Estimating Differential Mortality from EU-SILC Longitudinal Data

Additional Technical Information

FACTAGE – WP 4
Deliverable 4.3

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Statistics Austria

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Preface

This report was written by Senior Researchers of Statistics Austria, which is one of five members of the FACTAGE project consortium. FACTAGE is a project funded in the framework of the first call of the Joint Programming Initiative 'More Years, Better Lives' ('Extended Working Life and its Interaction with Health, Wellbeing and beyond'). FACTAGE is funded nationally by the Austrian Federal Ministry of Science, Research and Economics. Details regarding the project can be found at http://www.factage.eu. Details regarding the Joint Programming Initiative can be found at www.jp-demographic.eu.

This report is the final in a series of three reports to be produced in FACTAGE Work Package 4. It contains the additional technical details on estimating differential mortality from EU-SILC longitudinal data, together with some discussion points on future research. To get the most out of this report we strongly encourage reading the first two reports, since it is based on those and refers to them heavily.

This report was reviewed within the FACTAGE project consortium by University Koblenz-Landau. Of course, any errors are solely the authors' responsibility.

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Keywords

Mortality; Socio-economic status; EU-SILC; Longitudinal Data; Europe.

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Abstract

This is the last report in a series of three reports dealing with estimation of differential mortality from EU-SILC longitudinal data. Here we provide additional technical information on the subjects that were not yet solved in the first report (Klotz and Göllner 2017). We strongly encourage reading the first two reports to get the most out of this third report.

The report covers three chapters: First we check validity of mortality information from EU-SILC data by benchmarking and validation of mortality rates broken down by age, sex, calendar year, country and highest educational level completed. Then we give an outlook on open topics for future research, such as weighting of observations and transformation from hazard ratios to life expectancy gaps, for which some preliminary findings are available. Finally, since the UDB longitudinal data received an overhaul since publication of our first report we present an improved software code, this time implemented in R and not in SAS. This change in statistical software - hopefully - broadens the potential user base, seeing that R is open source and free of charge. We highlight the changes in data structure and how this affects our methodology.

1. Benchmarking and Validation

1.1. Internal Validation of Mortality Hazard Ratios

The FACTAGE method of estimating mortality differences between socio-economic groups uses EU-SILC longitudinal sample survey information on respondents' vital status (Klotz and Göllner 2017). Given that demographic statistics are usually based on high-quality population estimates and mortality register data, a key issue is the quality of such sample survey information. We have checked the data both internally, by looking at typical mortality patterns within the EU-SILC data, as well as externally, by comparing figures with external benchmarks. First we present the internal validation.

The data on which our estimates below are based is the same which was used in Klotz, Göllner and Till (2019), for estimation of relative mortality risk of Europeans classified as "severely materially deprived". Their data contain some 1.8m person years-lived by 740,000 distinct individuals aged 35-79 years, whereof 14,000 died in the follow-up period.

From a good mortality datasets one would expect that

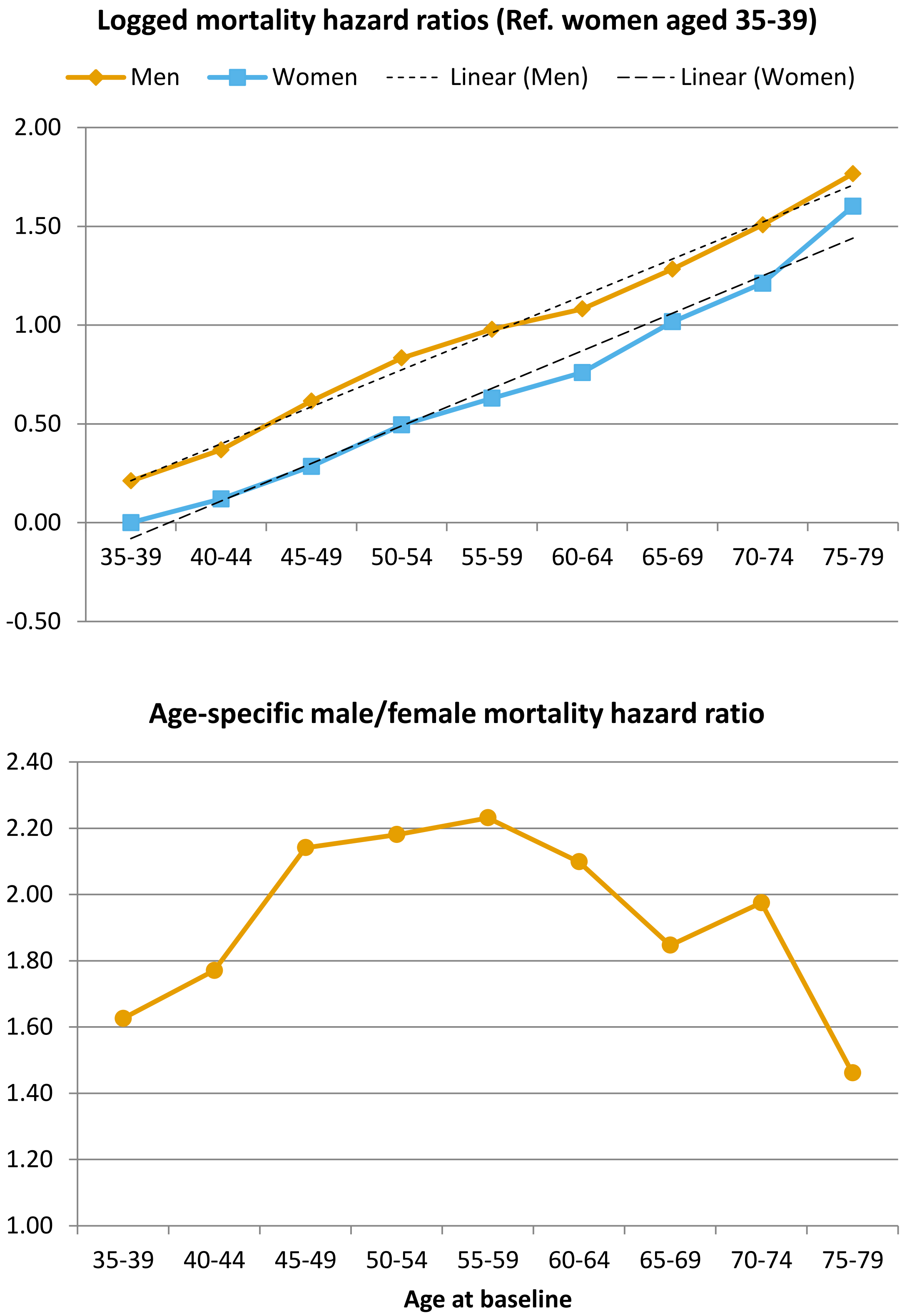
- males have a mortality risk higher than females,
- mortality rates increase exponentially with age,
- mortality risk decreases over time, with some mitigation after 2010 (OECD/EU 2018), and
- the ranking of countries resembles official figures on life expectancy.

In the following we test these expectations by estimated mortality (Cox regression) hazard ratios from our dataset.

By sex and age

In the upper panel of Figure 1 we can see that men in our sample constantly exhibit a greater mortality hazard than women. Even though the lines never intersect we see that the interval between them varies. To examine these differences between the sexes we drew the age-specific male to female mortality hazard ratio in the panel below. We can observe that the relative differences start out relatively low in the younger ages, reach a maximum at around 55-59 years and then drop again. Both findings are in agreement with demographic figures for most European countries.

Figure 1. Internal validation of mortality hazard ratios by sex and age.



Source: Statistics Austria.

We also see from Figure 1 that the “Gompertz” law of mortality risk increasing exponentially with age (at least for the age band considered here) is very well reflected in our data. To illustrate this further, the upper panel contains also log-linear trend lines of estimated mortality risk.

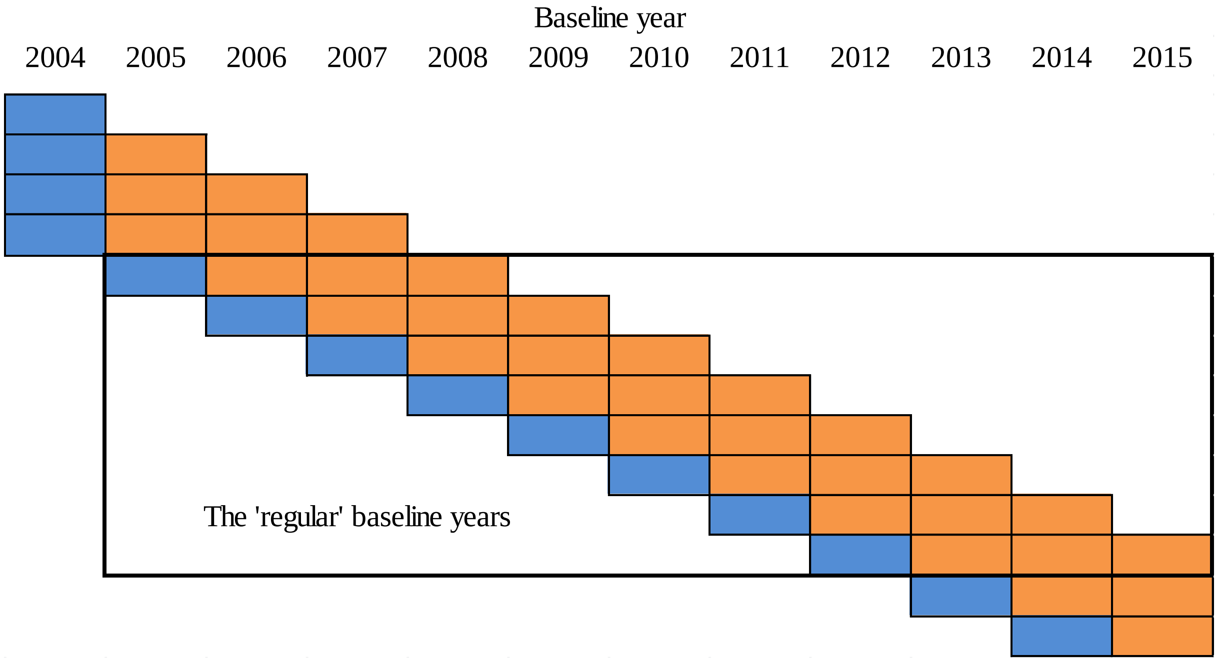
By baseline calendar years

Valid mortality data should come with a decrease in mortality risk over time (controlling for age), possibly with some slowdown in the decrease after 2010 (OECD/EU 2018; section “Trends in life expectancy”). We can test this with the FACTAGE data by estimating mortality hazard ratios for baseline calendar years. This was done by Klotz, Göllner and Till (2019), yielding a 0.96 hazard ratio for a continuous calendar year covariate, which in fact indicates a decrease of mortality risk of around 4 percent over time. For an accurate calculation however, some modifications are in order.

First, we exclude the countries where the scheduled follow-up period is not four years (France, Luxembourg, and Norway). Then we restrict the baseline calendar years for the remaining countries to “regular” years, meaning that each year a quarter of the sample is refreshed and then observed the entire follow-up period. Thus, we exclude the first baseline year in which parts of the sample are not scheduled to be followed-up four years, and the latest baseline years in which the four-year panel has not yet been completed. Figure 2 illustrates this for a country starting the longitudinal component of EU-SILC in 2004 and with mortality information available until 2015. [1] The reasoning is that survey response is correlated with health, which matters especially in the first year of follow-up (Klotz et al. 2018). For non-regular baseline years mortality risk in the follow-up period would thus be confounded by sample selection.

[1] The regular baseline years start with 2004 in GR; 2005 in AT, BE, EE, ES, FI, IT, PT, SE; 2006 in CY, CZ, HU, LT, LV, NL, PL, SK, UK; 2007 in MT; 2008 in RO, SI; and 2011 in HR. They end with 2011 in FI, MT, UK; and 2012 in all other countries.

Figure 2. Baseline years in EU-SILC.

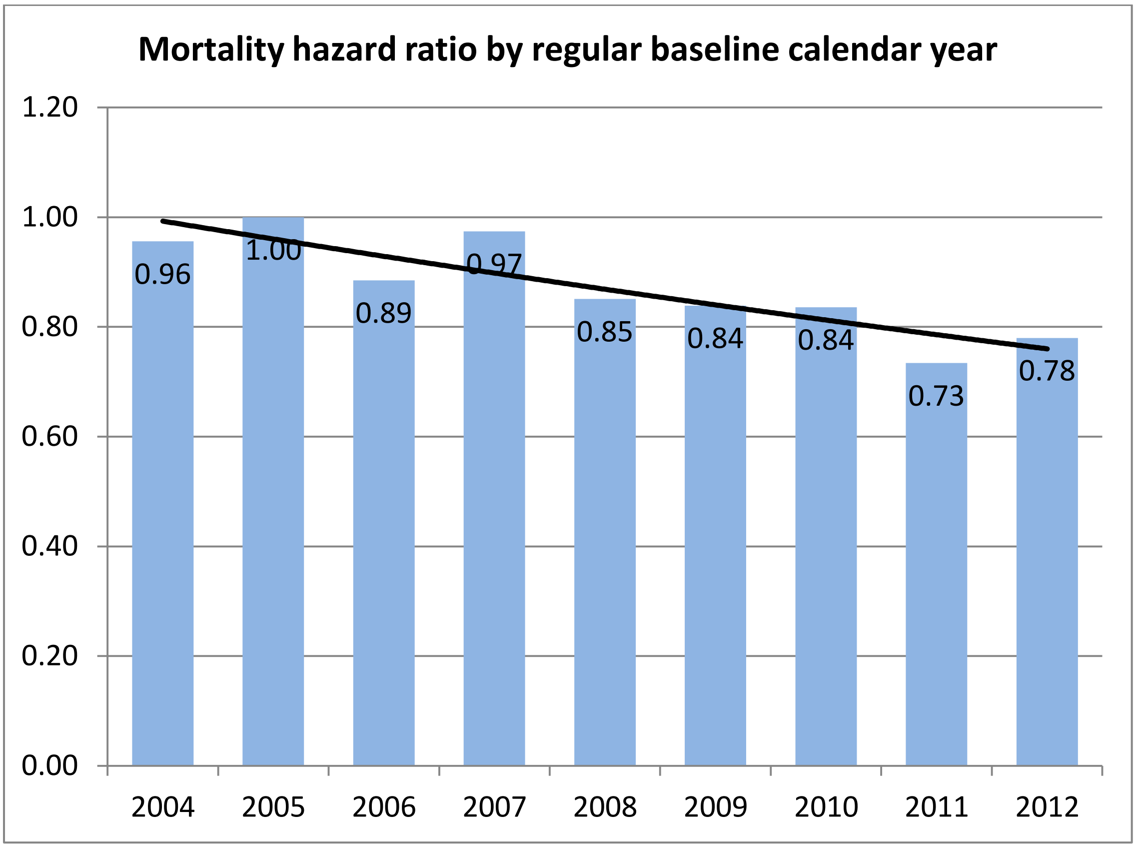


Source: Statistics Austria, redrawn after EU-SILC Methodological Guidelines.

Applying this filter rule to the data used in Klotz, Göllner and Till (2019), the remaining sample contains 447,880 observations and 9,700 deaths. We estimated a Cox regression model with calendar year as a categorical predictor, controlling for age, sex and country. Baseline year estimates are contrasted with 2005. Hazard ratios are given in Figure 3, including an exponential trend line.

In general, the decline of mortality risk over time in the general population is confirmed by tendency of declining mortality hazard ratios in the FACTAGE data. Compared to the reference category baseline year 2005, estimated hazard ratios are between 0.9 and 1.0 for baseline years 2004 and 2007, between 0.8 and 0.9 for 2006 and 2008-2010, and below 0.8 for 2011-2012. We do not observe a slowing of mortality reduction for the latest years, however the time series is short and subject to random fluctuations.

Figure 3. Internal validation of mortality hazard ratios by calendar years.



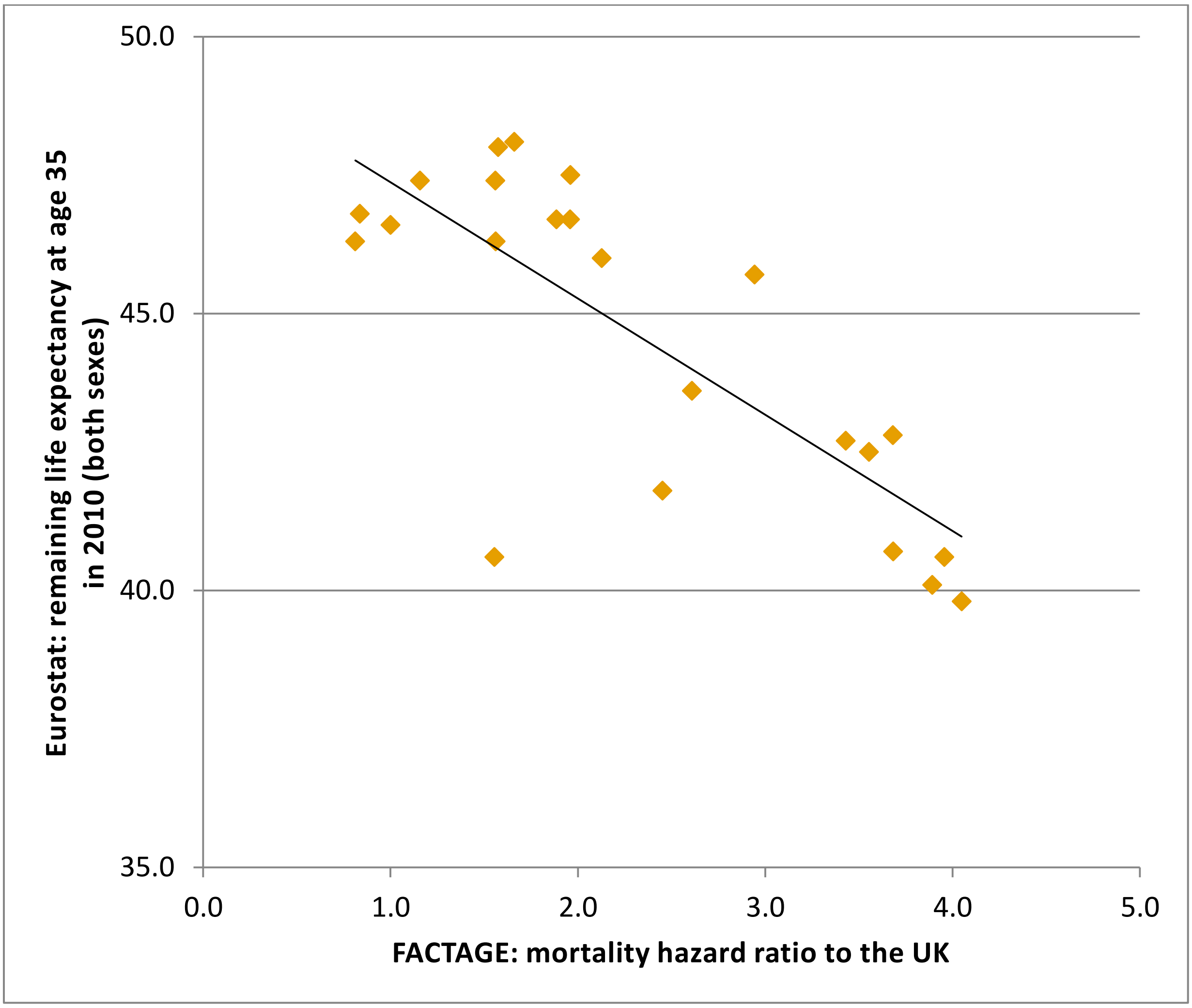
Source: Statistics Austria.

By countries

To assess the quality of mortality hazard ratios per country, we calculated two correlation coefficients, again using the same data as above. We extracted the remaining life expectancy at 35 years values from Eurostat as published in 2010 and created a ranking of countries of this measurement. Then we calculated the mortality hazard ratios for each country (UK being the reference[2], so 1), and ranked them accordingly. To account for different starting years in the countries we included them into the model.

[2] Any other country would also be possible as the reference. The selection of UK as the reference is arbitrary and has no impact on the results.

Figure 4. Internal validation of mortality hazard ratios by country.



Source: Statistics Austria.

A scatterplot of the data is given in Figure 4. The Pearson correlation coefficient is -0.78 and the Spearman rank correlation coefficient is -0.69. Data quality is doubtful for Romania (the dot in the lower left corner). Excluding Romania, the correlation coefficients are -0.88 and -0.81, respectively.

Conclusion

Our findings indicate that the EU-SILC longitudinal survey sample data are a valid data source for estimating relative mortality differences between men and women, by age and over time. In general, this holds also for comparisons between countries. Even if the absolute mortality level may be downwardly biased due to non-coverage of the institutionalized population and health-related nonresponse (Klotz and Göllner 2017, Klotz et al. 2018), the relative disparities between basic demographic groups can be measured accurately.

1.2 Benchmarking: ranking of EU countries by educational mortality gap

The ultimate goal of the FACTAGE method of mortality estimation is to assess the mortality gap between socio-economic groups. Among the many socio-economic variables available in EU-SILC is also the highest educational level completed (target variable PE040; ISCED-97 coding until 2013, ISCED-2011 coding from 2014 onwards). Many comparative international studies on country-specific mortality gaps by educational level are available, often based on population register data, at least for some countries (Mackenbach et al. 2016, Murtin et al. 2017, Corsini 2010). The question is now how well the ranking of countries obtained by such high-quality data is reflected in mortality hazard ratios estimated from FACTAGE data. This will serve as our external validation.

For that purpose, we extracted data on life expectancy by educational level from the Eurostat webpage (data on life expectancy by age, sex and educational attainment level [demo_mlexpecedu], accessed on 24 May 2018). Figures on 19 countries (16 EU countries plus Norway, North Macedonia and Turkey) are available from 2007 earliest to 2015 latest, broken down by sex and age. We calculated the average life expectancy gap in years between people with tertiary education and people with less than primary, primary and lower secondary education, for men and women separately. Life expectancy increases with educational level across all populations; the difference ranges from 1.8 years for women in Malta to 16.3 years for men in Estonia.

Note that the FACTAGE method uses data from 2003 to 2015, although the actual starting years of the survey are country-dependent. Note also that Eurostat, in its calculation, assumes equal mortality rates by educational group from age 75 onwards (Corsini 2010), and that the fraction of the population not living outside private households (and thus not covered by EU-SILC) is generally small below 80 years of age. It is thus reasonable to assume that the hazard ratios estimated by the FACTAGE method (age at baseline 35-79 years) and the Eurostat life expectancy gaps refer essentially to the same populations. In other words, the ranking of countries by the educational mortality gap obtained by the FACTAGE method should resemble, apart from chance fluctuations, the ranking of countries in the Eurostat data.

As mentioned in earlier reports (Klotz and Göllner 2017; Klotz, Göllner and Till 2019), data quality in the EU-SILC UDB longitudinal data is country-specific and the FACTAGE method should not be used without question for any country-specific analysis. A rule of thumb to guard against low data quality is to exclude countries with a death count of less than 500 from country-specific analyses. So hazard ratios are estimable for 12 countries with the FACTAGE method, namely Czechia, Estonia, Spain, Finland, France, Greece, Hungary, Italy, Lithuania, Latvia, Poland and Slovenia. For eight out of these twelve countries, Eurostat figures on the educational life expectancy gap are available (all but Spain, France, Lithuania and Latvia).

Table 1. Comparison of mortality hazard ratios and their ranks between FACTAGE and Eurostat.

	FACTAGE Mortality hazard ratio of ISCED 0-2 to ISCED 5+, cumulative EU-SILC longitudinal data 2003-2015				**Eurostat** Difference in life expectancy years between tertiary and lower secondary or less educated, average 2007-2015			
	Men		Women		Men		Women	
Country	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Czechia	2.32	5	1.24	1	15.2	7	4.1	5
Estonia	2.82	8	2.21	7	16.3	8	9.2	8
Finland	1.96	2	1.41	3	6.6	3	3.9	3
Greece	2.68	6	1.53	4	6.0	2	2.2	1
Hungary	1.99	3	2.39	8	12.8	6	5.7	7
Italy	1.58	1	1.26	2	5.0	1	2.8	2
Poland	2.00	4	1.88	6	12.7	5	5.4	6
Slovenia	2.81	7	1.85	5	9.2	4	3.9	3

Source: Statistics Austria and Eurostat.

Table 1 compares the mortality hazard ratios estimated by the FACTAGE method with the Eurostat figures on life expectancy gaps. Countries are ranked by ascending figures. Accordance is generally high, with rank correlation coefficients of 0.73 for men and 0.64 for women (admittedly, a sample of eight countries is small). Rather large rank deviations are observed for Greece, where the FACTAGE method indicates a worse position than the Eurostat life expectancy differences, and for Czechia, where the opposite holds.

To conclude, the country ranking (in terms of socio-economic mortality gap) published by Eurostat is mostly reflected in the FACTAGE data, albeit with a smaller degree of accordance than observed for the disparities mentioned in 1.1.

2. Further Outlook

This section is dedicated to future research needed in the context of socio-economic mortality research based on EU-SILC longitudinal data. We hope that even after the expiration of the FACTAGE project, we will find time to continue research on this topic, and that our work has inspired other scholars to do so. We present ideas on how to deal with certain open issues and give some examples.

2.1. Weighting of observations

EU-SILC is a sample survey with unequal sampling fractions per country and—as any survey has in practice—nonresponse, so its observations have to be properly weighted for unbiased estimation. Besides correction of unequal sampling probability and nonresponse, weights are often necessary to account for complex sampling designs. Also, weights are usually calibrated to known external distributions (such as sex and age groups) to smooth out random fluctuations in the drawn sample. In the case of EU-SILC, additional weighting is required for the subsample of selected respondents (in those countries which apply it) and for the longitudinal component, conditional on its length (two-, three-, and four-year weights).

According to the Commission Regulation on sampling and tracing rules (EC No 1982/2003,§7.4): "*Weighting factors shall be calculated as required to take into account the units' probability of selection, non-response and, as appropriate, to adjust the sample to external data relating to the distribution of households and persons in the target population, such as by sex, age (five-year age groups), household size and composition and region (NUTS II level), or relating to income data from other national sources where the Member States concerned consider such external data to be sufficiently reliable*."

The FACTAGE method is somewhat special in that it a) pools data over several longitudinal releases, b) calculates a vital status indicator and a time-at-risk variable by comparing information from different survey waves for the same individual, and c) estimates relative mortality risks in a multivariate nonlinear regression model. It is thus not clear which weighting is appropriate.

Theoretically, cross-sectional weights for households, persons and selected respondents are available in the UDB data, but they do not take into account if a respondent is to be and can actually be traced in the following years. Longitudinal weights, on the other hand, are nonzero only if a respondent was actually re-interviewed and are zero if a respondent died between two survey waves, so they cannot be used for our purposes either.

The task is to construct special weights which allow for unbiased (and hopefully efficient) estimation when applying the FACTAGE method. For that purpose, we have to clarify some points from the outset:

Although the principal guidelines of weights construction should be applied by all participating countries, in practice there is variation in weights construction and the exact procedures applied by countries are only partly known to the external researcher. Then, since the FACTAGE method estimates a regression coefficient (precisely, a mortality hazard ratio), it is sufficient to know relative weights (observation A has a weight twice as high as observation B) rather than absolute weights; the total of weights is not of interest for our purposes. Furthermore, it is not necessary that the weights allow for unbiased estimation of general mortality levels, but it is sufficient that relative mortality risk (the ratio of mortality rates between socio-economic groups) is estimated unbiasedly.

Which weights are available in the longitudinal data of the UDB? [3]

- DB080 “Household design weight”: No.
- DB090 “Household cross-sectional weight”: Yes.
- DB095 “Household longitudinal weight”: Yes.
- RB050 “Personal cross-sectional weight”: No.
- RB060 “Personal base weight”: Yes.
- RB062 “Longitudinal weight (two-year duration)”: Yes.
- RB063 “Longitudinal weight (three-year duration)”: Yes.
- RB064 “Longitudinal weight (four-year duration)”: Yes.

Follow-up of a single survey wave

Let us first look at the case when we do not pool data over several releases, i.e. when only one annual EU-SILC survey is taken as the baseline and followed up for vital status and time at risk information. When executing the software code provided (Göllner and Klotz 2018), this is achieved by specifying the same calendar year as `yr_from` and `yr_to` (SAS code) or as `year_from` and `year_to` (R code).

Then the data applied in the FACTAGE method is essentially a subsample of the cross-sectional EU-SILC sample of the baseline calendar year: out of the original sample, we exclude those respondents which are not to be re-interviewed in following years[4] (mostly because they have completed the four year panel). For the remaining part (usually three quarters) of the sample, we add two additional variables, namely the vital status indicator (died or censored) and the time at risk between the survey and either death or censoring. Respondents do not actually have to be re-interviewed; what matters is that their vital status and time at risk can be assessed.

Although the FACTAGE method uses UDB longitudinal data, it is not a longitudinal analysis of EU-SILC data in a proper sense because no changes in socio-economic status are measured[5], but only the vital status is actually followed up. This can be further illustrated by

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[3] Of course, if you are applying for data at Eurostat you can probably request cross-sectional weights for your data extraction. By default cross-sectional weights are not included in longitudinal data.

[4] In the new R code this is done via the `setEligibility()` function.

[5] Note that in both codes (SAS and R) you can of course build your own longitudinal variables, e.g. by calculating a mean over all measurements for income per person. Analyses with such longitudinal variables was out of scope in this report series, but we strongly encourage further development in this regard.

an alternative linkage of EU-SILC records with mortality information from national mortality registers. In that case, one would actually use the cross-sectional EU-SILC sample of the baseline calendar year (which of course does contain proper cross-sectional weights) and add the two variables.

The following recommendations are guided by the American "Analytic Guidelines for NCHS 2011 Linked Mortality Files" (NCHS, 2013). For each record in the original cross-sectional sample, one constructs a follow-up eligibility status indicator, which is a binary variable indicating if this record is eligible for follow-up (1) or not (0). In the case of EU-SILC, non-eligibility essentially means that a household has completed the maximum number (usually four) of survey waves and is thus no longer to be re-interviewed, but may cover also other cases such as loss of contact, refusal to further cooperation, or on the person level, movement of a household members to a non-sample household. Then the total of ones in the follow-up eligibility status column divided by the original sample size is the fraction of records which are actually followed up, and its reciprocal value is a weight inflation factor to correct for non-eligibility.

For example, if in a country the EU-SILC panel duration is four years and no other factors other than scheduled withdrawal from the panel influence follow-up eligibility, then the weight inflation factor accounting for eligibility of mortality follow-up is 4/3. If the panel duration is eight years, then the weight inflation factor is 8/7.

The advantage of using the weight inflation factor is that the original weight construction method applied by the country (design weights, adjustment for nonresponse, post-stratification, etc.) which is summarized in the personal cross-sectional weights (target variable RB050) is still in use. Of course, if in a country only selected respondents are interviewed, then the weight inflation factor has to be applied to their weights.

Table 2 gives an example for an arbitrary dataset with five observations for two countries. Note the country-specific weight inflation factors, corresponding to different panel durations (8 years in Norway, 4 years in Portugal). In the very right column, the newly constructed weights are scaled to a mean of 1, which can be easily compared to the scaled cross-sectional weights column.

Table 2. Possible weight construction for the FACTAGE method.

Country	Cross-sectional weight	Scaled cross-sectional weight	Weight inflation factor	New weight	Scaled new weight
NO	450.58	0.944	1.143	514.95	0.799
NO	933.12	1.955	1.143	1066.42	1.656
NO	801.17	1.678	1.143	915.62	1.421
PT	251.88	0.616	1.333	335.84	0.521
PT	290.95	0.711	1.333	387.93	0.602

Source: Statistics Austria.

Pooling of several survey waves

The FACTAGE method constructs the final dataset in such a way that an individual is included only once: each row corresponds to a distinct person, followed after the first survey when this person was part of the EU-SILC sample. This guarantees that the weights which have been inflated to account for eligibility of follow-up of the first interviewees of each survey wave can straightforwardly be used in the pooled dataset too: one constructs the follow-up eligibility status indicator and calculates the weight inflation factor for each survey wave, and then simply pools observations with this weight over all survey waves of interest. As discussed above, the absolute weights do not matter, but it is the relative weights that matter in the Cox regression model.

To avoid confusion, one may scale the final weights to a mean of 1.[6] Note also that the importance of an observation in parameter estimation depends not only on the baseline weight, but also on the time at risk observed in the follow-up period.

Other methods

If the cross-sectional weights are not available and/or weight inflation factors cannot be constructed, then one may apply a simplified weighting which was invented by Klotz, Göllner and Till (2019). This method does account for country-specific sampling fractions and if a country interviews all household members or only selected respondents in the personal questionnaire, but refrains from further weight calibration.

The idea is to take available population figures and calculate uniform weights per country (possibly conditional on sex and age group) in such a manner that the total of weights matches the known population totals. For example, Klotz, Göllner and Till (2019) took the sex-specific population totals from the latest 2010/2011 European census round (which is approximately the midpoint of their observational period) from the Eurostat website and calculated weights accordingly. Note that such weights are calibrated to the total population, whereas in fact the EU-SILC target population is the population in private households. However, this is of minor importance when the analysis is restricted to respondents younger than 80 years.

This alternative approach is relatively easy to implement. Its major disadvantage is that it does not exploit the information (such as on sampling design or nonresponse) which is implicitly available in the given cross-sectional weights.

[6] In SAS this is automatically done by specifying the `normalize` option in the `weight` statement of the `phreg` procedure. In R one can standardize weights in many different ways, one possibility is the `standardize()` function of the `jtools` package.

2.2. Transformation of hazard ratios into life expectancy differences

As indicated in the first report (Klotz and Göllner 2017), the EU-SILC longitudinal UDB data does not allow for direct estimation of life expectancy by socio-economic group because firstly, it does not contain the exact age of respondents aged 80 and over and secondly, mortality rates are biased due to non-coverage of the institutionalized population and health-related nonresponse. One can, however, estimate relative mortality risks up to ages 79 relatively accurately as long as one does control for country effects. But relative mortality risks (such as hazard ratios) are not as descriptive and politically relevant as life expectancy differences. As pointed out by Dalkhat M. Ediev in personal communication, "Absolut or relative difference? What really matters is the difference in years of life expectancy—and when it comes to insurance, maybe some discounted life expectancy". The question is thus what can be said about life expectancy differences[7] based on mortality hazard ratios estimable from EU-SILC data.

Regression parameters

First, a rule of thumb. Any reasonable model on relative mortality risks does control for age, since mortality disparities between populations which are only the result of different age distributions are not of interest to the social scientist. In our second report for example (Klotz, Göllner and Till 2019: p. 41), we estimated a Cox regression model for mortality explained by age, sex, calendar year and severe material deprivation. Key findings are reproduced here in Table 3. The mortality hazard ratio for an additional year of age at baseline was estimated to be 1.10, and the mortality hazard ratio for being severely materially deprived (compared to being not deprived) was estimated to be 1.69. The age effect cumulates multiplicatively, so when being two years older at baseline, mortality risk increases by 1.21 (= 1.1x1.1), when 3 years older at baseline by 1.33, and so on. But this means we can find the age difference which is statistically equivalent, in terms of increased mortality risk, to being severely materially deprived. In this case, the logarithm of 1.69 to the base 1.10 is 5.5, so being severely materially deprived has the same impact on mortality risk than being 5.5 years older.

[7] For an overview on life expectancies in Europe see Mosquera et al. (2019).

Table 3. Mortality hazard ratios.

Predictor	Model without morbidity		Model with morbidity	
	Estimated hazard ratio	95 percent confidence interval	Estimated hazard ratio	95 percent confidence interval
Age	1.10	(1.10-1.10)	1.08	(1.08-1.09)
Sex=Male	1.90	(1.83-1.97)	1.98	(1.91-2.05)
Calendar year	0.96	(0.96-0.97)	0.96	(0.95-0.97)
Severe material deprivation=Yes	**1.69**	**(1.60-1.78)**	**1.39**	**(1.32-1.47)**
Global activity limitation instrument			0.47	(0.46-0.48)

Source: Reproduced from Klotz, Göllner and Till (2019).

A deprived individual aged 40 years is thus as mortal as a non-deprived individual aged 45.5 years, holding other factors constant. In life table terminology, this means a horizontal shift of the force of mortality schedule on the age axis: for each age x, the force of mortality (instantaneous risk of death) $\mu(x)$ in the deprived population is the same as $\mu(x+5.5)$ in the non-deprived population. But since life expectancy is a deterministic function of the force of mortality schedule (Keyfitz 1977), this means that the remaining life expectancy of the deprived population at x is just the remaining life expectancy of the non-deprived population at age x+5.5. The difference of 5.5 years can thus be seen as a rule of thumb "guesstimate" of the life expectancy difference between the deprived and the non-deprived population.

Model-assisted life table estimation

All countries participating in the EU-SILC survey provide annual life tables by age and sex. These life tables are based on fully enumerated death records and either population registers or high-quality population estimates and are thus of very high statistical quality. Alas, for most countries no disaggregation by socio-economic status is available (which is the very reason why have developed the FACTAGE method). On the other hand, the FACTAGE method allows for estimating sufficiently precise mortality hazard ratios, but is biased in terms of general mortality levels (see Klotz et al. 2018). Can we combine the strengths of both methods?

Effect coding of mortality hazard ratios

First, a note on contrast specification in model estimation. When estimating a Cox regression model, dummy coding is usually applied to the categorical predictors such as socio-economic status groups. In Table 3 for example, we applied dummy coding to contrast those who are severely materially deprived (1) with the reference group of those who are not (0). Although such a coding is useful in comparing the mortality risks between groups, it does not allow for comparing the group-specific mortality risk with the total population. The latter can be achieved by effect coding, comparing groups with the total population ("grand mean"). If the groups are not of equal size (which is usually the case when working with observational rather than experimental data), then the mortality rate in the total population is a weighted average of the group-specific mortality rates.

Some software packages allow for automatic implementation of effect coding. If this is not the case, one can easily obtain effect coding by pooling the data with itself (i.e., doubling the rows), then assigning a uniform new code to all observations in the second half, and then contrasting the codes of interest with this new code via dummy coding. Table 4 shows an example of applying this to a sample with 5 observations and two socio-economic groups, A and B.

Table 4. Example of pooling data with itself.

Original data				Data pooled with itself, then recoded			
Obs. #	Time at risk	Event	Group	Obs. #	Time at risk	Event	Group
1	4.67	0	A	1	4.67	0	A
2	5.11	1	A	2	5.11	1	A
3	2.84	0	B	3	2.84	0	B
4	5.50	0	B	4	5.50	0	B
5	1.76	1	B	5	1.76	1	B
				1	4.67	0	C
				2	5.11	1	C
				3	2.84	0	C
				4	5.50	0	C
				5	1.76	1	C

Source: Statistics Austria.

In the right panel, the lower half is identical to the upper half, apart from the group variable, which is there C. Contrasting groups A and B with group C each gives the mortality hazard ratio of groups A and B to the total population. For the data above, the estimated hazard ratio A/B is 0.82, the A/C ratio is 1.11, and the B/C ratio is 0.91. One must be careful, though, that the significance levels of the two latter ratios which are output by default by statistical software packages are invalid, for the events and times at risk in the pooled dataset are not statistically independent, but one half is a copy of the other, so the effective sample size is only half as large.

Constant hazard ratio

The hazard ratios to the total population can be multiplied with the age specific death rates obtained from a national life table to obtain estimated age and group specific death rates. Given a complete array of age and group specific deaths rates, the remaining columns of the group specific life table are obtained deterministically by standard life table methodology (Chiang 1984). Table 5 illustrates this procedure for the hazard ratios given above applied to an artificial abridged life table starting at age 35.

Table 5. Estimating group specific age specific death rates

National life table

Age group x	Age-specific death rate m_x	Probability of dying q_x	Survivor function l_x
35-39	0.001087	0.005419	1.000000
40-44	0.001552	0.007729	0.994581
45-49	0.002830	0.014050	0.986894
50-54	0.004948	0.024439	0.973028
55-59	0.007688	0.037714	0.949248
…	…	…	…

Group specific hazard ratios to total population

A	1.11
B	0.91

Estimated life table for group A

Age group x	Age-specific death rate m_x	Probability of dying q_x	Survivor function l_x
35-39	0.001206	0.006013	1.000000
40-44	0.001723	0.008576	0.993987
45-49	0.003141	0.015584	0.985463
50-54	0.005493	0.027091	0.970106
55-59	0.008533	0.041776	0.943825
…	…	…	…

Estimated life table for group B

Age group x	Age-specific death rate m_x	Probability of dying q_x	Survivor function l_x
35-39	0.000989	0.004932	1.000000
40-44	0.001412	0.007036	0.995068
45-49	0.002575	0.012794	0.988067
50-54	0.004503	0.022264	0.975425
55-59	0.006996	0.034378	0.953709
…	…	…	…

Source: Statistics Austria.

A question in this respect is which national life table should be used if the follow-up covers several calendar years. One can either use an average of annual life tables (maybe some weighted average) or the life table of the middle period. The latter is easier and valid if the change in mortality rates over time is constant (but cf. OECD/EU 2018). Also, in many countries very detailed and accurate life tables are produced around a census, often covering several calendar years. It might make sense to use such accurate life tables here too.

Age-specific hazard ratio

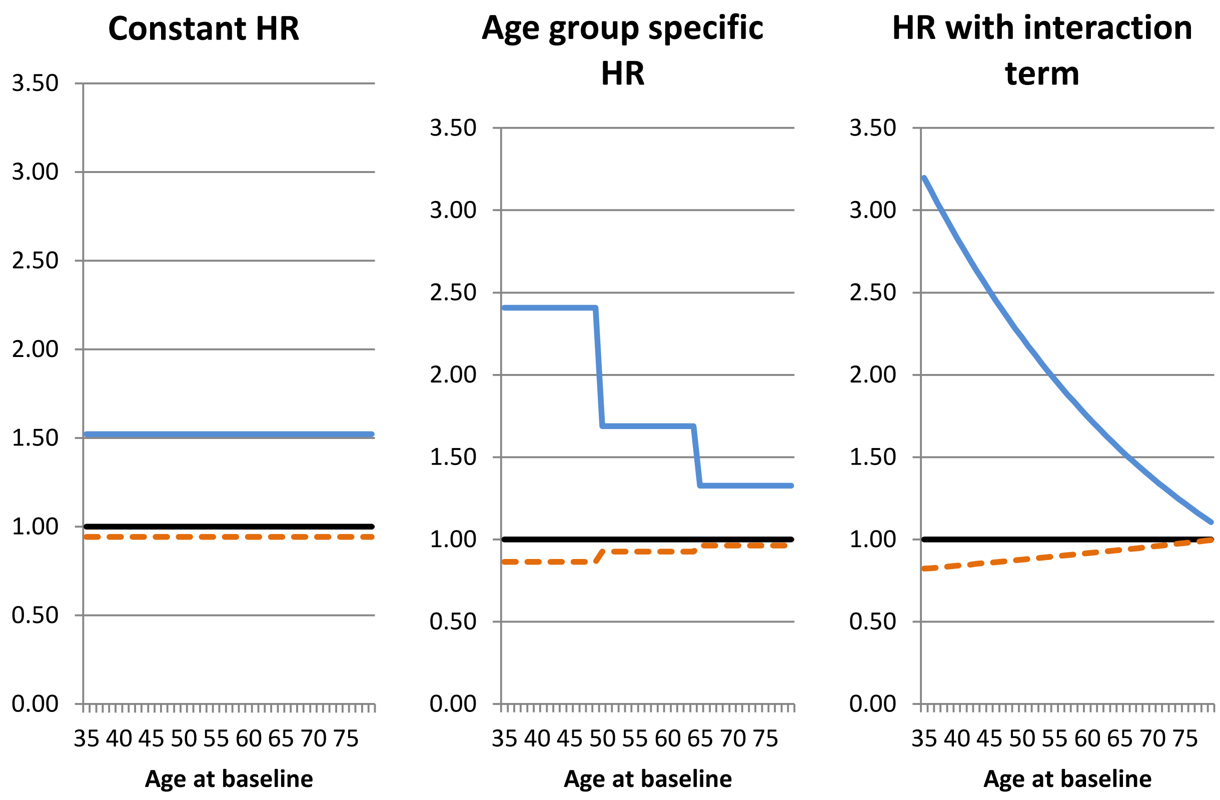
The major deficiency of the procedure described above is that a constant mortality hazard ratio is assumed over all ages. This is unlikely both for theoretical reasons (group-specific survival, see Keyfitz 1977) and from empirical observations (Klotz et al. 2019, Reques et al. 2015, Huisman et al. 2005,). Usually relative socio-economic mortality disparities are greater at middle than at higher ages. It is thus advisable to allow for age-specific hazard ratios.

Age-specific hazard ratios may be obtained either by partitioning the whole age band into some age groups and estimate a hazard ratio for each age group (Lampert et al. 2019), or by including an interaction term between age and socio-economic group in the model specification (Klotz et al. 2018). The advantage of the latter is that the model is usually more parsimonious and that in reality hazard ratios do not change abruptly between single years of age. Its disadvantage is that the estimated mortality hazard ratios at the margins of the age band may be implausible (such as a mortality cross-over at highest ages).

Age-specific hazard ratios can then be applied to national life tables. One has to be careful that when the individual follow-up time is long, then an individual's age at baseline is inaccurate for the entire follow-up period. In the case of the FACTAGE method, where the individual follow-up time is usually bound by at most 3 years, application to the age at baseline might be sufficiently accurate.

Figure 5 compares the age-specific hazard ratios of the severely materially deprived and the non-deprived to the total population for the model specified in the left panel of Table x, according to three estimation methods. In the left panel, just one group-specific parameter is estimated, so hazard ratios are constant over the age band. In the middle panel, hazard ratios are estimated for three 15-year age groups, namely 35-49 years, 50-64 years and 65-79 years. In the right panel, an interaction term between age and socio-economic group is included. One clearly observes the narrowing of relative mortality disparities between the deprived and the non-deprived at the higher ages.

Figure 5. Hazard ratio (HR) conditional on age at baseline, for the severely materially deprived (blue, solid) and the non-deprived (orange, dashed).



Source: Statistics Austria.

Applying the hazard ratios depicted in Figure 5 to the age-specific mortality rates of the 2009 life table for the European Union,[8] partial life expectancies at ages 35-79 for 35-year old Europeans in 2009 can be estimated. The partial life expectancy gap between the severely materially deprived and the non-deprived is 2.3 years when applying age-specific hazard ratios in the left panel, 3.0 years in the middle panel, and 3.6 years in the right panel of Figure 5. Thus, a constant hazard ratio applied to all age groups (as it was estimated by Klotz, Göllner and Till 2019) underestimates the actual life expectancy gap. This is not surprising, given that the true hazard ratio is higher at younger ages, where excess deaths come with a particularly large number of potential years of life lost.

One must be careful, though, that in such calculations the contribution of ages under 35 years and of 80 years and over to life expectancy differences are not accounted for. Extrapolation methods or assumptions on hazard ratios beyond the 35-79 age range could be used to compensate for this.

[8] Data extracted from Eurostat database (demo_mlifetable) on 29 March 2019. European Union means 28 countries. Males and females combined. The calendar year 2009 was chosen because it is the middle year of the follow-up period.

To conclude, we present several techniques to transform mortality hazard ratios, which are estimable from EU-SILC longitudinal data with sufficient quality, into life expectancy differences, which are the figure most relevant in social policy discourse. We recommend including an interaction term of age and hazard ratio into model estimation, since this is closer to reality than a constant hazard ratio and still a parsimonious model. Results should focus on the partial life expectancy gap between ages 35 and 79, because for the outside age groups estimation is more difficult (non-exponential increase of mortality levels below ages 35, low precision and health-related bias in sample data above age 80).

3. Code update: R code description

3.1. Changes in the UDB

Changes in file and folder structure

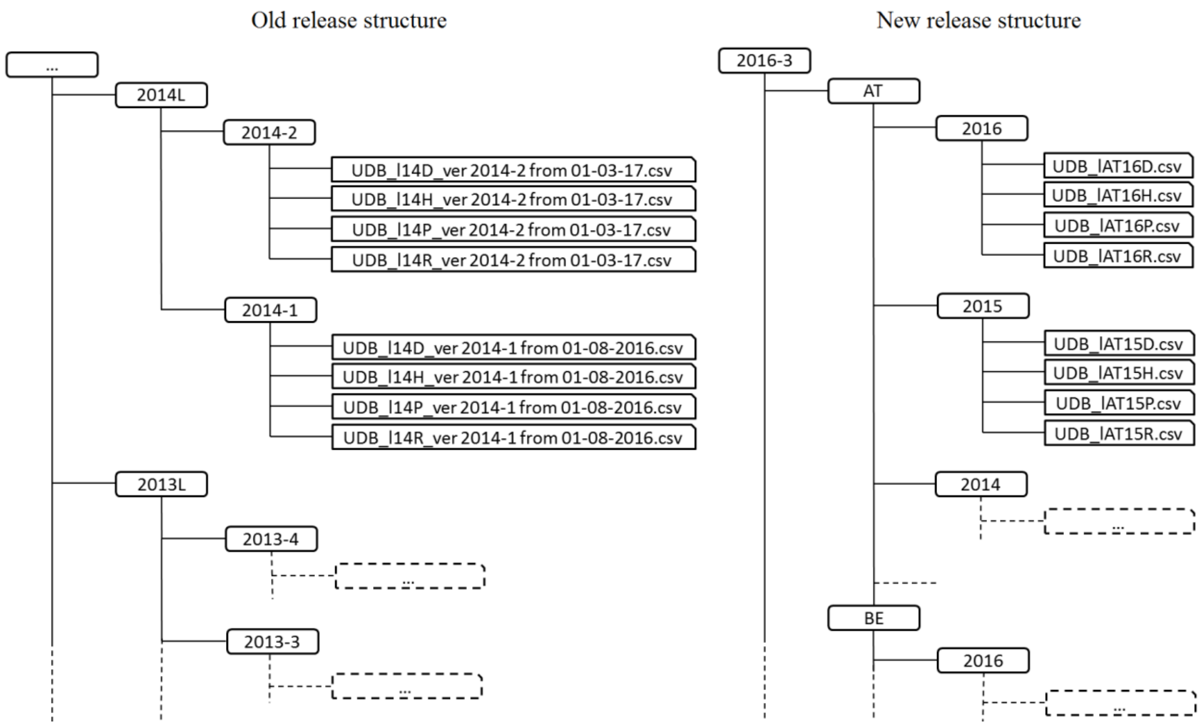
In our first report of this series we used the UDB files from before 2015. Since then the files and folder structure has changed. Note that for users coming from academia, who have to apply for the data from Eurostat, on the outside not much has changed, but there is one significant change. Since 2015 personal and household identifier from longitudinal data is linkable to the cross-sectional data. This will open up new analysis possibilities from 2015 onwards, for instance cross-sectional modules, some of which are repeated from time to time, can be enriched with longitudinal information. However, this great opportunity comes with a break in the values of personal and household identifiers, which will be discussed later in this report. Along with this change there was also a change in how data is released.

Firstly, now a release encompasses data of all previous years. Previously, there could have been updates to any release year at any given time. A fictional example for the old release logic would be that in the calendar year 2012 there could have been an update of the release year 2008 from version 3 to 4. A fictional example for the new release logic would be that the new release is 2018 version 2 which includes updates to the files in 2018, 2017 and 2012. So now users do not have to worry about missing any crucial updates of old release years, and they can simply rely on the most recent data release.

Secondly, it used to be that each file contains information of one release year, spanning four calendar years, for all UDB countries. Now files are split by countries. This is also depicted in the new folder structure (see Figure 6). The SAS code which we released along with our first report (Göllner and Klotz 2018) is still based on the old release structure. The newly released R code is aimed at the new structure.

Figure 6. New and old file structure of EU-SILC UDB.

On the left side the old folder structure where each new release of a longitudinal file was stored in the respective calendar year folder and each file itself contained information on all UDB countries. On the right side the new folder structure, where each release contains data of all countries and each previous year.



Source: Statistics Austria.

Reassignment of personal and household IDs

With this new form of releasing data, there has also been a shift to allow linkage between cross-sectional and longitudinal data. In our first report, the feasibility study, we already found some reassigned personal IDs without this shift. But since this change in data logic and the allowance of linkage, the problem affected basically all countries and observations. Additionally, it also affects the household identifier variable.

Our newly developed R code deals with this in three steps: First, it defines unique persons through the personal ID (RB030), the country (RB020), sex (RB090) and month and year of birth (RB070 + RB080). Then, it creates new household identifiers based on consistent person histories (at least one original household member must remain). And finally, it creates new personal IDs. In the old SAS code we do not account for reassigned household identifier. We advise to use the newly developed R code since it produces more accurate results.

Change in death indication

In EU-SILC data in general, there are two variables which may indicate the death of a sample person. In the personal register, RB110 = 6 indicates an individual that normally should have been re-interviewed but has passed away since the last survey wave. But there is also the possibility that an entire household died (of course, usually this refers to a single-person household) and so no personal register at all is filled out for this household. Such cases are instead indicated in the household register by DB110 = 5.

In EU-SILC UDB data obtained by the old release structure (like we used it in our first report, see Klotz and Göllner 2017), around one third of all deaths were recorded in the household register file (D-file). Since the change in file structure, it seems that the way in which this information is recorded has been changed. In the data since 2016 we see that the great majority of death indication comes from the personal register file (R-file). This change in recording somehow leads to slightly fewer cases of deaths in the UDB, however the big picture seems to be the same. In the previous data we used, in some rare instances, there were cases where the entire household dies but not all persons received the death indication via DB110 = 5 or RB110 = 6. This is not the case anymore and thus our R code doesn't need to correct for this.

3.2. Differences between SAS and R implementation

The R code, just like the SAS code, is designed to use the EU-SILC UDB files as described in earlier reports. The basic functionality of the R code is the same as the SAS code. A minor difference is the naming of certain variables, which should pose no problem, since users probably rename the variables to their own liking anyway. More progress has been made at the issue of the reuse of personal and household IDs (see above), which is solved in a more satisfactory way in the R implementation. The SAS code does not deal with reassigned household IDs. Since this is the last report on this project the R code will be released and then only marginally maintained. The code is freely available at GitHub (https://github.com/TobiasGold/FACTAGE-method_Mortality) and we encourage further development on it.

3.3. Quick Start Guide

Download the code from GitHub and use the `source()` command to get the functions into R. We recommend running the example pipeline which can be found in the file "`pipeline.R`". Each function is basically one step that you need to take in order to get the final output data. You can run the pipeline with minimal modifications. Mainly you have to change the arguments of the first function `readUDB()`. We recommend spending some time to think about what you want to extract and to change those parameters. Afterwards you also have to change the parameters in the last function `castUDB()`, don't forget to include all the variables you specified in the first function as `vars`, as `analyticalVars`. The final dataset can be used for mortality analyses. An exemplary analysis is provided in section 3.4.

```
# load the functions
source("R/readUDB.R")
source("R/mergeUDB.R")
source("R/recodeID.R")
source("R/setEligibility.R")
source("R/calcDates.R")
source("R/castUDB.R")
# Specify the path to your data:
path <- "/path/to/my/SILC_UDB_Longitudinal"
# Specify the year range which you want to extract
# One release year inlcudes four calender years.
year_from <- 2008
year_to <- 2016
# Select your countries. Use any two letter codes. Or specify NULL
for all available countries.
countries <- c("AT", "BE", "FR")
# Choose your analytical variables from the SILC UDB!
vars <- c("PH010","PH030", "HY020")

# read in the data
SILC_UDB <- readUDB(path,year_from,year_to,countries,vars)

# merge data
SILC_UDB_M <- mergeUDB(copy(SILC_UDB))

# reassign IDs
SILC_UDB_MC <- recodeID(copy(SILC_UDB_M))

# flag for eligibilty for follow up
SILC_UDB_E <- setEligibility(copy(SILC_UDB_MC))

# optional:
# save non-eligible respondents
SILC_UDB_nonEligs <- SILC_UDB_E[ELIGIBLEforFU==FALSE]

# calculate entry and exit dates
SILC_UDB_D <- calcDates(copy(SILC_UDB_E))

# get final data set
SILC_UDB_X <- castUDB(copy(SILC_UDB_D),
                      analyticalVars=c("PH010","PH030","HY020"),
                      extractMethod="baseline",
                      DurationUnits="years")
```

3.4. Function Explanation

Here we want to describe the basic functionality of each function. A more detailed explanation is included inside the header of each function. The functions have to be called in the sequence they are described here, which is also given in the "`pipeline.R`" file.

readUDB()

This function reads in the EU-SILC UDB files in their latest folder structure. The user has to specify a folder which contains the csv files of data. The folder structure is: specified folder containing country folders, which contain yearly folders, which contain the csv files. See the right hand side of Figure 6 in section 3.1 for a visual representation. Besides defining where the data is, the user can specify which years, countries and variables are to be extracted. The output of the function is a nested list object.

mergeUDB()

This function merges the contents of the nested list object created by `readUDB()` into one data.table. The user only has to specify the name of nested list object.

recodeID()

This function deals with the issue of reassigned personal and household IDs as described in 3.1 and 3.2. Again the user doesn't need so specify anything besides the data which should be used, which is of course the data created by `mergeUDB()`. In short this function does three things: 1. It defines unique persons through certain variables; 2. It creates new household IDs; 3. It renames the personal IDs. The new ID variables follow the nomenclature of EU-SILC, but are not linkable to any other data, and will be different each time you create a new data extraction.

setEligibility()

This function is new and was not represented in the SAS code. When doing differential mortality analyses we can only look at respondents where we can determine a vital status after the initial interview. One can also deal with this by simply removing all respondents with a time at risk in the panel of 0 or less, which should be done anyway as a quality insurance measurement. But crucially, this function also deals with persons who have a valid first interview and withdrew from the sample before the second interview. These persons are not accounted for in the old SAS code. This function simply requires as data the output from `recodeID()` and creates a new variable called "`ELIGIBLEforFU`" meaning eligible for follow-up. Should you, for whatever reason, not want to call this function but still carry on with the pipeline, you can simply add a variable called "`ELIGIBLEforFU`" to the data.table created by `recodeID()` and set it to "`TRUE`" for every respondent. The next function called will only include those lines where "`ELIGIBLEforFU`" is set to "`TRUE`".

calcDates()

This function calculates the entry and exit date of each respondent into the sample. If no valid exit date can be read from the last line, then date of the penultimate line is read and half a year is added. This is the same logic which we used in the SAS code. The data used is the output of `setEligibilty()` and no other parameters need to be specified.

castUDB()

This function needs some more parameters than just parsing the data from the previous function. Additionally, the user can specify the analytical variables, which usually are just the variables which were also specified for extraction with `readUDB()`. For these variables the user can specify the extraction method, meaning at which point the information of the variable should be extracted, either the first or the last observation. Since this function calculates the time at risk of each respondent inside the panel, one can specify in which unit this time should be calculated, e.g. years or days. Lastly, the user can specify additional variables which should be kept in the final dataset as the default columns. We recommend to keep the household ID, the sex, and the dates of entry and exit.

3.5. Results and Exemplary Analysis Code

After the execution of our pipeline, you should end up with data as shown in Figure 7. This data can then be used for further differential mortality analyses, such as estimating a Cox regression model.

Figure 7. Exemplary output viewed in R-Studio.

	Country	PID	HHID	FirstSurveyYear	Sex	AgeBaseline	DurationTime	Died	HY020_baseline
2774	AT	24540002	245400	2008	1	20	1.5041096	FALSE	57982.00
2775	AT	24540003	245400	2008	1	47	1.5041096	FALSE	57982.00
2776	AT	24580001	245800	2008	1	57	2.0000000	FALSE	19625.77
2777	AT	24580002	245800	2008	1	53	2.0000000	FALSE	19625.77
2778	AT	24580003	245800	2008	1	45	1.0000000	TRUE	19625.77
2779	AT	24590001	245900	2008	2	58	1.5041096	FALSE	49440.22
2780	AT	24590002	245900	2008	1	39	1.7479452	FALSE	49440.22
2781	AT	24590003	245900	2009	1	41	0.7479452	FALSE	62664.31
2782	AT	24600001	246000	2008	1	58	2.0000000	FALSE	29561.19
2783	AT	24600002	246000	2008	2	56	2.0000000	FALSE	29561.19
2784	AT	24610001	246100	2008	1	52	1.7479452	FALSE	12661.27
2785	AT	24620001	246200	2008	2	64	1.7561644	FALSE	9571.53

Source: Statistics Austria.

Note that here we did not yet restrict the age range in any way, something we strongly recommend if you are doing differential mortality analyses; the maximum age range is 16 to 79. As a difference to the SAS code the variable names slightly changed, but since the labeling is arbitrary anyway, feel free to change it according to your own needs. With this data set you can estimate mortality hazard ratios similar to the model in Klotz, Göllner and Till (2019). Assuming that you have specified `HY020`, the annual total disposable household income, as the analytical variable and extracted it from the first observation (baseline), you can do the following analysis:

We estimate a simple Cox proportional hazards regression by comparing the mortality risk of individuals in three household income groups: (1) Less than 10,000 euros; (2) Between 10,000 and 30,000 euros; (3) More than 30,000 euros. Mortality hazard ratios of the two marginal income groups are compared with the reference middle income group. We restrict the sample to individuals aged 30-79 years and with known and positive household income at baseline. We control for differences in age distribution between the income groups.

<u>Disclaimer</u>: This is only a crude model to give you a brief overview of the code. A social scientist would probably specify the model in a more sophisticated way, such as accounting for household size, adjusting for inflation over time and purchasing power differences between countries, including additional control variables, etc.

Exemplary Analysis Code in R

```
# We assume you have already finished the pipeline and
# your final dataset is called SILC_UDB_X

# (Install and) load packages
install.packages(c("haven", "survival"))
library(haven)
library(survival)

# Create an analysis object
analysis <- SILC_UDB_X[which(AgeBaseline >= 30 & AgeBaseline <= 79 &
HY020_baseline > 0),]

# Add a crude income_group variable
analysis$income_group[analysis$HY020_baseline < 10000] <- 1
analysis$income_group[analysis$HY020_baseline >= 10000 &
analysis$HY020_baseline <= 30000] <- 2
analysis$income_group[analysis$HY020_baseline > 30000] <- 3

# Model I: Estimating mortality hazard ratio by household income
category (middle income group is reference category)
Model_I <- coxph(Surv(time=DurationTime, event=Died) ~ AgeBaseline +
factor(income_group, levels = c(2,1,3)), data = analysis)
summary(Model_I)

# An alternative model stratified by sex
Model_IIa <- coxph(Surv(time=DurationTime, event=Died) ~ AgeBaseline
+ factor(income_group, levels = c(2,1,3)), subset = Sex=="1", data =
analysis)
summary(Model_IIa)
Model_IIb <- coxph(Surv(time=DurationTime, event=Died) ~ AgeBaseline
+ factor(income_group, levels = c(2,1,3)), subset = Sex=="2", data =
analysis)
summary(Model_IIb)
```

Further Information

Github: @TobiasGold and the repository https://github.com/TobiasGold/FACTAGE-method_Mortality

https://www.factage.eu/ – for further information on FACTAGE

http://ec.europa.eu/research/era/joint-programming-initiatives_en.html – for more information on the various Joint Programming Initiatives

http://www.jp-demographic.eu/ – for information on the JPI – More Years, Better Lives

http://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions – for information on EU-SILC

http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:EU_statistics_on_income_and_living_conditions_(EU-SILC) – for brief information on EU-SILC

https://circabc.europa.eu/ – navigate "Browse categories" → "Eurostat" → "EU-SILC" → "Library". There you find nearly all available information on EU-SILC in general and specifically for the UDB. Under "02. Guidelines" you find the DocSILC065 with all variable information. Under "04. Data and Indicators Dissemination" → "4.1 User Database (UDB)" you find information regarding the UDB.

http://statistik.at/web_en/statistics/index.html – for more information on Statistics Austria and our products

References

Chiang, C. L. (1984): The life table and its applications. Malabar, FL: Krieger Publishing.

Corsini, V. (2010): Highly educated men and women likely to live longer: Life expectancy by educational attainment. *Eurostat: Statistics in focus* (24).

Göllner, T., and Klotz, J. (2018): Editing EU-SILC UDB Longitudinal Data for Differential Mortality Analyses. SAS code and documentation. *FACTAGE project report*, May 2018.

Huisman, M., Kunst, A., Deeg, D., Grigoletto, F., Nusselder, W., & Mackenbach, J. P. (2005): Educational inequalities in the prevalence and incidence of disability in Italy and the Netherlands were observed. *Journal of clinical epidemiology*, *58*(10), 1058-e1.

Keyfitz, N. (1977): Introduction to the mathematics of population: with revisions. *Addison-Wesley Series in Behavioral Science: Quantitative Methods*.

Klotz, J., and Göllner, T. (2017): Estimating Differential Mortality from EU–SILC Longitudinal Data. A Feasibility Study. *FACTAGE project report*, D4.1.

Klotz, J., Göllner. T., and Till, M. (2019): Relationships between morbidity, mortality and severe material deprivation in Europe. In: Klotz, J., and Göllner, T. (eds.): Differential Mortality: Estimation and Implications for Pension Systems. *FACTAGE Project Report*, Deliverable 4.2, March 2019.

Klotz, J., Till, M., Göllner, T., Charafeddine, R., Demarest, S., Renard, F. (2018): Excess mortality in the Europe 2020 AROPE target group. D1: Methodological Guidelines. Paper presented at the first *NetSILC-3 International Conference,* Session 4, Athens, 20 April 2018.

Lampert, T., Hoebel, J., and Kroll. L.E. (2019): Soziale Unterschiede in der Mortalität und Lebenserwartung in Deutschland – Aktuelle Situation und Trends. *Journal of Health Monitoring* 4(1): 3-15.

Mackenbach, J. P., Kulhánová, I., Artnik, B., Bopp, M., Borrell, C., Clemens, T., et al. (2016): Changes in mortality inequalities over two decades: register based study of European countries. *BMJ,* pp. i1732.

Mosquera, I., González-Rábago, Y., Martín, U., Bacigalupe, A. (2019): Socio-Economic Inequalities in Life Expectancy and Health Expectancy at Age 50 and over in European Countries. *Sozialer Fortschritt*. 68(4). https://doi.org/10.3790/sfo.68.4.255

Murtin, F., Mackenbach, J. P., Jasilionis, D., Mira d'Ercole, M. (2017): Inequalities in longevity by education in OECD countries: Insights from new OECD estimates. *OECD Statistics Working Papers* 2017/02.

National Center for Health Statistics. Office of Analysis and Epidemiology. Analytic Guidelines for NCHS 2011 Linked Mortality Files, August, 2013. Hyattsville, Maryland. http://www.cdc.gov/nchs/data_access/data_linkage/mortality/linkage_methods_analytical_support.htm

OECD/EU (2018), Health at a Glance: Europe 2018: State of Health in the EU Cycle, *OECD Publishing*, Paris. https://doi.org/10.1787/health_glance_eur-2018-en

Reques, L., Santos, J. M., Belza, M. J., Martínez, D., & Regidor, E. (2015): Inequalities in mortality at older ages decline with indicators of material wealth but persist with educational level. *The European Journal of Public Health*, *25*(6), 990-995.