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Differential Mortality in Europe and the U.S.

Estimates Based on Subjective Probabilities of Survival

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Abstract

Estimates of differential mortality by socioeconomic status play an important role in several domains: in public policy for assessing distributional effects of public programs; in financial markets for the design of life insurance and annuities; and in individual decision making when figuring out how much to save for retirement. Traditionally, reliable estimates of differential mortality require rich panel data with large sample size. This paper proposes a new, less data-intensive approach relying on just a single cross-section of data. Rather than using observations on actual mortality in panel over time we propose relating individuals' subjective probabilities of survival to variables of socioeconomic status in cross-section. We formulate the method in a model of survey response and provide an empirical validation based on data from the Health and Retirement Study comparing the alternative estimates to the traditional estimates of differential mortality for the same sample of baseline respondents. We present two applications. First, we document an increase in differential mortality in the U.S. over time, and second, we produce comparable estimates of differential mortality for 10 European countries and the U.S. based on subjective probabilities of survival.

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1. Introduction

Estimates of differential mortality by socioeconomic status (SES) play an important role in several domains: for assessing distributional implications of public programs (taxes, public goods, health care). They are also relevant for the design of annuities and life insurance in financial markets, and for individual decision-making such as how much to save for retirement and which financial products to invest in. Finally, they matter for empirical research when presenting age patterns of a variable, such as income or wealth, based on cross-sectional data or on synthetic panel data which tend to be biased by differential mortality. To obtain reliable estimates of differential mortality one needs very rich panel data with consistent observations of SES over time, sufficient sample size and minimal attrition. These ideal conditions are rarely met. When interested in comparing differential mortality across countries the data requirements become even more demanding with the additional need to match the time period of observation and the definition and measurement of socioeconomic status.

In this paper, we propose an alternative method for estimating differential mortality using respondents' subjective probabilities of survival.[1] To elicit these, respondents are asked:

"*What is the percent chance that you will live to be [X] or more.*"

The target age X varies as a function of the respondent's own age.

Subjective probabilities of survival have been collected in this form in the U.S. Health and Retirement Study (HRS) every two years since its baseline interview in 1992. Validation studies based on the HRS show that these subjective probabilities of survival vary systematically with known risk factors of survival such as smoking, evolve in panel in response to new information such as parental death or the onset of a disease, and predict actual mortality (Hurd and McGarry 1995, 2002; Smith, Taylor and Sloan 2001; Siegel, Bradley and Kasl 2003; Bloom, Moore and Song 2007; Elder 2007). The survival expectations in the HRS have also been used to construct cohort life tables that predict an unusual revision to U.S. life expectancy made by the Social Security Administration (Perozek 2008). They have been shown to be predictive of actual and expected economic behavior (Hurd et al. 2004; Bloom et al. 2007; Elder 2007; Delavande and Willis 2008). Hurd, Rohwedder and Winter (2005) document comparable systematic variation in subjective probabilities of survival in data from 11 European countries in the English Longitudinal Study of Ageing (ELSA) and in the Survey of Health Ageing and Retirement in Europe (SHARE). They also highlight the strong relationship with objective measures of health, such as grip strength which itself is known to be a strong predictor of morbidity and mortality.

In this paper we propose using this systematic variation in the subjective probabilities of survival to estimate differential mortality. In the first part of the paper we establish the reliability of our approach by estimating differential mortality on panel data from the HRS and comparing the resulting traditional estimates with those obtained from subjective probabilities collected at baseline on the *same* respondents. The HRS is sufficiently rich to support also the traditional approach based on panel data as it has data spanning a period of up to 14 years and it links to the National Death Index (NDI). We find that for wealth the alternative estimates are strikingly

[1] See Manski (2004) for an overview and discussion on the state of knowledge about subjective expectations data.

similar to the ones obtained from actual survival, and for income and education they are very similar as well.

Prior studies have estimated differential mortality by wealth (e.g., Attanasio and Hoynes 2000; Attanasio and Emmerson 2003), income and income inequality (e.g., Duleep 1986, 1989; Deaton and Paxson 2004, Bommier et al. 2003), occupational status (e.g., Marmot 1999), education (e.g., Feldman et al. 1989, Lleras-Muney 2005) and broader measures of socioeconomic status (e.g., Adams et al. 2003; Deaton and Paxson 2001). The general finding is a strong association between the various measures of economic status and mortality.[2] The prevailing approach is to study mortality in panel data with observations on actual deaths, allowing to estimate directly the association between socioeconomic variables and the probability of death (e.g., Duleep 1986; Attanasio and Emmerson 2003; Adams et al. 2003).

After having validated our method, we present two applications. First, we estimate trends in differential mortality in the U.S. between 1992 and 2006 using data from HRS. Earlier studies have documented increases in differential mortality from the 1960 to the 1980s (e.g., Duleep 1989; Feldman et al. 1989; Pappas et al. 1993). Economic inequality has been observed to have increased further in recent years in the U.S. (e.g., Chevan and Stroke 2000) raising the question whether this has or will translate into further increases in differential mortality. Consistent with the results in Hadden and Rockswold (2008), we find an increase in inequality in mortality with respect to wealth, income and education in the U.S..

Second, we produce directly comparable estimates of differential mortality for 10 European countries and the U.S. for the year 2004. Numerous studies of differential mortality by socioeconomic status focus on the U.S. and the U.K.. While there are also some studies using data from other countries, it is difficult to compare their findings due to differences in the time period covered or different definitions of the SES variables.[3] However, international comparisons of differential mortality could provide an insightful starting point for understanding the role of institutions, such as the health care systems, in reducing health and therewith mortality differences. Our proposed method of estimating differential mortality by SES with its much more modest data requirements makes is it a lot easier to produce estimates that are comparable across countries, especially when taking advantage of the recent emergence of data sets such as SHARE and ELSA which were designed to be comparable to the HRS.

There are some studies that present international comparisons (Kunst and Mackenbach, 1994a, b; Mackenbach et al. 1997, 2004) and highlight international heterogeneity in how socioeconomic status is associated with mortality. For example, Kunst and Mackenbach (1994) find that inequalities in mortality are relatively small in the Netherlands and Scandinavian countries, compared to the U.S., France and Italy. Mackenbach et al. (1997) challenge this result and find large inequalities in mortality in Nordic countries. A major caveat of these international comparisons is that they rely on datasets that differ along several dimensions limiting their comparability: the data are collected using different survey instruments or in some cases even use information from administrative data bases that are not available in other countries; the data

[2] In addition to quantifying the relationship between mortality and economic variables, most of the mentioned studies are also concerned with the direction of causality between health and socioeconomic status, which is beyond the scope of this paper where we focus on the association between mortality and SES. To conduct those analyses, authors have in some cases combined cross-sectional data on birth cohort mortality with pooled time-series on income, education and poverty (e.g., Deaton and Paxson 2001, 2004).

[3] Examples of studies for other countries are Desplanques (1991) or Bommier et al. (2006) for France, Nelissen (1999) and references therein for the Netherlands, and Hoffmann (2005) for Denmark.

sets do not cover the same time period and groups; and they differ, often substantially, in the amount of detail available to construct variables describing SES.

The data from SHARE, and ELSA were designed to be comparable to the HRS. In addition to collecting information on income, wealth and education in ways that are closely comparable across countries they also elicit respondents' subjective probabilities of survival, demographics, income, wealth and education from 12 different countries for the year 2004 which we use to conduct cross-country comparisons of differential mortality. We find for every country that those in high wealth have higher survival probabilities than those with low wealth. However, there is heterogeneity in the strength of the association across countries. According to our estimates countries with a smaller gradient are Belgium, France and Italy while we find the gradient to be strongest in Sweden, Austria and England.

2. Theoretical Framework of Survey Response

We present a simple theoretical framework of survey response that shows how we estimate differential mortality from subjective probabilities of survival.

Define the survival function $I_{TA} = X_t\beta + \varepsilon$ representing the probability of being alive at target age *TA* of a respondent with characteristics X_t at time *t* before he has reached age *TA*. The survival function determines the outcome $A_{TA} = 1$, being alive at the target age *TA*, according to the following rule:

$$A_{TA} = 1 \text{ if } I_{TA} = X_t\beta + \varepsilon > C,$$
$$A_{TA} = 0 \text{ if } I_{TA} = X_t\beta + \varepsilon < C,$$

where *C* is a constant and the ε are iid across individuals, i.e. the ε are individual-specific shocks that affect individual survival.[4]

Given this assumption, the (objective) probability $P\left(A_{TA} = 1 \middle| X_t\right)$ of being alive at *TA* conditional on X_t is equal to:

$$P\left(A_{TA} = 1 \middle| X_t\right) = P(X_t\beta + \varepsilon > C)$$

Denoting G the cumulative distribution of ε, we get:

$$P\left(A_{TA} = 1 \middle| X_t\right) = G(X_t\beta - C) \tag{1}$$

If respondents know the shape of their survival function and the relevant X_t, their predictions Π_{TA} about their chance of survival to age *TA* is given by:

$$\Pi_{TA} = G(X_t\beta - C) \tag{2}$$

To derive equation (2) from equation (1), we implicitly assume that that there is no systematic unexpected shift in longevity (e.g. due to improvements in medical technology) occurring between time *t* and the time respondents reach their target age *TA*, or at least, that such a shift affects everybody's mortality in a proportional manner. In the latter scenario the levels of the survival probabilities would change, but not the differentials by observables X_t. If (2) is

[4] Subscripts denoting individuals have been omitted for ease of presentation.

verified, we can obtain estimates of differential mortality using the subjective survival probabilities Π_{TA} .

3. Empirical Validation in the HRS

In the empirical validation we use the rich, longitudinal data from the HRS and proceed in two stages: first, we illustrate at the population level that subjective probabilities of survival have predictive power for actual survival to the target age *TA*. In the second stage of the empirical validation, we apply the method derived in the previous section to estimate differential mortality by wealth, income and education from the subjective probabilities of survival and compare the resulting estimates to those obtained from estimating the same relationship using actual survival to target age *TA*.

3.1. HRS Data

The HRS is a nationally representative panel survey of persons born in 1953 or earlier, designed to investigate the health, social, and economic implications of the aging of the American population. The HRS combines five cohorts that were enrolled at different points in time and were interviewed every two years after enrollment: the original HRS cohort born in 1931 through 1941 and surveyed since 1992; the AHEAD cohort born between 1890 and 1923 and enrolled since 1993; the Children of the Depression Age (CODA) cohort born between 1924 and 1930 and the War Babies cohort born between 1942 and 1947, both added to the HRS in 1998; and finally the Early Baby Boomers cohort born between 1948 and 1953 and first interviewed in 2004. Spouses were also included regardless of age.[5] We use data from 1992 to 2006. Spanning a period of fourteen years, we observe a significant number of deaths among respondents and their spouses.

3.1.1. *Vital status of HRS respondents*

The HRS determines the vital status of respondents in any particular survey wave through tracking: A respondent is considered alive if she was interviewed or contacted directly by an interviewer during the wave, or was said to be alive by a spouse or partner, or was not reported dead. If no informative contact was made, the respondent's vital status is classified as unknown.[6]

In addition the HRS matches respondent records to the National Death Index (NDI) for those who are reported deceased or who are of unknown vital status during tracking. This NDI information is available up to 2004. For the latest HRS wave collected in 2006 it is not yet available. We construct our vital status variable as follows:

Vital status in 2004. A respondent is considered dead in 2004 if she was reported dead by HRS through tracking;[7] a respondent is considered alive if he answered the questionnaire in 2004, or if he has never been reported dead according to HRS and had no match in the NDI.

[5] See Juster and Suzman (1995) for an early overview and the HRS website at http://hrsonline.isr.umich.edu or St Clair et al, 2008, for further information about later waves.
[6] Source: Data description and usage of the HRS Tracker file for 2006 (Final, Version 2.0).
[7] The vast majority of cases determined to be dead by HRS also have a match in the NDI. The small fraction without a match in the NDI is most likely due to respondents leaving the country or other forms of loss to follow-up.

Vital status in 2006. A respondent is considered dead in 2006 if she was dead in 2004 according to our criteria above or if she was reported dead to HRS in 2006; a respondent is considered alive in 2006 if she was reported alive to HRS in 2006.

We apply these definitions to all 30,890 respondents who have ever been interviewed by HRS. Table 1 presents the results. Twenty-one percent have died by 2004; by 2006 this fraction increases to 26%. Note that the vital status is unknown for 10.5% of the respondents in 2006 due to the fact that the NDI information is not yet available for that year.

3.1.2. The analytical sample

In the first waves of HRS, respondents were asked their survival to age 75 and 85. To validate our methodology, we identify a sample of respondents who – by the last available wave of HRS – reached or would have reached if still alive the target age that they were queried about when asked about their subjective probability of survival question at baseline. We focus on the target age 75, denoted P75 hereafter, because this results in a sample that was younger at baseline (age 61 to 66). Focusing on younger respondents is advantageous for two reasons: first, for a population in their early sixties selection through mortality is fairly small. Second, aging is associated with cognitive decline and low cognition has been found to introduce bias into subjective expectations of survival (Elder, 2007).

Our analytical sample is therefore composed of respondents who (*i*) were asked their survival to age 75 (P75), (*ii*) for whom we know their vital status at age 75, and (*iii*) for whom the distance to age 75 at the time of the subjective survival question was between 9 and 14 years ahead. A total of 1,234 observations meet these criteria. Of these, 15 observations had a missing value for P75. This corresponds to an item non-response rate of 1.2 percent which is very low. Our final analytical sample consists of 1,219 respondents. Thirty percent of them died before reaching age 75. Sixty-five percent were asked their survival expectations in 1992, 34% in 1994 and less than 1% in 1996.[8] Note that this subset is not a random sample: while 35% are HRS respondents who were age-eligible in 1992, 65% are older spouses of the HRS respondents. Also, 70% of the respondents are males. The non-randomness of our analytical sample does not affect the validity of the empirical validation which only verifies that for a given population our method yields the same or closely comparable results as the one based on actual mortality observed in panel. The verification exercise does not attempt to produce population representative estimates of differential mortality.

3.2. Predictive Power of Subjective Probabilities of Survival for Actual Mortality

The most fundamental prerequisite for our proposed method is that subjective probabilities of survival are strong predictors of subsequent actual survival at the population level (not necessarily at the individual level since mortality is a stochastic event).

Prior studies demonstrated correlation of subjective probabilities with risk factors for morbidity and mortality, and their predictive power for actual mortality in short panel (Hurd and McGarry, 1995, 2002; Smith et al., 2001; Siegel et al., 2003). These studies focus on earlier waves of the HRS. In the meantime, with HRS data available up to the year 2006, a sizeable fraction of the HRS sample has reached the target age that they were asked about at baseline. With that it is now possible to verify the predictive power of the subjective probabilities with

[8] The vast majority of observations that come from 1994 pertain to respondents who were asked both in 1992 and 1994 about their subjective probability of survival to age 75. We use their 1994 response because at that time the distance to age 75 (11 or 12 years) matches more closely that of the rest of the sample.

respect to the event that respondents were actually queried about: survival to a particular target age. This constitutes the most direct test of the predictive power of subjective probabilities of survival.

Figure 1 presents the mean of the variable "dead in 2006" by the answer to P75 elicited at baseline. The left panel pertains to our analytical sample. We find a clear gradient in mortality based on panel observations by reported subjective probability of survival. In earlier work, subjective probabilities in the HRS have been found to exhibit bunching at the focal values of 0, 50 and 100 (e.g., Hurd and McGarry 1995; Lillard and Willis 2002). In Figure 1, the zeros and 50's do not show as outliers; the 100's, however, do somewhat as respondents who answered 100 show higher actual mortality than those who reported lower subjective probabilities such as 70, 80 and 90. Nevertheless the 100s contain information as well because they still exhibit lower mortality than those who provided answers smaller than 50%, but they seem to attract more responses than they should.

For comparison we have produced in the right panel of Figure 1 the same graph of 14-year mortality by P75 for the sample of age-eligible HRS respondents (age 51-61) interviewed in 1992. Qualitatively the same pattern emerges for this random sample reassuring that the patterns in our analytical sample are not driven by our sample selection. Note that the overall level of mortality is lower in the original HRS cohort because they are younger than members of our analytical sample.

Table 2 presents the mean and percentiles of P75 by vital status at 75 in the analytical sample: the overall distribution of P75 for respondents who are alive at 75 is clearly located to the right of the one of respondents who are reported dead at 75. Overall, Figure 1 and Table 2 clearly show that the subjective probabilities of survival to age 75 have strong predictive power of actual mortality by the age of 75.

3.3 Comparing Estimates of Differential Mortality from Vital Status with those from P75

The second requirement for our proposed method to work is that subjective probabilities capture mortality differentials by measures of SES – wealth, income and education in our case. As empirical validation we present estimates of differential mortality based on vital status and compare them to those based on P75. To investigate the possibility that our results might be sensitive to the choice of functional form we conduct our empirical validation in three ways: first, we present Kernel estimates of differential mortality by wealth and income; then we show the differentials in mortality by categorical variables (terciles of wealth and income, and education categories), followed by parametric estimates that account for additional covariates.

Wealth is defined as the sum of financial assets (including IRAs), housing (excluding second home), other real estate, and transportation minus all debt of the household. Pension or Social Security Wealth are not included. Our measure of income sums all sources of income for the respondent and spouse if married. These include earnings, and income from investment, pensions, annuities, Social Security, transfers and benefit income.[9] We use wealth and income from the last calendar year measured at the same time as the subjective probability of survival P75. All the analyses below are based on the analytical sample described in Section 3.1.2.

[9] We use the RAND HRS data, version H. The RAND HRS Data file is an easy to use longitudinal data set based on the HRS data. It was developed at RAND with funding from the National Institute on Aging and the Social Security Administration. For further details of the definitions of wealth and income see the RAND HRS documentation (http://www.rand.org/labor/aging/dataprod/randhrsh.pdf), variables hwatota and hwitot.

3.3.1 Kernel estimates

Figure 2 presents the estimates of the kernel regressions

$$E(A_{TA} | X) = m(X)$$
$$E(\Pi_{TA} | X) = m(X),$$

where X denotes household wealth or household income. With couples' wealth and income levels being much higher than that of singles we run the kernel regressions separately for singles and couples. Figure 2 focuses on couples because the vast majority of our sample lives in a couple household.[10] It shows a positive relationship between wealth and actual mortality: the higher the level of wealth, the larger the fraction of respondents who are alive. This finding is in line with previous work. The relationship between survival and income is similarly increasing, though a bit flatter at high levels of income. Note that the lines pertaining to actual survival are parallel to the ones pertaining to P75. This lends support to the hypothesis that both variables exhibit closely comparable patterns of differential mortality by wealth and income. Separating out men and women yields very similar patterns (not shown). Note however that the levels of the two curves are different: respondents seem to provide answers that accurately reflect the *differential* in mortality, but that under-estimate on average the likelihood of survival.[11]

3.3.2 Average answers by wealth and income terciles and education

As an alternative non-parametric way of assessing differential mortality based on vital status and on P75 we use categorical versions of our measures of SES. For wealth and income we define terciles over all respondents interviewed in the same wave, stratifying by marital status (singles vs. couples) and age category (60 to 64 and 65 to 69).[12] Using terciles has the advantage that these are insensitive to outliers and stratifying by marital status in their construction allows us to pool singles and couples in the analysis. Figure 3 presents the fraction alive at 75 alongside the average of P75 by wealth and income terciles measured at the time the subjective expectation was elicited, and by education levels. For all three measures of SES we find the anticipated gradient indicating higher survival rates for those of high SES. As before the levels of survival are found to be lower for the P75 estimates. More importantly, though, the slopes of actual survival and of P75 are strikingly similar for all three measures of SES indicating that P75 captures the differentials in survival very closely.

3.3.3 Parametric Estimates of Differential Mortality

To estimate the survival function presented in section 2 we need to make a parametric assumption about the distribution G. We present results under the assumption that G is a logistic

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[10] Recall that older spouses of HRS-age-eligible respondents make up a large fraction of our analytical sample of persons who reach their target age by 2006.

[11] These findings are consistent with those reported in Elder (2007). In work conducted in parallel to ours, Elder investigates the predictive power of the subjective probabilities for the level of actual mortality and documents biases. Biases in the level do not affect the working of our proposed method as long as the differentials across SES groups are preserved.

[12] Results are qualitatively similar with income quartiles. We however focus on terciles because, due likely to small sample size, the 2nd quartile is not statistically significantly different from the first in the parametric regressions presented in section 3.2.

distribution with mean 0 and variance $\frac{3}{\pi^2}$. Let $X = [W, Z]$ where *W* denotes wealth (or income or education level) and *Z* denote the non-wealth covariates. To simplify the notation, we omit the subscript *t* in this section. Our empirical strategy is to:

(*i*) Estimate the effect of *W* on **actual survival,** β_{WT}, using a logit model. The dependent variable is the binary event whether the respondent is alive at 75 and we estimate the equation

$$P\left(A_{TA} = 1 \middle| X\right) = \Lambda(W\beta_{WT} + Z\beta_{ZT} - C), \tag{3}$$

where $\Lambda(x) = \frac{e^x}{1+e^x}$. The scale and location normalization ensures identification of the parameters β_{WT}, β_{ZT} and C.

(*ii*) Estimate the effect of *W* on **elicited subjective survival,** β_{WS}, using an analogous regression

$$E\left(\Pi_{TA} \mid X\right) = \Lambda(W\beta_{WS} + Z\beta_{ZS} - C) \tag{4}$$

This estimation is performed over the **same sample** as the one in step (*i*). To estimate equation (4), we use the quasi-likelihood method presented in Papke and Wooldridge (1996) based on a Bernoulli log-likelihood function.[13] Papke and Wooldridge show that the quasi-maximum likelihood estimator is consistent, asymptotically normal, and efficient in a class of estimators containing weighted non-linear least squares estimators.

(*iii*) Test the hypothesis that the coefficients associated with the SES variables in the model of actual survival are equal to those in the model of subjective survival:

$$H_0: \beta_{WT} = \beta_{WS}$$

Tables 3, 4 and 5 present the estimation results for wealth, income and education, respectively. In addition to the variables of interest, we include categorical variables for age at the time when the survival expectation was asked and sex as independent variables. We do not condition on any additional observable characteristics because we are interested in the unconditional association between wealth and survival. The estimated coefficients on the wealth terciles based on actual survival and those based on subjective survival are remarkably similar. They are equal to 0.26 and 0.47 for the second and third wealth tercile when estimated using actual survival, while they are equal to 0.21 and 0.43 when estimated using the subjective survival. Those for income and education are also quite close.

To test the equality of the coefficients on SES for equations (3) and (4) we formulate the hypotheses:

[13] Our estimate is based on the following Bernoulli log-likelihood function:
$l_i(\beta) = \Pi_{TA,i} \log\left[\Lambda(X_i\beta)\right] + \left(1 - \Pi_{TA,i}\right)\log\left[1 - \Lambda(X_i\beta)\right]$

$$H_0 : \beta_{WT} - \beta_{WS} = 0$$
$$H_1 : \beta_{WT} - \beta_{WS} \neq 0,$$

where β_{WT} and β_{WS} are vectors of size K containing the coefficients on the wealth terciles (or income terciles or education categories) in the actual survival function and in the subjective survival function, respectively. Under the null hypothesis, we have $\left(\hat{\beta}_{WT} - \hat{\beta}_{WS}\right)' \left(Var\left(\hat{\beta}_{WT} - \hat{\beta}_{WS}\right)\right)^{-1} \left(\hat{\beta}_{WT} - \hat{\beta}_{WS}\right) \sim \chi^2_{(K)}$. To test the hypothesis H_0, we estimate the variance-covariance matrix of $\left(\hat{\beta}_{WT} - \hat{\beta}_{WS}\right)$ using a bootstrap technique. We create 1,000 samples of size 1,219 by re-sampling with replacement from the analytical sample and compute the variance-covariance matrix. The resulting values of the test statistics are 0.088, 2.31 and 1.70 for wealth, income and education, respectively, indicating that for each specification we cannot reject the null hypothesis H_0 at the 5% confidence level. These results suggest once more that subjective survival probabilities provide a suitable alternative for estimating differential mortality by wealth, income and education.[14]

Under the logistic assumption for *G*, the coefficients we estimate can be interpreted in terms of odds ratios. For example, the coefficient β_2 on the second wealth tercile can be interpreted as the log odds ratio for survival of the second wealth tercile to the first wealth tercile. The log odds ratio, considering that the lowest wealth tercile is the omitted variable, is given by:

$$\log\left[\frac{\dfrac{P\left(A_{TA}=1\middle|Z,W=2\right)}{P\left(A_{TA}=0\middle|Z,W=2\right)}}{\dfrac{P\left(A_{TA}=1\middle|Z,W=1\right)}{P\left(A_{TA}=0\middle|Z,W=1\right)}}\right] = \log\left(\frac{e^{Z\beta_Z+\beta_2}}{e^{Z\beta_Z}}\right) = \beta_2.$$

3.4 Robustness Checks

We have conducted extensive robustness checks with respect to a number of dimensions. For example, we verified that our validation results are robust to the estimation strategy. Using non-linear least squares rather than the quasi-maximum likelihood method yields essentially the same results (see Appendix Table A1). Similarly, our results are robust to using a different distributional assumption for *G*. For example, using a normal distribution rather than a logistic distribution in equations (3) and (4) yields very much the same results once again. We decided to present the logistic specification in this paper because the coefficients on wealth (or income or education) can be directly interpreted as log odds ratios.

Our primary interest is to obtain unconditional estimates of differential mortality, but how would our method perform if we included additional covariates? When we include both wealth terciles and education as right-hand variables, in addition to gender and age group the

[14] Note however that we do reject the hypothesis that all coefficients are equal in both sets of regressions. The difference comes from the constant term. We determined this by testing in addition the hypothesis that all coefficients associated with demographic characteristics are statistically different in both regressions which we cannot reject at the 5% confidence level.

results are similar. Performing the formal test of equality of the coefficients on wealth terciles we cannot reject the hypothesis $H_0 : \beta_{WT} - \beta_{WS} = 0$.[15]

One aspect of the subjective probabilities deserves more detailed attention which is measurement error and the prevalence of focal answers.

3.4.1 Measurement error and focal answers in subjective probabilities

Rounding to the nearest 5 and focal answers at 0, 50 and 100 are common patterns of answers to subjective probability questions. Manski and Molinari (2008) discuss these as forms of measurement error in subjective probabilities. People who answer "50%" can be thought of as respondents who either truly believe that their chance of survival is about half or who are uncertain about their chance of survival (e.g., Bruine de Bruin et al., 2000; Hill et al., 2006). One concern that we might have for our methodology is whether the tendency to provide focal answers varies systematically by wealth. For example, if many respondents in the lowest wealth tercile do not know what their chance of survival is and just answer "50%," the average subjective probability of survival may be biased for this group, but less so for the other wealth terciles. That would affect the estimates of differential mortality. Focal answers of 0 and 100 are different from the 50s in that they most likely convey actual information for most respondents, conveying that they consider their chances of survival to the target age extremely low or very high. Table 6 presents the percentage of respondents from the analytical sample in each of the wealth terciles who provided focal answers. The percentage of respondents who provide 50 and 100 as an answer is similar across wealth terciles.[16] There is a difference, however, in the prevalence of zeros, which is consistent with respondents in the lowest wealth tercile having lower actual survival than other respondents on average. One might have expected similarly noticeable differences across wealth terciles for the 100s, but this is not the case.

Even though the overall fraction of 50% answers does not vary across wealth terciles it could still be the case that the fraction of 50% answers that reflect "don't know's" varies by wealth tercile and potentially introduces bias into the estimates based on subjective survival. While this is unlikely because of the good match with the results based on actual mortality we nevertheless investigate this possibility. To this end we use variables that have been shown to correlate strongly with subjective probabilities of survival to impute P75 and replace the 50% answers with the imputations. The set of covariates for imputation includes basic demographics, a number of health related variables and parental mortality.[17,18] Once again we find that the

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[15] For coefficients associated with both wealth and education, we get a test statistics equal to 2.07.

[16] Using a simple ANOVA test, we cannot reject the hypothesis that the average fraction of 50s and 100s is equal across wealth terciles.

[17] The set of health variables we use includes information on drinking alcohol, smoking, the number of chronic conditions, self-rated health, number of ADL limitations and BMI.

[18] Different interpretations of the 50% would suggest slightly different implementations of the imputation. If one believes that respondents who answer 50% merely express epistemic uncertainty, one would want to exclude them from the regression to produce the imputations. However, if one believes that the 50s are informative, one would keep them. The truth is probably a mix of the two but we have no way in our data to separate respondents who truly believe they have about a fifty percent chance of survival to their target age from respondents who are simply uncertain. We follow both strategies and find that the results are not affected by this issue. In HRS 2006, respondents who answer 50% to the subjective probability of survival are given a follow-up question asking whether they just do not know their survival probabilities or whether their belief is really that the chances are about 50 percent. It turns out that the fraction of 50s being simply uncertain is high – a little over 60 percent. Unfortunately we do not have this information for the earlier waves of HRS which provide the baseline observations in our analysis.

coefficients on the wealth terciles are very similar in both the logit regression on actual survival at 75 and the quasi-maximum likelihood estimator on P75 where any original 50% answers were replaced with the imputation (tables not shown).

Detailed results from all the robustness checks we performed are available upon request.

4. Applications

Having established the suitability of the subjective probabilities of survival for estimating differential mortality, we present two applications: first, we estimate trends of differential mortality over time in the U.S. using data from the HRS. Second, we use data from HRS, ELSA and SHARE – which were designed to provide comparable variables across countries – to produce estimates of differential mortality that are directly comparable for 10 European countries.

4.1 Estimates of the trend in differential mortality in the U.S.

We take advantage of the long time span covered by the HRS to estimate differential mortality from *P75* elicited in 1992 and from *P75* elicited in 2006. Comparing the results provides insight into trends in differential mortality over this time period for cohorts that on average have not yet reached the end of their life span. As such our estimates are forward looking. We focus on respondents aged 51 to 60 so that we do not include the same respondents both in the 1992 and in the 2006 sample.

We follow the approach described in Section 3.3.3, and estimate equation (4) on the 1992 and 2006 HRS data:

$$E\left(\Pi_{TA} \mid X\right) = \Lambda(W\beta_{WS} + Z\beta_{ZS} - C).$$

That is, we use the quasi-likelihood method presented in Papke and Wooldridge (1996) based on a Bernoulli log-likelihood function and logit distribution with *P75* as the dependent variable. Our explanatory variables are indicator variables for age band (51-55, 56-60), female, and wealth terciles (or income terciles or education categories). In constructing wealth and income terciles we stratify by age category (51-55, 56-60), couple and wave. All the regressions apply respondents' weights.

Table 7 presents the estimates of differential mortality by wealth tercile for 1992 and 2006. It shows an increase in differential mortality in this 14 year-period. Exponentiating the coefficients to obtain the odds ratios with respect to the lowest tercile we find that the odds ratio for the highest wealth terciles has increased from 1.61 to 1.88 between 1992 and 2006 which corresponds to a 14.6% increase.[19]

Item non-response might be a concern if it is not randomly distributed by wealth tercile or health status. Item non-response is relatively low in the HRS for this age group (2.2% in 1992 and 4.0% in 2006) but it is not randomly distributed across wealth terciles or by self-reported health: item non-response is significantly higher in the lower wealth terciles and among

[19] We can reject the hypothesis that the 1992 and 2006 odd ratios for the third wealth tercile are the same at the 5% confidence level, but we cannot reject this hypothesis for the second wealth tercile.

respondents who report being in poor health.[20] We address this issue by imputing the subjective probabilities for respondents who did not give an answer to *P75*. We use the same explanatory variables as for the imputations in previous robustness checks, i.e., basic demographics, health information and parental mortality. Replacing the missing observations with imputed values basically does not change our estimates for differential mortality.

Similarly, the tendency of people to answer 50% when asked their subjective beliefs might bias our results if it varies systematically by wealth. In this sample, the fraction of 50% answers increases slightly with wealth terciles. The difference in the fraction of 50s is statistically significant at the 5% level for 2006 but not for 1992.[21] Again, we can address this issue by replacing subjective survival probabilities that are equal to 50% with imputed values as a function of demographics, health and parental mortality. Doing so results in slightly higher estimates of differential mortality and the magnitude of the increase in inequality.[22] With this specification, the odds ratio for the highest wealth tercile compared to the lowest wealth tercile increases from 1.73 to 2.08 between 1992 and 2006, which represents a 16.4% increase.[23]

We also produced the estimates of trends in differential mortality by income tercile and education categories, both with and without imputations of *P75* for missing values and/or 50% answers. As with wealth terciles, performing the imputations for the 50% answers leads to slightly higher estimates of the mortality differentials. Table 8 presents the results with the imputations for missing and 50%. Figure 4 gives a graphical representation of our estimates of the trends in differential mortality for all three indicators of SES alongside each other, based on comparable estimates (all with imputations for missing P75 and 50% answers). The height of the bars reflects the odds ratio of a particular group's chances of survival compared to the reference group with lowest SES. The overall levels and the increase in inequality in mortality by income are very similar to those observed by wealth. The premium of a college degree in terms of increased chances of survival has increased substantially between the two time periods: the odds ratio rose from 2.04 to 2.89; that is an increase of almost 30%.

Earlier studies have emphasized that differential mortality by SES has increased in the U.S. since the 1960s (e.g., Duleep 1989; Feldman et al. 1989; Pappas et al. 1993, Hadden and Rockswold 2008). For example, Hadden and Rockswold analyze mortality data from 1960, 1986 and 2000 and conclude that there was a large increase in inequality in mortality by education for non-Hispanic white men and women. The increase was somewhat smaller for non-Hispanic Blacks. Our results suggest that the increase in differential mortality is likely to continue in the future.

[20] For example, in 1992, item non-response is 3.12% in the lower wealth tercile, compared to 1.83% and 1.23% in the second and highest wealth tercile respectively. It is equal to 1.26% among respondents who report being in excellent health, compared to 5.89% among those who report being in poor health.

[21] In 2006, the proportion of 50% is 25.07% in the lower wealth tercile, compared to 23.83% and 20.62% in the second and highest wealth tercile respectively. For both 1992 and 2006, there is no statistical difference in the fraction of 100% answers by wealth tercile. The rate of zeros is higher in the lower wealth tercile, which is consistent with the fact that they experience lower mortality.

[22] The imputations are based on regressions including the subjective survival probabilities equal to 50%. Excluding them does not change our results much.

[23] As before, we can reject the hypothesis that the 1992 and 2006 odds ratios for the third wealth tercile are the same at the 5% confidence level, but we cannot reject this hypothesis for the second wealth tercile.

4.2 *Estimates of Differential Mortality for the U.S. and Europe using Subjective Survival Probabilities*

In our second application we use our method to produce comparable estimates of differential mortality across countries. The data come from survey instruments that were designed to be comparable across the participating European countries and the HRS for the U.S.

4.2.1 Data: SHARE wave 1, ELSA wave 2 and HRS 2004

In 2004, SHARE administered the same survey instrument in 11 European countries, except for small adjustments to accommodate institutional differences. The selection of countries reflects the different regions of Europe with Sweden, Denmark covering Scandinavia; the Netherlands, Belgium, Germany, France, Austria, and Switzerland representing Central Europe; and Italy, Spain and Greece covering the south of Europe.[24] The sample in each participating country is representative of the population age 50 and older when weights are applied.

ELSA is the English counterpart of HRS and SHARE. In 2002, it collected its first wave of data. The sample was drawn from households that had previously participated in the Health Survey for England in 1998, 1999 or 2001. We use the second wave of ELSA which was administered in 2004.[25]

Just as in the HRS, the target population of SHARE and ELSA covers the population age 50 plus and their spouses.[26] Sample sizes vary by country from about 1,000 respondents in Switzerland to about 3,000 in Germany, Sweden and the Netherlands in SHARE, more than 9,000 in ELSA and about 20,000 in HRS 2004 (see Table A2 in the Appendix for the number of respondents in each country). All variables of interest to our study (subjective probabilities of survival, wealth, income and education) are observed in all countries. Also the subjective probabilities of survival were asked in all countries in the same way as in the HRS with the target age being a function of the respondent's own age. We therefore use in our analysis respondents aged 51 to 65 who were asked about their survival to age 75.[27]

At a descriptive level the subjective probabilities of survival in SHARE show similar patterns and characteristics as those collected in the HRS. Hurd, Rohwedder and Winter (2005) document how they compare to life tables, rates of item non-response, and the frequency of focal answers. In particular, they show strong variation in the subjective probabilities as a function of health conditions, objective measures of health, as well as by income quartiles, wealth quartiles and education.

Table 9 presents the average of P75 by wealth tercile for individuals aged 51 to 65 in SHARE/ELSA/HRS.[28] Wealth terciles are defined separately within country, by marital status (single/couple), and by age band (51-58; 59-65).[29] Our measure of wealth is total household net worth in euros with adjustment for purchasing power parity. Entitlements to public or private pensions are not included. As one would expect, we find that average subjective probabilities of survival are higher for higher wealth terciles for most countries. The gradient is particularly marked for the U.S., England, Austria, Spain and Sweden. There are some differences in the

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[24] See http://www.share-project.org/ for more details on the sampling and features of SHARE.

[25] See http://www.ifs.org.uk/elsa/documentation.php for more details on the sampling and features of ELSA.

[26] The target population in HRS is those age 51 and older.

[27] 0ne small deviation occurred in the administration of the target ages with cut-off points for the target age 75 being 51-65 in SHARE compared to 50-65 in HRS.

[28] The averages are weighted. For HRS, SHARE and ELSA, we use individual weights (Börsch-Supan and Jürges, 2005).

[29] We get very similar results if we define the wealth terciles for the age group 51-65.

levels of subjective probabilities across countries, similar to the ones we can find in life tables. For example, according to 2002 life tables, a 55-year old Austrian man had a 67.3% chance of surviving to age 75, while a 55-year old Swedish man had a 72.5% chance.

4.2.2 Estimation of Differential Mortality by Wealth using Subjective Survival Probabilities

We follow the same approach that we applied to the HRS data, described in Section 4.1, and use *P75* to estimate equation (4) on the SHARE/ELSA/HRS data:

$$E\left(\Pi_{TA} \mid X\right) = \Lambda(W\beta_{WS} + Z\beta_{ZS} - C)$$

The explanatory variables are indicator variables for age band, female, and wealth terciles. We define four age bands (51-54, 55-58, 59-61, 62-65).[30] All the regressions we present use respondents' weights.

Table 10 presents the estimates and their significance levels for each one of the country regressions as well as for the pooled regression for the European countries and the U.S..[31] We find for every country that those with high wealth have higher survival probabilities than those with low wealth, and that at least one of the two wealth coefficients is significant. However, the gradient in the probability of survival is less pronounced in some countries than in others. According to our estimates countries with a smaller gradient are Germany, France and Belgium. For example, in Belgium the odds ratio for individuals in the second and third wealth tercile is about 1.07. We find the gradient to be strongest in Sweden, Spain and England, where the odds ratios for the highest wealth tercile appear to be between 1.25 and 1.30. In the Netherlands, there is a large difference between the first and second tercile, but very little difference between the second and the third. When estimating the gradient for the European countries as a whole for comparison with the U.S. we find a larger gradient in the U.S. than in the European countries.

4.2.3 Robustness checks

Item non-response might be a concern if it is not randomly distributed by wealth tercile and health status. Table 11 reports the rate of item non-response by wealth terciles (as defined in the regression) and by self-rated health for each of the countries. Item non-response varies a lot by country: it is quite low in Austria, Germany and England (less than 2.5%); it is the highest in France with 15%, followed by Italy and Spain (about 10%). Moreover, item non-response tends to vary by wealth. For example, in the Netherlands, Spain, Denmark, Italy or the U.S. item non-response is lower for higher wealth terciles.[32] It also varies by self-reported health, with item non-response being higher among people who report to be in fair or poor health.

To address the issues of item non-response, we follow the strategy discussed in Section 3.4.1 and impute subjective probabilities for respondents who did not answer the subjective probabilities of survival question. We use the same variables as the ones for the imputations in HRS (i.e., basic demographics, health information[33] and parental mortality). We do so using a separate regression for each country (tables not shown). The alternative estimates of differential

[30] The sample is relatively small in some countries so we use narrow age bands rather than age dummies.

[31] The pooled regression includes indicator variables for the different countries as to allow for differences resulting from sampling or different survey agencies and alike. The weights in the pooled regressions reflect the countries' population (i.e., the sum of the weight in a country is equal to the population aged 51-65 in that country).

[32] Those differences are statistically significant at 5% for Germany, Spain, the U.S. and England.

[33] The only difference is regarding drinking behavior. In SHARE, we use an indicator for more than 2 drinks a day, rather than more than 3 drinks a day in HRS. The question about drinking in the first two waves of HRS does not distinguish between 1 drink a day and 2 drinks a day, so we use more than 3 drinks a day.

mortality and their significance levels after having imputed a predicted probability of survival for missing answers are very similar to those presented in Table 10, even in countries with high item non-response. It reduces slightly the impact of wealth on survival in Spain.

Another potential issue could be focal answers. The tendency to answer 50% to subjective probability questions might bias our results if it varies systematically by wealth.[34] Table 12 presents the percentage of respondents who answer "50%" by wealth terciles for each country. The rates are quite similar for each wealth tercile in Germany, Italy and Belgium. However, it tends to decrease with wealth in the Netherlands, Spain, England and the U.S..[35] Again, we use basic demographics, health information and parental mortality to impute subjective probabilities for respondents who answered 50%. Table 13 presents the new estimates of differential mortality and their significance levels after having imputed a predicted probability of survival for missing answers and 50% answers, and Figure 5 shows the exponential of the coefficients associated with the middle and highest wealth tercile.[36] The estimates with the imputations for missing and 50% present overall a relatively similar picture of differential mortality, though the differentials in mortality by wealth appear larger in many countries, in particular in Austria, Germany, Sweden, France, Denmark, England, Belgium and the U.S.. In Spain the estimated differential is smaller. We find the gradient to be strongest in Sweden, Austria and England, and the weakest in Belgium, France and Italy. When estimating the gradient for the European countries as a whole for comparison with the U.S. we find a larger gradient in the U.S. than in the European countries.

4.2.4 Heterogeneity in wealth distribution and heterogeneity in differential mortality

Heterogeneity in mortality by wealth terciles across European countries could simply reflect heterogeneity in the wealth distribution. Figure 5 shows that the odds ratio for the second wealth tercile is similar for Germany and Sweden, but that of the highest wealth terciles is much larger in Sweden. Is the difference in wealth between the second and third wealth terciles larger in Sweden than in Germany? Table 14 presents the median wealth levels for each wealth tercile and country. The medians do not suggest that heterogeneity in the wealth distributions can explain the heterogeneity in differential mortality. To keep the same example, Germany and Sweden have similar medians for the second wealth tercile, but Germany has a higher median for the third wealth tercile. The same conclusions hold when considering additional points of the wealth distributions within wealth terciles. For example, comparing the 25th, 50th and 75th percentiles within each wealth tercile for Spain and England we find that England in the second and third wealth terciles has a more compressed wealth distribution than Spain while it has a much steeper gradient in differential mortality. We also compared the support of the distributions of wealth with the gradient in survival across countries. For this purpose we performed kernel regressions $E(\Pi_{TA}|W) = m(W)$ for each of the countries.[37] We find, for example, that Spain has a smaller support than France, though a steeper relationship between subjective survival

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[34] Like in the HRS, there is no statistical difference in the proportion of 100% by wealth tercile. The rate of zeros is higher in the lower wealth tercile, which is consistent with the fact that they experience lower mortality.

[35] The difference is statistically significant at the 5%-level for the U.S., England, the Netherlands and Spain.

[36] The predicted probabilities that we impute are based on regressions including respondents who answered 50%. Excluding them does not change our results much.

[37] The estimation is done for respondents between the 10th and 90th percentiles of the wealth distributions of their country.

probabilities and wealth. Taken together these results suggest that the heterogeneity in differential mortality across European countries is more likely driven by heterogeneity in institutional settings, policy, cultural and social factors.

4.2.5 Caveats

Unit non-response varies across countries in SHARE (Börsch-Supan and Jürges, 2005). Weighting reduces this effect somewhat, but to the extent that unit non-response varies within age and gender groups in a non-random manner and in particular in a way that is correlated with wealth, it could affect the estimates of differential mortality, both *actual* (if sufficient follow-up data was available) and *subjective*. Due to a particularly low unit response rate in Switzerland (36%), we decided to exclude it from our analysis. We also excluded Greece because of anomalies in the data.

4.2.6 Estimation of the Differential Mortality by Income and Education using Subjective Survival Probabilities

We conduct similar estimations to the ones presented above using income terciles and education levels as explanatory variables of interest. Income terciles are defined separately within country, by marital status (single/couple), and by age band (50-58; 59-65). To allow an easy comparison of countries with different educational systems, we use the three following categories for education: less than secondary schooling, secondary and tertiary. We present results with imputation for missing probabilities and 50% to deal with the issues of focal and missing answers raised in 4.2.3.

Figure 6 shows the exponential of the coefficients attached to the middle and highest income tercile, which can be interpreted as the odds ratio of survival compared to the first income tercile. Except for the U.S., differential mortality by income shows a different picture than the one by wealth. In Europe, there is less inequality in mortality by income than there is by wealth. Note for example that for Germany, Spain and Italy, the odds ratio of the second income tercile compared to the first is equal to one, or even a little less than one, emphasizing that there is no difference in mortality between these two groups. The strongest gradients are for France, Denmark and England. Austria, the Netherlands and Spain have the weakest gradients.

Figure 7 shows the exponential of the coefficients attached to secondary and tertiary education, which can be interpreted as the odds ratio of survival compared to less than secondary schooling. Differential mortality by education also differs from that by wealth, though they share similar magnitudes. By education, Austria and Italy show the strongest gradients, while the Netherlands, France, Spain and Belgium show the weakest gradients. When we look at differential mortality by education, the difference between Europe and the U.S. is very large. Whether we control for wealth or not does not change the overall picture of the differential mortality by education, it just tends to reduce the level of the odd ratios (figure not shown).

4.2.7 Comparison with existing studies

It is quite difficult to draw direct comparisons of our results to existing studies because these either cover a different period, or age group or they use different measures of SES. Nevertheless, we reference here a few results found in existing work to compare with our own findings. The strong gradient for Sweden and England is also found in the study of Mackenbach et al. (1997) which looks at morbidity and mortality for several European countries. Their mortality results are hard to compare with ours because they study mortality by occupational class in men in manual versus non-manual occupation for a much larger age group. Contrary to our findings, they find that France has the highest mortality gradient by occupation (however, France is found to have a low gradient for morbidity). Mackenbach et al. (1997) also look at morbidity (measured by perceived general health) by education and find, like us, high differentials in Sweden and Italy. They however find a large gradient for the Netherlands. Huisman et al. (2004) look at mortality by two education levels and find the following ranking from the weakest differential to the strongest: France, Belgium, Denmark and England/Wales. Hofmann (2005) finds less differential mortality in Denmark compared to the U.S..

5. Conclusions

Obtaining reliable estimates of differential mortality from panel data is a very data intensive exercise and in some countries the necessary data do not exist. Estimates that are comparable across countries are even harder to come by, because measures of wealth or income usually come from different survey instruments and surveys with different designs. In this paper we investigated an alternative approach that is much less data intensive in that it relies on cross-sectional observations of subjective probabilities of survival. In addition the data for our cross-country estimates come from the same survey for many countries (SHARE) and comparable survey instruments for the remaining countries (U.S. and England).

To establish the reliability of our approach we first estimated differential mortality on panel data from the HRS and compared the resulting traditional estimates with those obtained from subjective probabilities collected at baseline. For wealth we find this approach to work very well. We then provide two applications. First we study the trend in differential mortality in the U.S. between 1992 and 2006 for two different cohorts of 51-60 year olds. Our results suggest that the increase in differential mortality observed for several decades before the 1990s is likely to continue in the future. Given that one of the goals set out in the program Healthy People 2010 (U.S. Department of Health and Human Services, 2000) is to reduce health disparities this finding of increasing trends of differential mortality is troubling.

In the second application we estimate differential mortality based on *P75* collected in 2004 in 10 European countries and in the U.S. Overall the gradient by wealth tercile is quite comparable between the European countries as a whole and the U.S. even though the gradient is somewhat smaller in Europe. Within Europe, Sweden, Italy and Spain show strong differentials in mortality as a function of wealth, while Austria, Germany, the Netherlands and France show smaller differentials.

Our approach seems to perform well enough to constitute a powerful alternative in the absence of comparable longitudinal data across countries to provide international comparisons of differential mortality. It opens the door for investigating the role of institutional settings, policy and social factors in explaining health inequalities. It also demonstrates the potentials of subjective probabilities of survival to study the effects of mortality on behavior or construct alternative life tables without waiting for a significant fraction of a cohort to have died.

Appendix

Table A1: Estimates of differential mortality by wealth tercile using non-linear least squares

	Logit on actual survival to 75		Non-linear least squares on subjective survival to 75	
	Coefficients	P-value	Coefficients	P-value
Wealth terciles				
Lowest	(ref)		(ref)	
2nd	**0.256**	0.094	**0.207**	0.014
Highest	**0.466**	0.003	**0.421**	0.000
Age at baseline				
61	(ref)		(ref)	
62	0.336	0.201	0.392	0.011
63	1.041	0.000	0.296	0.042
64	1.374	0.000	0.356	0.038
65	1.123	0.000	0.596	0.001
66	0.894	0.010	0.211	0.005
Female	-0.004	0.978	0.009	0.907
Constant	-0.211	0.396	0.033	0.817
N	*1,219*		*1,219*	

Table A2: Number of observations in each country

Country	N
United States	20,129
England	9,432
Austria	1,893
Germany	3,008
Sweden	3,053
Netherlands	2,979
Spain	2,396
Italy	2,559
France	3,193
Denmark	1,707
Greece	2,898
Switzerland	1,004
Belgium	3,827
Total	58,078

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Table 1: Vital Status of HRS respondents in 2004 and 2006

	Vital status in 2004		Vital status in 2006	
	N	%	N	%
Alive	23,163	75.0	19,740	63.9
Dead	6,513	21.1	7,898	25.6
Unknown	1,214	3.9	3,252	10.5
Total	30,890	100.0	30,890	100.0

Table 2: Summary statistics of subjective survival to 75 by vital status at 75

	Subjective survival at 75				
	mean	25th percentile	median	75th percentile	N
Alive at 75	67.52	50	70	90	850
Dead at 75	57.26	40	50	80	369
All	64.42	50	70	90	1,219

Table 3: Estimates of differential mortality by wealth tercile

	Logit on actual survival to 75		Quasi maximum-likelihood on subjective survival to 75	
	Coefficients	P-value	Coefficients	P-value
Wealth terciles				
Lowest	(ref)		(ref)	
2nd	**0.256**	0.094	**0.211**	0.019
Highest	**0.466**	0.003	**0.431**	0.000
Age at baseline				
61	(ref)		(ref)	
62	0.336	0.201	0.390	0.025
63	1.041	0.000	0.294	0.078
64	1.374	0.000	0.362	0.058
65	1.123	0.000	0.597	0.002
66	0.894	0.010	0.577	0.009
Female	-0.004	0.978	0.020	0.811
Constant	-0.211	0.396	0.026	0.874
N	*1,219*		*1,219*	

Table 4: Estimates of differential mortality by income tercile

	Logit on actual survival to 75		Quasi maximum-likelihood on subjective survival to 75	
	Coefficients	P-value	Coefficients	P-value
Income terciles				
Lowest	(ref)		(ref)	
2nd	**0.381**	0.013	**0.305**	0.001
Highest	**0.823**	0.000	**0.576**	0.000
Age at baseline				
61	(ref)		(ref)	
62	0.312	0.239	0.378	0.030
63	1.043	0.000	0.290	0.083
64	1.397	0.000	0.374	0.052
65	1.091	0.001	0.576	0.003
66	0.893	0.011	0.580	0.009
Female	0.048	0.741	0.056	0.502
Constant	-0.372	0.142	-0.061	0.719
N	*1,219*		*1,219*	

Table 5: Estimates of differential mortality by education

	Logit on actual survival to 75		Quasi maximum-likelihood on subjective survival to 75	
	Coefficients	P-value	Coefficients	P-value
Less than High School	(ref)		(ref)	
High School & GED	**0.162**	0.292	**0.146**	0.115
Some college	**0.421**	0.027	**0.380**	0.000
College graduate	**0.818**	0.000	**0.540**	0.000
Age at baseline				
61	(ref)		(ref)	
62	0.397	0.133	0.436	0.012
63	1.074	0.000	0.310	0.061
64	1.428	0.000	0.398	0.038
65	1.162	0.000	0.626	0.001
66	0.945	0.007	0.618	0.005
Female	0.026	0.857	0.040	0.636
Constant	-0.282	0.265	-0.003	0.984
N	*1,219*		*1,219*	

Table 6: Prevalence of focal answers by wealth terciles, in percent

	0	50	100	N
Lowest wealth tercile	9.8	22.5	22.7	409
2nd wealth tercile	2.4	27.1	20.5	414
Highest wealth tercile	2.8	26.5	23.0	396

Table 7: Estimates of trends in differential mortality in the U.S. based by wealth tercile based on P75

		1992		2006	
		Coefficients	P-value	Coefficients	P-value
Lowest wealth tercile		(ref)		(ref)	
2nd wealth tercile		**0.243**	0.000	**0.311**	0.000
Highest wealth tercile		**0.478**	0.000	**0.636**	0.000
Age	51-55	(ref)		(ref)	
	56-60	-0.027	0.372	-0.011	0.812
Female		0.163	0.000	0.267	0.000
Constant		0.290	0.000	0.070	0.184
N		*8,281*		*3,769*	

Table 8: Estimates of trends in differential mortality in the U.S. by income tercile and education based on P75, imputations for missing and 50% answers

		1992		2006	
		Coefficients	P-value	Coefficients	P-value
Income					
Lowest income tercile		(ref)		(ref)	
2nd income tercile		**0.305**	0.000	**0.381**	0.000
Highest income tercile		**0.562**	0.000	**0.761**	0.000
Age	51-55	(ref)		(ref)	
	56-60	-0.028	0.355	-0.028	0.523
Female		0.248	0.000	0.370	0.000
Constant		0.320	0.000	0.060	0.262
	N	*8,463*		*3,915*	
Education					
Less than High School		(ref)		(ref)	
High School		**0.349**	0.000	**0.439**	0.000
Some college		**0.566**	0.000	**0.696**	0.000
College graduate		**0.713**	0.000	**1.063**	0.000
Age	51-55	(ref)		(ref)	
	56-60	-0.009	0.774	-0.009	0.839
Female		0.246	0.000	0.392	0.000
Constant		0.220	0.000	-0.235	0.002
	N	*8,463*		*3,915*	

Table 9: Average P75 by wealth tercile for respondents age 51 to 61, weighted.

Wealth terciles	Austria	Germany	Sweden	Netherlands	Spain	Italy	France	Denmark	Belgium	England	Europe all	U.S.
Lowest	62.3	62.9	66.1	66.6	68.3	68.0	65.9	68.5	62.5	59.4	60.5	56.6
Second	63.5	68.2	72.6	72.9	72.0	72.8	68.6	74.5	64.9	65.2	65.2	64.6
Highest	69.9	67.5	74.9	73.6	76.8	72.5	70.2	73.9	64.7	68.3	68.7	70.5

Source: Authors' calculations

Table 10: Estimates of differential mortality by wealth terciles, all countries, weighted.

	Austria		Germany		Sweden		The Netherlands		Spain		Italy	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Lowest wealth tercile	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
2nd wealth tercile	0.036	0.506	0.144	0.002	0.191	0.000	0.185	0.000	0.111	0.086	0.142	0.022
Highest wealth tercile	0.214	0.000	0.129	0.006	0.264	0.000	0.203	0.000	0.254	0.000	0.132	0.044
Age band												
51-54	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
55-58	0.065	0.317	-0.059	0.235	-0.102	0.053	0.022	0.630	0.020	0.785	-0.075	0.305
59-61	0.041	0.545	-0.090	0.091	-0.063	0.298	0.069	0.238	-0.026	0.730	-0.069	0.389
62-65	0.093	0.127	-0.040	0.418	-0.120	0.029	0.063	0.209	-0.011	0.886	-0.108	0.144
Female	0.039	0.385	0.043	0.247	0.133	0.001	0.075	0.038	0.073	0.175	-0.090	0.084
constant	0.238	0.000	0.346	0.000	0.417	0.000	0.359	0.000	0.442	0.000	0.578	0.000
N	*974*		*1,606*		*1,569*		*1,597*		*955*		*1,249*	

	France		Denmark		Belgium		England		Europe-all*		U.S.	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Lowest wealth tercile	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
2nd wealth tercile	0.073	0.159	0.174	0.011	0.065	0.091	0.150	0.000	0.124	0.000	0.204	0.000
Highest wealth tercile	0.122	0.018	0.161	0.026	0.060	0.123	0.238	0.000	0.221	0.000	0.370	0.000
Age band												
51-54	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
55-58	0.057	0.266	-0.078	0.273	0.064	0.102	-0.017	0.530	-0.017	0.536	0.023	0.389
59-61	0.003	0.968	0.100	0.229	0.050	0.269	-0.012	0.682	-0.021	0.469	0.013	0.678
62-65	0.046	0.438	0.012	0.887	0.050	0.277	0.041	0.178	0.044	0.127	0.070	0.005
Female	-0.040	0.339	0.193	0.001	0.057	0.072	0.085	0.000	0.085	0.000	0.127	0.000
constant	0.402	0.000	0.387	0.000	0.250	0.000	0.195	0.000	0.373	0.000	0.078	0.004
N	*1,332*		*830*		*1,815*		*4,184*		*16,111*		*7,552*	

Source: Authors' calculations.
* Includes categorical variables country.

Table 11: Rates of item non-response to *P75* across countries by wealth terciles, in percent

	Austria	Germany	Sweden	Nether-lands	Spain	Italy	France	Denmark	Belgium	England	Europe all	U.S.
Wealth terciles												
Lowest	0.9	3.4	4.2	5.9	11.9	7.1	13.3	5.1	3.7	3.0	5.3	6.3
Second	0.9	0.9	2.8	5.7	7.9	10.0	10.9	6.2	3.3	1.9	4.4	2.9
Highest	1.8	2.4	3.3	3.7	7.7	11.8	13.0	3.5	3.2	1.5	4.5	1.7
All	1.3	2.4	3.7	6.3	10.0	10.1	15.1	5.7	3.6	2.3	5.3	3.5
Self-rated health												
Excellent/very good	1.3	1.7	2.0	5.2	8.1	6.5	11.2	4.5	1.9	0.9	3.1	1.3
Good	1.1	1.7	4.9	5.3	10.5	11.4	15.1	5.3	4.8	0.9	5.7	4.5
Fair/poor	1.8	4.2	7.7	10.2	10.9	11.0	19.9	8.6	4.5	2.1	7.1	6.2
All	1.3	2.4	3.7	6.3	10.0	10.1	15.1	5.7	3.6	2.3	5.3	3.5

Table 12: Prevalence rates of 50% answers to *P75* across countries by wealth terciles, in percent

Wealth terciles	Austria	Germany	Sweden	Nether-lands	Spain	Italy	France	Denmark	Belgium	England	Europe all	U.S.
Lowest	28.9	25.9	25.1	24.2	25.5	23.4	24.9	19.7	25.4	27.1	26.4	26.0
Second	32.2	25.6	19.2	17.3	18.0	22.0	25.8	24.1	28.0	24.8	24.8	24.7
Highest	26.0	26.6	21.1	15.8	16.2	24.0	28.1	22.5	26.4	20.3	20.6	20.1

Table 13: Estimates of differential mortality by wealth across countries with imputations of missing and 50%

	Austria		Germany		Sweden		The Netherlands		Spain		Italy	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Lowest wealth tercile	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
2nd wealth tercile	0.062	0.258	0.200	0.000	0.196	0.000	0.172	0.000	0.050	0.387	0.138	0.015
Highest wealth tercile	0.240	0.000	0.182	0.000	0.295	0.000	0.191	0.000	0.202	0.001	0.145	0.015
Age band												
51-54	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
55-58	0.068	0.292	-0.077	0.114	-0.114	0.025	-0.004	0.919	0.050	0.434	-0.103	0.125
59-61	0.063	0.350	-0.120	0.022	-0.072	0.216	0.045	0.406	-0.044	0.513	-0.120	0.099
62-65	0.101	0.092	-0.074	0.126	-0.109	0.039	0.047	0.318	-0.023	0.736	-0.126	0.059
Female	0.060	0.175	0.075	0.040	0.139	0.000	0.091	0.007	0.091	0.056	-0.126	0.008
constant	0.308	0.000	0.418	0.000	0.518	0.000	0.475	0.000	0.581	0.000	0.743	0.000
N	*986*		*1,643*		*1,625*		*1,682*		*1,051*		*1,381*	

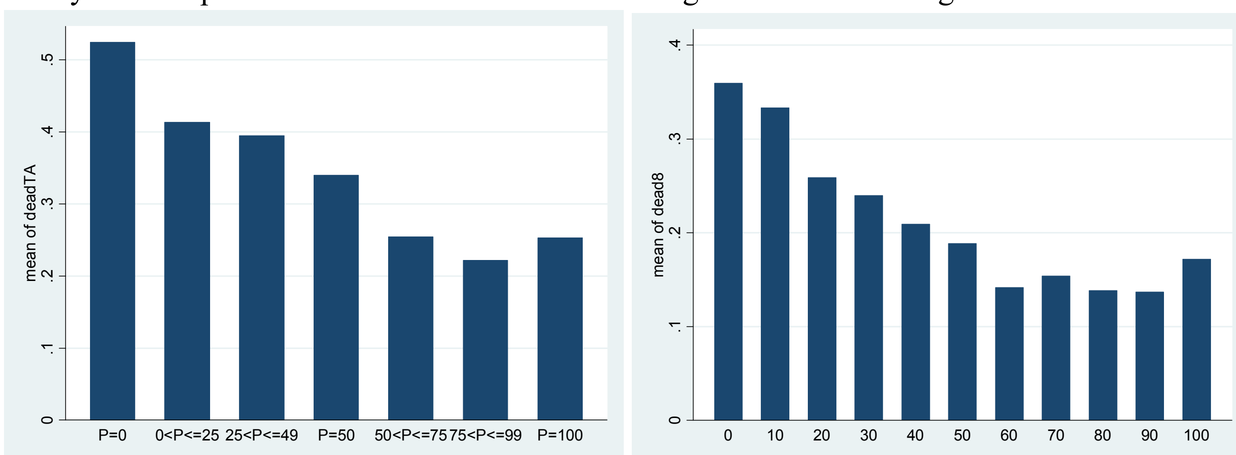
	France		Denmark		Belgium		England		Europe-all*		U.S.	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Lowest wealth tercile	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
2nd wealth tercile	0.117	0.011	0.218	0.001	0.093	0.012	0.169	0.000	0.146	0.000	0.239	0.000
Highest wealth tercile	0.166	0.000	0.201	0.004	0.088	0.020	0.262	0.000	0.247	0.000	0.414	0.000
Age band												
51-54	(ref)		(ref)		(ref)		(ref)		(ref)		(ref)	
55-58	0.046	0.304	-0.093	0.172	0.073	0.055	-0.024	0.376	-0.020	0.455	0.040	0.138
59-61	-0.014	0.808	0.086	0.270	0.052	0.239	-0.013	0.661	-0.014	0.633	0.017	0.574
62-65	0.033	0.525	0.037	0.641	0.046	0.289	0.036	0.217	0.046	0.103	0.103	0.000
Female	-0.045	0.217	0.224	0.000	0.071	0.019	0.121	0.000	0.117	0.000	0.139	0.000
constant	0.491	0.000	0.458	0.000	0.307	0.000	0.243	0.000	0.379	0.000	0.109	0.000
N	*1,521*		*873*		*1,879*		*4,255*		*16,896*		*7,833*	

Table 14: Median wealth by wealth terciles and countries in thousand euros, purchasing power parity adjusted (weighted data)

Wealth terciles	Austria	Germany	Sweden	Nether-lands	Spain	Italy	France	Denmark	Belgium	England	Europe all	U.S.
Lowest	5.9	5.5	10.6	10.7	48.5	23.1	18.8	34.1	84.2	49.0	53.4	21.0
Second	138.4	133.4	119.7	184.0	186.7	187.4	214.0	171.0	235.2	186.2	184.9	170.0
Highest	369.6	429.7	377.0	472.3	576.2	468.6	643.4	441.3	693.3	400.0	405.9	633.4

Figure 1. Fraction dead at age 75 by subjective survival to age 75 reported at baseline

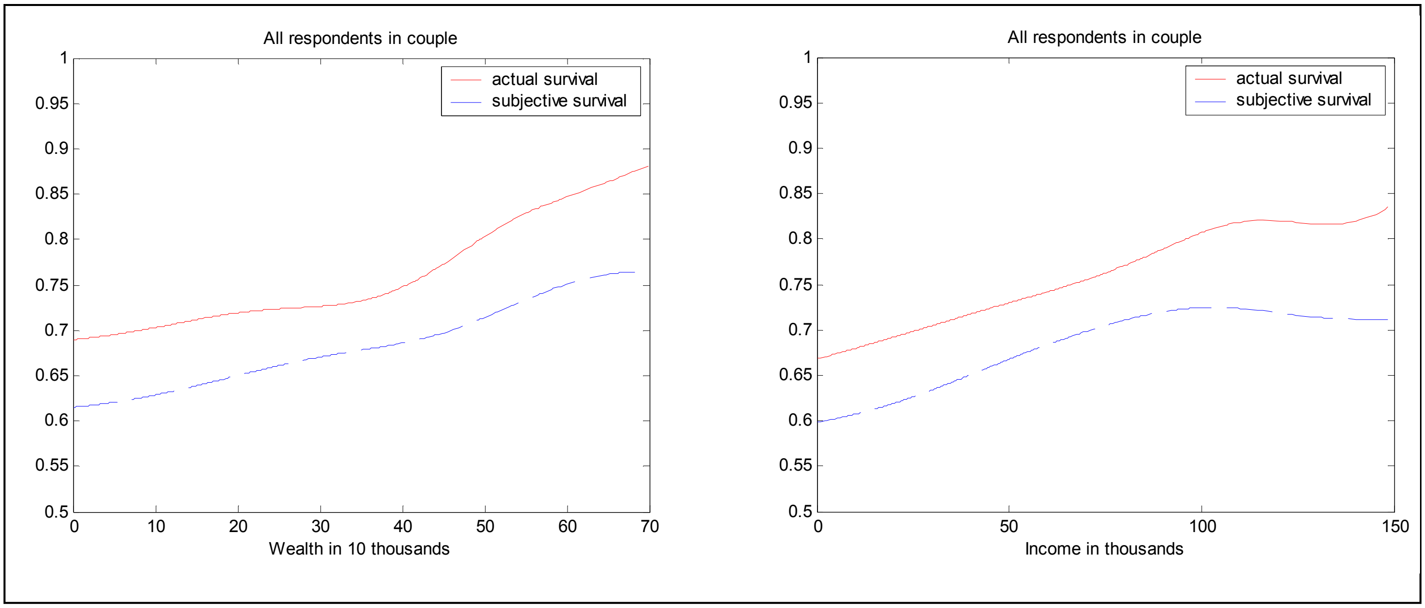
Analytical sample | Original HRS cohort: age 51-61 in 1992



Source: Authors calculations. N=1,219.
Overall fraction alive in 2006: 70.0%

Source: Authors calculations. N=8,014.
Overall fraction alive in 2006: 81.2%

Figure 2: Kernel regressions for wealth and income



Source: Authors' calculations.
Regressions are based on Gaussian kernel with bandwidth equal to 10. Due to small sample size in the extreme, the kernel estimations are based on a truncated distribution of wealth with truncation at the bottom and top 2%.

Figure 3: Average survival at age 75 by SES

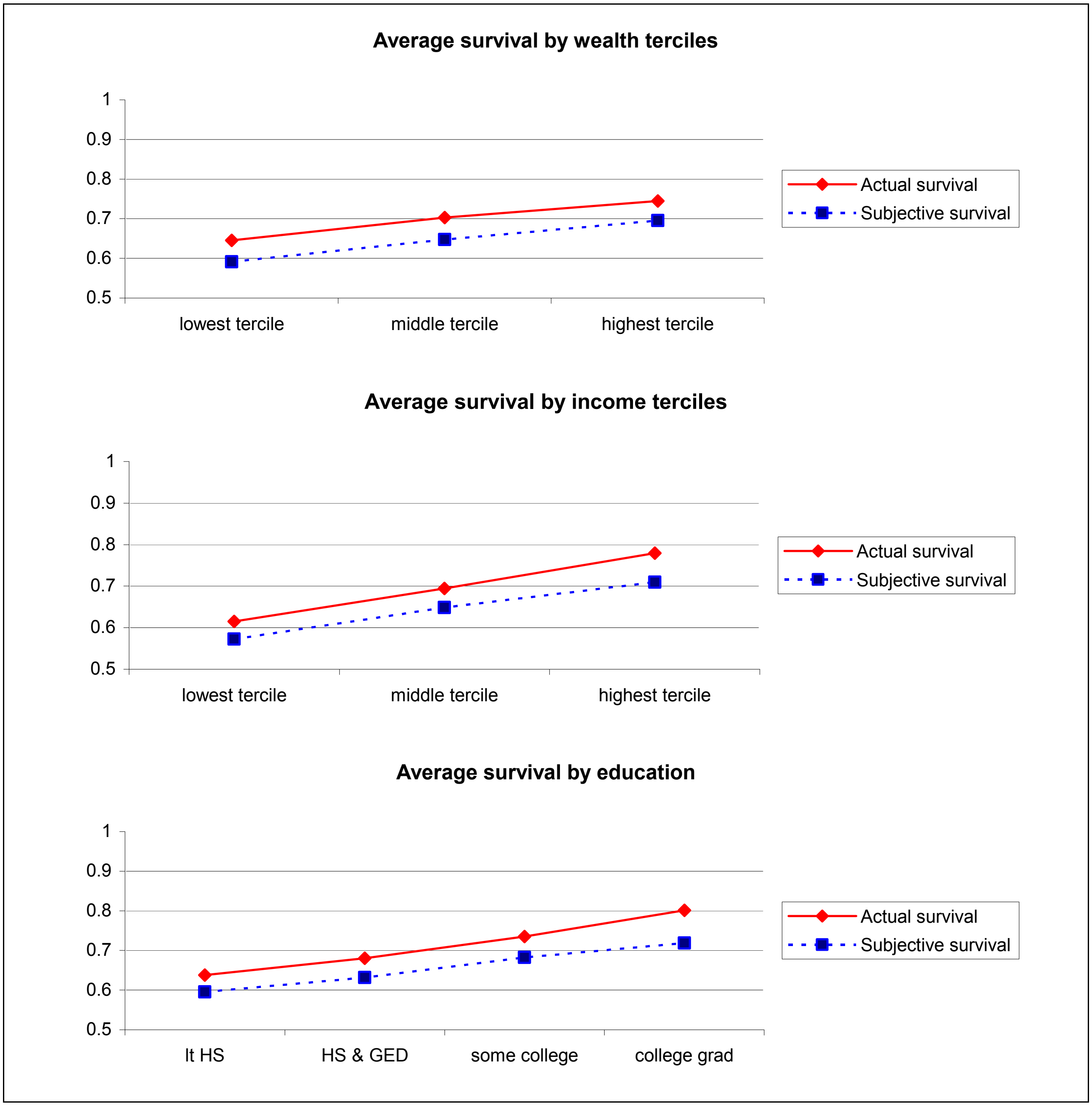
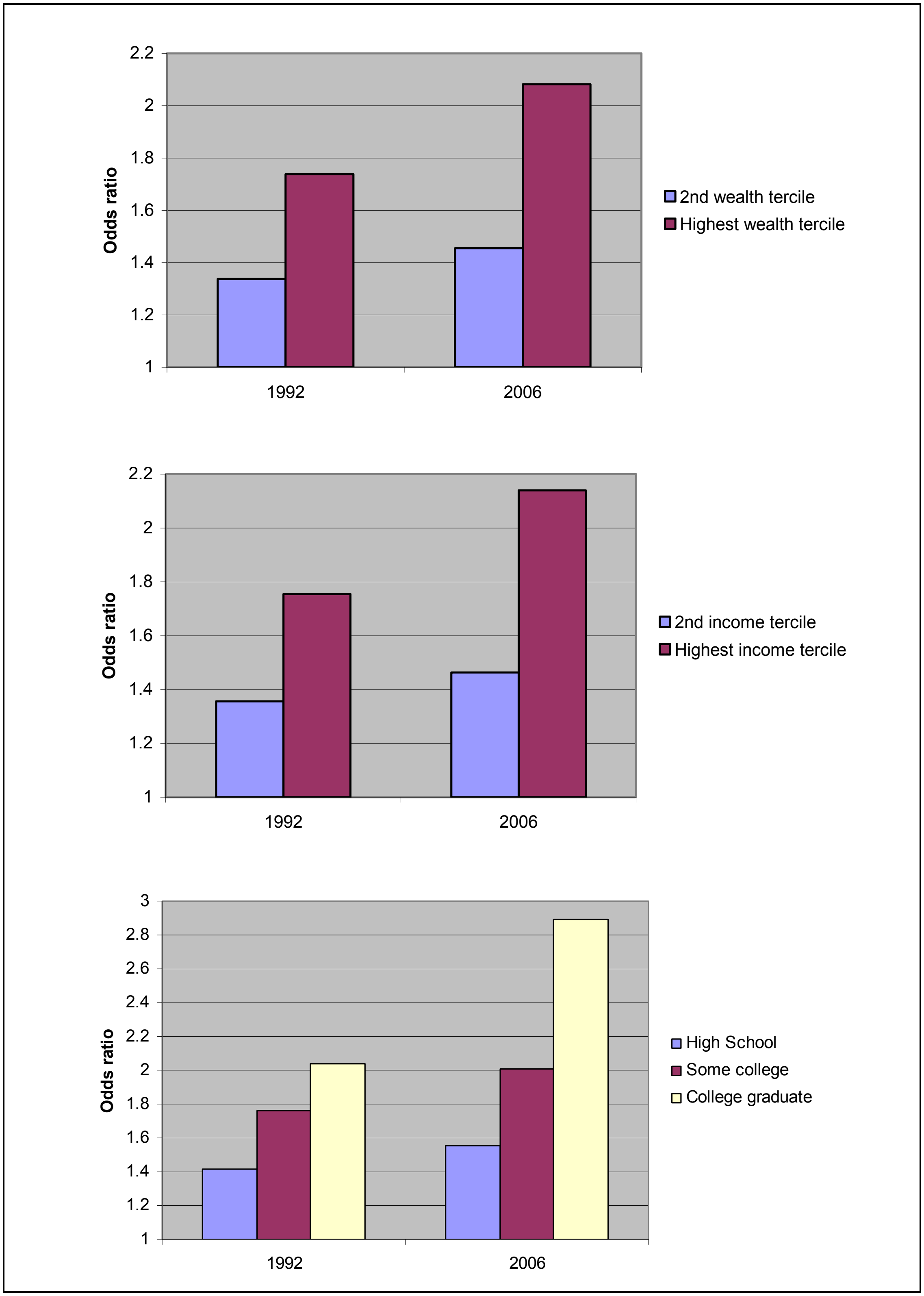


Figure 4: Differential mortality by wealth and income terciles and by education



Source: Authors' calculations.

Notes: In estimation missing values for P75 and 50% answers were imputed.

Figure 5: Differential mortality by wealth across countries – Imputation for missing probabilities of survival and 50%

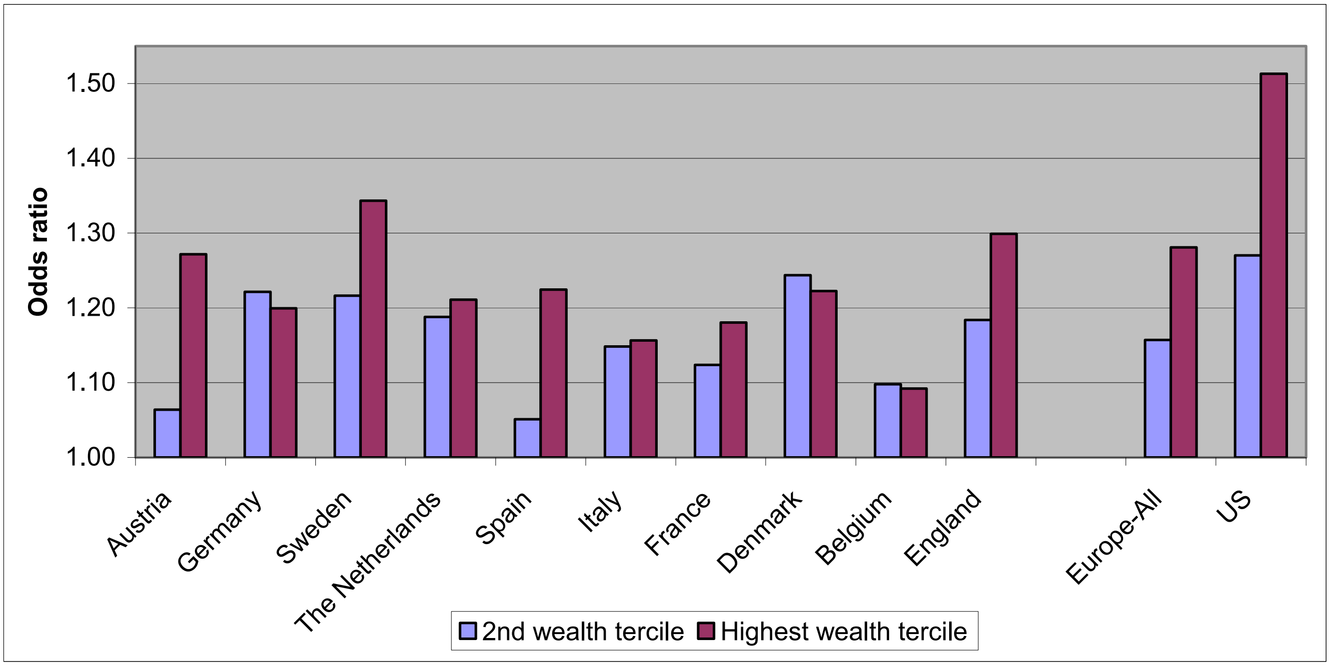


Figure 6: Differential Mortality by income across countries – Imputation for missing probabilities of survival and 50%

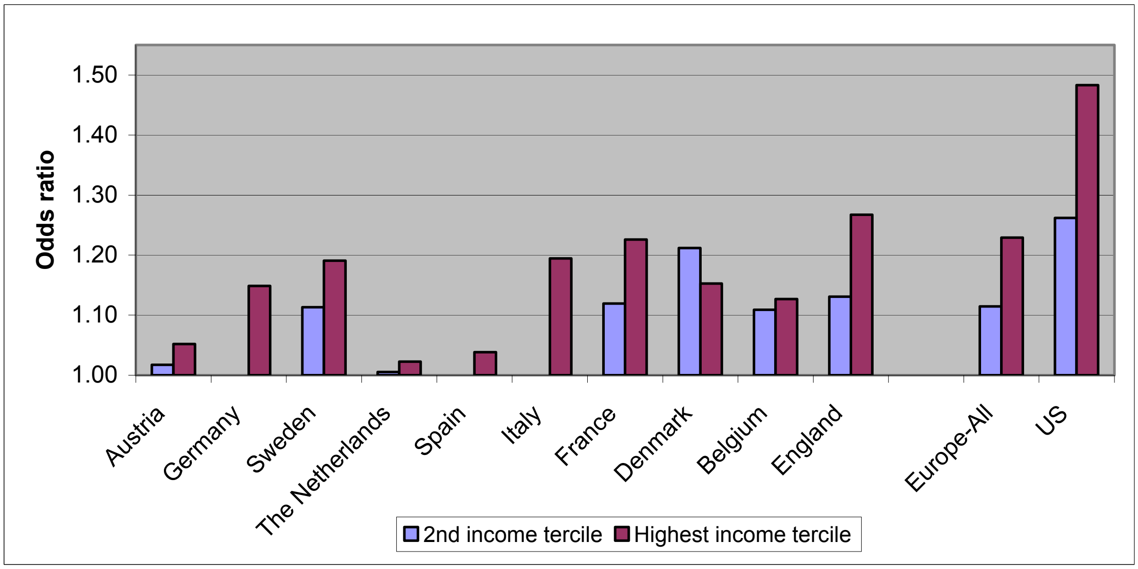


Figure 7: Differential Mortality by education across countries – Imputation for missing probabilities of survival and 50%