Cross-sectional estimates of population health from the survey of health and retirement in Europe (SHARE) are biased due to health-related sample attrition

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\section*{ABSTRACT}

Cross-sectional data from the Survey of Health, Ageing and Retirement in Europe (SHARE) are a common source of information in comparative studies of population health in Europe. In the largest part, these data are based on longitudinal samples, which are subject to health-specific attrition. This implies that estimates of population health based on cross-sectional SHARE datasets are biased as the data are selected on the outcome variable of interest.

We examine whether cross-sectional datasets are selected based on health status. We compare estimates of the prevalence of full health, healthy life years at age 50 (HLY), and rankings of 18 European countries by HLY based on the observed, cross-sectional SHARE wave 7 datasets and full samples. The full samples consist of SHARE observed and attritted respondents, whose health trajectories are imputed by microsimulation. Health status is operationalized across the global index of limitations in activities of daily living (GALI). HLY stands for life expectancy free of activity limitations.

Cross-sectional datasets based on longitudinal samples are subject to attrition, which is the dropout of participants from the samples between subsequent interviews. Attrition reduces the sample size and leads to erroneous results and conclusions as it biases the sample by changing its composition and making it no longer representative of the study population. It is particularly important to examine the effect of attrition when the sample is selected on the variable of interest or other characteristics correlated with the dependent variable (Deng, Hillygus, Reiter, Si, & Zheng, 2013; Goodman & Blum, 1996). The effect of attrition on study results is particularly apparent in health studies, where the outcome variable, health status, is a known determinant of attrition from the sample (Ahern & Le Brocque, 2005; Desmond, Bagiella, Moroney, & Stern, 1998; Graaf, Bijl, Smit, Ravelli, & Vollebergh, 2000; Hoeymans et al., 1998; Levin, Katzen, Klein, & Llabre, 2000; Michaud, Kapteyn, Smith, & Van Soest, 2011). Health status is a determinant of all the sources of attrition: failure to locate, refusal to participate, morbidity, and mortality (Graaf et al., 2000). In addition, demographic characteristics related to health, such as sex, old age, marital status, and educational attainment, are known determinants of attrition from the sample (Ahern & Le Brocque, 2005; Desmond et al., 1998; Graaf et al., 2000; Hoeymans et al., 1998; Levin et al., 2000). This implies that in cross-sectional health studies based on attritted samples, it is likely that inferences are made based on not only non-random samples, but also selected on the outcome variable of interest (Ahern & Le Brocque, 2005; Desmond et al., 1998; Graaf et al., 2000; Hoeymans et al., 1998; Levin et al., 2000).

We conclude that estimates on population health based on cross-sectional datasets from longitudinal, attritted SHARE samples are over-optimistic.
Graaf et al., 2000). While the problem of sample attrition and its potential bias on the measurement of phenomena and their relationships is commonly acknowledged in longitudinal studies, it is not mentioned in cross-sectional studies with data derived from longitudinal samples of panel studies. The only exception, to our knowledge, is Michaud et al. (2011), who studied the effect of bringing attrited individuals to the survey on cross-sectional estimates of health, socio-economic status, and family composition in the Health and Retirement Study.

On the example of the Survey of Health, Ageing and Retirement in Europe (SHARE), this article aims to demonstrate that cross-sectional estimates of health based on longitudinal samples are biased by attrition. We assess to what extent attrition from the SHARE panel up to wave 7 is related to health status and whether a health-related attrition bias is present in cross-sectional estimates of population health in European countries based on cross-sectional wave 7 SHARE datasets. The importance of this study lies in the fact that cross-sectional datasets of SHARE are the most common source of information on the health status of the Europeans in comparative studies, and, in consequence, a large number of studies is potentially affected by health-related sample attrition.

As we hypothesize that attrition from the SHARE longitudinal sample is related to decreased health status, we expect that the share of respondents in full health is overestimated in SHARE cross-sectional datasets. As a result, in studies based on SHARE cross-sectional datasets, we underestimate health expectancy in European countries. As cross-sectional estimates of health expectancy based on SHARE are often applied to study differences between countries in health expectancy, we additionally hypothesize that the ranking of countries by healthy years lived is distorted when based on the non-representative samples. In this study, full samples representative of the European populations are created by adding back attrited individuals whose health trajectories are imputed by microsimulation based on transitions between health states (including death) observed in the longitudinal samples.

2. Data

This study is based on waves 1–2, 4–7 of the Survey of Health, Ageing and Retirement in Europe (SHARE) (Börsch-Supan, 2020; Börsch-Supan et al., 2013). The cross-sectional data that is subject of this study refers to wave 7. Wave 7 was conducted in 2017, except for a small part of the sample in Portugal, with an interview conducted in 2018. Because a different questionnaire was used in wave 3, data from this wave is excluded from the analyses. We include the 18 countries that participated in wave 7 and at least one wave before and had non-missing information on NUTS-1 place of residence, as NUTS-1 is required for the calibration of cross-sectional weights. 2017 life tables required as additional data input for calculating health expectancies applying the Sullivan method (Sullivan, 1971) come from Eurostat (2022). Regional NUTS-1 data on population by sex and age for the calibration of weights come from Eurostat (2022).

Descriptive statistics of the cross-sectional wave 7 datasets for each study country and their corresponding panel developments are provided in Table 1. The composition of the datasets by the origin wave is different across the countries, as they joined the survey at various waves and also the existence of refreshment samples is not universal. The attrition rate in the table refers to the share of the panel samples missing from the survey at wave 7 for causes other than death. Although one would expect that the attrition rate across the study countries would strongly depend on the time since the samples were originally drawn, this is not always the case in the SHARE study. The attrition rate of the study panel samples varies between 13% in Croatia and 52% in Germany. In the case of Croatia, the low attrition rate is related to the fact that the panel sample was drawn only in wave 6. However, other countries do not present this relationship between the panel length and attrition rate. The potential bias in cross-sectional estimates of any statistic caused by panel attrition is reflected in the sample retention for the wave 7 cross-sectional samples (column % All in Table 1). Cross-sectional wave 7 SHARE datasets retain between 41% (France) and 85% (Croatia) of respondents ever interviewed over the study years. In half of the countries, sample retention is 54% or less.

In this study health states are operationalized across the limitations in activities of daily living with the Global Activity Limitation Indicator (GALI), based on the question: ‘For at least the past six months, to what extent have you been limited because of a health problem in activities people usually do? Would you say you have been …?’ with the answer options “Severely limited”, “Limited but not severely” and “Not limited at all”. The study allows proxy responses to the GALI question (Bergmann, Scherpenzeel, & Börsch-Supan, 2019). GALI has been systematically accessed as a comparable health measure instrument across European countries (Berger et al., 2015; Jagger et al., 2010; Van Oyen, 2011).

Table 1

| Country | Code | Name      | Joined in | Refreshment | No. of Respondents | Attrition | Respondents in Wave 7 |
|---------|------|-----------|-----------|-------------|---------------------|-----------|----------------------|
|         |      | Wave      | Year      | Wave        | Panel Died Attrited | Rate      | Number % All          |
| AT      | AT   | Austria    | 1         | 2004        | 4                   | 6221      | 587 2463 40 3219 51   |
| BE      | BE   | Belgium    | 1         | 2004-01     | 2                   | 9551      | 856 3860 40 4932 51   |
| CH      | CH   | Switzerland| 1         | 2004        | 2                   | 4501      | 271 1848 41 2417 53   |
| CZ      | CZ   | Czech Rep. | 2         | 2006-07     | 4.5                 | 8429      | 748 3496 41 4264 50   |
| DE      | DE   | Germany    | 1         | 2004        | 2                   | 8615      | 350 4480 52 3865 44   |
| DK      | DK   | Denmark    | 1         | 2004        | 5                   | 5686      | 866 1620 28 3257 57   |
| EE      | EE   | Estonia    | 4         | 2010-11     | –                   | 7694      | 902 1734 23 5136 66   |
| ES      | ES   | Spain      | 1         | 2004        | 2                   | 8686      | 1184 2832 33 4732 54   |
| FR      | FR   | France     | 1         | 2004-05     | 2.6                 | 8118      | 708 4124 51 3341 41   |
| GR      | GR   | Greece     | 1         | 2004-05     | 2.6                 | 6395      | 762 2601 41 3119 48   |
| HR      | HR   | Croatia    | 6         | 2015        | –                   | 2844      | 100 373 13 2788 85   |
| HU      | HU   | Hungary    | 4         | 2011        | –                   | 3050      | 296 1226 40 1595 51   |
| IT      | IT   | Italy      | 1         | 2004        | 2                   | 8380      | 731 3140 27 4616 54   |
| LU      | LU   | Luxemb.    | 5         | 2013        | 6                   | 2120      | 26 856 40 1320 60   |
| PL      | PL   | Poland     | 2         | 2006-07     | 7                   | 6162      | 441 1097 18 7766 83   |
| PT      | PT   | Portugal   | 4         | 2011        | –                   | 2147      | 129 742 35 1290 60   |
| SI      | SI   | Slovenia   | 4         | 2011        | 5                   | 5393      | 247 1472 27 3834 69   |
| SE      | SE   | Sweden     | 1         | 2004-05     | 2.5                 | 6591      | 742 2669 40 3217 49   |

Notes: Number of respondents in panel - All respondents interviewed at least once in any wave prior to wave 7; Attrition rate = no. of respondents who attrited in relation to the panel sample size; % All = interviewed in wave 7 as percent of all respondents ever interviewed.

Source: Authors’ estimations based on Börsch-Supan (2020); information on start wave and refreshment samples from Bergmann, Kneip, De Luca, and Scherpenzeel (2015, p.10-11)
### 3. Methods

#### 3.1. Attrition in longitudinal samples

In the first part of the study, we assess to what extent the samples that form the cross-sectional wave 7 datasets are selected based on health status. We study the pattern of attrition according to health or health-related characteristics from wave to wave in the panel that, in the end, constitutes the wave 7 cross-sectional datasets. Attrition for reasons other than death, labeled further as attrition, is studied separately from mortality. Attrition due to death is an expected phenomenon in panel samples. If not higher than the officially registered mortality or selected on the characteristics of interest differently than the patterns observed in the general population, it is unlikely to bias the sample (Mihelic & Crimmins, 1997; Smith, Lynn, & Elliot, 2009). As shown by Friedel and Birkenbach (2020), when compared to data registry SHARE longitudinal panel undercounts deaths. We estimate multinomial logistic regression models where the outcome variable of interest is the interview status at the end of each wave: attrited or dead, compared to re-interviewed. The models are estimated separately for study countries and sex and include the interaction effect between health status and 10-year age groups. Health status is measured in two levels: full health versus limited in activities of daily living across the GALI. Apart from the interaction effect, we include the main age group effect in the models to control for the large differences between the age groups in the attrition levels per se. It has been demonstrated in previous studies that higher age (Chatfield, Brayne, & Matthews, 2005; Graaf et al., 2000; Mihelic & Crimmins, 1997), lower educational attainment (Banks, Muriel, & Brant, 1986) and being single (Lillard & Panis, 1998; Mihelic & Crimmins, 1997) is associated with a higher risk of attrition. Hence, we include educational attainment and marital status as control variables to exclude the spurious relationship between these variables, health status and risk of attrition. Since the focus of this article is to discuss the development of the panel samples, we estimate the models without the longitudinal weights, of which one of the aims is to adjust for attrition. The models are estimated using the `nnet` package in R (Ripley & Venables, 2016).

As in this part of the study, we are only interested in the attrition process and not between which two specific waves it occurred, the datasets in this part of the study are created by pooling observations across all pairs of waves. As pooled datasets include repeated measurements on individuals, it is likely that the assumption of the logistic models that the error terms for each observation are independent is violated, and confidence intervals for the model estimates are underestimated (Hanley, Negassa, Edwards, & Forrester, 2003). In our particular case, once re-interviewed respondents are more likely to stay in the longitudinal sample than those interviewed only once, as the highest attrition occurs after the first interview (results not shown in Tables). This indicates a time series autoregressive correlation structure of order one for the panel observations (Hardin & Hilbe, 2002) and hence a potential violation of the assumption in the logistic model of independence of error terms across measurements of individuals. To study sensitivity of the study results to this assumption, we estimated alternative logistic regression models, only for attrition, with a generalized estimating equations method (Li, 2006). The new models account for the potential autocorrelation of the error term across the repeated observations, but not for a competing risk of death. The models were estimated using the `geepack` package in R (Højsgaard, Halekoh, & Yan, 2005). Similar to the results of Mihelic and Crimmins (1997), no differences in the sign of the health-related coefficients or their significance between the ordinal regression models and those controlling for the autocorrelation between panel observations were observed (results not shown in Tables).

#### 3.2. Cross-sectional estimates of population health

We assess the bias caused by attrition in cross-sectional estimates of health by comparing the prevalence of full health, and the differences in health expectancy at age 50, in the observed cross-sectional wave 7 datasets with the prevalence of full health in a full sample. As full sample, we refer to the entire panel sample of SHARE, where the missing health status at wave 7 of respondents who attrited is imputed by microsimulation.

The scheme of wave 7 observed dataset and full sample generation across the SHARE panel data in a country that participated in all waves of the panel (1–7) is presented in Fig. 1. To simplify this illustration, it does not include respondents who missed an interview (or interviews) and were re-interviewed at any wave before wave 7. In the study, these respondents are not considered attrited, as their health status and other observed characteristics are included in the panel sample upon their return wave prior to wave 7. In the scheme, a new sample drawn at each wave X is denoted by SX. Out of the dataset WX, the respondents are either re-interviewed at the next wave (WX,[X + 1]), die before the next wave (DX), or attrit from the panel sample (AX). The observed dataset at the next wave X + 1, marked in the scheme by a rectangle, consists of those re-interviewed respondents from the sample of the previous wave (WX,[X + 1]) and the new sample drawn at this interview, SX[X]. The full sample, marked by a circle, consists of the observed sample and respondents who attrited from the panel sample prior to wave X + 1, whose health status at wave X + 1 is simulated according to the procedure described below. The part of the full sample that consists of the respondents who attrited from the panel prior to wave X + 1 is marked on the scheme by an orange circle. It is a sum of respondents who attrited at each of the waves prior to X + 1 and are returned to the full sample.

![Fig. 1. Scheme of the generation of wave 7 observed data and full sample across the SHARE panel samples.](image-url)

*Notes: Full sample refers to the entire panel sample of SHARE, where the missing health status at wave 7 of respondents who attrited is imputed by microsimulation, as described in the Methods Section. This scheme does not include respondents who missed an interview (or interviews) and were re-interviewed at any wave before wave 7. Source: Authors’ own conceptualization*
These respondents are denoted as $AY_1, \ldots, Y_n$, where $Y$ stands for the last wave the respondents participated in the survey.

The health status of respondents missing from the panel is simulated under the assumption that the transition rates of these attritted respondents are identical to the observed transition rates. For example, we simulate the health state at wave 2 (A1.2 on the scheme in Fig. 1) of those who attritted between wave 1 and 2 (A1) by applying observed probabilities to be in a specific health state wave 2 dependent on the health state at wave 1 and other observed individual characteristics included in this study. These probabilities are estimated from the observed transitions between the health states of the respondents in dataset W1 and W2. Unlike the previous part of the study, in this part, the transition probabilities are estimated for every two waves. For each two panel waves, country and sex, we estimate transition rates between (non-missing) health states in the panel samples based on a multinomial logistic regression model with the outcome states defined by all possible states across the study health dimensions, including death as the absorbing state. Apart from an interaction effect between health state at the starting wave and age group, we include marital status, educational attainment as explanatory variables. We also control for the main effect of age group. Age is grouped into 5-year-age groups between 50 and 90 years and an open age interval of 90+ years. Like in the attrition model, we include interactions between age group and health status. Marital status is classified into two categories: married or living with a partner in a consensual union, single. Educational attainment is classified into three categories according to the International Standard Classification of Education (ISCED): low (0–2), medium (3–4), and high (5–8). The datasets used to estimate the transition rates between marital states between the waves come from panel data created by pooling all the observations across waves.

As discussed in the previous section, probabilities of transition between health states are applied to simulate the state of health at wave 7 of the attritted individuals. In the simulation model, age, health, and marital status are time-varying characteristics, and educational attainment is time constant. Age, marital status and health status are updated at each wave. As in Wolf (2001, pp. 313–339), microsimulation is used in this study as a multiple imputation method for missing responses due to attrition.

Weights applied in the cross-sectional estimates are derived in a raking procedure, which calibrates the distribution of the full sample, weighted by the design weights, by sex, age group (50–59, 60–69, 70–79, 80+ year), and NUTS-1, to the marginal distribution of the registered population of the same characteristics. This procedure is identical to the original method to derive cross-sectional, individual weights in the SHARE survey (De Luca & Claudio, 2019). To avoid potential errors resulting from differences between our and the original raking procedure in SHARE, we estimate these individual weights for both the cross-sectional wave 7 datasets and full samples. Observations with missing information on NUTS-1 place of residence were assigned missing values; hence, their design weights were raked only to the remaining margins (sex and age group). In both cases, i.e., for the respondents who were observed in the SHARE wave 7 and those whose health state at wave 7 was determined by microsimulation, we applied the design weights at the last observation (the SHARE variable $w_{\text{sex}x}$ = 1, 2, 4–6). We applied the function anesrake from the anesrake package in R (Pasek & Pasek, 2018).

First, we compare the ratio of the prevalence of full health in the observed datasets with that of the full samples in 10-year-age groups. Confidence intervals (CIs) for the ratio are derived following Method C proposed by Katz, Baptista, Azen, and Pike (1978, pp. 469–474). Next, the health expectancy at age 50 (HE) of the respondents of the observed datasets and full samples are estimated with the Sullivan method, which redistributes years lived at a certain age from a life-table into the healthy and unhealthy parts, according to the prevalence of health limitations. HE based on the GALI indicator, is called Healthy Life Years (HLY), and no limitations across the GALI are referred to as full health. CIs for the difference between the two HLYs are estimated according to the guidelines of Jagger et al. (2010). We apply age groups as in the data provided in the Eurostat’s life-tables (5-year age groups between age 50 and 84 and an open interval of 85+ years) to derive the prevalence of full health in the HLY estimations.

4. Results

The longitudinal samples that form cross-sectional wave 7 SHARE datasets are selected based on health status. These result, however, is not uniform across the age groups, as the effect of health limitations on the odds of attritting from the longitudinal SHARE samples, as compared to the odds of being re-interviewed, depends on the respondent’s age (Fig. 2). For both sexes and in most countries, decreased health reduces the odds of attrition for respondents in younger age groups (below age 70) and increases attrition in older age groups (above age 70). Although this pattern is not universal across countries, and for many country-sex-age-combinations the effect is not significant, its persistent nature across the countries indicates that it is likely that the health limitations have an opposite effect on leaving the sample between the younger and the older respondents.

In Fig. 3, we present the ratio of the prevalence of full health in the observed, cross-sectional datasets of SHARE wave 7 and the corresponding full samples by country, sex and age. In many countries, particularly for men, the ratio of the prevalence of full health in the two samples increases with age. This implies that the higher the age, the more the prevalence of full health is overestimated in the observed dataset compared to the full sample. The outliers in the study are men in Czech Republic and Hungary, and women in Austria and Poland. In these countries, prevalence of full health is significantly underestimated at age 80+ in the observed datasets. As samples in the country-sex-age sub-groups of the SHARE survey are small, the confidence intervals for both odds and the ratio of the two prevalence values are wide. Hence, the ratios are significant only for some sub-groups.

In Table 2, healthy life years at age 50 (HLY) estimated based on the observed datasets are compared to HLY estimated based on the full samples. Due to selective sample attrition, HLY is overestimated based on the observed wave 7 datasets, as the HLY values are higher in observed than in full samples in many countries. Based on attrited, cross-sectional datasets, HLY is overestimated up to 9.1% for women in the Czech Republic and 6.4% for men in Portugal. HLY is overestimated by at least 1% in 8 out of 18 countries for women and 11 - for men. As in the case of the prevalence ratios, due to the small SHARE samples, the standard errors, and hence confidence intervals, of HLYs and the difference between the two HLYs are large. Countries with the largest and significant difference between HLYs (e.g., France) are those that are characterized by a significantly higher ratio of the prevalence of full health in the observed datasets in older age groups, and in particular in the age group 80+ (compare Fig. 3). In a small number of cases, however, the opposite effect to the expected can be observed: HLY is underestimated when based on the observed data by at least 1% in 5 out of 18 countries for women and 3 - for men. In these cases, HLY is underestimated as the prevalence of full health in younger age groups is underestimated and this effect is not counterbalanced by a higher prevalence of full health at older ages in the observed datasets of wave 7. For example, for men in Croatia, HLY based on the observed dataset is underestimated by 0.4 years, compared to the HLY value based on the full sample. The share of men in full health in Croatia is underestimated in the observed dataset for all but those 80+ years old (compare Fig. 3) by up to 5.5% at age 60–69. Although the share of those in full health at age 80+ years is overestimated based on the observed data by 6%, this difference is not large enough to counterbalance, in HLY’s estimates, the opposite pattern in the younger age groups.

In Table 3, we compare the ranking of the SHARE countries according to the HLY at age 50 estimated based on the two datasets. As expected, the ranking of countries according to HLY based on the
observed datasets differs from ranking according to HLY based on the full samples. For men, we observe more changes in the rankings, reflecting the larger number of significant differences in the HLY between the two samples than for women. Most of the changes occur at the lower positions in the ranking, i.e., lower health expectancy values. The observed changes in the rankings are due to the countries characterized by an overestimated HLY based on the observed data lowering their position in the ranking for HLY based on the full samples (compare Table 2). These countries are France, Portugal, the Czech Republic, and Poland for women, Italy, France, Czech Republic, Germany, and Portugal for men.

5. Summary and discussion

Cross-sectional datasets from the Survey of Health and Retirement in Europe (SHARE) are the most common source of information in comparative studies of population health in European countries. Apart from the first wave of each country, and since the replacement samples are drawn irregularly, SHARE cross-sectional datasets in the largest part consist of attrited, longitudinal samples. As health status and socio-demographic characteristics such as age, sex, educational attainment, and marital status are well-recognized determinants of attrition, SHARE longitudinal samples - and hence cross-sectional datasets based on these samples - are likely non-representative and selected on the variable of interest in population health studies. We studied the development of panel samples according to the health status of the respondents. We examined to what extent the health-related attrition in SHARE influences the cross-sectional estimates of population health and changes the ranking of countries in comparative studies. To do so, we compared the prevalence of good health and estimates of health expectancy in the wave 7 cross-sectional datasets with values estimated based on simulated full samples, where attrited respondents are replaced by microsimulation.

In most countries, cross-sectional datasets are selected on health status as we demonstrated that health status has a significant effect on attrition from the SHARE longitudinal samples. The effect is, however, the opposite in young and older age groups: In most countries, at younger ages (50–69), we observe higher attrition of those in full health. At older ages, those in full health are more likely to remain in the sample compared with respondents limited in their activities of daily living across GALI. As the panel samples are getting older, it is likely that in some countries, the observed negative effects of health on attrition odds in young age groups cancel out in older-age groups and hence are not present anymore in the cross-sectional data: the younger respondents of the early waves, with an over-represented share of health limitations, reach older ages, at which they are more likely to attrit or die. This explains why the gap in the prevalence of full health and HLYs between the two samples are small for some countries, or even negative. Results of this study concerning the development of the panel samples are consistent with the results of previous studies. For example, Di Gessa and Grundy (2014) demonstrated an increased risk of attrition among respondents with less than good self-rated health status between SHARE wave 1 and 2 in Denmark, France, Italy, and England. Stolz, Mayerl, Raisky, and Freidl (2018) showed that, in 9 European countries, those who attrited from the SHARE sample between waves 1 and 6 were considerably frailer than respondents who remained in the sample, and
Fig. 3. Ratio of the prevalence of full health in cross-sectional wave 7 dataset to the prevalence in the full sample, in 10-year age groups, by country and sex.

Notes: 90% confidence intervals; Full sample refers to the entire panel sample of SHARE, where the missing health status at wave 7 of respondents who attrited is imputed by micro-simulation, as described in the Methods Section.

Source: Authors’ estimations based on Börsch-Supan (2020); Eurostat (2022).

Table 2

Healthy life years (HLY) based on the cross-sectional wave 7 datasets (Observed), HLY based on the full panel samples in wave 7 with replaced missing health status for those who attrited before wave 7 (Full). Difference between the HLY based on the observed sample and the full sample. Standard errors of the HLY difference (SE). HLYs’ gap relative to HLY based on the observed sample. At age 50, by country and sex.

| Country | Women | | | | | Men | | | |
|---------|-------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Code    | Name  | HLY              | Difference in HLY | Absolute | SE   | Relative | HLY              | Difference in HLY | Absolute | SE   | Relative |
| AT      | Austria | 15.7  | 15.7  | 0.0 | 0.7 | 0.1 | 15.4  | 15.3  | 0.1 | 0.5 | 0.6 |
| BE      | Belgium | 15.8  | 16.1  | −0.3 | 0.3 | 2.0 | 16.1  | 15.9  | 0.3 | 0.3 | 1.6 |
| CH      | Switzerland | 21.7  | 21.8  | −0.1 | 0.9 | 0.5 | 21.7  | 21.6  | 0.1 | 0.6 | 0.4 |
| CZ      | Czech Rep. | 13.4  | 12.2  | 1.2** | 0.5 | 9.1 | 14.0  | 13.3  | 0.7* | 0.4 | 5.1 |
| GE      | Germany | 13.1  | 12.9  | 0.3 | 0.3 | 2.0 | 13.4  | 12.9  | 0.5 | 0.3 | 3.6 |
| DK      | Denmark | 18.2  | 18.2  | 0.0 | 0.4 | 0.1 | 18.6  | 18.9  | −0.3 | 0.4 | 1.7 |
| EE      | Estonia | 10.9  | 11.1  | −0.2 | 0.3 | 1.2 | 13.1  | 13.0  | 0.1 | 0.3 | 0.5 |
| ES      | Spain | 19.3  | 19.7  | −0.4 | 0.5 | 2.0 | 19.9  | 19.9  | 0.0 | 0.4 | 0.1 |
| FR      | France | 16.9  | 16.3  | 0.6 | 0.4 | 3.5 | 19.0  | 18.0  | 1.1*** | 0.4 | 5.6 |
| GR      | Greece | 22.6  | 22.5  | 0.1 | 0.3 | 0.7 | 24.5  | 23.7  | 0.8** | 0.3 | 3.2 |
| HR      | Croatia | 12.7  | 13.0  | −0.2 | 0.4 | 1.9 | 13.2  | 13.7  | −0.4 | 0.4 | 3.3 |
| HU      | Hungary | 14.3  | 14.0  | 0.4 | 0.4 | 2.5 | 16.1  | 15.6  | 0.5 | 0.4 | 3.2 |
| IT      | Italy | 20.5  | 20.1  | 0.4 | 0.3 | 1.7 | 20.0  | 19.6  | 0.4 | 0.3 | 1.9 |
| LU      | Luxembourg | 16.3  | 16.3  | −0.0 | 0.6 | 0.2 | 16.5  | 16.6  | −0.1 | 0.7 | 0.6 |
| PL      | Poland | 11.1  | 10.8  | 0.2 | 0.3 | 2.2 | 12.6  | 12.8  | −0.2 | 0.3 | 1.6 |
| PT      | Portugal | 15.9  | 15.4  | 0.5 | 0.5 | 2.9 | 13.3  | 12.4  | 0.9 | 0.7 | 6.4 |
| SE      | Sweden | 18.9  | 19.4  | −0.5 | 0.5 | 2.7 | 18.1  | 17.1  | 1.0** | 0.4 | 5.3 |
| SI      | Slovenia | 14.5  | 14.3  | 0.3 | 0.4 | 1.9 | 16.2  | 15.9  | 0.3 | 0.4 | 1.9 |

***p < 0.01, **p < 0.05, *p < 0.1.
Source: Authors’ estimations based on Börsch-Supan (2020); Eurostat (2022).
that the effect of frailty on attrition risk did not increase linearly with age.

In cross-sectional datasets, a persistent pattern was documented in many countries, particularly for men: the older the age group, the higher the ratio of the prevalence of full health in the observed, cross-sectional datasets and the full samples. In many of the study countries, in younger age groups, the prevalence of full health was demonstrated to be even underestimated when based on observed data. In older age groups, particularly at age 80+, the prevalence of full health is likely overestimated. The gap in HLYs is consistently linked to the prevalence of full health being overestimated in older age groups. We demonstrated that based on the attrited, cross-sectional SHARE datasets of wave 7, we overestimate the prevalence of full health in most countries. In very few countries, as a result of a lower prevalence of full health in the observed samples at younger age groups not being counterbalanced by the opposite effect at older age groups, HLY based on the observed data is underestimated. For both sexes, the ranking of countries according to HLYs of the observed data and full datasets change accordingly to the observed differences in HLYs between the two samples.

We also showed that the pattern of health-related attrition in the SHARE panel sample and its effect on cross-sectional estimates is not universal among countries and differs between sexes. A non-universal pattern of attrition between the SHARE waves across countries and sexes was also demonstrated by Bergmann, Scherpenzeel, and Borsch-Supan (2019). Differential attrition patterns across European countries were also reported in other surveys: the European Community Database, Eurostat (2022).

### Table 3

| Rank | Women Observed | Women Full | Men Observed | Men Full |
|------|----------------|------------|--------------|----------|
| 1    | Greece         | Greece     | Greece       | Greece   |
| 2    | Switzerland    | Switzerland| Switzerland  | Switzerland|
| 3    | Italy          | Italy      | Spain        | Italy    |
| 4    | Spain          | Spain      | Spain        | Spain    |
| 5    | Sweden         | France     | Denmark      | France   |
| 6    | Denmark        | Denmark    | Denmark      | Denmark  |
| 7    | France         | Sweden     | Sweden       | Sweden   |
| 8    | Luxembourg     | Luxembourg | Luxembourg   | Luxembourg|
| 9    | Portugal       | Belgium    | Belgium      | Belgium  |
| 10   | Belgium        | Austria    | Belgium      | Belgium  |
| 11   | Austria        | Portugal   | Hungary      | Hungary  |
| 12   | Slovenia       | Slovenia   | Austria      | Austria  |
| 13   | Hungary        | Hungary    | Czech Rep.   | Croatia  |
| 14   | Czech Rep.     | Czech Rep. | Germany      | Czech Rep.|
| 15   | Germany        | Germany    | Portugal     | Estonia  |
| 16   | Croatia        | Czech Rep. | Croatia      | Germany  |
| 17   | Poland         | Estonia    | Poland       | Portugal |
| 18   | Estonia        | Poland     | Portugal     | Poland   |

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### Declaration of competing interest

None.

### Data availability

The authors do not have permission to share data.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2022.101290.
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