES	0.2142***	0.2110***	0.1329**	0.1251*
	(0.0609)	(0.0609)	(0.0663)	(0.0665)
Wealth	0.0509**	0.3141***	0.0620***	0.3993***
	(0.0205)	(0.0846)	(0.0221)	(0.0823)
Wealth²	-0.0024		-0.0017	
	(0.0016)		(0.0021)	
Correlation coefficient	0.7188***	0.7193***	0.5105	0.5101
	(0.0937)	(0.9434)	(0.2186)	(0.2242)
Log Pseudolikelihood	-6,594.8	-6,594.1	-7,818.2	-7,817.4
Observations	9,351	9,351	11,248	11,248
- therof censored	2,305	2,305	2,849	2,849
Joint F-test on wealth coefficients (P-value)	5.1 0.61%	13.78 0.02%	10.74 0.00%	23.56 0.00%

Note: Dependent variable coded 0 (dead) and 1 (alive). Statistically significant coefficients are indicated by *,** and *** for 10, 5 and 1 percent confidence levels, respectively. Standard errors in parentheses calculated taking stratified sampling into account.

Table 7: Bivariate probit, survival equation

Similarly to the health score, all coefficient estimates for men's self-perceived health are significant at the 1% level. The outcome shows that the chances of survival until the fourth wave decrease with poorer self-perceived health. For women, however, only the coefficients for the two highest categories of self-assessed health are statistically different from zero. The estimated coefficient relating to a fair health status is statistically significant at the 10% level, whereas the one relating to a poor health status is significant at the 1% level. Figure 4 below depicts the impact of respondent's self-perceived health status on their survival probabilities. The presented results stem from the two specifications with wealth in levels for men and women – the results from the rank specifications are almost identical. As in the case with health scores, the five categories of self-rated health status differentiate the chances of survival stronger for men than for women. For instance, the difference of the predicted survival probability for 80-year-old men amounts to 26.3 percentage points between 81.5% (for self-perceived health = 1 "excellent") and 55.2% (for self-perceived health = 5 "poor"), while the respective difference is much smaller for women with 14.2pp between 83.5% and 69.3%. A second finding from Figure 4 is that there is little differentiation between the second and third category of self-perceived health for men, while the same is true for female respondents between the first and second category.

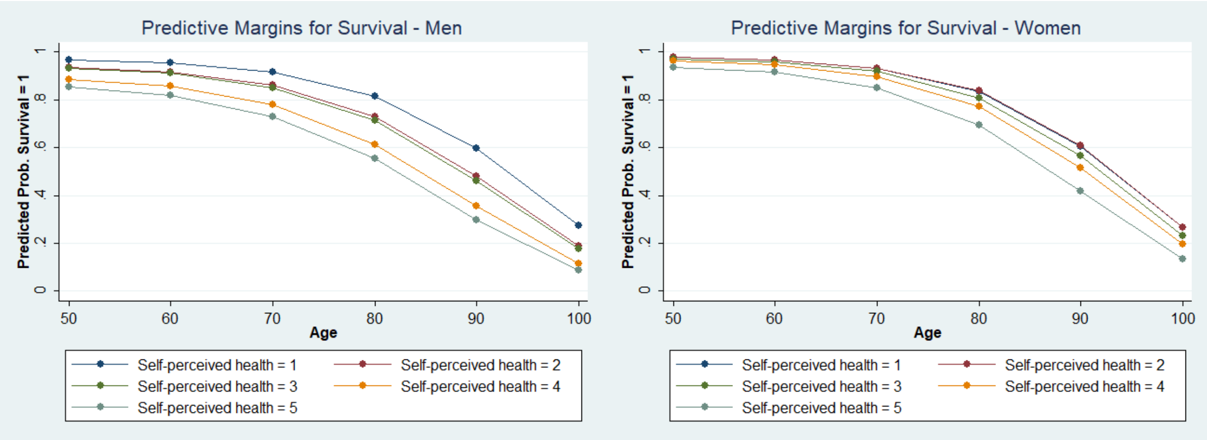

Figure 4: Predictive margins for survival by age and self-perceived health status

In the survival equation, the couple dummy is significant at the 10% level in the two specifications targeting men and significant at the 5% level in the two specifications for women. Sharing the household with a partner increases the chances of survival for men on average by 2.0pp in the specification with wealth in levels or by 1.9pp in the rank specification. Women's survival probabilities are expected to increase by 2.0pp in the level specification or by 1.7pp in the rank specification when they have a partner living in the same household.

As in the selection equation, the coefficient estimates for education are not statistically different from zero in the survival equation and therefore, no effect from educational attainment on survival probabilities is assumed. Typically, education is positively correlated with wealth since better education can be regarded as an investment in human capital that earns higher income and thus makes saving and the accumulation of wealth easier (Wolla & Sullivan, 2017). The insignificance of the education coefficients could therefore be due to the inclusion of the wealth variables in the selection and survival equation that could already capture the relevant effect on attrition and mortality. The correlation coefficient between respondent's ISCED-levels of educational attainment and their household net worth amounts to 0.24 ($P<0.01$) and excluding wealth variables from the regressions as a test increases the significance and magnitude of the education coefficients, which signals the presence of an omitted variable bias.

The regional dummies are significant, but with lower significance levels of 5% and 10% in three out of four model specifications. According to the estimates, the survival probability for male respondents decreases on average by 4.1pp in the level specification or by 3.7pp in the rank specification if they are living in Poland or the Czech Republic. For female respondents, the probability is estimated to decrease by 3.6 (level specification) or 3.4pp (rank specification) in these countries. Contrary, the regional dummy for Spain and Italy indicates that the survival probability of men increases on average by 4.2 or 4.1 percentage points in the level and rank specification respectively, while women's survival probability is expected to increase by 1.9 or 1.8pp on average.

These differences of survival probabilities suggest that there exist distinct regional factors that influence respondent's health, but the abundance of plausible factors such as environmental, cultural and behavioural factors next to the standard of the health care systems make it very difficult to pin down certain influencing factors and a proper investigation would consequently go well beyond the scope of this thesis. It is however noted that among the twelve countries in the sample, the Czech Republic and Poland have the lowest rankings in a WHO assessment on overall health system performance based on data from 1997 (WHO, 2000). Italy and Spain are ranked second and seventh out of 197 assessed countries respectively, while the only country in the sample with a better ranking is France on the first place. The apparent differences in survival probabilities could therefore be explained by the differing quality of health care systems in the sampled countries, but no strong stance for a causal relationship is taken here due to the broad nature of the health system performance index of the WHO and missing room and means for the demonstration of a causal effect.

For the key variable of interest, wealth, Table 7 shows that the basic scientific finding of a positive correlation between wealth and mortality can be reproduced in this work. The coefficient estimates are significant at the 1% in three model specifications and significant at the 5% in one specification, while the second order polynomials in the level specifications cannot be distinguished from zero. The wealth coefficients are however jointly significant at the 1% level. Figure 5 below gives an overview of the predictive margins for respondent's survival in wave 4. The margins were evaluated for men and women at the age of 70, 75 and 80 and for wealth levels ranging between zero and EUR 500,000 and wealth rankings between zero and 0.5. For instance, the survival probability of male respondents at the age of 75 is estimated at 74.2% with zero wealth and at 79.6% with wealth amounting to half a million euros. For men with the lowest wealth ranking of zero the survival probability amounts to 72.2%, while men with a mid-point rank of 0.5 have a survival probability of 76.8%. Note that a wealth ranking of zero does not imply a wealth level of zero, since the wealth level is not bound by zero when liabilities exceed assets. This applies to a small share of individuals with the lowest wealth rankings in their age group and partly explains the different survival probabilities between individuals with a zero-wealth level and those with a zero-wealth ranking. The survival chance for female respondents at the age of 75 amounts to 83.5% with a wealth level of zero and to 89.0% with wealth equalling EUR 500,000. In the rank evaluation, women's survival probability spans from 81.9% with the lowest wealth ranking to 86.4% with the mid-point ranking.

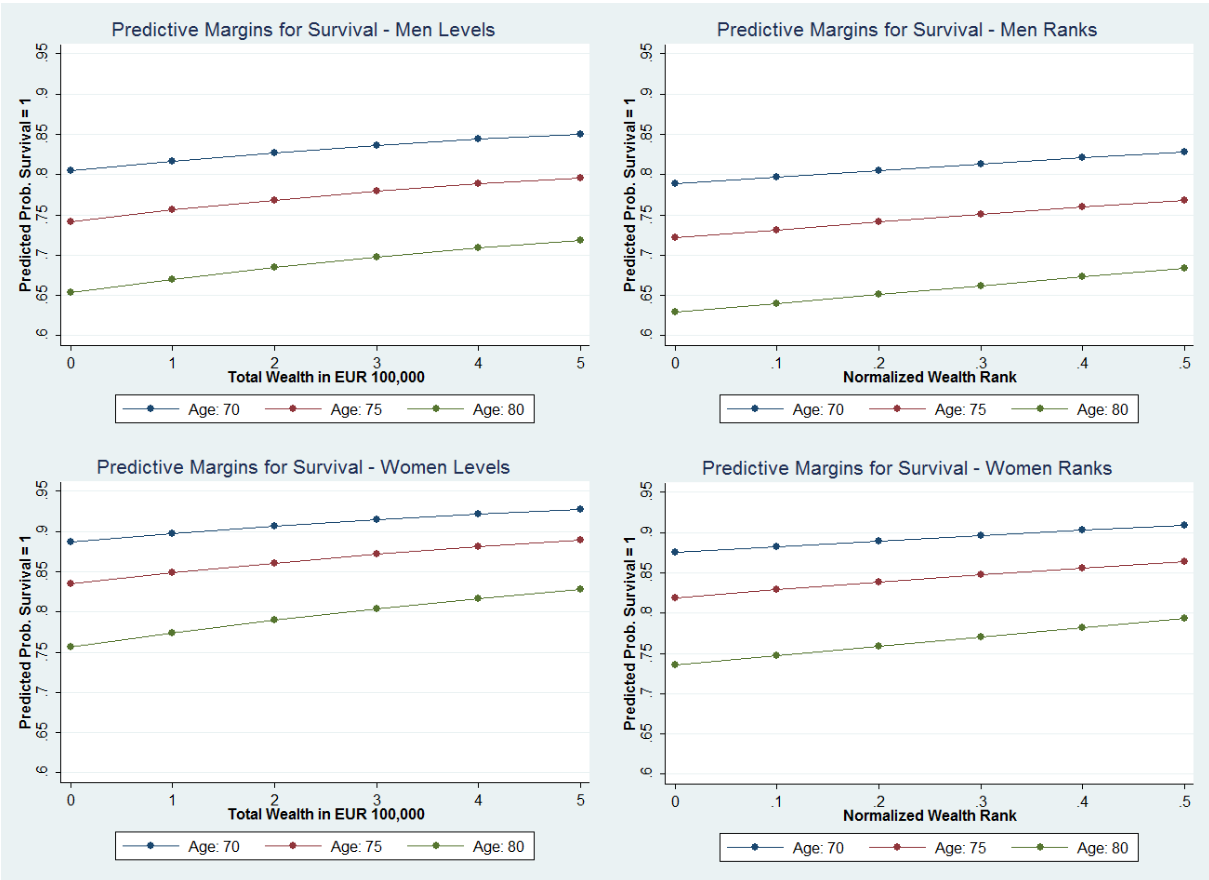

Figure 5: Predictive margins for survival by wealth and age

The findings presented in Figure 5 demonstrate that wealthier individuals tend to live longer. The estimated differences in the survival probability between a wealth level of zero and EUR 500,000 equal 4.1pp for men and 4.0pp for women on average over all sampled individuals. Model specifications with wealth rankings show that the average differences in survival probability between a wealth ranking of zero and the mid-point ranking amount to 3.5pp for all men and to 3.3pp for all women in the sample.

The question whether the rank or the level specification is the preferred setup is not trivial, but from a conceptional point of view the rank specification is more satisfying due to the change of wealth over individual's lifetime as argued in Section 3.4.1.. From a statistical point of view it is not easy to determine which model specification performs better, even though the log pseudolikelihood is slightly higher in the rank specification for men and women. For this reason, a direct comparison is presented in Table 8 where both specifications are considered in the regressions. In the table, only the wealth coefficients are reported. Apparently, the rank variable suppresses the level of wealth when estimated together in the bivariate probit model, as the level coefficients are far from significance and even have the wrong sign in both regressions. It is therefore evident, that the rank specification should be the preferred setup also from a statistical point of view.

	Men	Women
Level of equalized wealth	-0.1132*	-0.0419
	(0.0665)	(0.0731)
Rank of equalized wealth	0.8599***	0.4992
	(0.3326)	(0.3269)
Log Pseudolikelihood	-6,590.8	-7,816.1
Observations	9,351	11,248

Note: Dependent variable coded 0 (dead) and 1 (alive). Statistically significant coefficients are indicated with *, ** and *** for 10, 5 and 1 percent confidence levels, respectively. Standard errors in parentheses calculated taking stratified sampling into account.

Table 8: Direct comparison of level and rank specification

The careful reader might have noticed that in the two regressions for female respondents the correlation coefficient between the residuals is not statistically different from zero as reported in Table 7. This indicates that attrition and mortality can be regarded as independent if the coefficient is indeed zero and that consistent estimates can be obtained using only observations that do not attrit. To elaborate on this assumption, the results of a standard probit model describing the survival of female respondents is presented below. Only the coefficients of the wealth variables are shown, the other coefficients do not vary considerably from the results of the bivariate probit. Table 9 below lists the results of the two standard specifications for wealth levels and ranks, each estimated with two different assumptions on attrition. The first assumption considers only observations that do not attrit and alternatively all observations that drop out are presumed to survive in a second specification.

Before, in the bivariate probit case the respective difference of the survival probability with wealth in levels amounted on average to 4.0pp for women. The evaluation of predictive margins from the simple probit above yields a corresponding difference of 2.6pp with random attrition and a difference of 1.7pp when all who attrit are assumed survive. Also for the rank specification, lower differences are obtained with the simple probit approach. The difference of survival chances amounts to 2.1pp with random attrition and to 1.3pp when all who attrit presumably survive as compared to 3.3pp from the bivariate probit. These results show that the assumptions on attrition, whether determined by a certain process, occurring randomly or in another form, have a crucial effect on the magnitude of the wealth effect on mortality. Furthermore, as laid out in the initial argumentation for the direct modelling of the selection process in Section 4, mortality rates are underestimated if random attrition is assumed or the extremer assumption that all drop-outs survive is made. For instance, the estimated survival probability for a female respondent with a wealth level of zero is on average 86.3% in the bivariate probit, while the corresponding probability from the simple probit with random attrition is much higher with a mean value of 90.5%. Therefore, and despite the insignificance of the correlation coefficient, the full model that directly models attrition is the preferred specification also for female respondents.

	Types of wealth	
	Level	Rank
Attrition is random:		
Wealth	0.0557**	0.3736***
	(0.0236)	(0.0878)
Wealth²	-0.0012	
	(0.0022)	
Log Likelihood	-1,631.8	-1,632.1
Observations	8,399	8,399
All who attrit survive:		
Wealth	0.0408*	0.2783***
	(0.0217)	(0.0804)
Wealth²	-0.0006	
	(0.0020)	
Log Likelihood	-1,894.8	-1,895.5
Observations	11,248	11,248

Note: Dependent variable coded 0 (dead) and 1 (alive). Statistically significant coefficients are indicated with *, ** and *** for 10, 5 and 1 percent confidence levels, respectively. Standard errors in parentheses calculated taking stratified sampling into account.

Table 9: Standard probit estimates with different assumptions on attrition (only females)

To conclude, the notable differences of wealth-induced survival probabilities were obtained with an estimation procedure that takes the survey design and sample attrition into account to produce consistent coefficient estimates and standard errors. Furthermore, sources of endogeneity related to reverse causation were treated appropriately with the available means, while the presence of endogenous regressors in the model cannot entirely be ruled out mainly due to limited historical health data. This issue relates to the fact that poor health (e.g. during childhood and adolescence) may render the accumulation of wealth impossible for some individuals (Smith A. F., 1999). For this reason and since the positive correlation between wealth and survival probability does not imply a causal relationship, a further estimation approach after Meer et al. (2003), that examines the causal effect from wealth on mortality in an IV framework, is presented in this work. The approach and the corresponding results are subsequently discussed in Section 6, while the model diagnostics for the bivariate probit model are presented in the next section.

5.3. Model diagnostics

In contrast to the ordinary diagnosis procedures for nonlinear models with a binary response, the available tools for the current model are very limited due to the survey design that has been considered in the estimation. Typically for maximum likelihood estimation, the likelihood reflects the joint probability distribution of the data under the chosen model when independently distributed and non-weighted data is used. However, when complex survey data is used, this interpretation of the likelihood no longer holds, as survey data is generally not independently distributed, weighted, or both. A measure of the so-called pseudo likelihood and consistent parameter estimates can be obtained for a given model under appropriate weighting with survey data, but likelihood-ratio tests for the goodness-of-fit are no longer valid. Furthermore, the Hausman specification test or information criteria for model selection are not available with survey data (StataCorp, 2015).

Wald tests, adjusted for the design degrees of freedom, for all four model specifications in Table 7 indicate that the null hypothesis that all coefficients are equal to zero can be rejected. Further adjusted Wald tests for certain subgroups of coefficients (e.g. all coefficients except regional dummies or all without self-perceived health) similarly show that the null hypothesis can be rejected and that the covariates belong to the model.

In Appendix C several scatterplots of standardized Pearson residuals from the preferred wealth rank specifications of the bivariate probit model for men and women are shown to detect outliers and model misspecifications. The plot of the squared residuals from the survival equation against the index shows no worrisome structure, similarly to the plot against the normalized wealth rank (Figures 8 and 9). Also evident from the two diagrams and elaborated further in a plot of the residuals against the linear prediction for survival (Figure 10), is that the survival prediction deviates quite strongly from the actual observation in a couple of cases, which consequently elevates the Pearson residuals. A usual reference value for Pearson residuals is two, since residuals exceeding two in absolute value are a result of high predicted probabilities of roughly 80% for the outcome of a probit model, while the direct opposite occurred. The frequency of residuals above this threshold is almost the same in the rank specification for men and women (1.8% vs. 1.9% respectively), but the residuals from the model with female respondents show a larger dispersion, which indicates a somewhat lower predictive ability of that model.

Figure 11 shows scatterplots of the Pearson residuals from the survival equation against the variable age. The plots show that the highest residual squares are clustered between 50 and 70 years for men and between 50 and 80 years for women. This indicates that the prediction of a decease at younger ages is difficult for the chosen model, as it might be caused by unobservable or unexpected factors. The share of deaths due to external causes (ICD chapter 20) in relation to the total number of deaths in the twelve countries in the sample amounts on average to 5.2% according to WHO data for 2011 (WHO, 2016). This percentage could consequently serve as a reference value for wrong survival predictions in an ideal setting and is clearly exceeded by the share of residuals above the threshold of two in the specifications for men (23.5%) and women (31.0%) when only individuals whose decease is known are considered.

Regarding the correlation coefficient between residuals from the survival and selection equation, no inference can be made with the calculated Pearson residuals. This is because a pairwise comparison of residuals from both equations can only be done for observations that did not drop out in the fourth wave of SHARE, which consequently leaves out the highest residuals from the selection equation and would yield a wrong picture of the correlation. According to the correlation coefficient that is estimated by the statistical software package via a transformed version of the parameter and listed in

Table 7, the correlation between the residuals is positive despite being insignificant in the specifications for female respondents.

This concludes the model diagnostics of the bivariate probit model that has been employed to describe the possible magnitude of the wealth effect on mortality by using survey data from twelve European countries. The estimated positive correlation between wealth and mortality would justify transfers to the poor in order to improve their health status (Marmot, 2015). However, such inference solely based on correlations is not convincing, as it disregards the potential endogeneity of wealth. What is needed, is a proof of a causal link running from wealth to health. Establishing such a link is not straightforward, but there exist different approaches for the examination of causality in the field of economics. Hoover (2008) has reviewed all prevailing approaches to causality and provides a useful classification. In this work, causation shall be tested in the sense of a natural experiment, which often involves the usage of instrumental variables in regression analysis as a substitute for experiments to identify and measure the causally relevant effects (Hoover, 2008). Such an instrumental variables approach was already taken by Meer et al. (2003) to investigate the causal relationship between wealth and health, and building up on their work, a similar path is pursued in this thesis to evaluate the data from SHARE. In the section below, the IV approach, results and subsequent diagnostics are described.

6. Instrumental variables probit

In their investigation of the health-wealth nexus with data from the Panel Study of Income Dynamics (PSID), Meer et al. (2003) use information on inheritances as an instrument for the change of wealth to bypass the possible endogeneity of wealth. They argue that inheritances can serve as a suitable instrument for the wealth variation that individuals experience over four waves of the PSID between 1984 and 1999. A more detailed discussion about the rationale that inheritance qualifies as a valid instrument for changes of wealth is provided in Section 6.3. below.

The dependent variable that is examined with the means of an instrumental variables probit model in Meer et al. (2003) is the self-rated health status of the surveyed individuals. Given the five-year structure of the PSID, short-term changes in individual's self-assessed health status are examined for wealth-induced effects, which are instrumented with the information on inheritances. The question whether wealth causes long-term changes of health is left open for future research by the authors. Alike, with the available data from SHARE only possible short-term changes of health between waves 2 and 4, that maximally spans for 5 years and few months for some respondents interviewed in Germany, Poland or Sweden (see Appendix A), are assessed in this thesis. Similarly to the parameter in SHARE, the self-perceived health status from the PSID is on an ordinal scale between 1 and 5 with 1 being excellent and 5 being poor. Out of this information, Meer et al. form a dummy variable "healthy", that equals one if the individual assesses his or her health status as excellent, very good or good and zero otherwise. The focus of the paper by Meer et al. lies on whether changes of wealth induce transitions of this variable in a causal manner between the five-year intervals of the PSID data.

The question, whether self-rated health status and its changes provide valuable insights of individual's overall health, is passed on to a review by Idler and Benyamini (1997). In their review of twenty-seven studies, Idler and Benyamini find that self-rated health status is an independent predictor of mortality. This finding is consistent and holds in nearly all reviewed studies irrespective of the inclusion of numerous health-specific variables and other relevant factors. Additional evidence comes from Adams et al. (2003) who employed data from the AHEAD study to assess the causal links from socio-economic factors to health innovations and mortality. They find correlations between self-rated health status and the onset of severe diseases, limitations for (instrumental) activities of daily living and depression, while Hurd and McGarry (1995) conclude that self-reported health is highly predictive of mortality in the Health and Retirement Study (HRS).

It is therefore plausible to argue that self-rated health status is closely connected to mortality and thus is a meaningful indicator of health. For this work, however, not only the health transition based on respondent's self-perceived health status is assessed, but also health transitions based on the more objective constructed health score that has already been used in the bivariate probit above are examined in separate regressions. Meer et al. (2003) performed similarly and estimated additional specifications on the basis of health variables other than self-rated health status as robustness checks for their initial setup.

6.1. Model setup

An efficient method for the estimation of limited-dependent variable models with endogenous regressors has been developed by Newey (1987), who built upon the results of Amemiya (1978, 1979). With higher computational power, the estimation of an instrumental variable probit via maximum likelihood is also feasible and consequently, this method is applied for the following regressions since the two-step procedure is not available in the statistical software for data that exhibits survey design features such as weights and stratification. According to Wooldridge (2002), a probit model with endogenous explanatory variables can be written in the following way:

$$y_1^* = z_1\beta_1 + y_2\gamma_1 + u_1$$
$$y_2 = z_1\beta_{21} + z_2\beta_{22} + v_2 = z\beta_2 + v_2$$

While y_1^* cannot be observed, instead, only y_1 is observed as:

$$y_1 = \begin{cases} 0 & y_1^* < 0 \\ 1 & y_1^* \geq 0 \end{cases}$$

where the error terms u_1 and v_2 have zero mean, are bivariate normally distributed and independent of z. The second equation above is a reduced form for y_2, which is endogenous if u_1 and v_2 are correlated and exogenous if both are independent. Typically, IV estimation is possible when y_2 is correlated with u_1 due to omitted variables or measurement error, which in turn means that the set of instruments z has explanatory power towards y_1. Thereby, z should not suffer from the same deficiencies as y_2, which requires that the set is exogenous (i.e. uncorrelated to u_1).

The likelihood function of above model can be derived given that the joint density of y_1 and y_2 conditional on z is given by: $f(y_1, y_2| z) = f(y_1| y_2, z) f(y_2| z)$. The log likelihood for any observation i is

$$L_i = y_{1i} \, log \, \Phi(w_i) + (1 - y_{1i}) \, log\big(1 - \Phi(w_i)\big) - \frac{1}{2} log(\tau_2^2) - \frac{1}{2\tau_2^2} \, (y_{2i} - z_i\beta_2)^2$$

where $\Phi(\cdot)$ is the standard normal distribution function, τ_2^2 the variance of v_2 and where w_i is determined by the parameters β_1, γ_1, ρ_1, β_2 and τ_2 in the following way:

$$w_i \equiv \left[z_{1i}\beta_1 + \gamma_1 y_{2i} + \frac{\rho_1}{\tau_2}(y_{2i} - z_i\beta_2)\right] / (1 - \rho_1^2)^{1/2}$$

with $\rho_1 = corr(u_1, v_2)$. Summing L_i across all i and maximizing with respect to all parameters gives the maximum likelihood estimators of β_1, γ_1, ρ_1, β_2 and τ_2^2. Standard errors can be calculated via the estimated Hessian matrix, the estimated expected Hessian, or the outer product of the score, since the general theory of conditional maximum likelihood estimation applies (Wooldridge, 2002). Identification of above model requires the number of excluded instruments to be at least as large as the number of included endogenous variables (StataCorp, 2015). In this work, the model is exactly identified as there is one instrument (inheritance) for one endogenous variable (change of wealth).

6.2. Sample description and weights

Out of the 20,599 observations that were used for the analysis after Attanasio and Emmerson (2003) above, 14,134 individuals are known to have survived until wave 4 (see Table 2), which does not imply that an interview was conducted with every individual during wave 4. The final sample for the IV model comprises 12,334 observations mainly because some respondents did either not participate in the fourth wave or were not listed as household members anymore. For a smaller share of individuals, a calculation of survey weights was not possible due to missing information.

Since sample attrition is not directly modelled in the IV probit, recourse is made to calibrated longitudinal weights for waves 2 and 4 to mitigate potential selection effects due to unit non-response and panel attrition. The key feature of these calibrated weights is that they allow the mortality of the target population to be taken into account across several SHARE waves. The survey designers of SHARE provide calibrated longitudinal weights for several wave combinations and the two basic units of analysis, either individuals or households. It is unfeasible to provide these weights for every possible wave combination, since the number of possible combinations rises dramatically when new waves are added to the panel, but a guideline on the calculation of weights for wave combinations other than those provided is available in the SHARE documentation and allowed to compute individual calibrated longitudinal weights for the second and fourth wave in the current analysis (SHARE Release Guide 6.0.0, 2017).

In Table 10 the observations by country and gender are listed. As before in the bivariate probit model, most observations stem from Belgium and France and fewest observations are available for Austria. The overweight of female respondents is with 55.0% of total observations similar to the one in the analysis with 20,599 observations.

Country	Male	Percent	Female	Percent	Total	Percent
Austria	196	3.5	286	4.2	482	3.9
Belgium	712	12.8	726	10.7	1,438	11.7
Czech Republic	288	5.2	574	8.5	862	7.0
Denmark	571	10.3	578	8.5	1,149	9.3
France	551	9.9	736	10.9	1,287	10.4
Germany	425	7.7	441	6.5	866	7.0
Italy	599	10.8	674	9.9	1,273	10.3
Netherlands	516	9.3	627	9.2	1,143	9.3
Poland	433	7.8	598	8.8	1,031	8.4
Spain	370	6.7	542	8.0	912	7.4
Sweden	559	10.1	563	8.3	1,122	9.1
Switzerland	333	6.0	436	6.4	769	6.2
Total	5,553	100	6,781	100	12,334	100

Note: Columns may not sum to 100 due to rounding

Table 10: Observations by country and gender (reduced sample)

Table 11 below summarizes the health transitions and mean values of change of wealth between the second and fourth wave of SHARE. Wealth increases or decreases over EUR 2mn are capped at EUR 2mn in this analysis. Out of the 12,334 individuals, 1,190 experience positive transitions of health (that is from a poor or fair self-rated health status in wave 2 to a good, very good or excellent self-rated health status in wave 4) and 1,795 experience negative health transitions. 71.0% of those who are initially sick are also sick in the fourth wave and 78.2% of those who are healthy in the second wave remain healthy in the fourth wave. Perhaps surprisingly, the average change of wealth between the two waves is smaller for the 1,190 respondents with positive health transitions, as compared to the individuals who remain ill. The strongest (negative) average changes of wealth are prevalent for the 1,795 individuals with negative health transitions, while only those individuals, who are healthy in both waves, experience on average an increase of wealth.

	Whole sample	Sick in wave 4	Healthy in wave 4
Sick in wave 2			
Mean of wealth change	-0.09	-0.02	-0.29
Std. deviation	2.44	2.26	2.66
Sample size	4,105	2,915	1,190
Healthy in wave 2			
Mean of wealth change	0.02	-0.35	0.15
Std. deviation	3.31	3.06	3.39
Sample size	8,229	1,795	6,434

Note: Means are computed using calibrated longitudinal sample weights

Table 11: Health transitions and mean values of wealth changes between waves 2 and 4

6.3. Instrumental variable

The information on inheritances comes from the following question, that was directed to the SHARE respondents during the interviews of wave 4:

> "*Have you or your husband/wife/partner ever received a gift or inherited money, goods, or property worth more than EUR 5,000?*"

If the respondents answered this question with yes, then they were asked to specify in which year they received the gift or inheritance. Unfortunately, during the fourth wave of SHARE the value of the gift or inheritance was not surveyed in contrast to the procedure for the first and second wave of SHARE (SHARE English generic questionnaire Wave 1-4, n.d.), and also contrary to the PSID that forms the basis for the analysis by Meer et. al (2003). Consequently, only the number of gifts or inheritances, now only referred to as inheritances, received by the respondents between the second and fourth wave of SHARE is known. The maximum number of inheritances in the sample equals five, which means that these individuals at least received a value of EUR 25,000.

To the question, whether inheritance is a suitable instrument, Meer et al. (2003) argue that the "receipt of an inheritance is clearly correlated with the change in individual's wealth, but is plausibly unrelated to changes in his or her health, conditional on initial health status" (p. 714). Specifically, inheritance is a valid instrument if two conditions are met: 1. Inheritance must be relevant and thus partially correlated with the endogenous variable change in wealth and 2. Inheritance must be exogenous and thus uncorrelated to the error term, similarly to the other covariates in the general equation (Wooldridge, 2002).

6.3.1. Relevance

It is straightforward to investigate whether the first condition is fulfilled. In the sample, the correlation coefficient between inheritance and the change of wealth between the second and fourth wave amounts to 0.03 and the one between inheritance and the declared wealth from wave 4 equals 0.11. Both coefficients are statistically significant at the 1% level. While the magnitude of the correlations is not overwhelming, one may ask whether inheritance is a weak instrument for changing wealth. As an illustration, average wealth at wave 4 amounts to EUR 261,868 for the 11,556 individuals who did not report an inheritance between the second and fourth wave. For the other 778 respondents who received an inheritance at least once during that time frame, average wealth equals EUR 472,040. To properly assess whether inheritance is a weak instrument, an ordinary least squares (OLS) regression where the change of wealth is regressed on inheritance and the other covariates is carried out. The motivation behind this exercise is to examine the strength of the correlation between inheritance and change in wealth in the first stage of a hypothetical two-step instrumental variables regression (Meer et al., 2003). Additional explanatory variables next to inheritance that enter this OLS regression and subsequent probit models are respondent's initial wealth level and health status from the second wave, their age at the time of wave 4, time-invariant indicators for education and region, a couple identifier (all similarly to the analysis in Section 5), and dummy variables indicating whether an individual is divorced, widowed or has at least one child at the time of wave 2. The interview gap between the second and fourth wave of SHARE is included as a control factor, since the gap varies between individuals and countries due to different sampling periods and could therefore affect the health transitions. Summary statistics of all variables are available in Appendix D.

Contrary to above regressions that were carried out separately for men and women, the following models are jointly estimated due to the smaller sample size, few observations with inheritances and following the assumption that changes in wealth possibly cause the same impact on health for men and women. Nevertheless, a gender dummy is incorporated in the regressions. In common with the analysis after Attanasio & Emmerson (2003), separate regressions are presented that incorporate the change of individual's wealth ranking instead of the change of their wealth level. This time, however, the change of absolute wealth ranks irrespective of age groups is included due to the dynamic nature of the analysis. Considerations regarding the validity of inheritance as an instrument for the change of wealth levels apply in a similar way to the change of wealth ranks.

In Table 12 the result of the OLS regression of change in wealth on inheritance is presented. The coefficient estimate for inheritance is statistically significant at the 1% level in both specifications. Receiving an inheritance is on average expected to boost the increase of wealth by EUR 58,286 in the level specification. Regarding normalized wealth rankings that are between 0 and 1 for all individuals, an additional increase of 0.06 is on average expected with an inheritance. Other statistically significant predictors of the wealth change are individual's initial wealth level or ranking in the second wave, the variables indicating whether respondents are healthy according to their self-rated health status or have children at wave 2, next to age and educational and regional indicators. Most interesting is the apparent relation between respondent's initial health status in the second wave and the dependent variable. Individuals with a good, very good or excellent self-perceived health status in wave 2 (denoted as healthy) are expected to experience a wealth change that is higher by EUR 22,783 on average as compared to individuals with an initially poor or fair self-perceived health status.

Regarding the change of wealth rankings, an average increase of 0.03 is expected for healthy individuals. These results reveal the following: 1. The partial correlation between change of wealth and the instrument inheritance could be established and inheritance seems to have sufficient strength in an IV setup 2. Reverse causality is prevalent in the data, as initial health status significantly affects changes of wealth. Additionally, the instrumentation of change of wealth can eliminate a possible bias due to measurement error of the imputed wealth levels in the second and fourth wave of SHARE. Consequently, the instrumentation via inheritance is needed for a careful assessment of the relationship between wealth and health and the still open question whether the instrument is not only relevant, but also exogenous is discussed in the next section.

	Types of wealth			
	Level		Rank	
Constant	1.4301**	(0.6142)	0.1695***	(0.0509)
Inheritance	0.5829***	(0.1571)	0.0572***	(0.0097)
Initial wealth	-0.3354***	(0.0233)	-0.3012***	(0.0125)
Initial health	0.2278***	(0.0699)	0.0341***	(0.0065)
Age	-0.0073*	(0.0042)	-0.0006*	(0.0004)
Male	0.0190	(0.0728)	-0.0027	(0.0061)
Couple	0.0848	(0.1542)	0.0220*	(0.0130)
Divorced	0.1176	(0.1881)	0.0033	(0.0154)
Widowed	0.0886	(0.1686)	0.0132	(0.0137)
Child	-0.3361**	(0.1434)	-0.0248**	(0.0110)
High-school degree	0.1181	(0.0775)	0.0125*	(0.0071)
Some college degree	0.6249***	(0.1772)	0.0402***	(0.0135)
College degree	0.8444***	(0.1334)	0.0647***	(0.0096)
Regional dummy CZ/PL	-0.5337***	(0.0745)	-0.0465***	(0.0084)
Regional dummy IT/ES	0.0573	(0.0978)	0.0112	(0.0079)
Interview gap	-0.0516	(0.1080)	-0.0048	(0.0096)
R^2	15.71%		16.43%	
Observations	12,334		12,334	
Joint F-test (P-value)	19.16 (0.00%)		46.42 (0.00%)	

Note: Continuous dependent variable change of wealth (either level or rank specification). Statistically significant coefficients are indicated by *, ** and *** for 10, 5 and 1 percent confidence levels, respectively. Point estimates and std. errors calculated taking stratified sampling and calibrated longitudinal weights into account.

Table 12: Ordinary least squares regression of change of wealth on inheritance

6.3.2. Exogeneity

The condition that the instrument is exogenous, i.e. uncorrelated with the error term in the general equation and affecting the dependent variable only through the endogenous regressor, is necessary for inheritance being a valid instrument. Meer et al. (2003) highlight two possible issues why inheritance might not be exogenous, also referred to as failing the exclusion criterion.

The first reason is that the receival of an inheritance could signal something about the heir's own health. This happens if a family member passes away due to a genetically determined disease and bequests another family member that is also affected by the same disease. As a result, inheritance is correlated with the error term in the health status equation and fails the exclusion criterion. Since no further details other than the identity of the donor are known in SHARE, reference is made to other studies which might shed some light on the issue. In their study of the effect of inheritances on retirement decisions, Holtz-Eakin, Joulfaian and Rosen (1993) found that the inclusion of information on donee's age, while increasing the explanatory power of the model, leaves the inheritance coefficients merely unchanged and yields insignificant age coefficients. Since individual's retirement decisions are closely connected to their health according to McClellan (1998), this result suggests that the extent to which inheritance serves as a signal for recipient's wealth is small, as if it were a strong signal, it would be reasonable to assume that also younger donee's have a higher propensity of leaving the labor force. A different issue that could lead inheritance to signal something about the heir's health is that the death of the donor causes stress and illness for the recipient. Such negative health effects after a decease should be mostly pronounced for close relatives. Evidence for this issue was, however, not found in the study by Holtz-Eakin et. al (1993), who show that the effect of inheritance on retirement decisions was unaffected of whether the deceased was a close relative or not. Meer et al. (2003) then argue "that whatever health effects might accompany receipt of an inheritance, they are not sufficient to generate a change in labor force behavior" (p.724). Hence, it seems unlikely that inheritance is a signal of beneficiary's health. A study by Brown, Coile and Weisbenner (2010) identified the mere size of the inheritance and whether it was anticipated or not as the relevant factors guiding an inheritance and determining the retirement decision, which furthermore weakens the assumption of inheritance being a strong signal of recipient's health.

The second reason that could cause inheritance to fail the exclusion criterion is that there might be third factors that affect inheritances and health. Meer et al. (2003) acknowledge a privileged background as such a third factor that could plausibly determine both. Individuals raised in affluent families benefit from an environment that increases the chances of living a healthy life for many reasons such as better knowledge about a healthy lifestyle, lower probability of risk factors (smoking, drinking, overweight), more future time preference (Smith & Kington, 1997), better access to medical services, lower impact of medical costs on savings and less exposure to environmental hazards (Adams et al., 2003). Smith (1999) notes that the effect of economic resources on health outcomes may be strongest during childhood and early adulthood when health levels and trajectories are being determined, therefore children who receive substantial inheritances could be on a favorable lifetime health trajectory. This connection between inheritance and health could make inheritance an unsuitable instrument for the examination of the wealth-health nexus, but there is evidence why this might not be the case.

Firstly, SHARE respondents were asked whether they experienced periods of financial hardship in their lifetime during the interviews for wave 3, which allows to directly investigate the issue. While 6.2% of respondents in the sample who never experienced financial difficulties reported the receival of an inheritance, 6.5% of those who did face such difficulties are known to have inherited. This shows that the favor to inherit does not only befall wealthier individuals, hence an improvement of the health trajectory of poorer individuals appears feasible. Secondly, the inclusion of the information on periods of financial hardship in the IV regression yields insignificant coefficients for that variable and does not alter the coefficient on change of wealth in great measure. And thirdly, the wealth coefficient is largely unaffected when the IV regression is step by step augmented with other factors that relate to a privileged background such as the initial wealth level and education. This indicates that the presence of a possible bias of the coefficient on change of wealth is rather unlikely.

To conclude, inheritance and health being linked via a privileged background or inheritance serving as a signal for poor health seem rather implausible reasons for the instrument to fail the exclusion criterion. It might, however, still be possible that the two factors cancel each other resulting in a zero coefficient as noted by Meer et. al (2003), but the robustness of the results in different specifications and the theoretical considerations suggest that this is not the case in the current analysis.

6.3.3. Inheritance and the true wealth effect

Another issue that determines the relevance of the instrument is that the coefficient estimate on inheritance becomes less informative if individuals anticipate inheritances and consequently adjust consumption and savings decisions. In such a case, inheritance is not related to the true wealth effect anymore and casts little light on the underlying relationship between wealth and health (Meer et al., 2003). Fortunately, SHARE contains information regarding respondent’s anticipation of inheritances that can be used in the analysis. In the expectations module of all waves except for SHARELIFE, respondents were asked to quantify their chances of receiving an inheritance in the next ten years from 0 to 100. An additional question was raised to assess the chances of receiving an inheritance worth EUR 50,000 or more. The IV regression in this thesis is carried out with the method of maximum likelihood, but the inclusion of the information on anticipated inheritances in a hypothetical first stage IV regression yields an insignificant coefficient and leaves the general inheritance coefficient almost unchanged. This suggests that the SHARE respondents do not alter their wealth accumulation in anticipation of an inheritance. The result is in line with the literature, for instance, Brown et al. (2010) find that the effect of entering retirement due to an inheritance is more than twice as large for unexpected inheritances and note that uncertainty about the occurrence and actual value of an inheritance, as well as liquidity constraints to borrow in advance of an inheritance, might play a crucial role that limit the probability of individuals to drastically change their wealth accumulation.

A further issue that was raised by Meer et al. (2003) and could pose a problem in the evaluation of the wealth effect on health status relates to the typically concave nature of the relationship between socio-economic status and health. At a certain wealth level, no or only miniscule wealth-induced health improvements are plausible, so a health assessment performed in the flat region of the wealth-health curve can hardly identify significant health changes. In the sample at hand, this issue could theoretically arise, since people who inherit tend to be wealthier and the following failure to identify health changes for wealthy individuals seems to be an undesired result. It is in fact true, that the average wealth is higher for individuals who receive an inheritance compared to those who do not. In the sample, average wealth at the second wave of SHARE equals EUR 252,251 for the 11,556 respondents who did not report an inheritance until the fourth wave and EUR 393,603 for the 778 respondents who did. It is, however, noted that not only wealthy individuals benefit from an inheritance. 217 respondents that represent 27.9% of all those who received an inheritance in between the two waves, have a wealth level that is below the overall median of EUR 183,286. It is therefore unlikely that the possible failure to identify the actual wealth effect on health is due to the fixation on the flat region of the relationship.

6.4. Results

The remarks above indicate that inheritance is a valid instrument due to it being relevant and exogenous. To the extent that an inheritance is unanticipated, it represents a true wealth shock to individuals, and even if they fully anticipate receival of an inheritance, liquidity constraints for borrowing and the still existing uncertainty for the receipt prevents beneficiaries to perfectly react in advance of an inheritance also given their possibly irrational behavior and lack of knowledge. As a result, inheritance can be regarded as a reasonable measure of the true wealth effect on health and can thus be used in a IV probit setting. But to start with, a standard probit regression that does not take the endogeneity of change of wealth into account is carried out to give the reader an idea of the wealth effect and to enable a comparison with the IV estimates. Again, as in the bivariate probit case, the plain coefficient estimates are reported, while predictive margins or marginal effects evaluated at representative values of the covariates are mentioned.

Table 13 below lists the results of the standard probit estimation and shows that the basic result in the literature can be reproduced. Changes of wealth are positively correlated with health. According to the estimates, the probability of SHARE respondents being healthy increases on average by 1.1pp with every EUR 100,000 higher change of wealth. For instance, the predictive margin of the binary variable healthy equaling one is 55.4% for respondents with a constant wealth level between the second and fourth wave and 60.8% for respondents who experience an increase of wealth by half a million euros. In the rank specification, an increase of the rank by 0.1, so for instance from the middle rank 0.5 to 0.6, is on average expected to increase the probability of being health by 1.0pp. Respondents with a constant rank between the two waves are healthy with a probability of 55.4% and respondents who experience a jump of rank by 0.5 have a probability of 60.3%. To put these wealth effects into perspective, a level increase by EUR 100,000 and an increase of the wealth rank by 0.1 are above the 75%-percentile in each distribution, which means that the required wealth change to trigger an 1.1pp or 1.0pp increase in the probability of being healthy can be regarded as large. If compared to other covariates, this impression is furthermore enhanced. Completion of high school increases the chances of being healthy by 4.8pp in both specifications, while being ten years older decreases those chances by 6.2pp on average. It is therefore evident, that the wealth-induced health changes are small given the large wealth changes needed for a respective response of the dependent variable and given the magnitude of the other effects.

	Types of wealth			
	Level		Rank	
Constant	0.7405*	(0.3841)	0.6072	(0.3865)
Δ Wealth	0.0364***	(0.0096)	0.3368***	(0.1137)
Initial wealth	0.0558***	(0.0086)	0.6383***	(0.0863)
Initial health	1.2172***	(0.0431)	1.2056***	(0.0431)
Age	-0.0206***	(0.0024)	-0.0206***	(0.0025)
Male	0.0157	(0.0428)	0.0160	(0.0428)
Couple	-0.0321	(0.0833)	-0.0638	(0.0846)
Divorced	0.0202	(0.0952)	0.0288	(0.0957)
Widowed	-0.1018	(0.0930)	-0.1089	(0.0938)
Child	0.0325	(0.0723)	0.0313	(0.0723)
High-school degree	0.1620***	(0.0522)	0.1597***	(0.0527)
Some college degree	0.1192	(0.1510)	0.1178	(0.1513)
College degree	0.3475***	(0.0687)	0.3417***	(0.0693)
Regional dummy CZ/PL	0.0118	(0.0646)	0.0666	(0.0665)
Regional dummy IT/ES	-0.0227	(0.0530)	-0.0383	(0.0533)
Interview gap	-0.0441	(0.0739)	-0.0417	(0.0744)
Log Pseudolikelihood	-6,473.0		-6,457.0	
Observations	12,334		12,334	
Joint F-test (P-value)	88.04		87.40	
	0.00%		0.00%	

Note: Dependent variable coded 0 (unhealthy) and 1 (healthy). Statistically significant coefficients are indicated by *, ** and *** for 10, 5 and 1 percent confidence levels, respectively. Point estimates and std. errors calculated taking stratified sampling and calibrated longitudinal weights into account.

Table 13: Standard probit regression of health status

Remarkably, the small wealth effects strongly increase once change of wealth is treated as endogenous in an IV probit setup. The output of this new IV regression is shown in Table 14. If wealth truly suffers from endogeneity, as discussed previously in this thesis, then it becomes apparent that its possible effect on health was biased downwards in the regular probit from Table 13. Ettner (1995) similarly finds this surprising downward bias when comparing OLS and IV estimates of the relationship between health outcomes and income and notes that "if health increases income and income improves health, then normally one would expect the ordinary estimates to overstate the structural effect of income on health if reverse causality were the only source of bias." (p.79). As a further source of bias, Ettner brings in a possible measurement error of income, which could in the same way affect the imputed wealth data from SHARE and consequently cause the regular probit estimates to be biased downwards.

According to the estimates in Table 14, every additional increase of the change of wealth by EUR 100,000 raises the probability of being healthy by 6.4pp on average while keeping the other covariates at their actual values. A 6.3pp increase is expected with every additional improvement of respondent's wealth rank by 0.1 in the rank specification. If compared to other covariates, the instrumented wealth effect is now on an equal level. Being ten years older decreases the chances of being healthy on average by 5.2pp in the level specification and by 5.3pp in the rank specification, while the completion of high school increases the chances by 3.8pp on average in both specifications.

	Types of wealth			
	Level		Rank	
Constant	0.3907	(0.4274)	0.2482	(0.4484)
Δ Wealth (instrumented)	0.2189**	(0.0971)	2.1428*	(1.0988)
Initial wealth	0.1120***	(0.0286)	1.1410***	(0.2962)
Initial health	1.0609***	(0.1591)	1.0698***	(0.1395)
Age	-0.0171***	(0.0039)	-0.0180***	(0.0035)
Male	0.0119	(0.0408)	0.0210	(0.0413)
Couple	-0.0484	(0.0755)	-0.1032	(0.0829)
Divorced	-0.0100	(0.0892)	0.0146	(0.0922)
Widowed	-0.1098	(0.0835)	-0.1274	(0.0904)
Child	0.0920	(0.0733)	0.0746	(0.0731)
High-school degree	0.1255**	(0.0587)	0.1279**	(0.0581)
Some college degree	-0.0105	(0.1613)	0.0351	(0.1588)
College degree	0.1550	(0.1433)	0.1997	(0.1240)
Regional dummy CZ/PL	0.1126	(0.0821)	0.1496*	(0.0813)
Regional dummy IT/ES	-0.0293	(0.0519)	-0.0542	(0.0528)
Interview gap	-0.0304	(0.0690)	-0.0304	(0.0724)
Log Pseudolikelihood	-3,008.4		-2,994.9	
Observations	12,334		12,334	
Joint F-test (P-value)	111.85		100.98	
	0.00%		0.00%	

Note: Dependent variable coded 0 (unhealthy) and 1 (healthy). Statistically significant coefficients are indicated by *, ** and *** for 10, 5 and 1 percent confidence levels, respectively. Point estimates and std. errors calculated taking stratified sampling and calibrated longitudinal weights into account.

Table 14: IV probit regression of health status

Figure 6 depicts the predictive margins of being healthy for changes of the wealth level between EUR -200,000 and EUR 200,000 and changes of the wealth rank between -0.2 to 0.2. Note that these boundaries represent large changes of wealth which are close to the lower and upper 10%-percentiles in each specification. What is evident from the figure is that the predictive margins are almost identical in the two specifications and that they exhibit large confidence intervals that widen at the tails (all single margins are statistically different from zero at the 1% level). Only in the region with a wealth change between zero and EUR 50,000 (0 to 0.05 in the rank specification) the confidence intervals seem reasonably narrow to ascertain with safety that the probability of being healthy is higher with every additional increase of the wealth level or rank. This finding yields two conclusions: 1. Overall, the model performs not very well in predicting the health status as the predictions are subject to high uncertainty 2. Relatively small improvements of the wealth level or wealth rank seem to have a noticeable impact on respondent's health status that is in the same league as the essential health determinants age and education.

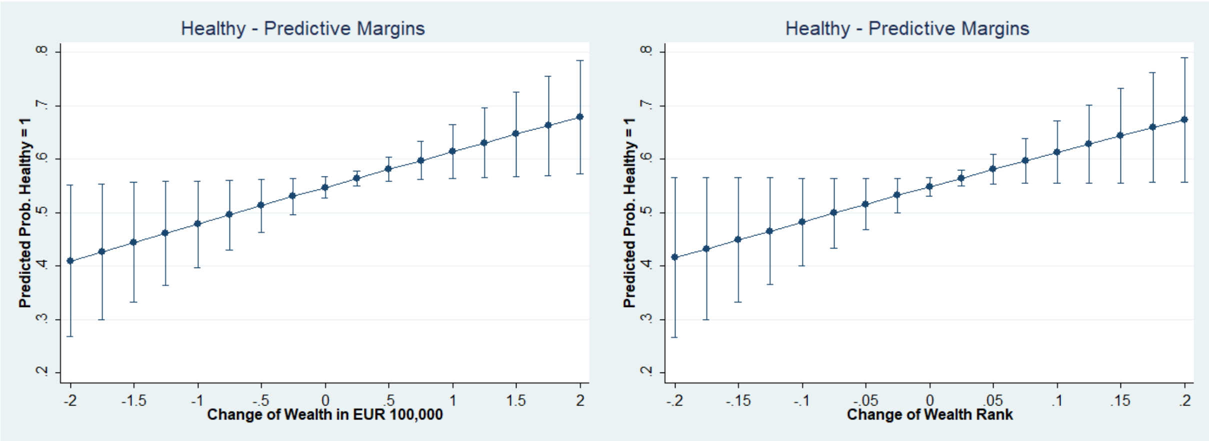

Figure 6: Respondent's chances of being healthy - predictive margins

6.5. Model diagnostics

These conclusions rest on the assumption that inheritance is a valid instrument for change of wealth and adequately measures the true wealth effect that the SHARE respondents experience between the second and fourth wave of the survey. The reported F-test on a transformation of ρ, which is defined as:

$$atanh\,\rho = \frac{1}{2}\,ln\left(\frac{1+\rho}{1-\rho}\right)$$

where ρ is the correlation coefficient between the errors in the probit equation and the reduced-form equation for the endogenous regressor, can serve as an indication of whether change of wealth is endogenous and IV probit is appropriate. Without survey-set data this test is reported as a Wald test (StataCorp, 2015). With a P-value of 10.6% in the level specification and 13.4% in the rank specification, the transformation is not statistically different from zero at typical significance levels, which would suggest that change of wealth is exogenous and that a regular probit instead of IV probit suffices. The null of the transformation being zero (i.e. change of wealth is exogenous) is, however, not rejected with overly high confidence. Following this closely-decided test result and the theoretical considerations of change of wealth being endogenous, it is assumed that the IV coefficients are consistent although not efficient, which means that the results presented in Table 14 stem from the preferred specification.

As in the bivariate probit case, likelihood ratio and Hausman tests or information critieria for model selection are not available since the IV results have been obtained by taking sampling design into account and by assigning longitudinal weights to the observations. Scatter plots of the Pearson residuals from the IV probit model in two specifications with wealth levels and ranks are presented in Appendix D to give an indication of possible model misspecifications and troubling outliers. The plot of the squared residuals against the index (Figure 12) shows no worrisome structure. Only in the level specifications, the residuals for observations from the Czech Republic (index numbers 1,921 to 2,782) and Poland (index numbers 10,182 to 11,212) are slightly elevated above zero. This indicates on the one hand, that the prediction is less accurate for these countries and that the regional dummy could possibly excluded from the model, but on the other hand, the squared Pearson residuals for observations from Poland exhibit less extreme values as compared to all other residuals. In the rank specification, no such pattern is observable.

The plot of the squared Pearson residuals against change of wealth in both specifications (Figure 13) shows that the residuals are clustered around wealth changes of zero where most observations reside. Compared to the level specification, the residuals from the rank specification are a bit more widespread at greater positive or negative wealth changes. Similarly to the diagnostics of the bivariate probit model, the residual plots against respondent's age in Figure 14 exhibit a higher spread at lower ages, which indicates that the prediction whether respondents are healthy in the fourth wave is less precise for younger individuals. The same reasoning as in the mortality model applies, according to which younger individuals are exposed to sudden and unforeseen events that can hardly be predicted with the SHARE data.

In Figure 15 the scatter plots of the squared Pearson residuals against the instrumental variable inheritance proof that both specifications perform well in predicting the health outcomes for respondents who inherited at least once between the second and fourth wave of SHARE. Especially for respondents who received an inheritance more than twice, no drastically high residuals are observable.

The last figure in Appendix D shows plots of the Pearson residuals against the linear prediction. Out of the 12,334 observations, 5.3% of predictions in the level specification (6.5% in rank specification) yield Pearson residuals above the threshold of 2 in absolute terms. This threshold is exceeded if individuals are predicted to be healthy or unhealthy in the fourth wave with a probability of 80%, while the opposite occurred. The plots indicate that the predictive ability of the model specification with wealth in levels is higher than with wealth rankings. Not visible in the figures is the higher share of Pearson residuals below the -2 mark in the rank specification (3.7% vs. 2.7% in the level specification), which means that the rank specification predicted more individuals to be healthy in wave 4 although they are truly unhealthy according to their self-rated health states.

As a robustness check the IV probit model is re-estimated by replacing the dependent variable and the dummy variable indicating respondent's initial health status. The model is estimated with a new dependent variable that equals one if respondent's constructed health score is below 3 in the fourth wave and zero otherwise. Similarly, initial health status is indicated with a dummy that is one if respondent's health score is below 3 at the second wave and zero otherwise. The exchange of these two variables leads to insignificant point estimates for the instrumented change of wealth and initial wealth in both specifications, while the other coefficient estimates remain roughly the same. The reason for that could lie in the construction of the health score itself, whose categories exhibit a completely different distribution in the sample as compared to the self-rated health status. Histograms of the constructed health score and the self-assessed health status are depicted in Figure 7.[3]

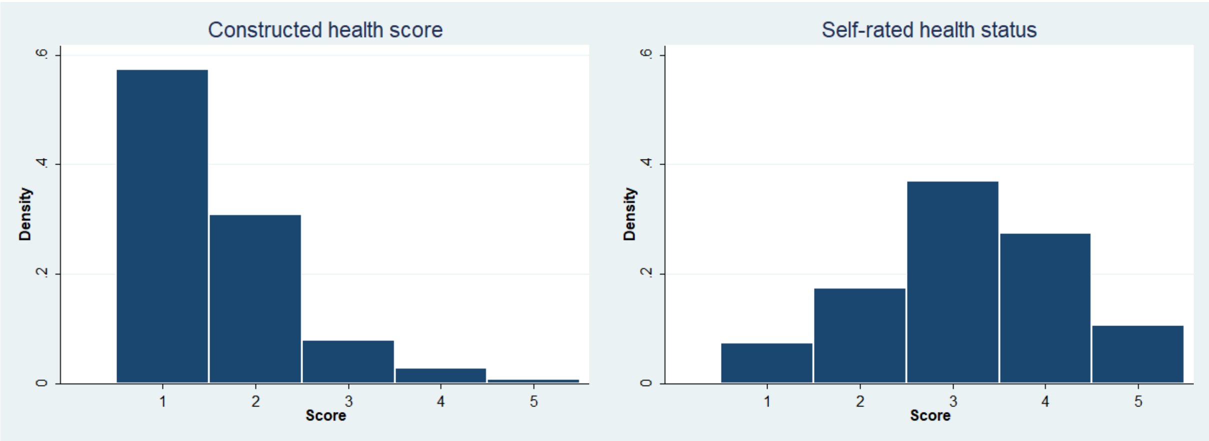

Figure 7: Histograms of constructed health score and self-rated health status in wave 4

Given that the relevant coefficient estimate for change of wealth turned insignificant in the different setup with the constructed health score, cautiousness is advised in the interpretation of a causal effect running from wealth to self-assessed health status. Also Meer et al. (2003) found no evidence for the presence of such an effect with similar data, while the IV regression from Table 14 suggests the presence of a significant causal relationship. Depending on the specification, the IV results point towards increases of the probability of being healthy by 6.4pp or 6.3pp on average with every additional wealth increase by EUR 100,000 or increase of the wealth rank by 0.1. That response of the dependent variable is on an equal level with the effect of other important determinants such as age and education. Furthermore, these changes of respondent's financial standing between waves 2 and 4 of SHARE are not implausible, since 18.4% of them experience changes of the wealth level above EUR 100,000 and 23.7% see an improvement of their wealth rank higher than 0.1.

Other robustness checks of the IV model that left out certain covariates or that were estimated by neglecting stratification and sample weights did not result in alternating wealth coefficients, so the 6.4pp and alternatively 6.3pp increase in the probability of being healthy is robust in that regard.

7. Conclusion

A replication of the main result of the literature was successful with both, the bivariate probit model and the IV probit model. The results indicate that SES, as measured by individual's wealth levels and rankings, are associated with mortality and changes of health states. With the available data from two waves of SHARE, the models indicate that mortality rates vary on average between 3.5pp for all male

[3] Note that the worst score of 5 refers to a very poor health status for the first, while it refers to a poor self-rated health status for the second. The best score of 1 represents a very good health score or an excellent self-perceived health status.

respondents and 3.3pp for all female respondents in the preferred specification between zero-wealth ranks and midpoint-wealth ranks. Further, the IV approach with inheritances suggests that wealth changes between the two waves cause differentials in respondent's probability of being healthy according to self-rated health status. Additional increases of the normalized wealth rank by 0.1 are expected to increase that probability by 6.3pp on average. The validity of the results rests upon whether the implied model conditions are met. In that regard, the IV model showed a deficiency as it yields insignificant estimates of the wealth effect on health outcomes when the specification is changed to a more objective health measure. Other specifications either to test whether explanatory variables truly belong to the model or to test the validity of inheritance as an instrument were robust.

Further research, preferably on the basis of the expanding number of SHARE waves, would be desirable to put the obtained results into perspective, especially since the available econometrical studies on the wealth-health nexus predominantly failed to find a causal path between the variables. Despite this evidence, the general picture of widening income and wealth levels in many countries may harm the social cohesion in society at the potential cost of fostering extreme political views and endangering the democratic order. Next to the ongoing climate change, the distribution of economic resources will be the major challenge in this century and requires policy makers, the scientific community and dedicated individuals to act in order to reduce the prevailing inequalities both within and across countries.

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9. Appendix A

9.1. Country participation in SHARE

ISO-coding	Country	Wave 1	Wave 2	SHARELIFE	Wave 4	Wave 5	Wave 6
AT	Austria	2004	2006/07	2008/09	2011	2013	2015
BE	Belgium	2004/05	2006/07	2008/09	2011	2013	2015
HR	Croatia	-	-	-	-	-	2015
CZ	Czech Republic	-	2006/07	2008/09	2011	2013	2015
DK	Denmark	2004	2006/07	2008/09	2011	2013	2015
EE	Estonia	-	-	-	2010/11	2013	2015
FR	France	2004/05	2006/07	2009	2011	2013	2015
DE	Germany	2004	2006/07	2008/09	2011/12	2013	2015
GR	Greece	2004/05	2007	2008/09	-	-	2015
HU	Hungary	-	-	-	2011	-	-
IE	Ireland	-	2007	2009/10/11	-	-	-
IL	Israel	2005/06	2009/10	-	-	2013	2015
IT	Italy	2004	2006/07	2008/09	2011	2013	2015
LU	Luxembourg	-	-	-	-	2013	2015
NL	Netherlands	2004	2007	2008/09	2011	2013	-
PL	Poland	-	2006/07	2008/09	2011/12	-	2015
PT	Portugal	-	-	-	2011	-	2015
SI	Slovenia	-	-	-	2011	2013	2015
ES	Spain	2004	2006/07	2008/09	2011	2013	2015
SE	Sweden	2004/05	2006/07	2008/09	2011/12	2013	2015
CH	Switzerland	2004	2006/07	2008/09	2011	2013	2015

Table 15: Overview of country participation in SHARE

9.2. Questionnaire modules in SHARE

Module Code	Questionnaire Module	Wave 1	Wave 2	Wave 4	Wave 5	Wave 6
AC	Activities	X	X	X	X	X
AS	Assets	X	X	X	X	X
BR	Behavioral Risks	X	X	X	X	X
BS	Blood Sample					X
CF	Cognitive Function	X	X	X	X	X
CH	Children	X	X	X	X	X
CO	Consumption	X	X	X	X	X
CS	Chair Stand		X		X	
CV_R	Coverscreen on individual level	X	X	X	X	X
DN	Demographics and Networks	X	X	X	X	X
EP	Employment and Pensions	X	X	X	X	X
EX	Expectations	X	X	X	X	X
FT	Financial Transfers	X	X	X	X	X
GS	Grip Strength	X	X	X	X	X
HC	Health Care	X	X	X	X	X
HH	Household Income	X	X	X	X	X
HO	Housing	X	X	X	X	X
IT	Computer Use				X	
IV	Interviewer Observations	X	X	X	X	X
MC	Mini Childhood				X	
MH	Mental Health	X	X	X	X	X
PF	Peak Flow		X	X		X
PH	Physical Health	X	X	X	X	X
SN	Social Networks			X		
SP	Social Support	X	X	X	X	X
WS	Walking Speed	X	X			
	Special Questionnaire Modules					
DO	Drop-off	X	X	X	X	X
TC	Technical Variables	X	X	X	X	X
VI	Vignettes	X	X			
XT	End-of-Life Interview		X	X	X	

Table 16: Overview of questionnaire modules in SHARE waves excluding SHARELIFE

Module Code	Questionnaire-Module
AC	Accommodation Section
CS	Childhood Section
CV_R	Coverscreen on individual level
DQ	Disability
FS	Financial History Section
GL	General Life
GS	Grip Strength
HC	Health Care
HS	Health Section
IV	Interviewer Observations
RC	Retrospective Children
RE	Retrospective Employment
RP	Retrospective Partner
ST	Demographics
WQ	Work Quality
XT	End-of-Life Interview

Table 17: Overview of questionnaire modules in SHARELIFE

10. Appendix B

10.1. Construction of health score

18 different variables enter the calculation of the respondent's health score. These variables cover the following determinants of health: diseases, mobility limitations, eyesight and hearing ability, body mass, habits (smoking, drinking), physical activity, communication, cognitive skills, grip strength, depression and health care. The different values of the variables are then given a certain score. For instance, the highest scores are assigned to variables related to mobility limitations and body mass (up to 12 points), while not passing an orientation test is only graded with a maximum of one point. All the scores are subsequently added together. In the sample, the sum of scores ranges from 0 for totally healthy individuals to 63 for individuals in a severe state of health. Finally, this sum is transferred into categories from 1 to 5 according to the following formula:

Sum of scores	Health score
9 and below	1 (very good health)
10-19	2
20-29	3
30-39	4
40 and above	5 (very poor health)

Table 18: Allotment formula of health score

11. Appendix C

11.1. Summary statistics – Bivariate probit model

Variable	Description	Mean	Std. deviation	Min	Median	Max
Age	Age of respondent at wave 2, in years	65.89	10.41	50	64.33	104.25
Health score	Constructed health score at wave 2, from 1 (very good) to 5 (very poor)	1.33	0.69	1	1.00	5
Self-perceived health	Self-rated health status at wave 2, from 1 (excellent) to 5 (poor)	3.13	1.11	1	3.00	5
Couple	= 1 if respondent has a partner at wave 2	0.63	0.48	0	1.00	1
High-school degree	= 1 if respondent completed high-school, equivalent to ISCED-level 2 or 3	0.48	0.50	0	0.00	1
Some college degree	= 1 if respondent has some college diploma, equivalent to ISCED-level 4	0.03	0.18	0	0.00	1
College degree	= 1 if respondent has a college diploma, equivalent to ISCED-level 5 or 6	0.19	0.39	0	0.00	1
Regional dummy CZ/PL	= 1 if respondent lives in Czech Republic or Poland	0.18	0.38	0	0.00	1
Regional dummy IT/ES	= 1 if respondent lives in Italy or Spain	0.17	0.38	0	0.00	1
Wealth level	Household networth in EUR 100,000 at wave 2, capped at -200ths and 1.5mn	2.56	3.06	-2	1.59	15
Wealth rank	Wealth ranking of respondent in one of four age groups at wave 2, normalized between 0 and 1	0.48	0.30	0	0.48	1
Complete answers	Complete answers on respondent's value of main residence by country at wave 2, classified in quartiles	2.35	1.10	1	2.00	4

N = 20,599

Table 19: Summary statistics of variables in bivariate probit model

11.2. Residual diagnostics – Bivariate probit model

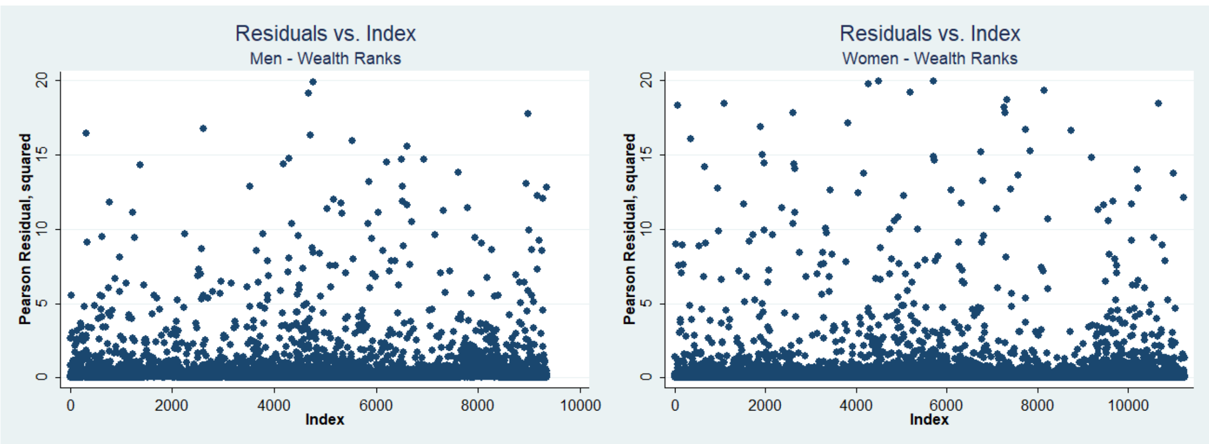

Figure 8: Squared Pearson residuals vs index number

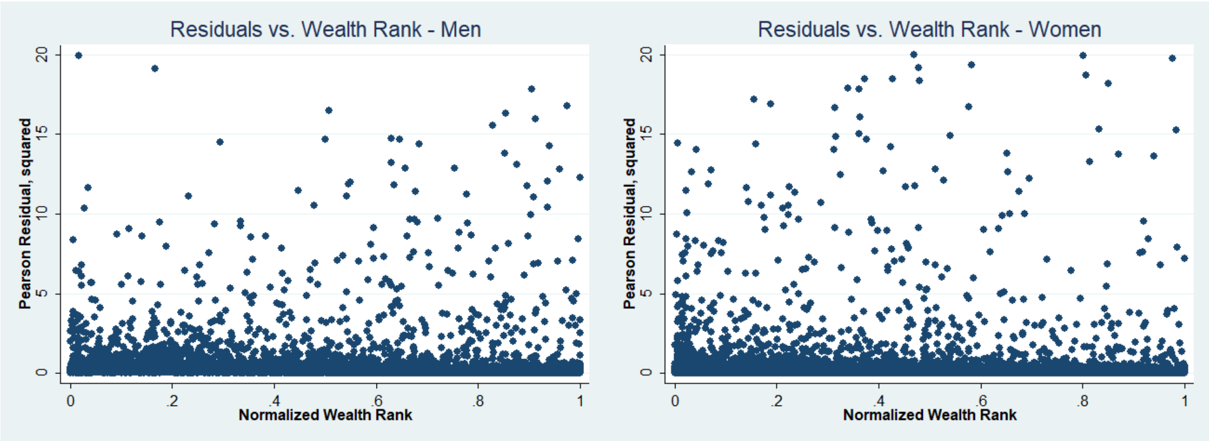

Figure 9: Squared Pearson residuals vs. normalized wealth rank

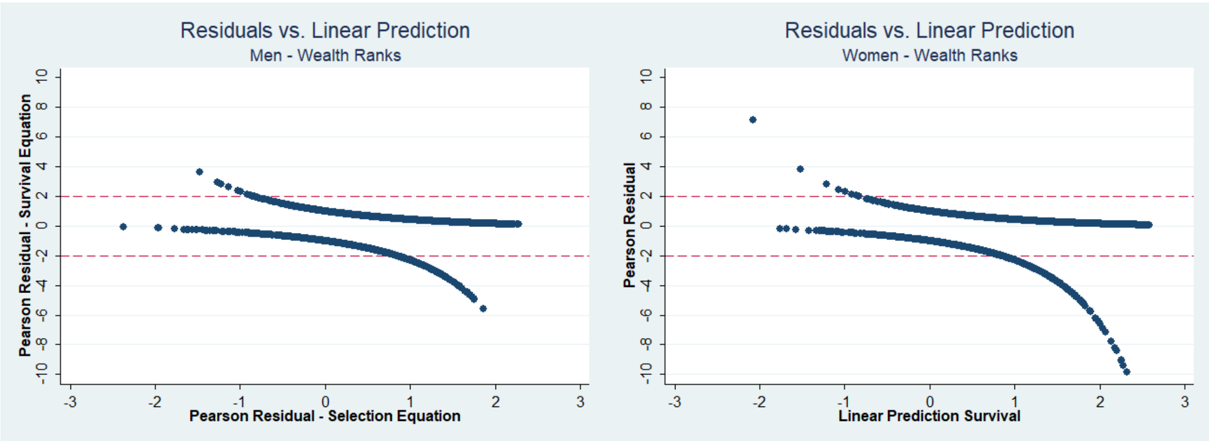

Figure 10: Pearson residuals vs. linear prediction

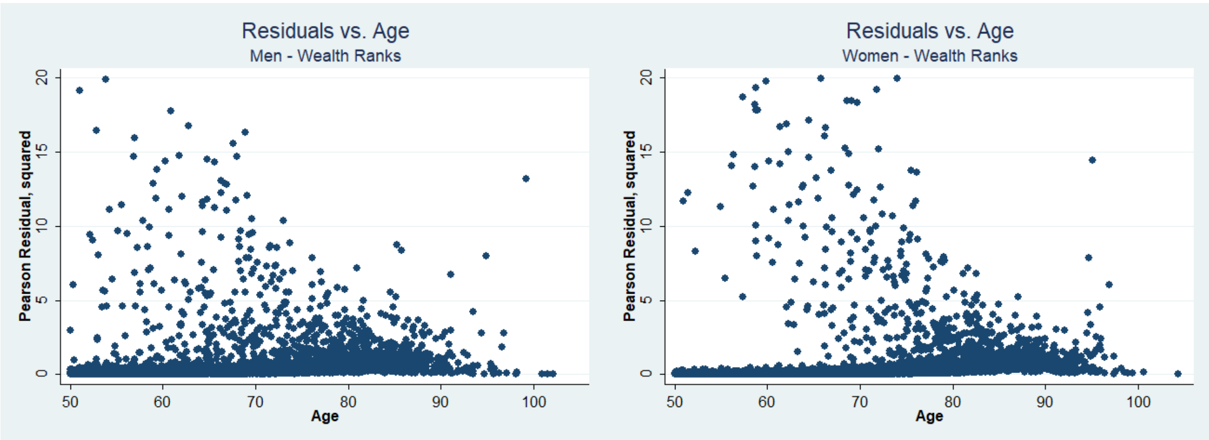

Figure 11: Squared Pearson residuals vs. age

12. Appendix D

12.1. Summary statistics – IV probit model

Variable	Description	Mean	Std. deviation	Min	Median	Max
Δ Wealth level	Change of household networth between wave 2-4 in EUR 100,000; capped at -1mn and 1mn	-0.02	2.46	-10	0.00	10
Δ Wealth rank	Change of absolute wealth rank between wave 2-4	0.00	0.20	-0.96	0.01	0.98
Inheritance	Amount of inheritances received between wave 2-4	0.06	0.27	0	0	5
Initial wealth level	Household networth in EUR 100,000 at wave 2, capped at -200ths and 1.5mn	2.60	3.02	-2	1.83	15
Initial wealth rank	Absolute wealth ranking of respondent at wave 2, normalized between 0 and 1	0.46	0.30	0	0.47	1
Initial health	= 1 if self-perceived health at wave 2 is good, very good or excellent	0.61	0.49	0	1	1
Age	Age of respondent at wave 4, in years	69.02	0.15	54.08	67.92	103.92
Male	= 1 if respondent is male	0.45	0.50	0	0	1
Couple	= 1 if respondent has a partner at wave 2	0.60	0.49	0	1	1
Divorced	= 1 if respondent is divorced at wave 2	0.10	0.29	0	0	1
Widowed	= 1 if respondent is widowed at wave 2	0.22	0.41	0	0	1
Children	= if respondents has children at wave 2	0.88	0.33	0	1	1
High-school degree	= 1 if respondent completed high-school, equivalent to ISCED-level 2 or 3	0.48	0.50	0	0	1
Some college degree	= 1 if respondent has some college diploma, equivalent to ISCED-level 4	0.03	0.16	0	0	1
College degree	= 1 if respondent has a college diploma, equivalent to ISCED-level 5 or 6	0.19	0.39	0	0	1
Regional dummy CZ/PL	= 1 if respondent lives in Czech Republic or Poland	0.13	0.34	0	0	1
Regional dummy IT/ES	= 1 if respondent lives in Italy or Spain	0.29	0.45	0	0	1
Interview gap	Gap between wave 2 and 4 interviews, in years	4.35	0.33	3.25	4.25	5.33

N = 12,334; means and std. deviation are computed using calibrated longitudinal sample weights

Table 20: Summary statistics of variables in IV probit model

12.2. Residual diagnostics – IV probit model

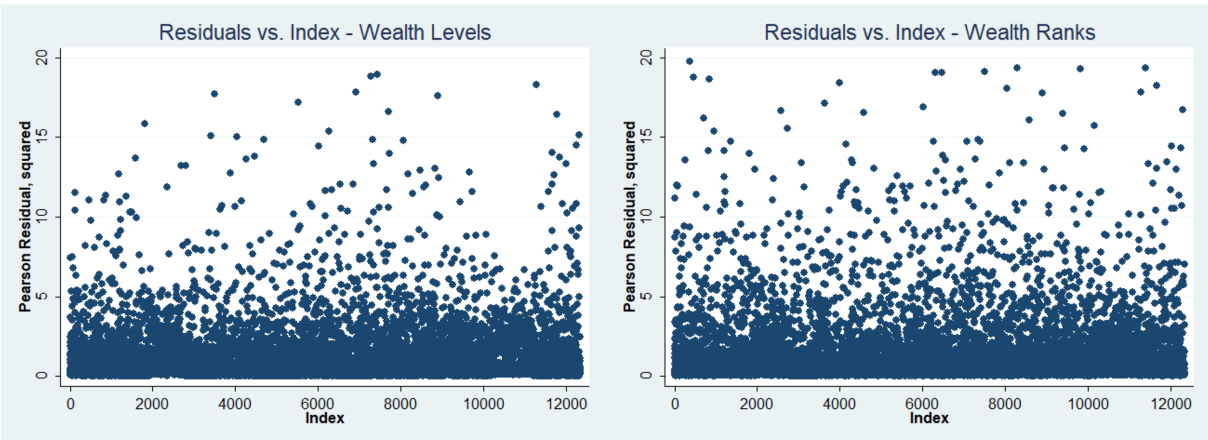

Figure 12: Squared Pearson residuals vs. index number (IV)

Figure 13: Squared Pearson residuals vs. change of wealth (IV)

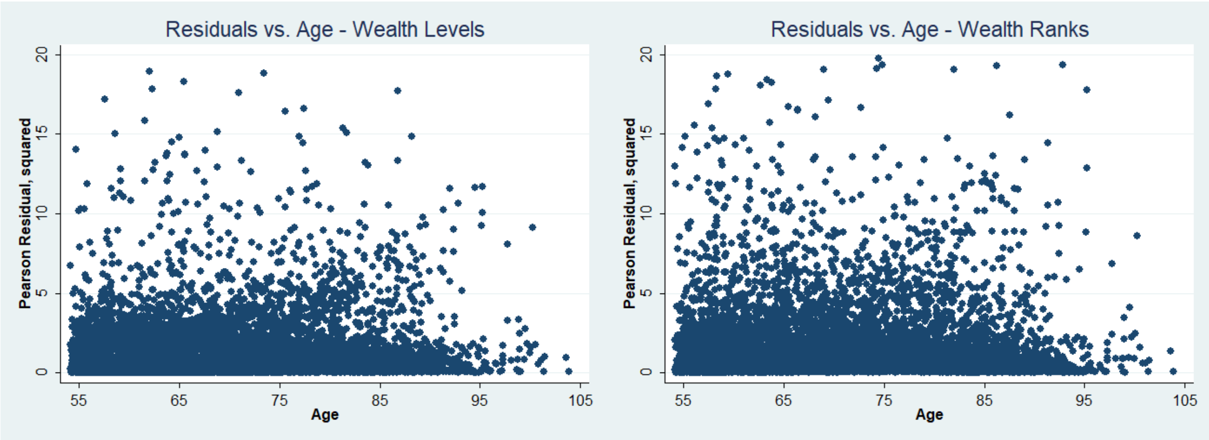

Figure 14: Squared Pearson residuals vs. age (IV)

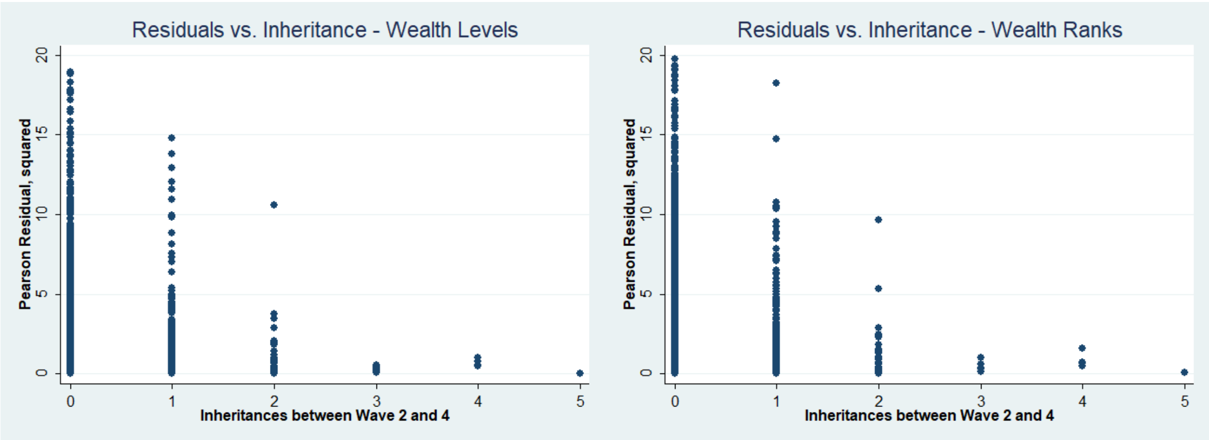

Figure 15: Squared Pearson residuals vs. inheritance (IV)

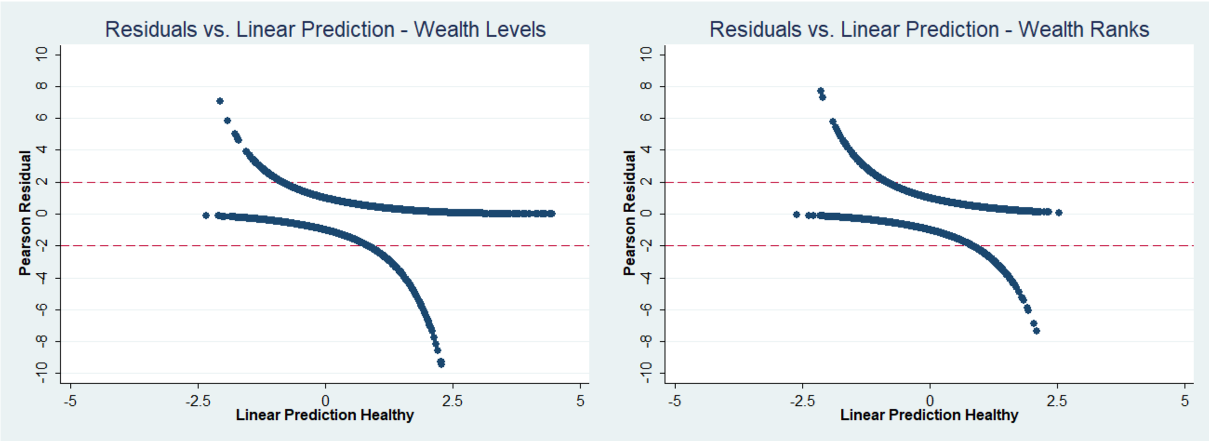

Figure 16: Pearson residuals vs. linear prediction (IV)