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Possibilities to deal with unknown vital status in the Survey of Health, Ageing and Retirement in Europe (SHARE)

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Abstract: Longitudinal surveys aim to correctly represent the population of interest over time. In this respect, panel attrition, i.e. the systematic drop-out of sample members, is a major challenge for maintaining long-running panel surveys. A second problem might arise when some sample members die during the life of the panel. This holds in particular for panel surveys that consider (mainly) older people, because here the overall mortality rate is higher than in studies including all age groups. Distinguishing between mortality and other forms of attrition hence is crucial as the death of respondents in a longitudinal survey is a natural process that needs to be considered in order to maintain representativeness of the panel sample. If mortality is not taken into account properly, attrition analyses might overestimate the effect of systematic drop-outs for variables that are highly correlated with mortality, such as age or health of the respondents. Therefore, lacking information on the reason why a former respondent cannot be contacted anymore is a huge problem in many longitudinal studies that further increases from wave to wave. Using the Survey of Health, Ageing and Retirement in Europe (SHARE), three methods are implemented in this paper to examine the extent of missing death reports. The first method randomly assigns people with unknown vital status to death. The second method uses mortality rates from life-expectancy tables to extrapolate the expected number of deaths among the panel members with unknown vital status. The third method models deaths from data internal to the survey. The correction methods are compared to the original, uncorrected sample as well as to a high-quality death register that can serve as a validation benchmark. Finally, implications for analyses of deceased sample members and attrition analyses are explored.

Abstract: Ein zentrales Ziel von längsschnittlichen Umfragen ist die repräsentative Abbildung der Zielpopulation über die gesamte Untersuchungsperiode. In dieser Hinsicht ist Panel Attrition, also der systematische Ausfall von Befragten, ein Kernproblem für jede Panelstudie, da hierdurch nicht nur die zu analysierende Fallzahl abnimmt, sondern es auch zu substanziellen Verzerrungen kommen kann. Hiermit eng verbunden ist eine weitere Schwierigkeit bei Panelstudien, nämlich das natürliche Ausscheiden von Befragten durch Mortalität. Dies gilt in besonderer Weise für Panelstudien, die (mehrheitlich) ältere Menschen befragen, da hier die natürliche Mortalität höher ist als in Umfragen, die alle Altersgruppen umfassen. Die präzise Unterscheidung zwischen unterschiedlichen Arten eines systematischen Ausscheidens aus dem Panel auf der einen und natürlicher Mortalität bzw. deren Berücksichtigung auf der auf der anderen Seite ist demnach zentral für eine Aufrechterhaltung der Repräsentativität des Panelsamples. Sofern Mortalität nicht angemessen berücksichtigt wird, besteht die Gefahr einer Unterschätzung ihrer Konsequenzen sowie gleichzeitig einer Überschätzung des Ausmaßes systematischer Ausfälle – insbesondere für Variablen wie etwa Alter und Gesundheit der Befragten, die eine hohe Korrelation mit Mortalität aufweisen. Fehlende Informationen über die konkrete Ursache, weshalb ehemalige Befragte nicht mehr kontaktiert und interviewt werden konnten, ist daher ein großes und sich über die Zeit verschärfendes Problem zahlreicher Panelstudien. Auf der Grundlage des Survey of Health, Ageing and Retirement in Europe (SHARE) werden in diesem Papier drei Korrekturmethoden vorgestellt, die das Ausmaß und die Folgen einer Unterschätzung des Ausmaßes natürlicher Mortalität der Befragten untersuchen. Die erste Methode erhöht dabei die

absolute Zahl tatsächlich Verstorbener, indem zufällig bestimmte Panelbefragte als verstorben markiert werden, die nicht mehr kontaktiert werden konnten und deren vitaler Status demnach unbekannt ist. Die zweite Methode verwendet Mortalitätsraten auf der Basis von offiziellen Sterbetafeln, um die zu erwartende Anzahl an Toten unter den Panelbefragten mit unbekanntem Status zu extrapolieren. Die dritte Methode modelliert schließlich den vitalen Status der Befragten anhand verfügbarer Informationen direkt aus den Paneldaten. Die Korrekturmethoden werden mit dem ursprünglichen, nicht korrigierten Panelsample sowie einem qualitativ hochwertigen Sterberegister verglichen, das als Benchmark zur Überprüfung der Validität dient. Abschließend werden die Implikationen für Mortalitäts- und Attrition-Analysen untersucht.

Key words: SHARE; mortality; attrition; unknown vital status; life tables; death register

Acknowledgement: This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6 and 7 (DOIs: 10.6103/SHARE.w1.700, 10.6103/SHARE.w2.700, 10.6103/SHARE.w3.700, 10.6103/SHARE.w4.700, 10.6103/SHARE.w5.700, 10.6103/SHARE.w6.700, 10.6103/SHARE.w7.700, 10.6103/SHARE.wXcvr.700), see Börsch-Supan et al. (2013) for methodological details. Further, internal data regarding register (w7_mortality_register_rel7-0-0) and gross sample information is used. The SHARE data collection has been funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982) and Horizon 2020 (SHARE-DEV3: GA N°676536, SERISS: GA N°654221) and by DG Employment, Social Affairs & Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged *(see www.share-project.org)*.

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1. Introduction

In longitudinal surveys there is a recurring problem of people leaving the sample, either on purpose or because they could not be contacted any more. This unit non-response of people who formerly participated in a survey is referred to as attrition (e.g. Binder, 1998). There are different reasons for the phenomenon of attrition. It occurs when respondents cannot be located anymore after an initial interview (1), when they cannot be contacted (2), or when they refuse to participate (3). This can affect surveys in different ways. First, depending on the amount of attrition, the initial sample can be greatly reduced, which is accompanied by a loss in statistical power. Second, no matter of its size, if attrition does not occur by chance, i.e. if some people are more likely to leave the sample than others, attrition can induce bias to estimates based on the survey (e.g. Lynn, 2018, pp. 144-145). And finally, if the underlying reasons for attrition are not known, calculating reasonable response or cooperation rates becomes more problematic (Sadig, 2014, p. 2).

Longitudinal surveys aim to correctly represent the population of interest not only at the start of the survey, but also during the course of the study. To draw reliable conclusions when working with panel data it is therefore important to carefully address systematic attrition that can lead to biased estimates. While high attrition rates are often seen as a problem for panel studies, it is important to understand how attrition is composed and what causes it. This holds in particular for surveys that consider (mainly) older people, because here the overall mortality rate is higher than in datasets including all age groups. Distinguishing between mortality and other forms of attrition hence is crucial as the death of respondents in a longitudinal survey is a natural process that needs to be considered in order to maintain representativeness of the panel sample. If mortality is not taken into account properly, attrition analyses might overestimate the effect of a systematic drop-out for certain variables that are highly correlated with mortality, such as age or health of the respondents. Therefore, lacking information on the reason why a former respondent cannot be contacted anymore is a huge problem in many longitudinal studies. Unfortunately, the share of respondents who for some reason dropped out of the study and for whom no information concerning their vital status is available increases from wave to wave.

Concerning this issue, Watson (2016) introduced different approaches to adjust the number of unreported deaths among respondents with unknown vital status for the survey on Household, Income and Labour Dynamics in Australia (HILDA). The “gold standard” in this respect is to match the sample with data from national death or mortality registers. By this, unreported deaths can be accurately determined. However, such external sources have to be available – a condition that in many European countries is not fulfilled and/or places considerable high demands in terms of complying to national data protection regulations. As another way to account for unreported deaths, Watson (2016, pp. 992-993) used age- and sex-specific mortality rates from life tables. Although not as exact as linking the sample to

death registers, using mortality rates is a quite common approach in today's extrapolation of the expected number of deaths among cases with unknown vital status. Lynn and Borkowska (2018), for instance, used cumulative annual mortality rates in each age group to correct the number of non-respondents in the British Household Panel Survey (BHPS) and the Understanding Society General Population Sample (GPS). In a similar way, Sadig (2014) used age- and sex-specific mortality rates from the Office of National Statistics to estimate the likelihood of survival for sample members of the BHPS. In this respect, he was able to calculate an adjustment factor to correct for unreported deaths. In the present work we follow this second approach and match individuals with age-, sex- and region-specific mortality rates to examine the extent of missing death reports among respondents whose vital status is unknown and further to decide which people are more likely to actually have died. In addition, the corrected data then can be used to better explore the implications of unreported deaths for both mortality and attrition analyses.

The remainder of this article is organized as follows: Section 2 describes the data used for the following analysis and introduces three different correction methods to account for unreported deaths. Afterwards, we compare the results of these alternative strategies regarding their sensitivity, specificity and accuracy based on internal and external data (section 3). In section 4, we take a further look at the sample and examine how the additionally declared dead sample members differ from those that actually have been reported dead and to what degree such corrections might change the interpretation of mortality analyses as well as systematic attrition. Section 5 discusses and summarizes our results.

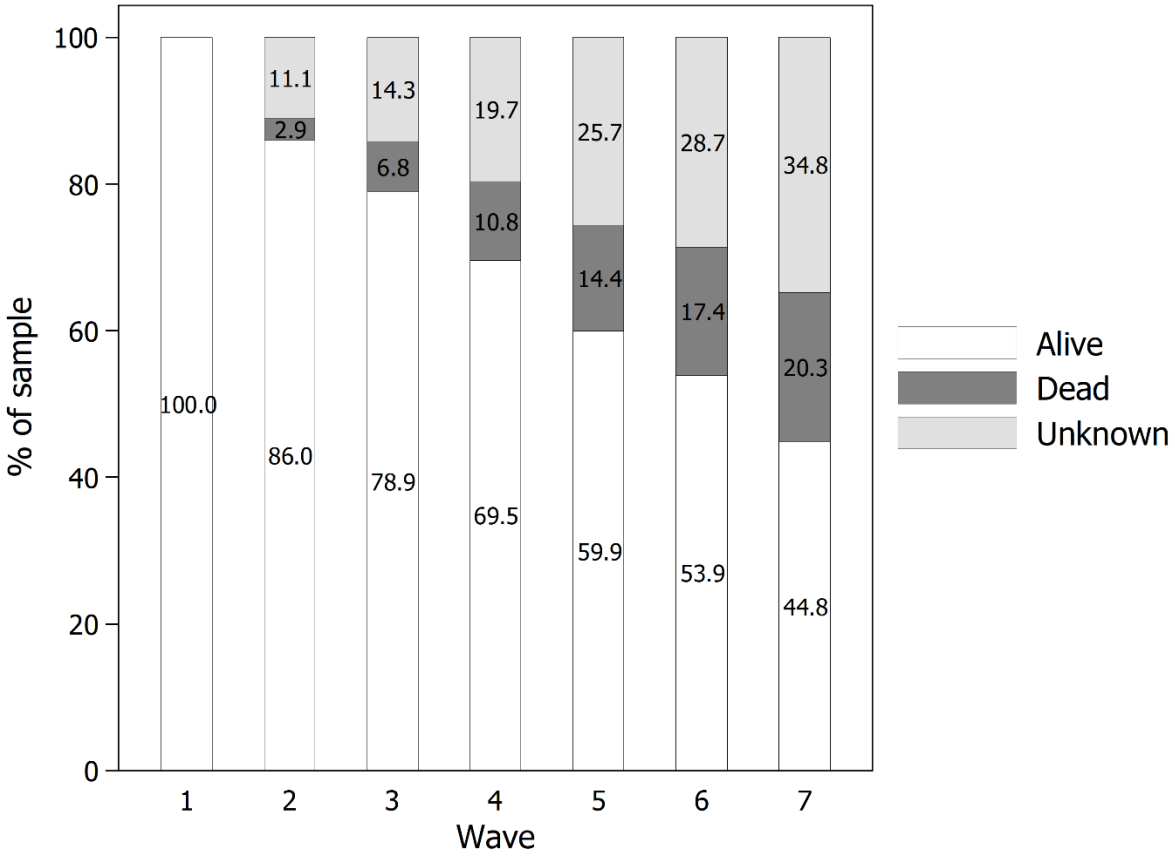
2. Data and methods

In this paper, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE; Börsch-Supan et al., 2013). SHARE is a multidisciplinary and cross-national panel study, which is conducted biannually since 2004 and by now includes all continental EU member states plus Switzerland and Israel. By collecting data on health, socioeconomic status, and social and family networks from individuals aged 50 and older and their partners, it strongly contributes to the understanding of the ageing process in Europe. Like other panel surveys focusing on the elderly population, such as HRS or ELSA, SHARE suffers from the problem of increasing attrition rates (see Bergmann, Kneip, De Luca, & Scherpenzeel, 2019) in connection with missing information on respondents' vital status, i.e. whether they refuse to participate or whether they actually have died.

For the following analyses, we use data based on public release 7-0-0 (Börsch-Supan, 2019a, 2019b, 2019c, 2019d, 2019e, 2019f, 2019g, 2019h) as well as internal data regarding register and gross sample information and consider all individuals that were interviewed for their first

time in Wave 1, making them the first sample of SHARE. Based on this, 27,976 people from eleven countries[1] are eligible in the first wave of our analysis sample. Figure 1 shows the development of vital status over the respective waves. While in Wave 1 all respondents per definition had been alive, this fraction decreases from wave to wave. In Wave 7, conducted in 2017, only 44.8 percent of the Wave 1 respondents were still alive and part of the panel sample, while 20.3 percent have died up to this time. The remaining 34.8 percent could not be contacted anymore and thus are of unknown vital status.

Figure 1: Vital status of Wave 1 respondents over time



Data: SHARE Release 7.0.0; unweighted.

In light of these numbers, we will focus in the following on the increasing share of panel members whose vital status is unknown. To account for the expected number of unreported deaths among individuals with unknown vital status, age-, sex- and region-specific mortality rates are used. The mortality rates are calculated from data published by Eurostat for each of the relevant years until 2017. Eurostat releases the numbers of population and deaths according to sex and age in every region corresponding to the Nomenclature of Territorial

[1] Not including Israel, since comparable data on age-, sex- and region-specific mortality rates were not available for Israel up to 2017.

Units for Statistics (NUTS level).[2] Exact mortality is calculated by dividing the number of deaths in one year by the respective total population.

Before employing these individual mortality rates we did some data adjustments. First, individuals with unknown vital status in one wave but known to be alive (or dead) in a later wave, are treated as "alive" (or "dead", respectively) in every previous wave. Second, for respondents who are lacking information concerning the month of birth, we randomly assigned a number between one and twelve by assuming a uniform distribution over the year. In addition, we estimated the date of the interview for panel members with unknown vital status. Since no interviews are available for these people, we applied the average time when SHARE interviews with respondents were conducted in the respective country. In countries that did not participate in a particular wave at all, we used the average date of interviews in the other participating countries. Based on these calculations, we are able to specify the age of respondents with unknown vital status at the time an interview would have been conducted. By this, mortality rates can be determined much more precisely.

To estimate the number of unreported deaths, a mortality rate between Wave *t* and Wave *t+1* is calculated for each person (or better group of persons) with certain characteristics. This rate is the proportion of deaths that occur between exact age *x* and *x+1*, and is denoted as p_x. To apply these death rates to the SHARE sample where a sample member is aged *x* years and *m* months at the date of the last interview, a weighted combination of and p_x and p_{x+1} is used (see Watson, 2016 for a similar proceeding). That is, the probability that a person aged *x* years and *m* months at Wave *t* dies between Wave *t* and Wave *t+1* is:

$$p_{txm} = \frac{(12-m)}{12} p_x + \frac{m}{12} p_{x+1} \,,$$

where p_x corresponds to the age-, sex- and area-specific mortality. The specific mortality rate p_{txm} from Wave *t* to Wave *t+1* is then matched to each person.

Based on these data, three different methods to adjust for unreported death among people with unknown vital status using specific mortality rates are examined in the following. Each method uses the values of p_{txm} to calculate how many people have probably died and which people are more likely to die than others. The actual calculation of the number of unreported deaths in each wave and the assignment of deaths are carried out in two distinct steps. In a first step, the expected number of deaths per wave among the group of panel members with unknown vital status is calculated. For this, the specific mortality rates of people with unknown vital status are summed up in the respective waves. This yields a number that we equate with the number of unreported deaths in each wave. Afterwards, different correction (or imputation) techniques to decide which concrete respondents of this group of people are

[2] https://ec.europa.eu/eurostat/databrowser/view/demo_r_d2jan/default/table?lang=en
https://ec.europa.eu/eurostat/databrowser/view/demo_r_magec/default/table?lang=en
Population numbers and numbers of deaths for most countries are summarized for age 89 and older.

most likely to die are applied in a second step. While the estimated number of unreported deaths hence is the same in all three methods for the transition from Wave 1 to Wave 2, the number of estimated deaths differs when summing up the mortality rates in later waves. This is because the different methods are declaring different people as dead, which in turn leads to differences in the number as well as in the composition of imputed deaths (see Table 1 and Table 2).

Method 1: Wave-to-wave adjustment of unreported death based on random assignment

After calculating the number of unreported deaths in each wave, this method decides by chance which people with unknown vital status might have died. Each person among the unknowns is hence assigned a random value of the uniform distribution. Those people with the lowest values of this distribution are flagged as dead in the respective wave. This procedure is repeated for all subsequent waves. Over all waves this results in 3696 people with a formerly unknown vital status who then are declared dead. As no additional information is used here, this method serves as a basic scenario for comparisons with the other applied methods that will be explained in the following. In addition, it is clear that this method implicitly assumes a data pattern that is comparable to the missing completely at random (MCAR) mechanism in the imputation literature (see, e.g., Rubin, 1976, 1987).

Method 2: Wave-to-wave adjustment of unreported death based on mortality

In Method 2, we assume that groups of respondents with higher mortality rates are more likely to die than others. After the number of unreported deaths has been calculated for a certain wave as a cut-off, deaths are assigned according to the probability to die expressed by the age-, sex- and region-specific mortality rates from Eurostat. Thus, in each wave those unknown cases with the highest mortality rates are declared dead. As especially elderly tend to have higher mortality rates they are more likely to be declared dead in this method. In total 2873 people are assumed to have died in addition to those actually known to be dead by Wave 7.

Method 3: Wave-to-wave adjustment of unreported death based on individual information

In Method 3, we use available survey information about all respondents from Wave 1 to decide which people are most likely to die. For this, a large number of auxiliary survey variables, which were found to be correlated with mortality (e.g. Hayat et al., 2018; Huisman et al., 2004; Kröger, Kroh, Kroll, & Lampert, 2017; Olshansky & Ault, 1986; Seeman, Kaplan, Knudsen, Cohen, & Guralnik, 1987) and that have been asked to all respondents in the analysis

sample are used. These include age, sex, level of education, household composition, type of area (urban vs. rural), migrant status, subjective economic situation, self-rated health, chronic diseases, physical limitations, number of overnight hospital stays, social activity, and cognitive performance measures like numeracy as well as reading and writing skills.[3] This individual information is then applied as explanatory indicators in a logistic regression to determine which people are more likely to die. Models for males and females are built separately and values between 0 and 1 are predicted for all persons with unknown vital status in each wave. The models are unweighted as the aim is to predict deaths in the sample rather than the population, but otherwise Method 2 and Method 3 both implicitly assume a missing at random (MAR) mechanism, in which the lack of information (here: the unknown vital status) can be explained by further observed variables (e.g. Schafer, 1997), such as age and health of the respondent. Individuals with higher predicted values are assumed to be more likely dead than those with a value closer to 0. Examining the number of unreported deaths this way results in 3037 individuals that are additionally declared dead over all waves.

Table 1: Reported deaths and estimated number of additional deaths

	Wave						
	2	**3**	**4**	**5**	**6**	**7**	**Total**
Reported deaths (total)	816	1909	3007	4038	4879	5688	**20,337**
Estimated number of deaths (increase)							**Total increase** (%)
Method 1: Random	+87	+201	+375	+639	+972	+1422	**3696** +18.2%
Method 2: Mortality	+87	+168	+303	+501	+741	+1073	**2873** +14.1%
Method 3: Individual information	+87	+172	+320	+530	+790	+1138	**3037** +14.9%

Data: SHARE Release 7.0.0; unweighted.

Table 1 shows the number of reported deaths in each wave compared to the number of additional deaths that have been assigned by the three different methods described above. Between Wave 1 and Wave 2, all methods calculate the same number of additional deaths (n=87), because within each method the mortality rates are summed up the same way. Differences first occur in Wave 2, because a different assignment in a previous wave has consequences for further allocations of deaths based on the different adjustment methods. Method 1, where additional deaths are assigned completely at random, adds the most cases to the reported number of deaths (n=3696), followed by Method 3 (n=3037). The least number

[3] A list of the indicators used can be found in the Appendix. For persons for whom the information from Wave 1 are not completely available, a smaller regression is processed in which only age, sex and a country indicator are used as independent variables. This applies, however, only to very few cases.

of deaths is estimated when using Method 2 (n=2873), because here the panel members with the highest mortality rates are declared dead in each wave and thus summing up the mortality rates for the remaining sample of persons with unknown vital status leads to lower overall numbers of panel members who are likely to die. The increase of deaths over all waves is between 14.1 percent in Method 2 and 18.2 percent when considering Method 1.

When looking at the distribution of age and gender according to the different correction methods, Table 2 shows that the overall ratio of newly declared dead men and women differs a lot between the used methods. While the total number of actually reported deaths is about the same for male and female panel members, both Method 1 and Method 2 declare more women than men as dead, while the opposite is true for Method 3. In addition, it can be seen that only Method 1 assigns the vital status "dead" to persons of all age groups. This is due to the fact that in this method deaths are randomly assigned to persons of unknown vital status. In Method 2, where the allocation is based on mortality rates, only people aged 80 years and over are declared dead. Since older people naturally have a higher mortality rate, they are also more likely to be declared dead. In Method 3, people aged 70 and over (with some rare exceptions of 60-69 year-old males) are declared dead, while no deaths are assigned to younger people. In this method, additional determinants are considered, but again age is an important predictor, which is why older people are also more likely to be declared dead in this method.

Table 2: Estimated number of deaths by gender and age-groups (Wave 7)

		<60	**60-69**	**70-79**	**80-89**	**90+**	**Total**
Reported deaths	Male	1	231	559	1020	1029	**2840**
		0.0%	4.1%	9.8%	17.9%	18.1%	49.9%
	Female	2	160	428	859	1399	**2848**
		0.0%	2.8%	7.5%	15.1%	24.6%	50.1%
Method 1: Random	Male	4	196	234	132	42	**608**
		0.3%	13.8%	16.5%	9.3%	3.0%	42.8%
	Female	37	265	238	176	98	**814**
		2.6%	18.6%	16.7%	12.4%	6.9%	57.2%
Method 2: Mortality	Male				111	320	**431**
					10.3%	29.8%	40.2%
	Female				104	538	**642**
					9.7%	50.1%	59.8%
Method 3: Individual information	Male		11	58	272	275	**616**
			1.0%	5.1%	23.9%	24.2%	54.1%
	Female			8	124	390	**522**
				0.7%	10.9%	34.3%	45.9%

Data: SHARE Release 7.0.0; unweighted.

3. Accuracy of methods to adjust the number of unreported deaths

To evaluate which of the introduced methods performs best, one would need external data of high quality as a benchmark. In this respect, we have thoroughly investigated the possibilities of linking SHARE data to national (death) registers or other helpful sources (e.g. administrative records) to improve data quality regarding vital status. While this is indeed possible for some countries (see Table 3), many other countries participating in SHARE do not have such sources and/or restrict access for reasons such as data protection. SHARE is currently in the process of undertaking all measures to link the SHARE sample with external sources whenever this is possible. However, convincing national statistical offices is a long-term process, which is why we follow a multi-stage test approach here to examine how well the different methods perform regarding an adjustment of the number of deaths. As a first test, we therefore consider only those cases that are actually known to be alive or dead in Wave 7 and then simulate that their vital status is unknown as of Wave 2. Based on this internal data, we then can use the three introduced correction methods to calculate the expected number of deaths occurring up until Wave 7 and compare them to the actually known numbers that serve as a first internal benchmark. As a second test, we use national death register data from Denmark as an external benchmark, because the percentage of successfully linked respondents is by far the highest.

Table 3: Overview of linked mortality data in SHARE (Wave 7)

Country	Type of data source	Linked year(s)	Linked respondents (%)
Belgium	National register	2011, 2019	52.0 (French part), 40.4 (Dutch part)
Denmark	National register	2019	98.7
Estonia	National register	2012, 2014, 2017, 2019	89.9
Sweden	National register	2019	53.5
Netherlands	Commercial register	2019	57.0
Austria	National administrative data	2017	47.8
Germany	National administrative data	2017, 2019	51.6
France	National administrative data	2016	11.5

For the first test using internal data, overall, 18,221 panel members are taken into account for whom the vital status from Wave 1 to Wave 7 is known, with a total of 5688 reported deaths (incl. end-of-life interviews) until Wave 7. When omitting this information and applying the different methods to account for unreported deaths, Method 1 declares 6562 persons dead (+874). In Method 2 only 4803 people were assigned as dead (-885), while in the third method 5181 people are declared dead (-507). Thus, our results show that Method 1 based on a random allocation of deaths overestimates the number of actually reported deaths in our sample, while the other two methods depending on the mortality rate (Method 2) and

individual information (Method 3) underestimate the used internal benchmark. Similar to the prediction of unreported deaths among the persons with unknown vital status, Method 1 determines the highest number of deaths, while Method 2 calculates the lowest number.

With this simulated data it is also possible to investigate how well the different methods perform in the actual allocation of deaths to the observed cases. To determine the performance of each method we use an approach that is commonly used in diagnostic or screening tests (e.g. Davidson, 2002; see James, Witten, Hastie, & Tibshirani, 2013 for a slightly different notation) and measures a so called test's accuracy. The score combines sensitivity and specificity and calculates, respectively, the proportion of positive predictions that are actually correct and the proportion of actual positives that were identified correctly (see Table 4). Thus, accuracy is defined as the proportion of people who were correctly identified as either having or not having a condition (here: death) and reaches a value between 0 as its worst and 1 when sensitivity and specificity are perfect.

Table 4: Definition and calculation of sensitivity, specificity and accuracy

		Actual condition	
		Present	**Absent**
Predicted test result	**Positive**	true positives	false positives
	Negative	false negative	true negatives

$$Sensitivity = \frac{true\ positives}{true\ positives + false\ negatives}$$

$$Specificity = \frac{true\ negatives}{true\ negatives + false\ positives}$$

$$Accuracy = \frac{true\ positives + true\ negatives}{true\ positives + true\ negatives + false\ positives + false\ negatives}$$

Using our simulation data, Method 1 achieves an accuracy of only 60.3% (sensitivity: 23.9%, specificity: 76.8%). In contrast, Method 2 and Method 3 yield a much higher accuracy with 80.5% (sensitivity: 50.5%, specificity: 94.1%) and 82.0% (sensitivity: 53.7%, specificity: 94.8%), respectively. The latter two methods, which use additional information (i.e. mortality rates and individual characteristics) to decide which persons are more likely to have died are thus – as expected – much better suited to identify which respondents actually died or not than the first method that is based on a random selection of cases. In addition, Method 3 shows a smaller deviation regarding the number of additionally assigned deaths.

While the previous analysis used available data (i.e. known deaths) as an internal benchmark, it is obvious that the number of reported deaths in the sample underestimates the actual number of deaths to a certain degree. In this respect, mortality or death registers are better suited to give an appropriate picture of the actual vital status of sample members. However, as mentioned before, while death registers can be matched rather easily (if available at all) in single country studies, consistent mortality information in cross-national studies like SHARE is much harder to obtain. SHARE puts huge effort in integrating mortality information from reliable external sources. However, until now only some countries provided useful information on the vital status of all sample members (see Table 3). One country that has successfully matched the SHARE sample with an official national mortality register is Denmark. These data[4] can hence be used as an external benchmark to compare both the original sample with reported deaths and the corrected samples based on the different correction methods described above. The results in Table 5 show that the uncorrected sample of panel members with information on reported deaths is statistically indistinguishable from the death register (which is expected to adequately reflect reality) by Wave 7 on a number of sociodemographic characteristics and health conditions. The same is true for the three applied correction methods. Here, no coefficient reaches a significant level either. Although this is mainly due to the small sample sizes in the comparison groups and the used Bonferroni correction that accounts for multiple comparisons by adjusting the error rate, these results indicate that the sociodemographic characteristics of reported deaths in SHARE reflect the information on actually deceased sample members rather well.

When comparing the different correction methods, it can be seen that the overall performance of Method 1, which randomly declares respondents as dead, is slightly worse than Method 2 and Method 3, which both use additional information to more precisely select presumably dead respondents. Thus, the absolute standardized bias across all characteristics (see Wuyts & Loosveldt, 2019, p. 86) at the bottom of Table 5, which sums up the deviations of all characteristics and divides it by the standard error of the sample, is larger for Method 1 (abs. standardized bias = 0.8) than for Method 2 or Method 3 (abs. standardized bias = 0.6, respectively). Further, when looking at the number of reported or additionally declared dead sample members, it can be seen that this number is underestimated in the uncorrected sample by 37 cases or about eight percent, while Method 2 and Method 3 are rather close to the truth in the Danish example. This finding is in contrast to Watson (2016, p. 993), who speculated that the life-table approach might overestimate the number of deaths when people in institutions are underrepresented or even excluded in the study (and the mortality rates used are thus too high). However, as institutionalized persons are followed in SHARE and in some countries are even included in the sampling frame for the baseline interview, this does

[4] As of now, these data are only internally available. It is, however, intended to include this information in a future official release.

not seem to be a huge problem here – at least regarding the corrected samples that use additional information from life tables or individual characteristics.

Table 5: Mean characteristics of death-register matching compared to uncorrected and corrected samples of reported and additionally declared deaths in Wave 7

	Death register	Reported deaths	Method 1: Random	Method 2: Mortality	Method 3: Individual information
Age (years)	85.7	86.0	84.5	86.4	86.3
Female (%)	55.6	56.0	56.6	56.2	55.4
Education					
low (%)	31.2	31.4	29.9	31.8	31.6
medium (%)	48.6	49.1	49.0	48.7	48.9
high (%)	20.2	19.6	21.1	19.5	19.5
Partner living in household (%)	50.6	48.7	51.4	48.8	48.8
Urban area (%)	55.8	55.8	54.3	56.5	56.7
Born abroad (%)	4.8	4.2	4.0	4.2	4.2
Retired (%)	75.8	76.2	71.0	77.9	77.2
Ability to make ends meet (%)	76.9	76.1	77.0	76.9	76.9
Self-rated health					
very bad/bad (%)	15.6	16.0	15.7	15.8	16.2
fair (%)	33.8	34.9	33.3	35.1	35.5
good/very good (%)	50.5	49.1	51.0	49.1	48.2
Chronic diseases (%)	61.7	62.9	60.4	63.3	63.7
Limitations in ADL (%)	20.4	21.2	19.9	20.4	20.8
Limitations in mobility (%)	63.8	64.9	62.3	64.5	65.1
Stayed overnight in hospital (%)	24.8	25.1	23.9	24.7	25.3
Depression (%)	24.7	26.2	25.6	25.2	25.6
Socially active (%)	44.8	44.9	47.0	45.3	44.4
Numeracy score (0-100)	49.6	48.9	49.6	49.7	49.3
Self-rated reading skills (0-100)	66.3	65.7	67.0	65.8	65.9
Self-rated writing skills (0-100)	59.5	58.5	60.2	59.0	59.0
Absolute standardized bias (avg.)	-	*0.6*	*0.8*	*0.6*	0.6
N	462	425	479	457	457

Notes: Significance tests (based on two-sided t-tests) between death register and original sample with reported deaths as well as different correction methods.
Significance level: ***: p<.001, **: p<.01, *: p<.05.

4. Comparison of methods regarding sociodemographic characteristics and health conditions

In the following, we want to further explore how well the different correction methods reflect sociodemographic characteristics and health conditions of panel members who subsequently die. Because mortality registers as gold standard are not available for all countries

participating in SHARE (or are of insufficient quality), we base our analyses on the available internal data, recognizing the limitations of this proceeding. Nevertheless, this offers the possibility to compare different correction methods and their consequences for mortality and attrition analyses. In this respect, we are interested in two different comparative analyses: In a first step, we compare cases of reported deaths in Wave 7 in the uncorrected sample to cases with reported and additionally imputed deaths in the samples that are corrected via the correction methods mentioned above (sub-chapter 4.1). The comparison samples hence differ only by the varying number of cases declared dead in the respective corrected samples. Any occurring differences regarding Wave 1 characteristics, which are available for all sample members under consideration, should hence be caused by unreported deaths among the cases with unknown vital status in the original, uncorrected sample. We expect significant differences in particular with respect to age and health (as well as indicators that are strongly correlated with these characteristics), which should differ depending on the applied correction method. Thus, randomly declared additional deaths (Method 1) should be, on average, younger and healthier because this correction method does not take any respondent characteristics into account. In contrast, Method 2 and Method 3 should select, on average, older and less healthy respondents and declare these as dead as here respondent characteristics are taken into account.

In a second step, we carry out an additional analysis to investigate possible attrition effects (sub-chapter 4.2). For this purpose, we compare (alive) respondents that participated in the seventh wave of SHARE to non-respondents who are either known to be alive or for whom their vital status is unknown. To test the effect of unreported deaths on attrition, we carried out two consecutive comparisons, first with the uncorrected sample and afterwards with the respective sample that was corrected based on one of the three correction methods. These comparisons that are also based on respondents' answers from Wave 1 are made because we expect that unreported deaths might bias attrition analyses. Accordingly, in the first comparison with no correction of unknown vital status, we expect significant differences between the considered cases that should decrease when using a corrected sample in the second comparison. In this respect, we expect that differences are getting smaller the more information on panel members with unknown vital status is used to declare them dead. With this proceeding, we hence can examine how (alive) respondents differ from non-respondents and hence how severe systematic attrition is or rather if (and to which degree) it can be reduced when applying different correction methods regarding unreported deaths.

4.1 Effect of unreported deaths on mortality analyses

Table 6 shows the Wave 1 characteristics of the reported deaths in Wave 7 (first column) compared to reported and additional deaths identified via the three correction methods, again applying a Bonferroni correction that account for multiple comparisons. Similar to the

previous chapter with respect to accuracy, the random allocation of deaths (Method 1) is not capable to reflect the sociodemographic characteristics and health conditions (as reported in Wave 1) of the known deaths. Based on this correction method, sample members who have been additionally declared dead are more likely to be younger, better educated, live together with a partner, report a better health, and are more socially as well as cognitively active (i.e. have better numeracy, reading and writing skills). Further, these persons are less frequently retired, have fewer chronic diseases, physical limitations or indications of a depression, and less frequently stayed overnight in hospital. These findings clearly reflect the allocation procedure, where sample members with unknown vital status are randomly selected from a large group of people, who – although already aged 50 years and older in Wave 1 – are mostly in sufficient health. In contrast, Method 2 and Method 3, which both use additional information, are much better suited to reflect the sociodemographic characteristics and health conditions (as stated in Wave 1) of reported deaths. For both correction methods, most differences compared to reported deaths are not significant. This can be seen as an indication that both methods are able to identify rather well those sample members that are more likely to die. Overall, Method 2, which only uses region-, sex- and age-specific mortality rates, is even slightly better suited to minimize the differences for the characteristics considered in Table 6 than Method 3, which explicitly models death by using internal data. This can be seen when comparing the absolute standardized bias across all characteristics at the bottom of Table 6 (abs. standardized bias = 0.9 for Method 2 compared to 1.1 for Method 3), although both methods lead to very similar results.

Table 6: Mean characteristics of reported deaths compared to corrected samples of reported and additionally declared deaths in Wave 7

	Reported deaths	Method 1: Random	Method 2: Mortality	Method 3: Individual information
Age (years)	86.7	84.1***	87.9***	87.4**
Female (%)	49.7	51.4	51.5	49.0
Education				
low (%)	52.0	46.0***	49.8	48.8**
medium (%)	34.9	39.1***	37.2	38.2**
high (%)	13.1	14.9*	13.0	13.0
Partner living in household (%)	56.6	61.2***	56.1	56.3
Urban area (%)	53.4	53.1	53.4	53.6
Born abroad (%)	6.9	8.1	7.9	8.7**
Retired (%)	67.5	61.1***	69.5	69.6
Ability to make ends meet (%)	59.2	60.7	61.2	59.6
Self-rated health				
very bad/bad (%)	22.2	19.0***	21.1	23.5
fair (%)	38.0	35.9	38.5	39.7
good/very good (%)	39.9	45.1***	40.4	36.8**

Chronic diseases (%)	59.3	54.1***	59.2	60.6
Limitations in ADL (%)	24.2	20.2***	23.4	24.7
Limitations in mobility (%)	69.9	64.1***	70.1	71.9
Stayed overnight in hospital (%)	21.6	19.5*	21.2	22.6
Depression (%)	35.5	32.7*	34.6	35.8
Socially active (%)	34.4	37.3**	34.3	32.7
Numeracy score (0-100)	45.5	48.2***	45.8	45.3
Self-rated reading skills (0-100)	55.5	58.0***	55.7	55.0
Self-rated writing skills (0-100)	50.2	53.1***	50.5	49.5
Absolute standardized bias (avg.)	-	*2.4*	*0.9*	*1.1*
N	4917	6339	5990	6055

Notes: Significance tests (based on two-sided t-tests) between original sample with reported deaths and the different correction methods.
Significance level: ***: p<.001, **: p<.01, *: p<.05.

4.2 Effect of unreported deaths on attrition analyses

In addition to compare reported and additional declared deaths, a comparison between (alive) respondents that have been interviewed in Wave 7 and non-respondents with unknown vital status can give further insights on how severe systematic drop-out in SHARE is and to what extent attrition analyses are affected by unreported deaths. In this respect, Table 7 shows many significant differences between respondents and non-respondents regarding their Wave 1 characteristics when not applying any corrections to sample members with unknown vital status (second column titled “No correction”). On average, panel members who did not participate in Wave 7 in the uncorrected sample including unreported deaths are more likely to be older, male, obtain a medium educational degree, live in an urban area, are born abroad and have retired. In addition, non-respondents with unknown vital status in the uncorrected sample report worse health, more physical limitations and chronic diseases, are less socially active and show a lower cognitive performance.

The differences between these two comparison groups can be explained in large part by the fact that a certain number of actually deceased sample members could not have been contacted and hence have not been reported as dead and therefore remain in the sample with unknown vital status. Similar as above, the random allocation (Method 1) yields virtually the same results. When using Method 2 or Method 3 to correct the sample by declaring people as deceased based on additional information, most differences can be reduced to at least a certain degree. In contrast to the analyses of reported and declared deaths above, now Method 3, which models death explicitly by using a broad range of individual characteristics, works best (abs. standardized bias = 4.1). But even with this correction method, most differences remain statistically significant. Thus, the remaining sample members with formerly unknown vital status are more likely to be younger, have more often a medium educational degree and a partner living in the household, live in urban areas, are born abroad and are able to make ends meet. In addition, they report less physical limitations and chronic diseases,

have fewer indications of a depression, are more socially active, while their cognitive performance is slightly lower. Interestingly, for some characteristics the difference between respondents and non-respondents of unknown vital status vanishes nearly completely. This is true, for example, for self-reported health or being retired. On the other hand, it can be seen that characteristics that are known to be strongly correlated with attrition, such as level of education or migrant background (e.g. Bristle, Celidoni, Dal Bianco, & Weber, 2019; Uhrig, 2008; Watson & Wooden, 2009), show the largest differences.

Table 7: Comparison between (alive) respondents and non-respondents with unknown vital status in Wave 7 before and after correction of unreported deaths

	(Alive) respondents	No correction	Method 1: Random	Method 2: Mortality	Method 3: Individual information
Age (years)	73.3	74.4***	74.4***	72.8***	72.9*
Female (%)	57.4	56.5	56.4	56.2	57.6
Educational degree					
low (%)	32.4	25.8***	25.8***	24.5***	24.9***
medium (%)	43.2	53.2***	53.2***	53.7***	53.3***
high (%)	24.4	21.0***	21.0***	21.8***	21.8***
Partner living in household (%)	78.2	79.3	79.6	81.6***	81.6***
Urban area (%)	50.7	54.5***	54.8***	54.6***	54.5***
Born abroad (%)	5.7	10.8***	10.6***	10.6***	10.2***
Retired (%)	35.2	38.4***	38.3***	34.7	34.5
Ability to make ends meet (%)	60.3	68.3***	68.6***	68.1***	69.0***
Self-rated health					
very bad/bad (%)	5.4	7.5***	7.4***	6.7**	5.4
fair (%)	24.1	26.3**	26.0*	25.0	24.3
good/very good (%)	70.6	66.2***	66.6***	68.3**	70.3
Chronic diseases (%)	35.7	36.0	36.0	34.0	33.1**
Limitations in ADL (%)	5.7	6.9**	6.9**	5.7	4.9
Limitations in mobility (%)	42.2	42.6	42.4	40.0*	38.9***
Stayed overnight in hospital (%)	10.2	11.3	11.1	10.6	9.8
Depression (%)	22.8	21.9	21.7	21.1*	20.5***
Socially active (%)	56.5	52.2***	52.8***	53.8**	54.8
Numeracy score (0-100)	61.1	59.5***	59.8**	60.6	61.0
Self-rated reading skills (0-100)	69.4	67.4***	67.5***	68.3*	68.8
Self-rated writing skills (0-100)	66.1	63.4***	63.5***	64.5***	65.1
Average abs. standardized bias	-	*5.4*	*5.1*	*4.5*	*4.1*
N	9399	12,880	11,458	11,807	11,742

Notes: Significance tests (based on two-sided t-tests) between original sample with reported deaths and the different correction methods.
Significance level: ***: p<.001, **: p<.01, *: p<.05.

5. Conclusion

Attrition is one of the central challenges for longitudinal studies as substantial drop-out of respondents can lead to biased conclusions. However, the mere number of respondents who drop out over time in a panel study might overestimate the problem at hand. Especially in studies of the elderly, the death of respondents is a natural process that should be taken into account properly. This article examined different correction or imputation methods to adjust for unreported deaths in SHARE. Mortality rates are used to estimate the number of unreported deaths among people with unknown vital status, already accounting for one third of the whole sample in Wave 7. Our results indicate that using additional information on respondents helps to predict which people are more likely to die during the survey. In this respect, it could be shown that the use of age-, sex- and region-specific mortality rates that can be calculated from publicly available population figures or life tables is already sufficient to select plausible cases from the sample of panel members with unknown vital status. Using more individual information on respondents from their first interview only marginally improve these results (if at all), while a random allocation of sample members is not able to predict unreported deaths and thus should not be used. When applying the life-table approach or modeling death on available respondent characteristics, the large fraction of sample members in SHARE with unknown vital status can be adjusted by about 3000 deaths in total. As the number of respondents with unknown vital status increases with every further wave, adjustments of unreported deaths are getting more and more important when doing both mortality analyses with deceased sample members as well as attrition analyses with the remaining sample of participating respondents. In the latter case, our findings reveal that at least some of the occurring differences were caused by unreported deaths and can be reduced after adjusting the sample for these cases. By comparing the corrected sample with formerly unknown vital status to the participating respondents in Wave 7, we saw that differences in general got smaller and in some instances (e.g. self-reported health or cognitive performance) even disappeared when using available respondent characteristics.

Of course, our proceeding has limitations. First, we still do not have consistent external data for all countries that could hold as a gold standard to check if we were able to identify the correct cases that really have died. For this purpose, national mortality or death registers are certainly the best option. However, as most European countries do not have such registers or access to such sources is not always possible, the two correction methods that use additional information from life tables (Method 2) or internal information about respondents' individual characteristics (Method 3) can be seen as a good starting point to adjust unreported deaths in SHARE. Second, the used methods have to assume that the result of having an unknown vital status is not selective or at least that it is independent when using additional information as in Method 2 and Method 3 (missing at random assumption; see Rubin, 1976, 1987). Although applying this assumption is common practice in survey research when dealing with unknown eligibility (see Smith, 2009), it should not be taken for granted. However, the

presented comparison with the high-quality Danish death register in this paper at least points in the direction that selectivity might be less problematic and that reported deaths in SHARE are not substantially different from mortality data based on official death registers.

Given the small sample size of our validation analysis with the Danish death register as gold standard, additional comparisons with other available mortality registers are highly encouraged and should be one of the next steps. Further, as this paper only investigated the general possibility of adjusting unreported death, we should think about using these findings in a transparent way to construct valid imputations or weighting factors that account for missing deaths. As mortality is mostly used as a left-hand side variable, this is far from trivial and might create a tautology problem when right-hand side indicators are used to construct left-hand side variables of interest. On the other hand, this would be especially valuable for researchers that are interested in mortality analyses using the rich data that are available in SHARE from previous panel waves, but so far have been forced to exclude a large part of respondents with unknown vital status in their analyses.

Appendix

A1: List of respondent characteristics in Wave 1 used for analyses

	Mean	Min	Max	N
Age (years)	63.85	30	103	27,967
Female (%)	55.52	0	100	27,967
Educational degree				
low (%)	33.39	0	100	27,888
medium (%)	46.08	0	100	27,888
high (%)	20.52	0	100	27,888
Partner living in household (%)	74.44	0	100	27,967
Urban area (%)	53.03	0	100	27,967
Born abroad (%)	8.15	0	100	27,914
Retired (%)	43.15	0	100	27,967
Ability to make ends meet (%)	63.56	0	100	27,561
Self-rated health				
very bad/bad (%)	9.48	0	100	27,838
fair (%)	27.92	0	100	27,838
good/very good (%)	62.60	0	100	27,838
Chronic diseases (%)	40.63	0	100	27,823
Limitations in ADL (%)	9.78	0	100	27,825
Limitations in mobility (%)	47.84	0	100	27,822
Stayed overnight in hospital (%)	12.79	0	100	27,783
Depression (%)	24.77	0	100	27,239
Socially active (%)	50.29	0	100	27,967
Numeracy score (0-100)	57.32	0	100	27,723
Self-rated reading skills (0-100)	65.70	0	100	27,840
Self-rated writing skills (0-100)	61.71	0	100	27,840

Data: SHARE Release 7.0.0; unweighted.

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