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Modeling and forecasting healthy life expectancy with Compositional Data Analysis

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Abstract

Will the extra years of life gained by the increase in life expectancy be lived in good or poor health? As forecasts support social, economic and medical decisions, as well as individuals' choices, there is a clear rationale for forecasting healthy life expectancy (HLE). However, only a limited number of models is available to forecast HLE. We here suggest two models to forecast health and mortality simultaneously and coherently. One model is based on the Sullivan method to estimate HLE and the second one on the multistate life table method. Both models use Compositional Data Analysis (CoDA) to account for the coherence between health and mortality. Mortality and health at age 50 and above is forecast for Spanish and Swedish females. Both models provide similar estimates and forecasts of HLE, estimating and predicting a compression of morbidity in Sweden and a dynamic equilibrium in Spain.

1 Introduction

Life expectancy has continuously increased for over 200 years in most Western countries, with no visible limit (Oeppen and Vaupel, 2002). Whether the extra years of life are being lived in good or poor health is of importance to society. The quality of these extra years of life has implications for individuals and society, including an increased burden of caregiving for surviving family members, increased pressure on the healthcare systems, as well as changes in the dependency ratio (Beltrán-Sánchez et al., 2015). As forecasts support social, economic and medical decisions, as well as individuals' choices, there is a clear rationale for forecasting healthy life expectancy. However, forecasts of healthy life expectancy remain uncommon.

1.1 Healthy life expectancy

There are three main theoretical frameworks for assessing changes in morbidity related to mortality improvements: 1) Expansion of morbidity, or the "failure of success", where mortality decline emerges from individuals surviving with more health deficits (Gruenberg, 1977; Olshansky et al., 1991); 2) Compression of morbidity, where mortality decline results from lower incidence and later onset of diseases, resulting in shorter morbid life (Fries, 1980) and 3) Dynamic equilibrium, where disability is redistributed towards less severe states resulting in more years of life lived with moderate disability and equal or fewer years lived with severe disabilities (Manton, 1982).

In order to evaluate the three theories, it is necessary to consider a measure that accounts for mortality and morbidity simultaneously. Health expectancies are recognized as being the most suitable measures for the purpose (WHO, 1984). Among them, healthy life expectancy (HLE) is the most well-known and used. It summarizes the number of years expected to live in good health, by combining information on mortality and morbidity, and informs on the overall population health. As health is a multidimensional concept, and information is mainly collected through surveys, already in the 1960s three main dimensions were identified to be used for monitoring population health: presence/absence of (a) chronic diseases and (b) disabilities; and (c) self-perceived health state. Among them, the functional dimension (b) is often preferred as the indicator of morbidity as it is the least subjective measure (Robine et al., 2020). Furthermore, the functional health state of a person determines his/her ability to conduct an autonomous life and participate in family, social and economic activities in the society. This makes it very relevant when planning social, health and economic policies (Caselli et al., 2021). When considering the functional dimension of health, the measure of healthy life expectancy is named disability-free life expectancy (DFLE).

Analysis of HLE provides support for all three theories, depending on the country, data, indicators, populations and ages considered (Beltrán-Sánchez et al., 2015). For instance, a very recent study for the US did not find evidence for a substantial reduction in the proportion of years of life to be spent in disability for more cohorts, as previously suggested by other researches of older cohorts (Freedman et al., 2016; Payne, 2022). In Sweden, on the other hand, there is conflicting evidence on whether disability has been compressed or expanded. Results vary depending on the data, indicator, age and sex considered as well as whether the severity of the disability is taken into account (Lagergren et al., 2017; Sundberg et al., 2016). In general, health information is retrieved from surveys, sometimes from different surveys in the same country, leading to divergent within-country results and therefore within and between countries comparisons (Robine et al., 2020).

1.2 Estimating healthy life expectancy

Health data often have limited time series, making it difficult to evaluate change in HLE in the long term. The longest time series available is for the US, with data collected through the National Health Interview Survey. Reasonably long time series are also available for United Kingdom, Nordic countries (Sweden, Denmark and Norway), Belgium, France, Italy, the Netherlands and Spain. In Asia, recent time trends are available for Japan, China, India and Singapore. Elsewhere, data availability is still limited (Robine et al., 2020).

There are two main approaches to estimate HLE: Sullivan's method and the multistate life table (MSLT) method. The Sullivan method estimates the number of years lived in good or poor health using cross-sectional information on mortality and prevalence in each health-state. The MSLT model estimates health-prevalence as the result of transitions across states (e.g. healthy, unhealthy and dead). The latter is generally recognized as a more refined approach, as it acknowledges that poor health is the result of different processes (Majer et al., 2013). The MSLT is, however, more data demanding as it requires a follow-up of individuals over time. Studies have shown that the Sullivan method can provide similar estimates to the MSLT method, especially when the changes in prevalence are relatively regular (Mathers and Robine, 1997; Murakami et al., 2018).

1.3 Forecasting healthy life expectancy

Mortality forecast models have diversified in the last three decades. The wide range of options include models based on different indicators (Bergeron-Boucher et al., 2019); models including cohort effects, smoking effects and information on causes of death (Janssen et al., 2021; Kjærgaard et al., 2019; Li and Raftery, 2021; Renshaw and Haberman, 2006); models accounting for coherence between populations and components (Li and Lee, 2005; Oeppen, 2008); and so much more (Booth and Tickle, 2008). However, how to include information on health in the forecast has been neglected and only a few methods have been proposed to forecast healthy life expectancy.

Some authors forecast HLE based on the Sullivan approach and various scenarios. Manton et al. (2006) assumed a continuation of the decline in the rates of disability observed in two different time periods. Other authors assumed that the ratio between HLE and life expectancy (LE) will remain constant over time (Sanderson and Scherbov, 2010). Others relaxed the assumption of a constant HLE/LE ratio and explore the effect of different scenarios for HLY increases (Jagger et al., 2013). The main problem with scenario-based forecasts is that it is very difficult to assess the likelihood of each scenario (Booth, 2006).

Microsimulation models have also been used to forecast health and mortality for individuals.

The great benefit of the microsimulation approach is its incorporation of multiple characteristics affecting health and disability. A great disadvantage of the approach is that it is very data demanding, making it hard to apply to diverse populations and contexts (Jagger and Kingston, 2020).

Other authors used a multistate approach to estimate transition probabilities across health states by group of population (age, sex, etc.). A general assumption with these models is that the transition probabilities across health states by different components or variables, e.g. age, sex and education, remain constant in the forecast (Ansah et al., 2015; Biddle and Crawford, 2017). Majer et al. (2013) accounted for time-change in the transition probabilities and suggested using the Lee-Carter (LC) model (Lee and Carter, 1992) to forecast the age-specific transition rates from the MSLT, using separate forecasts for the mortality rates of the nondisabled, mortality rates of the disabled and the incidence rates. The authors only considered three transitions: Nondisabled-Dead, Disabled-Dead and Nondisabled-Disabled. Cao (2016) used a similar approach but added information on cohort smoking and obesity history. This approach has the advantage of using a well established model and allows one to incorporate uncertainty in the forecast. However, the model risks incorporating the bias of the LC model. The original LC model forecasts age-specific death rates log bilinearly and assumes a constant rate of mortality improvement over time. The latter assumption has been shown to be inappropriate at some ages, often leading to an underprediction of life expectancy (Bergeron-Boucher and Kjærgaard, 2022; Booth et al., 2006). In addition, the Majer et al. (2013) model assumes independence between mortality rates for non-disabled and disabled and incidence rates. There is, however, a dependence between the different states. If individuals become less and less disabled over time, more and more individuals will remain nondisabled and die in that state.

1.4 Aim

We aim to develop generalizable methods which can simultaneously forecast mortality and health prevalence, while considering dependence between ages and between health-states. We suggest two methods, one based on the Sullivan method and the other on the MSLT method. Both models make use of Compositional Data Analysis (CoDA), which has been shown to account for correlation between mortality components (Bergeron-Boucher et al., 2017). Both methods are used to forecast life expectancy and healthy life expectancy in selected countries. The results provide insights into the quality of the years that are expected to be added to life expectancy and fuel the discussion on the expansion or compression of morbidity.

2 Data

Health data were extracted from the European survey of Statistics on Income and Living Conditions (EU-SILC) (Eurostat, 2022). This survey offers yearly data on health prevalence by single-year of age between 2004 and 2020 for many European countries. The last age with available information is 80. EU-SILC has both a cross-sectional and longitudinal survey, allowing us to measure healthy life expectancy with the Sullivan and the MSLT methods. Health state was defined based on the question from the Minimum European Health Module (MEHM), available in EU-SILC, "For at least the last 6 months have you been limited in activities people usually do, because of a health problem?", with answer 1) Yes, severely limited, 2) Yes, limited and 3) Not limited. It allows one to calculate the Global Activity Limitation Indicator (GALI), as a measure of disability state (Robine et al., 2003).

Data on mortality and life expectancy were extracted from the Human Mortality Database (HMD, 2021). We extracted life tables and re-estimated them to have an open-age interval at 80+.

We provide an application of both introduced methods for Swedish and Spanish females aged 50 and above. In order to test the model, we only selected the populations with the longest time series, i.e. those with EU-SILC and HMD data from 2004 to 2020 in the cross-sectional survey and from 2005 in the longitudinal survey. Only six countries met these criteria: Belgium, Finland, Luxembourg, Norway, Spain and Sweden. To simplify the analysis, we only model and forecast trends for Sweden and Spain, as they have among the biggest sample sizes of the six options reducing uncertainty.

The fitting period is 2004 to 2019. We would need the survey data of 2021 to fit the MSLT model for 2020, which was not available at the time the study was done. We could use 2020 to fit the Sullivan approach. But, for a matter of comparison with the MSLT model, we used the same fitting period with both models. In addition, there was a decline in life expectancy in 2020 due to the pandemic (Aburto et al., 2022). Modelling and forecasting during pandemic require additional assumptions – e.g. how long will Covid affect mortality? or how does Covid affect health in the short and long run?

3 Methods

3.1 Sullivan-based forecast model (CoDAS)

The Sullivan method estimates the number of years lived in a given health state as:

$$L^s_{tx} = L_{tx} * \pi^s_{tx}, \tag{1}$$

where L_{tx} is the person-years lived at time t and age-interval $x : x + 1$ in the life table and π^s_{tx} is the proportion of individuals with the health state s at time t and age x. As L_{tx} is a function of life table deaths d_{tx} and survivors l_{tx}, the number of deaths and survivors in a given health state can be derived from the Sullivan equation, assuming that an individual in a given health state at the beginning of the age-interval can only die in that state within the interval:

$$L^s_{tx} = \pi^s_{tx}[l_{tx} - a_{tx}d_{tx}] = l^s_{tx} - a_{tx}d^s_{tx}, \tag{2}$$

where a_{tx} is the average number of person-years lived in the age-interval by those dying in the interval. By modelling and forecasting d^s_{tx}, we can derive the total mortality (d_{tx}) and health prevalence (π^s_{tx}) as:

$$\pi^s_{tx} = \frac{d^s_{tx}}{d_{tx}} \tag{3a}$$

$$d_{tx} = \sum_{s=1}^{S} d^s_{tx}. \tag{3b}$$

As $\sum_{x=1}^{X}\sum_{s=1}^{S} d^s_{tx} = 1$, this indicator is a composition. Compositional data are vectors of relative information constrained to sum to a constant, e.g. proportions or percentages. From a geometric standpoint, the constant sum forces compositions into a subspace of the real space, known as the simplex, where data can only vary between 0 and the constant. Specific methodology has been devised for such data, labelled Compositional Data Analysis (CoDA) (Aitchison, 1986; Pawlowsky-Glahn and Buccianti, 2011). Due to the constant sum constraint, deaths are directly dependent on each other at the aggregated level (Kjærgaard et al., 2019). If fewer deaths occur at younger ages and with limitations, than more deaths must occur at older ages and without limitations. CoDA enables a coherent and correct modelling of dependent components of mortality, such as ages, causes of death and health-states.

Methods to forecast mortality based on compositional data have been previously developed, forecasting life table deaths (Bergeron-Boucher et al., 2017, 2018; Kjaergaard et al., 2020; Oeppen, 2008). We suggest using the method of Oeppen (2008) to forecast state-and-age-specific life table deaths. The model, label CoDAS, can be written as:

$$clr(d_{t,x*s} \ominus \alpha_{x*s}) = \kappa_t \beta_{x*s} + \epsilon_{t,x*s} \tag{4}$$

where $d_{t,x*s}$ is a matrix of life table deaths by time t as rows and age-and-state $x*s$ as columns. α_{x*s} is the age-and-state-specific geometric mean. κ_t and β_{x*s} are the dominant components of a singular value decomposition applied to $clr(d_{t,x*s} \ominus \alpha_{x*s})$, where clr denotes the symmetric and isometric centered log-ratio transformation computing the logarithm of a compositional vector divided by its geometric mean. κ_t measures the change over time and β_{x*s} is the age-and-state sensitivity to κ_t. The symbol $\ominus$ is the standard subtraction operator in CoDa. Forecasts can be achieved by extrapolating κ_t using time-series models.

3.2 Multistate life table-based forecast model (CoDAM)

A second method to calculate healthy life expectancy is based on multistate life tables. The life tables include the probabilities of moving from state i to state j in a given age interval ($q^{i,j}_{tx}$),

$$q^{i,j}_{tx} = \frac{D^{i,j}_{tx}}{N^i_{tx}} \tag{5}$$

where $D^{i,j}_{tx}$ is the number of transitions from state i to state j between age x and $x+1$ and time t to $t+1$ and N^i_{tx} is the population at age x and time t and state of origin i. From the transition probabilities $q^{i,j}_{tx}$, the average duration of time lived in state i can be estimated (e^i_0). If one of the destination states j is death, life expectancy can be estimated directly from the multistate life table.

The probabilities $q_{tx}^{i,j}$ are compositional data as their sum over destination state is equal to one. Compositional data models can then be used to forecast $q_{tx}^{i,j}$. Multi-way models allow us to forecast transition probabilities for multiple ages and states of origin coherently, in one step. $q_{tx}^{i,j}$ can be arranged in a three-dimensional array by year (t), state of destination (j) and age-and-state of origin ($x*i$), written as $q_{t,j,x*i}$. Three-way principal component analysis can then be used to model and forecast the array, as described by Bergeron-Boucher et al. (2018). Here we propose the use of the PARAFAC decomposition (Carroll and Chang, 1970; Harshman et al., 1970). The tridimensional array is modelled in a structural part, given by the sum of an F number of three factors (triads), and an error term. The aim of the procedure is to find the best low-rank approximation of the array under the assumption that each factor of a triad represents the loadings of the corresponding dimension of the array (here t, j, and $x*i$) on the same latent construct. The probabilities $q_{t,j,x*i}$ can be model with a simple F=1 PARAFAC model, which can be expressed in an element-wise notation as:

$$clr(q_{t,j,x*i} \ominus a_{j,x*i}) = \kappa_t \beta_j \gamma_{x*i} + \epsilon_{t,j,x*i} \tag{6}$$

where $\alpha_{j,x*i}$ is the destination-specific geometric mean at each age and origin-state. κ_t, β_j and γ_{x*i} are the generic elements of the triad extracted by the model, representing the loadings of the year, state of destination, and age-and-state of origin dimensions respectively. We labeled the model CoDAM. As for the CoDAS model, κ_t models the change over time and β_j is the destination-state sensitivity to κ_t. γ_{x*i} is the age-and-origin marker, indicating how fast each age and origin-state experienced the transfer process $\kappa_t\beta_j$. Forecasts can be achieved by extrapolating κ_t using time-series models.

Instead of a three-dimensional array, the transition probabilities could be arranged in a four-dimensional array by year, destination, origin and age. We tested this approach in an appendix and similar results to the three-dimensional model were found in most cases (Appendix A).

Coherence between mortality components within this model is also considered. The coherence between state of destination is accounted for by the CoDA approach: if individuals transit less often towards a poor health state, they have to transit towards or remain in good health. The coherence between state of origin and age is accounted for by the use of the PARAFAC model. All ages and states of origin have a common transfer pattern.

In most surveys, information on mortality will be available. If information on death is not available, the model estimates how many years were lived within state i in the total age-range (e.g. 50 to 100). Healthy life expectancy can then be estimated as:

$$DFLE = \sum_x \frac{L_x^{NL}}{\sum_i L_x^i} * L_x^T \tag{7}$$

where L_x^{NL} are the person-year lived at age x with no limitations (NL) and L_x^T is the total number of person-year lived estimated from a standard life table. In this case, two separate forecasts are needed. In the SILC survey, while a variable was designed to record whether the individual died between two survey waves, no deaths were recorded or observed in both countries. We then used equation (7) to calculate the DFLE at age 50 and forecast mortality with the CoDA model of Oeppen (2008). More details on the model and related assumptions are presented in Appendix B.

3.3 Confidence and prediction intervals

We assumed that the mortality estimates are accurate. Confidence intervals around estimates of life expectancy are generally small (Villavicencio et al., 2021), especially when they are based on death registries and population-wide estimation. The uncertainty in the forecast comes from (1) the estimation of the number of years lived with and without disability and (2) extrapolating the trends with equations (4) and (6).

We calculated confidence intervals around the estimate of healthy life expectancy using bootstrapping. We resampled with replacement n times the distribution of health-state by age and year from the SILC survey. Life expectancy and healthy life expectancy are then calculated for each simulation. The 95% confidence intervals are estimated from the 2.5% and 97.5% percentiles of the n simulations.

For each simulation previously described, a new time index is found and extrapolated using the selected time series model. For each κ_t estimate, prediction intervals are calculated using simulations with resampled errors (bootstrap) m times. The 95% predictions intervals are estimated from the 2.5% and 97.5% percentiles of the $n \times m$ simulations.

For the multistate approach, mortality is forecast separately. We also include uncertainty from this forecast using bootstrapping.

4 Results

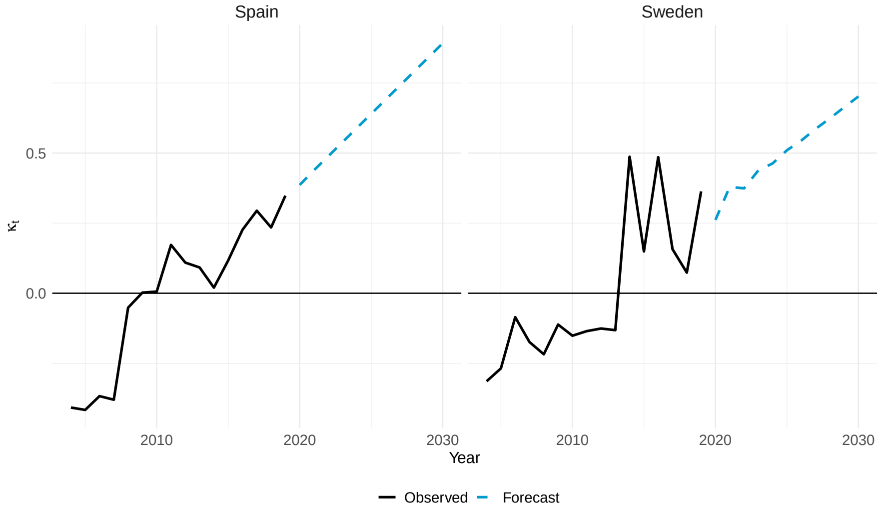
4.1 CoDAS parameters and forecast

Figure 1 shows the parameters of the CoDAS model for Swedish and Spanish females. The parameter κ_t is a time-index indicating how the death distribution has been changing over time. There is a lot of fluctuation over time in $d_{t,x*s}$, especially for Swedish females. Despite the fluctuations, we can see an increase over time in κ_t. We forecast κ_t with an ARIMA (1,1,0) as suggested by Bergeron-Boucher et al. (2017).

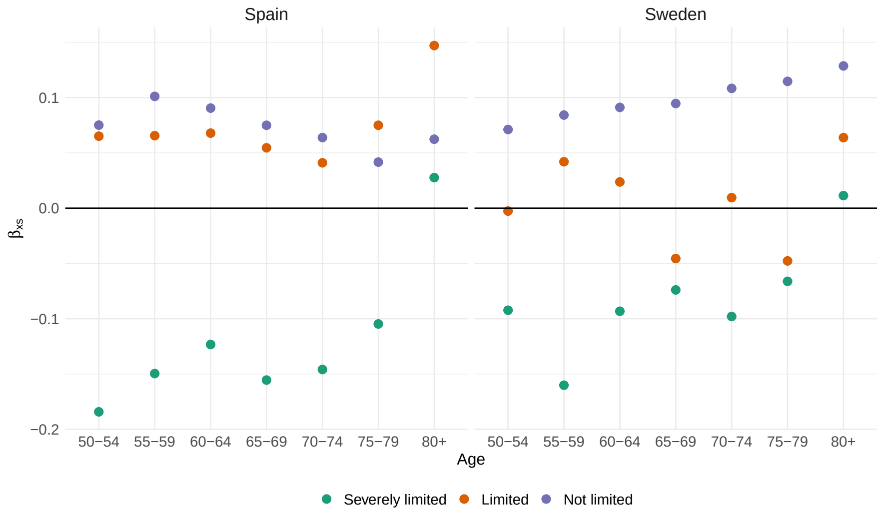
The parameter β_{x*s} indicates which age and state has been gaining or losing deaths over time, in relative terms. When κ_t increases over time, deaths are shifted from ages and states with negative values of β_{x*s} towards ages and states with positive values. From Figure 1, it can be seen that there was a transfer from death at younger ages with severe limitations towards older ages with no limitation for both countries. Deaths with mild limitations were also increasing, in particular at older ages, for Spanish females. From the model's parameters, we can assess that there was a compression of morbidity in Sweden and dynamic equilibrium in Spain.

Figure 1: Parameters of the CoDAS model for Swedish and Spanish females, 2004–2030

(a) Time-index



(b) Age-and-state-pattern



Note: The values in Figure 1.b are the mean β_{x*s} for 5-year age groups.

Figure 2 shows the life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) observed and forecast with the Sullivan and CoDAS models. All three indicators have been increasing over time in both countries, indicating more years lived in total, but also more years lived without limitations.

In Sweden, the DFLE and SDFLE have been increasing faster than the LE, resulting in a reduction in the number of years lived with severe and mild limitations. The compression of morbidity continues in the forecast. Figure 3 shows the proportion of remaining years of life lived in different health states. For Sweden, an increasing share of life will be lived without limitations. In 2004, 57% of the remaining lifespan was lived without limitations. This proportion increased to 77% in 2019 and is forecast to be 85% by 2030.

Figure 2: Life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) at age 50 estimated with the Sullivan model and forecast with the CoDAS model, Spanish and Swedish females, 2004–2030

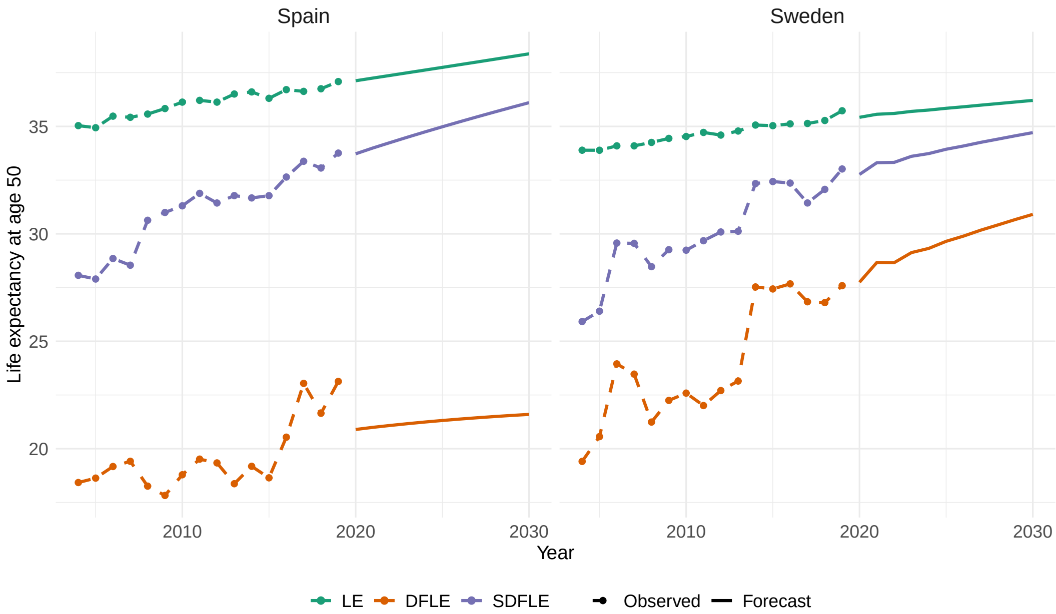
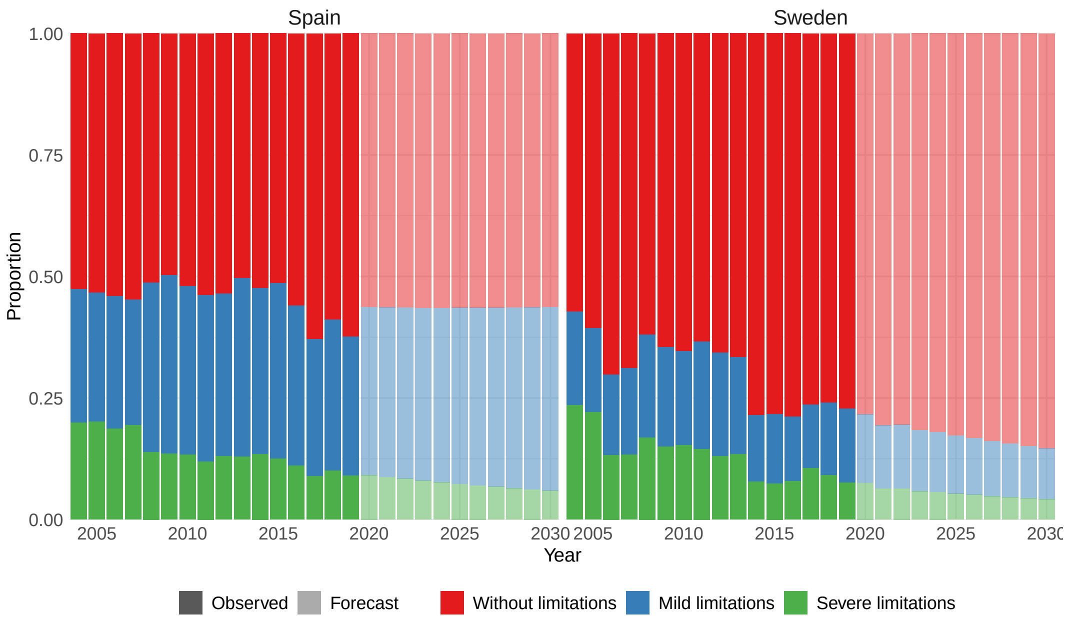


Figure 3: Proportions of remaining years of life at age 50 lived in different health states estimated with the Sullivan model and forecast with the CoDAS model, Spanish and Swedish females, 2004–2030



In Spain, there was also a reduction in the number of remaining years of life lived with severe limitations, with the SDFLE increasing faster than the LE. However, the DFLE has recorded a slower increase, which persists in the forecast, resulting in more years lived with mild limitations (both in absolute and relative terms) and therefore supporting the dynamic equilibrium theory. In 2004, 53% of remaining lifespan was lived without limitations. This proportion increased to 62% in 2019 and is forecast to be 56% by 2030.

4.2 CoDAM parameters and forecast

Figure 4 shows the parameters of the CoDAM model for Swedish and Spanish females. The parameters have a similar interpretation to that of the CoDAS model. The parameter κ_t is a time-index indicating how the the transition matrix has been changing over time. For Spanish females, the index increased over time. For Swedish females, we cannot detect any clear trends. As for the CoDAS model, we forecast κ_t with an ARIMA (1,1,0) model.

The β_j parameter indicates the state to which individuals have been transiting over time, in relative terms. When κ_t is increasing, the shift occurs from states with negative values towards states with positive values. In Spain, individuals transit increasingly towards mild limitations and no limitations and less and less towards severe limitations, suggesting a dynamic equilibrium scenario. For Sweden, individuals transfer increasingly towards no limitation and less and less towards the other states, suggesting a compression of morbidity. These trends are similar to those of the Sullivan model.

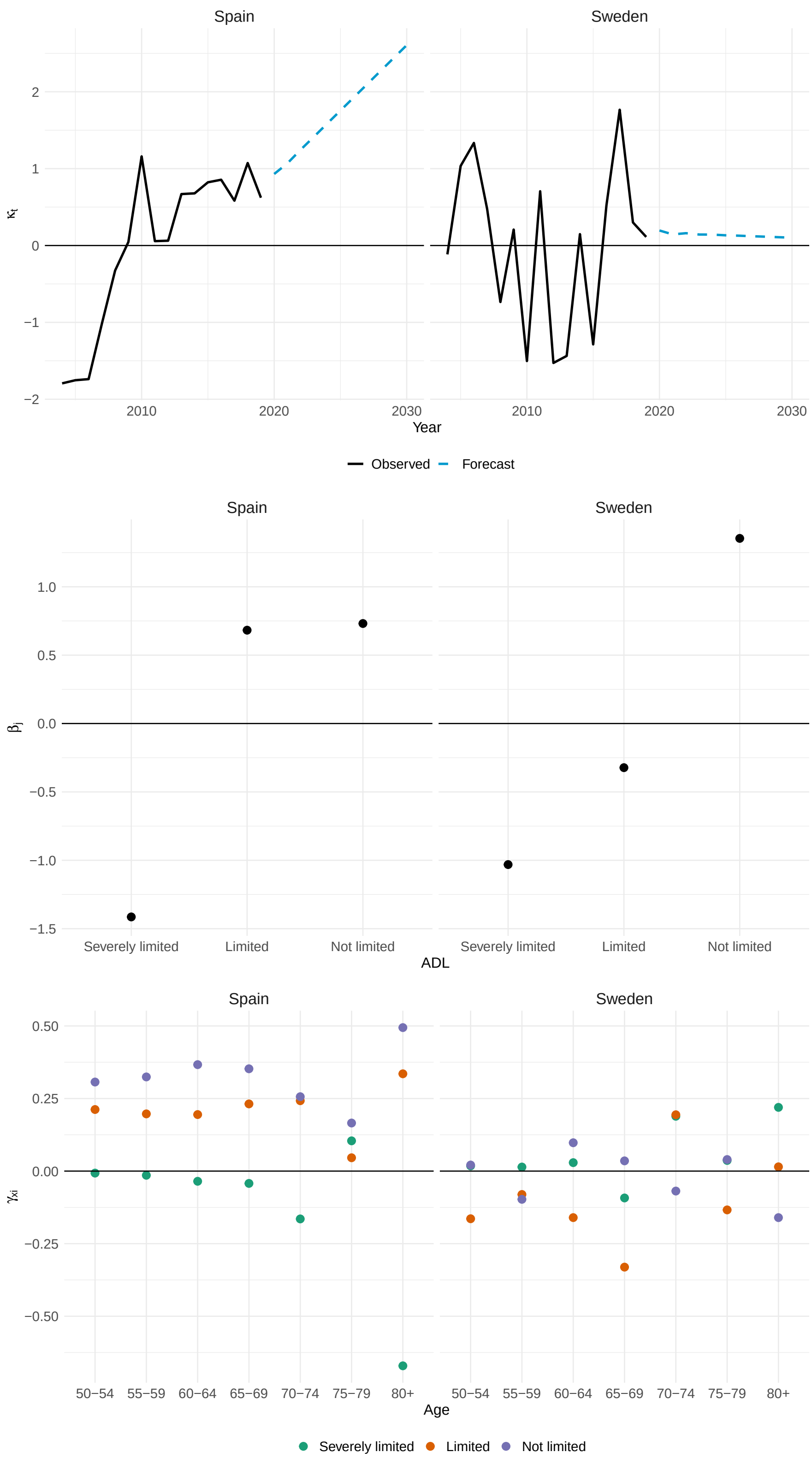
The parameter γ_{x*i} indicates how fast each age and origin state has been experiencing the common transfer process towards state j defined by $\kappa_t\beta_j$. For example, Spanish females aged 50 with an origin state without limitations transited less and less towards severely limited over time and more and more towards mildly limited or remained without limitations. A similar process was observed for individuals of the same age with an origin state with mild limitations, but to a lesser extent. On the other hand, Spanish females aged 80+ with severe limitations increasingly remained as severely limited over time.

Figure 5 shows the LE, DFLE and SDFLE observed and forecast with the MSLT and CoDAM models. All three indicators have been increasing over time in both countries, as also shown with the Sullivan-CoDAS approach.

For Swedish females, there was a compression of morbidity observed between 2004 and 2019. The forecast predicts that all three indicators will increase at a similar pace leading to a roughly constant number of years lived with mild and severe limitations. The proportion of remaining years of life lived with mild limitations was 12% in 2019 and is forecast to be 11% in 2030; the proportion for severe limitations decreases from 7% to 6% between 2019 and 2030 (Figure 6).

For Spanish females, the observed and forecast trends in the SDFLE have been increasing faster than that of the LE, leading to fewer years lived with severe limitations. But the model predicts more remaining years of life lived with limitations. In relative terms, the proportion of remaining years of life lived with mild limitations increased only slightly: 29% in 2004, 30% in 2019 and 31% in 2030 (Figure 6). As with the Sullivan approach, these results support a dynamic equilibrium scenario.

Figure 4: Parameters of the CoDAM model for Swedish and Spanish females, 2004–2030



Note: The values in Figure 4.c are the mean γ_{i*s} for 5-year age groups.

Figure 5: Life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) at age 50 estimated with the MSLT model and forecast with the CoDAM model, Spanish and Swedish females, 2004–2030

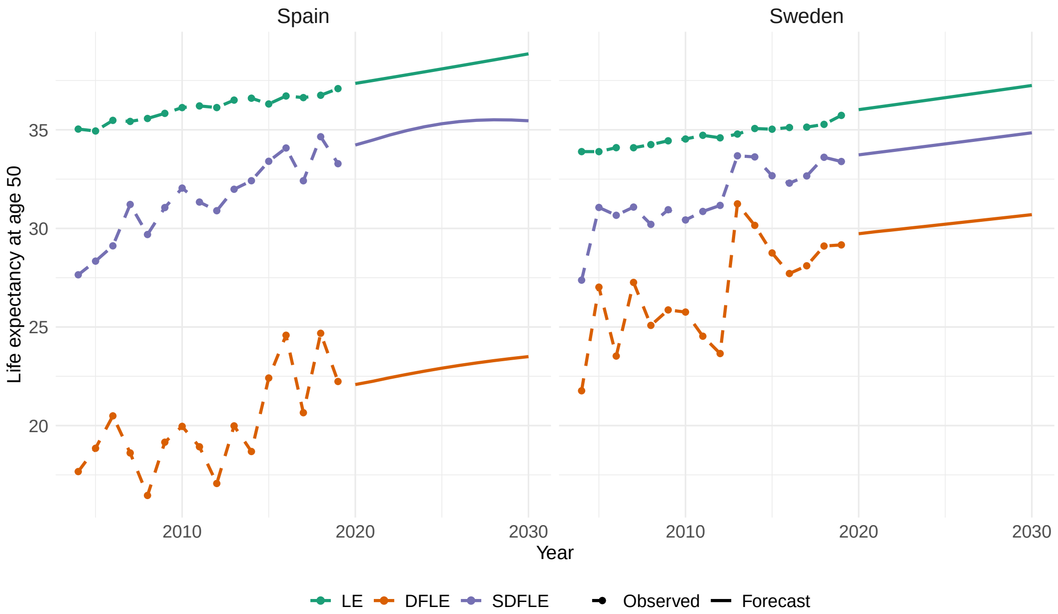
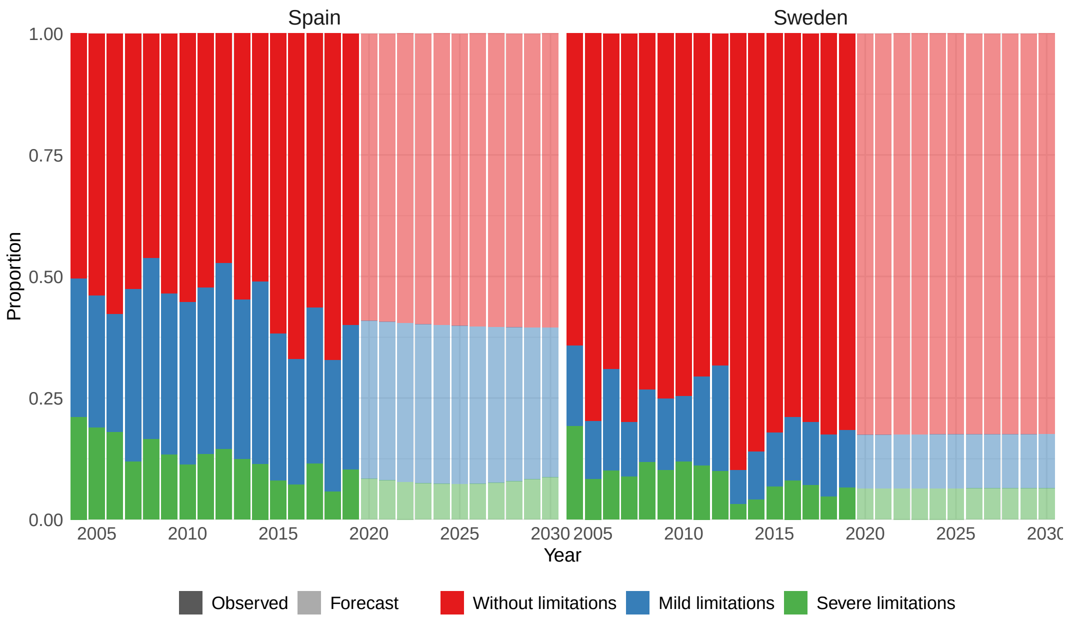


Figure 6: Proportions of the remaining years of life at age 50 lived in different health states estimated with the MSLT model and forecast with the CoDAM model, Spanish and Swedish females, 2004–2030



4.3 Comparison and evaluation

Table 1 compares the estimated and forecast number of years lived with and without limitations between the Sullivan and MSLT models and their corresponding forecast models (CoDAS and

CoDAM). While there are differences observed in all years and for all indicators, both the Sullivan and MSLT models estimate similar trends over time. The confidence intervals of both models often overlap, suggesting no significant differences between the estimation of the number of years lived with and without limitations between the Sullivan and the MSLT approaches.

Table 1: Number of remaining years of life lived with severe limitations, mild limitations and no limitations at age 50 estimated with the Sullivan and Multi-State models and forecast with the CoDAS and CoDAM models, Spanish and Swedish females, 2004, 2019 and 2030

	Spain			Sweden		
	2004	2019	2030	2004	2019	2030
Severe limitations						
Sullivan - CoDAS	7.0 [6.6,7.2]	3.3 [3.0,3.6]	2.3 [1.4,3.6]	8.0 [6.6,8.2]	2.7 [1.8,2.7]	1.5 [0.3,4.7]
Multi-State - CoDAM	7.4 [7.0,7.8]	3.8 [3.2,4.6]	3.4 [2.4,7.7]	6.5 [5.7,7.6]	2.3 [1.9,3.0]	2.4 [2.1,5.1]
Mild limitations						
Sullivan - CoDAS	9.6 [9.3,9.9]	10.6 [10.0,10.8]	14.5 [13.0,15.2]	6.5 [5.9,7.4]	5.4 [4.4,5.5]	3.8 [1.7,6.3]
Multi-State - CoDAM	10.0 [9.6,10.4]	11.0 [10.3,11.9]	12.0 [8.8,14.3]	5.6 [5.0,6.2]	4.2 [3.4,5.1]	4.2 [3.4,6.1]
No limitations						
Sullivan - CoDAS	18.4 [18.2,18.9]	23.1 [23.0,23.8]	21.6 [21.3,23.1]	19.4 [19.1,20.7]	27.6 [27.6,29.1]	30.9 [24.3,35.0]
Multi-State - CoDAM	17.7 [17.2, 18.1]	22.2 [21.4,23.2]	23.5 [21.2,25.5]	21.8 [20.6,22.7]	29.2 [28.0,30.1]	30.7 [26.6,33.1]
Life expectancy						
Sullivan - CoDAS	35.0	37.1	38.4 [37.9,38.9]	33.9	35.7	36.2 [35.3,37.0]
Multi-State - CoDAM	35.0	37.1	38.9 [36.2,42.2]	33.9	35.7	37.2 [35.9,38.1]

Similar trends are also found in the forecasts. For Spain, both CoDAS and CoDAM models forecast an increase in the number of years lived with mild limitations, but this increase is more pronounced with the CoDAS model. As the sum of the number of years lived with and without limitations sum to the total life expectancy, this difference in the number of years lived with mild limitations impacts the predicted number of years lived without limitations and vice-versa. Fewer years lived without limitations are forecast with the CoDAS model.

For Sweden, both the CoDAS and the CoDAM models forecast more years lived without limitations. But the CoDAM model forecasts a roughly constant number of years lived with severe and mild limitations, while the CoDAS model forecasts a decrease.

To evaluate which model is the most accurate, we performed an out-of-sample analysis. We used data from 2004 to 2014 to fit the model and forecast the trends over the period 2015-2019. Each forecast is compared to the estimated trends based on their own underlying model (CoDAM compared with MSLT estimates and CoDAS with Sullivan estimates). Figure 7 shows the results of the evaluation and table 2 shows the mean absolute errors of the forecasts. Both models forecast fairly accurately the trends in LE, DFLE and SDFLE, with the notable exception of the DFLE with the CoDAS model in Spain. There was no improvement in DFLE in Spain between 2004 and 2014 and the forecast continues this trend.

The CoDAS model was more accurate in predicting LE in both countries. The CoDAM model was more accurate in predicting the DFLE in both countries. Mixed results were found for the SDFLE. Very similar results are found for males (see Appendix C).

Table 2: Mean absolute errors in forecasting life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) using the CoDAS and CoDAM models for Spanish and Swedish females between 2015 and 2019

	Spain		Sweden	
	CoDAS	CoDAM	CoDAS	CoDAM
LE	0.22	0.46	0.11	0.18
DFLE	2.34	2.16	0.83	0.68
SDFLE	0.37	0.71	0.51	0.38

5 Discussion

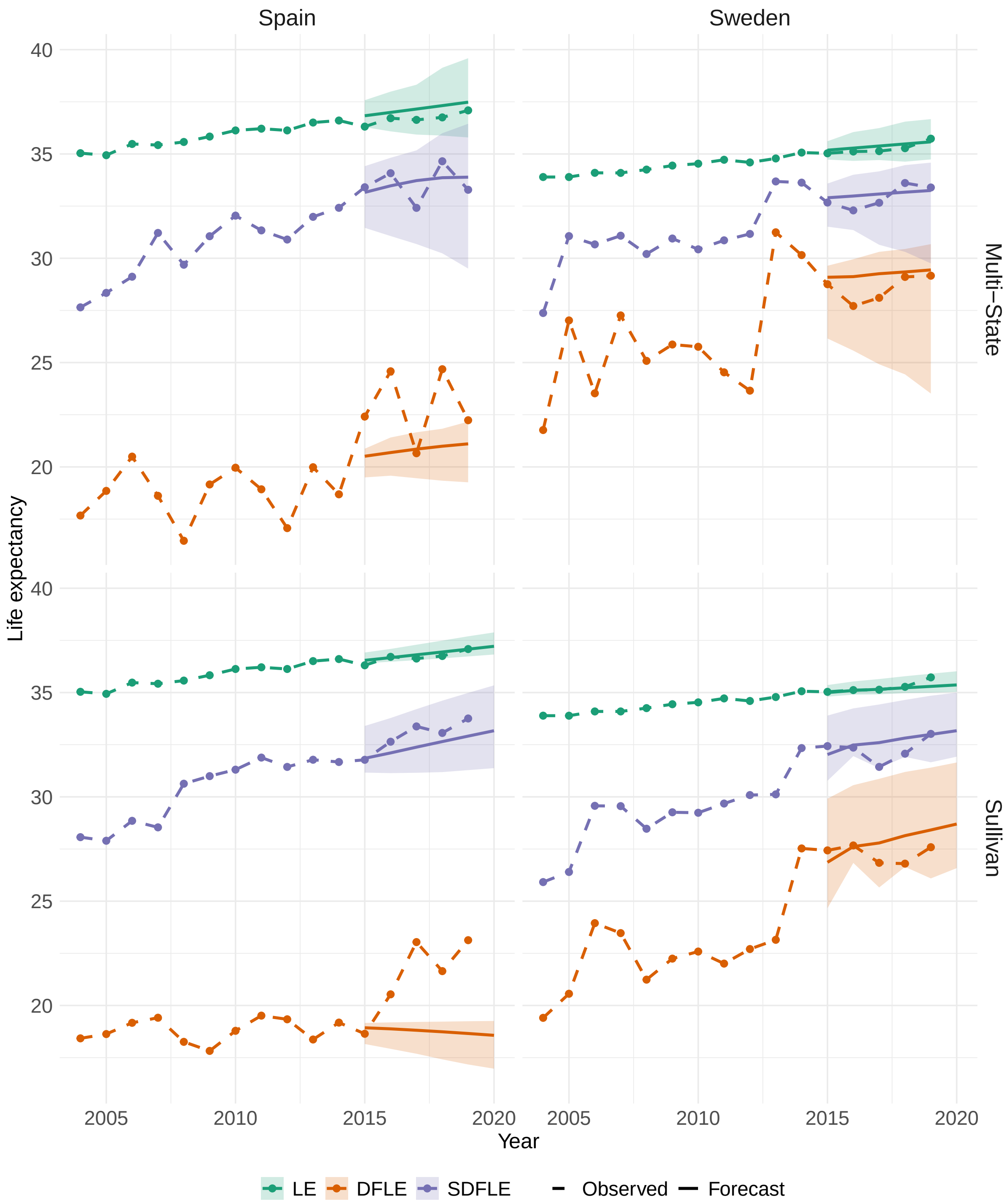
We introduced two forecast models based on the two most common procedures to estimate healthy life expectancy: Sullivan and MSLT. One of the main advantages of the proposed models is that coherence between health state and mortality is accounted for. Both introduced forecast models show that mortality and health can be forecast simultaneously and coherently. In addition, the CoDAM model can include all possible transitions. Other methods based on the MSLT do not allow for recovery, i.e. transition from poor health to good health (Majer et al., 2013). No such assumption is needed with the CoDAM model, while still keeping the model relatively simple.

These models are the first step towards simple and coherent forecasts of the number of years lived with and without limitations. There is space for improvement in the models. For example, the model could be adjusted to include smoking related mortality or some other covariates; and impose age and state weights. The CoDAM model assumes coherence across age and state of origin. But, if a different process occurs across age or state of origin, the model can be applied to each age or origin independently. Similar methods can be used to model and forecast an array of the transition probabilities by year, state of destination and age, for each state of origin ($q^i_{t,j,x}$); or by year, state of destination and state of origin, for each age ($q^x_{t,j,i}$). The former assumes some coherence in the change in the transition rates between ages, while the latter assumes coherence between states of origin. This approach would increase the complexity of the method, but might provide more accurate estimation. Similarly, a separate time trend could be estimated for each age or each state for the CoDAS model (see Kjærgaard et al. (2019)). It was outside the scope of the study to test all possible variants and extensions of the models.

The data on health states is taken from surveys with usually small sample sizes. There is then more uncertainty around the estimates and forecasts of healthy life expectancy, compared with that of the total life expectancy. This limitation applies also to EU-SILC. Furthermore, the scope of EU-SILC is to collect information on families' economic conditions. Health data collection is only a minor part of the survey, making the quality of such information more questionable (Sajani et al., 2014).

To test the accuracy of the models, we did an out-of-sample test over a short forecast horizon of 5 years. The time series available on health state are generally short. In our case, we had 16 years of observation. As the general rule of thumb is to have as long of a fitting period as the forecast horizon, we could not test the model for a long forecast horizon. It would then

Figure 7: Life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) at age 50 estimated in 2004-2019 with the Sullivan and MSLT models and forecast in 2015-2019 with the CoDAS and CoDAM models, Spanish and Swedish females



not be recommended to forecast healthy life expectancy far into the future. Studies have shown that the longer the fitting period, the more robust and accurate the forecast (Bergeron-Boucher et al., 2020; Janssen and Kunst, 2007).

There are differences in the estimation and forecast of healthy life expectancy whether we used the Sullivan-CoDAS or the MSLT-CoDAM models. The MSLT model is generally seen as the best one in estimating the number of years lived in good or poor health, as it can model the shift from one health-state to another over time, while the Sullivan method only accounts for the health prevalence at a given time. However, the MSLT model is more data demanding and the limitation of the Sullivan method is not critical in situations where changes in population health are smooth and relatively regular over the longer term. This makes the Sullivan method acceptable for monitoring such trends in health expectancies (Mathers and Robine, 1997; Murakami et al., 2018). Our results are in line with this argument. We found that the differences between models are not always significant. In fact, the differences were not significant in most cases. Both the Sullivan and MSLT models showed similar trends over time (observed and forecast): they both show a compression of morbidity in Sweden and a dynamic equilibrium in Spain. We were unable to determine which forecast model, the CoDAS or CoDAM, was the most accurate in forecasting the different health indicators. Comparing more countries and using different fitting periods and forecast horizons might help assessing in more detail the accuracy of the forecast. But, more data is required. Based on our results, we can draw similar conclusions using both models. If longitudinal data is not available to calculate the MSLT estimates, the Sullivan and CoDAS are a reasonable alternative from which we can expect similar trends and general conclusions. But we cannot conclude whether these results are generalizable to other countries or time-periods.

Our results fuel the debate on expansion or compression of morbidity. For Sweden we observe a reduction of the number of years lived with mild and severe limitations. This trend, arguing in favour of compression of morbidity, has been observed by other researchers considering individuals at age 65 (Lagergren et al., 2017) but not when analyzing oldest-old only (Sundberg et al., 2016). In general, results vary substantially when considering different age-groups, surveys and health indicators, even within the same country (Jagger and Kingston, 2020). For Spain, our results support the dynamic equilibrium theory, as opposed to the expansion scenario discussed by other scholars for relatively recent years (Solé-Auró 2014). This difference might be explained by both the indicator used for measuring disability-free life expectancy and the analysis of different level of severity of the limitations. In fact, our results suggest a (relative) increase in the number of years lived with mild limitations that would be included in the number of years spent with disability if we did not consider the severity of the limitations.

Only a few models were developed to forecast healthy life expectancy. The introduced models are then a welcome addition to the literature. Unlike previously developed models, the suggested approach can forecast simultaneously health and mortality in a coherent manner, while accounting for changes in prevalence and transition probabilities over time. These models solved some of the problems encountered when forecasting HLE and can be further developed.

Data statement

This paper is based on data from Eurostat, EU-SILC 2004-2020. The data cannot be made publicly available. The responsibility for all conclusions drawn from the data lies entirely with the authors.

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A Four-way CoDAM model

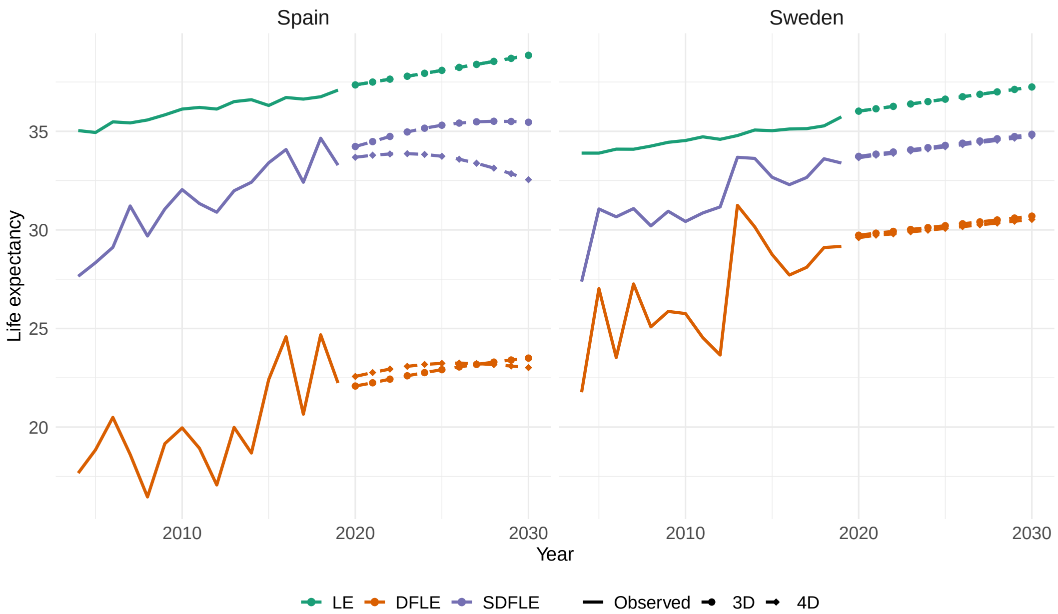
As mentioned in the main text, the CoDAM model can be adapted so that, instead of a three-dimensional array, the transition probabilities are arranged in a four-dimensional array by year, destination, origin and age. In this case, the model labeled CoDAM-4D, is written as

$$clr(q_{t,j,x,i} \ominus a_{j,x,i}) = \kappa_t \beta_j \gamma_x \rho_i + \epsilon_{t,j,x*i} \tag{8}$$

where $\alpha_{j,x,i}$ is the destination-specific geometric mean at each age and origin-state. κ_t, β_j, γ_x and ρ_i are the dominant components of a PARAFAC model applied to $clr(q_{t,j,x*i} \ominus a_{j,x*i})$. The parameter interpretations are similar to those of the CoDAM model, with γ_x and ρ_i being the age marker and origin marker.

Figure 8 shows that both models lead to very similar forecasts for Swedish females. Similar forecast results are also found for the DFLE for Spanish females, but more differences are found for the forecast of the SDFLE. The CoDAM-4D model forecasts an increase in the number of years lived with severe disability in Spain, unlike the CoDAM and CoDAS models.

Figure 8: Life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) at age 50 observed and forecast with the CoDAM model and the 4D variants, Spanish and Swedish females, 2004–2030



B CoDAM assumptions

We made some assumptions to simplify the CoDAM model and MSLT estimation:

1. We assumed that the health states at the time of the survey each year is representative of the states on January 1st of that year.

2. We assumed that missing values about the state of destination at age $x + 1$ are equal to the state of origin at age x. Missing values are not random and tend to be more important for individuals with limitations.

3. The radix of the life tables at each state i are assumed to be constant over time and equal to the average prevalence of state i at age 50. The method is not very sensitive to the choice of radix.

4. The number of years lived from age 80 is the same across health stateses, as we have no information on health and mortality after age 80 in the SILC survey.

5. When zero transitions between state i and j were recorded, we assume that half a transition was observed as the CoDA model cannot treat 0 values.

C Males

Similar conclusions are drawn when analyzing male health and mortality:

1. There is a compression of morbidity in Sweden.

2. There is a dynamic equilibrium in Spain.

3. The CoDAS model has a better forecast accuracy for the LE and the CoDAM for the DFLE.

However, males tend to live fewer years with limitations compared to females.

Table 3: Number of remaining years of life lived with severe limitations, mild limitations and no limitations at age 50 estimated with the Sullivan and Multi-State models and forecast with the CoDAS and CoDAM models, Spanish and Swedish males, 2004, 2019 and 2030

	Spain			Sweden		
	2004	2019	2030	2004	2019	2030
Severe limitations						
Sullivan - CoDAS	4.9 [4.7,5.2]	2.0 [1.7,2.1]	1.3 [0.6,2.2]	6.5 [5.2,6.5]	2.1 [1.3,2.2]	1.0 [0.2,4.0]
Multi-State - CoDAM	3.6 [3.3,3.9]	2.5 [1.9,2.8]	2.1 [1.7,5.0]	4.9 [3.9,5.7]	1.8 [1.4,2.2]	1.5 [1.3,6.0]
Mild limitations						
Sullivan - CoDAS	6.4 [6.0,6.5]	7.7 [7.4,8.0]	11.4 [9.4,13.3]	5.1 [4.4,5.6]	3.2 [2.4,3.5]	3.0 [1.3,5.0]
Multi-State - CoDAM	6.9 [6.5,7.3]	8.4 [7.9,9.1]	8.8 [6.6,10.7]	5.5 [4.5,6.8]	2.7 [2.2,3.3]	2.9 [2.3,9.2]
No limitations						
Sullivan - CoDAS	18.2 [17.9,18.6]	22.5 [22.3,23.0]	21.2 [20.7,22.5]	18.6 [18.6,20.2]	27.5 [27.5,28.8]	29.2 [22.7,33.1]
Multi-State - CoDAM	19.0 [18.7,19.4]	21.3 [20.5,22.1]	24.0 [21.2,26.8]	19.8 [18.9,20.9]	28.4 [27.6,29.1]	30.6 [22.9,32.6]
Life expectancy						
Sullivan - CoDAS	29.5	32.2	33.9 [32.7,35.4]	30.2	32.8	33.3 [31.8,34.7]
Multi-State - CoDAM	29.5	32.2	34.9 [32.6,38.7]	30.2	32.8	35.0 [32.8,37.1]

Table 4: Mean absolute errors in forecasting life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) using the CoDAS and CoDAM models for Spanish and Swedish males between 2015 and 2019

	Spain		Sweden	
	CoDAS	CoDAM	CoDAS	CoDAM
LE	0.12	0.46	0.28	0.44
DFLE	1.89	1.23	1.09	0.72
SDFLE	0.23	0.58	0.51	0.53

Figure 9: Life expectancy (LE), disability-free life expectancy (DFLE) and severe disability-free life expectancy (SDFLE) at age 50 estimated in 2004-2019 with the Sullivan and MSLT models and forecast in 2015-2019 with the CoDAS and CoDAM models, Spanish and Swedish males