### Supplemental material

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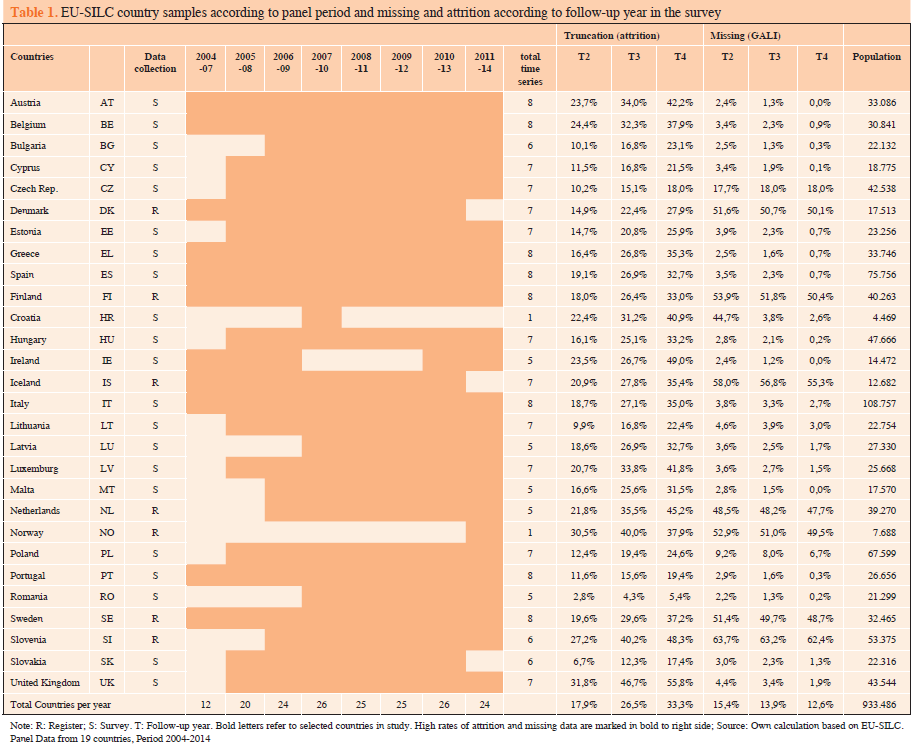
### eData1.-Truncation and missing data

Large percentages of missing and truncated data persist in EU-SILC countries that only provided register data (See Table 1 below). For example, there are high proportions of missing data at the first follow up (time 2) in Slovenia (64%) and the Northern European countries (52-60%), remaining quite constant across the period of study, while the surveyed countries show response rate ranging from 3% (Austria, Greece) to 17% (Czech Republic). Despite the fact that some researchers consider the coverage rates of register data to be generally better than survey data (particularly in the measure of gross disposable income), personal health variables are typically not available in register data 1. We therefore considered that estimates from both type of data could not be compared, as they would lead to possible biases in the results.

There were fewer country-differences in the proportion of attrition (with Ireland and Norway being notable exceptions). Instead, rates increased sharply over time, from mainly under 5% at the first follow-up to generally above 20% at wave 4 (Romania being an exception here with just 5%). Given the above described patterns, we removed the countries with register data from our analysis as well as those which reported high rates of attrition and missing data[[1]](#footnote-1) (in bold) in the health question. Countries for which it was not possible to identify rotational groups with at least two waves in the data files were also removed (e.g., France) because is required to observe at least one transition between one wave and another. This left us with 19 countries with data from 2004-07 to 2011-14.

In addition, we do not discuss the use of proxies for the personal interviews but acknowledge that there is potential bias. For instance, proxies are more likely to be employed when a sampled respondent is in very bad health or too old to answer the question 2.

The advantage of having such a large pooled sample of dataset is that it increases the accuracy of the final results 3. By pooling the data, we also deal with two problems that remain in the selected countries: 1) We were able to recover individuals that were dropped for one or two waves; 2) The small sample size that most countries had (except Spain, Italy and Poland) became less of a problem, although this became somewhat of an issue again when the data was disaggregated by the covariables gender, cohort, education, health status (in particular death) and living arrangements.



**eData2.-Data limitations**

Our study does have several limitations we ought to mention. We defined health status according to the Global Activity Limitation Index (GALI indicator) which is used to measure functional limitation. Unfortunately, this measure is not collected in most countries with register data, meaning that Nordic countries, known for their distinct pattern of co-residence, could not be analysed.

Another issue concerns the wording of the GALI question and its response categories that changed over time in several countries 4. This makes this indicator not always comparable 5, despite the fact that there are studies which support the validity and reliability of its use 6–8. We particularly raise the attention of possible bias in the results for Cyprus, Estonia, Greece, Lithuania, Latvia, Malta Portugal and Slovakia, which changed the wording in the middle of the analysed time series 4. Nevertheless, we consider the method used in our study to be a good approach of how to use random effects on survival probabilities in order to estimate predicted probabilities of health changes at older ages. It allows the inclusion of country-specific patterns of living arrangements as exogenous variables, which modify the mean risk to experience a specific event. In this way, we were able to estimate the size of the country-specific variability for older people to change their health status by taking into account their living arrangement. Applying a multilevel approach also permitted to ascertain whether the association between living arrangements and health transitions was modified by the exogenous variables.

Finally, we do not discard that the mortality estimation in this study is underestimated due to the small size of the death count in the survey 9 for countries like Belgium and Luxembourg as other study reported 7. An additional source of underestimation is the part of the initial survey population who was transferred to a health care institution at a later moment in time. These respondents were subsequently considered as truncated information and were most likely to come from Western and Eastern European and Baltic countries.

### eMethods1.- Modelling design

Three simple Cox PH models were fitted for each transition separately. Although results are the same as those obtained with a multistate Cox proportional model with stratified hazards for the three transition types (see eTable1) as it is shown by Putter in his work 10(p15) , a multilevel approach is difficult to be used in the latter[[2]](#footnote-2). As we were interested in identifying country-specific variation in the hazards of each type of health transition, we therefore needed to include country-specific random intercepts and coefficients for each transition, reason why each transition is modelled separately as it is shown below. In total, we fitted three different models for each health transition type (see **eMethods2**.Model description):

**Modelling process**

### Cox Proportional Hazards model

In order to evaluate the impact of different kinds of living arrangements on health transitions, a simple Cox PH model is used. This is a robust and flexible method known to fit the data very well 11,12, with results being similar to a PH model with a Poisson distribution and a logistic transformation 13. Cox PH models allow to estimate cumulative hazards by time (age) from the observed transition rates. Klotz and Göllner 9 applied this method to estimate socioeconomic mortality differentials, for which EU-SILC data was also used.

Using the R package “survival”, we then performed a covariate analysis on the hazard ratios (exponentiated coefficients), thereby obtaining the multiplicative effects of the predictors 14–16. In our model, we assume the existence of proportionality across time, which means that the relative hazard is constant over the time range used (in our case, the ages of the individuals in the study) for the possible transitions 16. The hazard ratio between two individuals at any point in time (ages in this study) is constant, and changes in the hazards depend on the covariates 12 .In this sense, it is also defined as the relative risk compared to the reference category, which corresponds to the baseline hazards 17:

Where is an unspecified baseline hazard function and is the log hazard ratio for individual or category *i* for a predictor , compared to the reference category 12,18.

The assumption of proportional hazards by age with the same level for the different health transition types studied here (i.e. health improvements (NH), health deterioration (HN) and death (ND)) is not always met in studies on recurrent events. This is due to distinct causal mechanisms governing each kind of transition12(p54). Fortunately, this can be resolved by relaxing the proportionality hypothesis of the Cox model by stratifying the baseline hazard function for the three transition types studied (see TABLE1). Although another option could be to introduce an interaction effect between time and the covariates 11,19, we apply a Cox model for the three studied transition types and introduce mixed effects modelling to test whether the control variables sex, cohort and educational attainment modify survival time and health changes according to living arrangements.

### Mixed effects Cox PH model

Studies which use mixed effects survival modelling are often medical trials, which study changes in health states. They focus on exploring treatment effects on specific diseases, recurrent infections or disease stages as chronic-degenerative diseases like cancers and Alzheimer. They also explore the association between exogenous factors in the onset of specific health disorders.

Changes in health status can be modelled as repeated event processes. Individuals as patients can therefore experience the event of interest multiple times throughout the period of observation, and the correlation at the individual level (occurrence of events for the same individuals) can be measured by using a hierarchical structure or a shared frailty term 20. This frailty is then described as the relative risk which individuals in the same group share.

In a similar way, health transitions can be correlated at the country level, and therefore, individuals can share unobserved characteristics that distinguish them from others from the very fact of living in another country. Using Mixed Effects Survival Modelling (MESM) with a Cox approach allows us to include this hierarchical structure and even include other kind of grouping as well. In this paper we use the multilevel aspect of this methodology to explore differences between countries according to each one of the interested covariates.

This kind of model, thus, controls for the existence of hierarchical correspondence 21, or nesting effects, very similar to multilevel modelling. This approach is also considered to be the same as introducing interaction terms between variables 22. Studies which include random effects in Cox PH have proven to be useful contributions for the description of diverse mechanisms interplaying in the ageing process and life course events in various contexts as countries 21,23,24.

To apply multilevel modelling to Cox PH model we use the recent version of the R package “coxME” developed by Therneau 25. This method fits a Cox PH model with a Gaussian frailty distribution. He showed that there is no closed formula to estimate variances. However, the key requisite is to have enough cases that contribute to each random effect, which our data set has. In this sense, we fit the following Cox PH model with mixed effects. Following Therneau 25:

“…where λ0 is an unspecified baseline hazard function, X and Z are the design matrices for the fixed and random effects, respectively, β is the vector of fixed-effects coefficients and b is the vector of random effects coefficients. The random effects distribution G is modelled as Gaussian with mean zero and a variance matrix Σ, which in turn depends on a vector of parameters θ”. Therefore, frailty assumed as “*random effects”,* is measured by the variance component as it has been shown by other studies on life span 23,26–29. Cox PH with mixed effects allows us to account for the shared frailty by all subjects within the same groups. Through the variance or the standard deviation, it is possible to observe the variability (increase or decrease) of hazards between groups, by considering the average event occurrence (hazard) for a reference subject. The exponential of the standard deviation provided by the model illustrates the excess risk that certain groups have (lower or higher) over the mean hazard of the sample. Random effects are represented by standard deviation equal the average relative risks associated with group or cluster membership, which are the different hierarchical levels analysed. Excess risk usually range from 1.1 (exp 0.1) to 1.3 (exp 0.3), while values greater than 2 are very rare (for further explanation see Therneau 25,30,31.

A Cox model with only fixed effects (simplest conditional model) and a Cox model with mixed effects are interpreted in different ways. Regression coefficients from a conditional model denote the main change in the event occurrence produced by changing status of the explanatory variables, keeping all else constant. The error-term indicates the combined effects of all excluded variables 32. Regression coefficients in the latter model denotes the effect of explanatory variables on the hazards, conditional on both fixed and constant random effects and the other covariates being fixed. Therefore, coefficients are sometimes described as having a cluster-specific interpretation 18.

Lastly, it is important to highlight some issues related to the population size and cluster-specific event counts. For the living arrangements variable, there were not enough events in the category of “living alone” for transition type “unhealthy to death”. For that reason, random effect estimations in this transition type are not shown.

### Random intercepts and random slopes as a tool for studying country effects

In this study we also take advantage of multilevel modelling as a tool to explore different dimensions of the country effect by adding levels of hierarchy between country variable at highest level and then, adding each covariate (sex, cohort, educational level and living arrangements at lowest level. This additional dimension of the country effect can be explored by analysing the random intercept and random slopes of these interactions.

## Model 3. Random effects between countries (1 level)

The country effect, equal to a random intercept coefficient in the model for the 19 countries observed takes the form:

With the coefficients for the country *j* where individual *i* lives, which follows a gaussian law with mean equal to 0. Its exponentiated value of its variance then represents the average excess of risk associated to country membership. As an application of this, we compute the variation of the reference risk[[3]](#footnote-3) (which is equal to male elder, born in 1924-33, with primary studies and living with a partner) for each country while holding all of other coefficients (sex, cohort, education and living arrangements) and the variance fixed.

## Model 3. Random slopes by living arrangements (level 1) within countries (level 2)

This model with living arrangements at level 1 and countries at level 2, with both having a varying random intercept coefficient, takes the form:

Where again is the coefficient for country *j* where individual *i* lives, is the coefficient for living arrangement *h* and country *j*, with both coefficients following a gaussian law with mean equal to 0.

### eMethods2.- Model description

* Model 1 is a classical Cox PH model with fixed effects of living arrangements, controlling for sex, birth cohort and educational attainment. This type of model is commonly used to represent effects of factors on the hazards (instantaneous transition probabilities) but doesn’t make any assumption on the baseline reference risk. Some authors have called this free baseline or free reference risk 12,14,17,33 and . The reference risk is based on a male individual, born between 1924 and 1933 (oldest cohort), with primary studies and living with a partner[[4]](#footnote-4).
* Model 2 is a multi-level model with 1 level, the response variable, which is the reference risk or random intercept in each health transition. This model includes a random intercept by country to account between-country heterogeneity in health status changes at older ages. There was also fit a model where the random intercepts were individuals (individual-level intercepts Model) to account intra individual correlation between waves, however, as this model doesn’t show significant differences, was excluded from the analysis.
* Model 3 is a multi-level model with 2 levels or random slopes that deal with different effects of covariates at each level. As Rabe-Hesketh 32(p125) explains, the response variable (here hazards of health status change) always varies at the lowest level. Because the values for individual-level intercepts Model was not substantial, we used living arrangements as the lowest level of analysis here. Each variable is nested within the level 2 country clusters to account for the varying effect of these predictors/covariates across countries. Lastly, explanatory variables (random slopes) can either vary at level 1 or at level 2. For purpose of this study, we focus our attention on the variation of explanatory variables at level 1 within the level 2 country cluster. Model 3 is therefore compared to Model 2.

The results show that all models with random effects fit significantly better than the simple Cox PH model for each transition type (see TABLE 3 in the main document). Nevertheless, when considering the log-likelihood and chi square values, the model with only the country level as random intercept - model 2- still does not have a good fit as the log likelihood is significantly lower when two hierarchical levels are introduced into the model. This is also reflected by the chi squared values which indicated the significant reduction in deviance when we fit 2 levels models. Although in models with higher hierarchical level the increment of the log-likelihood value decreases notably, model 2.1 that contained the individual as random intercept was excluded due the scarce variance reported for the random effect (see random effects and fixed effect in **eMethods1**)

**eTable1.-Multistate transition model, Cox Proportional Model with stratified hazard (by transition type)**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
|  |  |  | ***Health Deterioration*** | | |  |  |  | ***Health Improvement*** | | |  |  |  | ***Death from unhealthy*** | | |  | |  | |  | |
| **Fixed coefficients** |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *Living arrangements* |  |  | *N* | *event* | coef | HR | CI | Sig. | *% N* | *event* | coef | HR | CI | Sig. | *% N* | *event* | coef | HR | CI | | Sig. | |
| *\*Living with partner(ref)* |  |  | 43% | *40%* |  |  |  |  | 42% | *40.7%* |  |  |  |  | 42% | *5.2%* |  |  |  | |  | |
| Living with partner+kids |  |  | 30% | *32%* | -0.01 | 0.99 | *0.97-1.01* |  | 21% | *47.1%* | 0.12 | 1.13 | *1.10-1.15* | \*\*\* | 21% | *4.1%* | 0.18 | 1.19 | *1.12-1.27* | | \*\*\* | |
| Living Alone |  |  | 15% | *47%* | 0.06 | 1.06 | *1.04-1.08* | \*\*\* | 20% | *34.4%* | -0.09 | 0.92 | *0.89-0.94* | \*\*\* | 20% | *0.1%* | -4.56 | 0.01 | *0.01-0.02* | | \*\*\* | |
| Living with others |  |  | 12% | *43%* | 0.03 | 1.03 | *1.01-1.06* | \*\* | 16% | *32.3%* | -0.15 | 0.86 | *0.83-0.88* | \*\*\* | 16% | *10.8%* | 0.62 | 1.86 | *1.76-1.98* | | \*\*\* | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *Sex* |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *\*Male(ref)* |  |  | 47% | *36%* |  |  |  |  | 41% | *41.1%* |  |  |  |  | 41% | *6.5%* |  |  |  | |  | |
| Female |  |  | 53% | *42%* | 0.12 | 1.13 | *1.11-1.15* | \*\*\* | 59% | *38.3%* | -0.02 | 0.98 | *0.96-0.99* | \*\* | 59% | *3.6%* | -0.71 | 0.49 | *0.47-0.52* | | \*\*\* | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *Cohort born* |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *\*Cohort 1924-33 (ref)* |  |  | 15% | *60%* |  |  |  |  | 30% | *27.0%* |  |  |  |  | 30% | *9.8%* |  |  |  | |  | |
| Cohort 1934-43 |  |  | 26% | *46%* | 0.29 | 1.34 | *1.29-1.39* | \*\*\* | 30% | *40.1%* | 0.32 | 1.38 | *1.32-1.44* | \*\*\* | 30% | *3.8%* | 0.25 | 1.28 | *1.15-1.43* | | \*\*\* | |
| Cohort 1944-53 |  |  | 39% | *33%* | 0.55 | 1.73 | *1.64-1.82* | \*\*\* | 29% | *47.3%* | 0.56 | 1.75 | *1.65-1.86* | \*\*\* | 29% | *2.2%* | 0.76 | 2.15 | *1.76-2.63* | | \*\*\* | |
| Cohort 1954-63 |  |  | 20% | *26%* | 0.80 | 2.22 | *2.08-2.37* | \*\*\* | 11% | *50.1%* | 0.80 | 2.23 | *2.08-2.39* | \*\*\* | 11% | *1.3%* | 0.99 | 2.68 | *1.99-3.62* | | \*\*\* | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *Education* |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| *\*Primary (ref)* |  |  | 48% | *45%* |  |  |  |  | 59% | *37.6%* |  |  |  |  | 59% | *5.3%* |  |  |  | |  | |
| Secondary |  |  | 37% | *34%* | -0.17 | 0.84 | *0.83-0.86* | \*\*\* | 32% | *41.3%* | -0.04 | 0.96 | *0.95-0.98* | \*\*\* | 32% | *3.6%* | 0.04 | 1.04 | *0.98-1.10* | |  | |
| Tertiary |  |  | 15% | *28%* | -0.41 | 0.66 | *0.65-0.68* | \*\*\* | 9% | *49.6%* | 0.26 | 1.30 | *1.27-1.34* | \*\*\* | 9% | *3.3%* | -0.15 | 0.86 | *0.78-0.95* | | \*\* | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |
| N |  |  | 191,351 | 74,560 |  |  |  |  | 156,393 | 61,698 |  |  |  |  | 156,393 | 7,530 |  |  |  | |  | |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | |  | |

Note: Signification level: \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05. HR: hazard ratio. Coefficients calculated with “survival” R package, “coxph” function.

Source: Own calculation based on EU-SILC, Panel Data, Period 2004-2014

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1. Missing data refers to the non-responses from the question on the “Global Activity Limitation Index” (GALI). Truncation or attrition refers to the population who dropped out in any year during the four-year period of observation. [↑](#footnote-ref-1)
2. We were not able to introduce multilevel effects with multistate modelling, but we don’t discard the possibility that it can be done. [↑](#footnote-ref-2)
3. Baseline hazard without any proportionality assumption. It is linear function of covariates. [↑](#footnote-ref-3)
4. Without children but that may include other co-resident persons (including other type of kin). [↑](#footnote-ref-4)