Modeling and Forecasting Health Expectancy: Theoretical Framework and Application

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Abstract Life expectancy continues to grow in most Western countries; however, a major remaining question is whether longer life expectancy will be associated with more or fewer life years spent with poor health. Therefore, complementing forecasts of life expectancy with forecasts of health expectancies is useful. To forecast health expectancy, an extension of the stochastic extrapolative models developed for forecasting total life expectancy could be applied, but instead of projecting total mortality and using regular life tables, one could project transition probabilities between health states simultaneously and use multistate life table methods. In this article, we present a theoretical framework for a multistate life table model in which the transition probabilities depend on age and calendar time. The goal of our study is to describe a model that projects transition probabilities by the Lee-Carter method, and to illustrate how it can be used to forecast future health expectancy with prediction intervals around the estimates. We applied the method to data on the Dutch population aged 55 and older, and projected transition probabilities until 2030 to obtain forecasts of life expectancy, disability-free life expectancy, and probability of compression of disability.

Keywords Mortality · Longevity · Life expectancy · Health expectancy

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Background

Life Expectancy

Over the past decades, improving mortality conditions have resulted in increases in the length of human life and subsequent population aging in Western countries. The continuous rise of life expectancy is certainly welcome. However, the increasing life expectancy has been accompanied by low fertility rates, resulting in growth of the elderly proportion of populations in most Organisation for Economic Co-operation and Development (OECD) countries (OECD 2009). Because these developments have considerable consequences for the sustainability of two fundamental institutions of social security—namely, health care and pensions—the future of human survival has gained growing attention not only among demographers and epidemiologists but also among actuaries, economists, and financial specialists (Cairns et al. 2008; MacMinn et al. 2006). The concern is that health insurers and pension funds will have to provide provision for however long people will live.

Whether and to what extent life expectancy will continue to increase has been a source of discussion, dividing scholars into camps of optimists or pessimists (Garssen 2006). Various arguments have been used to support the potential upward or downward effects on mortality rates, including not only historical trends and biomedical and lifestyle arguments, but also the potential of medical breakthroughs. Reflecting on the uncertainty surrounding the evolution of future mortality and life expectancy, particularly at older ages, demographers began to consider improvements in mortality, and all other quantities depending on future mortality, as a stochastic process. A wide range of extrapolative empirical models have been proposed that share a common feature: based on historical data, they all estimate age-specific mortality as a function of time and project them into the future using probability distributions (Cairns et al. 2006; De Waegenaere et al. 2010; Dowd et al. 2010; Girosi and King 2008; Lee and Carter 1992). The earliest and still one of the most popular models is the Lee-Carter model (Lee and Carter 1992), which proved to perform very well and has become the “leading statistical model of mortality forecasting in the demographic literature” (Deaton and Paxson 2004:264). In many cases, however, forming expectations on future life expectancy alone is not sufficient. For example, if a further increase in retirement age is being considered, it is more appropriate to estimate how long people will be able to work instead of simply how long they will live. An important question in aging populations is whether increases in life expectancy will be accompanied with greater or lesser increases in life years spent in poor health and/or with disability (Nusselder 2003). Consequently, it would be useful to form expectations not only about how long people are expected to live but also about how healthy they will be in the future.

Health Expectancy and Compression of Morbidity

Health expectancy (or expected healthy life years) typically combines mortality and morbidity information to represent overall population health in a single indicator (Robine et al. 2003). It measures the number of remaining life years that a person at a certain age is expected to live without poor health and is increasingly used to
complement the conventional measure of life expectancy (Robine and Jagger 2003). Because health expectancy was developed to reflect that not all years of a person’s life are lived in perfect health, estimates of health expectancies have been very attractive and widely used tools for monitoring trends in population health (Robine et al. 2003).

Three distinct theories have been proposed regarding the evolution of health expectancy and life expectancy over time: compression of morbidity (Fries 1980), expansion of morbidity (Olshansky et al. 1991), and the so-called dynamic equilibrium theory (Manton 1982). Compression of morbidity postulates that survival and morbidity curves will become closer to each other as a result of strategies that effectively eliminate premature morbidity and mortality. Supporters of the pessimistic expansion theory assert that increases in life expectancy will not be followed by increases in healthy life expectancy because the declines in mortality stem from mainly those suffering from chronic, disabling diseases. The third hypothesis, dynamic equilibrium, emphasizes the link between morbidity and mortality and asserts that the increases in total life expectancy would likely entail increases in life expectancy both with and without morbidity, whereas years with severe morbidity remain stable. Compression (expansion) of morbidity can be measured in absolute values: (1) increases in healthy life expectancy are larger (smaller) than increases in total life expectancy; or (2) as a proportion: healthy life expectancy over total life expectancy is increasing (decreasing).

Modeling and Forecasting Health Expectancy

Two commonly used methods to estimate health expectancy are Sullivan’s method and the multistate life table method. They require different kinds of data and can yield different results (Barendregt et al. 1994). The simpler Sullivan method estimates health expectancy by combining mortality data with external information on cross-sectional prevalence in each health state (Sullivan 1971). The more refined multistate method models the prevalence of disability as the result of several transitions (e.g., incidence, mortality, and possibly remission) (Rogers et al. 1990). Although a multistate model has larger data requirements because it needs age-specific estimates of multiple transitions, it has several advantages. Most importantly, it acknowledges the fact that the stock of poor health is the result of different processes. Accordingly, one can interpret trends in health expectancy as a result of developments in the underlying transition rates.

Demographic literature offers many multistate projection studies that forecast the size of populations into the future. The projections are based on cohort components of demographic change, including births, deaths, and migration. The transitions between the modeled states are based on transition rates that may change in time (Hyndman and Shahid Ullah 2007) and/or may vary between subpopulations. Projections for subpopulations have been performed by region (Lutz et al. 1997), educational status (Lutz and Goujon 2001), household status (Yi et al. 2010), and labor force participation (Rogers et al. 1989), as well as by health/disability status (Manton et al. 1993). Recently, a large-scale research project was completed in the European Union. One of the goals of the research was to provide the size and age structure of future populations with and without disability (Willekens 2005).
With regard to forecasting morbidity by multistate models, we refer readers to a review of epidemiological approaches by Tabeau (Tabeau et al. 2002). The main output of the models discussed here are disease incidence numbers and cause-specific or total mortality counts. Several studies on health-based population forecasts and implications in terms of health service needs have been carried out by Manton and colleagues (Akushevich et al. 2007; Manton et al. 2007; Singer and Manton 1998). They proposed the use of a multidimensional stochastic process model to project population changes under simulated modifications in the distribution of major risk factors (Manton et al. 1992, 1993). None of these studies focused explicitly on forecasting the life years that a person is expected to live without poor health.

Although there is a clear rationale for forecasting health expectancy, efforts at improving forecasting models have been limited exclusively to life expectancy. This is partly because the primary object of interest for pension providers is the expected life years after retirement and not the expected healthy life years, and partly because the lack of long time series data on health status. Furthermore, compared with forecasting life expectancy based on mortality alone, forecasting health expectancy is more complicated because of the additional dimensions in the models. To our knowledge, only one recent study has forecast both life expectancy and a form of health expectancy. The authors employed Sullivan’s method to forecast active life expectancy for a number of years during the twenty-first century until 2080 for the United States (Manton et al. 2006), and for which they used future life tables estimated by the Social Security Administration and two scenarios on the expected rate of disability decline (1.7 % and 0.8 % per annum). Other studies forecasting health expectancy—Sullivan or multistate—are virtually non-existent.

Purpose of Our Study

Our study had two goals. The first was to build a theoretical framework for a multistate life table model in which the transition probabilities depend on age and calendar time. We aimed to describe how to model and forecast these transition probabilities using the Lee-Carter method, and to illustrate how this method can be used to forecast future health expectancy with prediction intervals around the forecasts. Second, we applied the method to data of the Dutch population aged 55 and older, and estimated health expectancies between 1989 and 2007 for men and women. We projected the transition probabilities until 2030 and applied multistate life table methods to obtain forecasts of life expectancy, disability-free life expectancy (DFLE), a frequently employed form of health expectancy, and life expectancy of nondisabled and disabled people. In addition, we analyzed the changing relationship between DFLE and life expectancy over time and attached probability distributions to different future scenarios of compression or expansion of disability.

A key concept in our work is the idea that the stochastic extrapolative models developed to forecast total life expectancy could be used to forecast health expectancy. However, instead of forecasting population mortality probabilities and using regular life tables, future health expectancies could be modeled by forecasting transition probabilities between the health states, and developments of future transition rates can be viewed as realizations of stochastic processes, like in the case of
mortality. Accordingly, future health expectancy could be modeled through transition probabilities that are extrapolated in a stochastic manner.

Methods

We specified three health states indicating the functional status of the individuals: nondisabled, disabled, and dead. Three possible transitions between these states were allowed: healthy persons may experience onset of disability, healthy persons may die, or disabled persons may die.\(^1\) Two crucial elements in our model are that transition probabilities depend not only on age but also on calendar year, and that they are treated as stochastic time series, which can be forecast by extending the Lee-Carter model (Lee and Carter 1992). In the following subsection, we describe how the Lee-Carter method can be used to forecast multiple transitions to forecast health expectancy. In particular, we pay attention as to how the joint tendency of the stochastic period effects of each transition type can be modeled. Limitations of the assumptions and their importance for the results are assessed in the Discussion section of this article.

Forecasting Transition Rates and Health Expectancy With the Lee-Carter Model

The Lee Carter model takes the following form:

\[
\ln m_{x,t}^{(i)} = \alpha_x^{(i)} + \beta_x^{(i)} \kappa_t^{(i)} + \epsilon_{x,t}^{(i)},
\]

\(m_{x,t}^{(i)}\) is the specific type \(i \in \{tr, g\} \in I\) transition rate for an \(x\)-year-old individual at time \(t \in \{1, 2, \ldots, T\}\), with gender \(g \in \{male, female\}\), and with \(tr \in \{nd, d, inc\}\) as the mortality rate of the nondisabled, mortality rate of the disabled, and the incidence rate, respectively. The parameters to be estimated are \(\alpha_x^{(i)}, \beta_x^{(i)}, \kappa_t^{(i)}, \epsilon_{x,t}^{(i)}\) is the error term.

Applying the Lee-Carter model is a two-step procedure. First, the parameters in Eq. 1 are estimated. Second, the transition rates are projected by forecasting the time-dependent parameter.

In the first step, parameters of Eq. 1—\(\alpha_x^{(i)}, \beta_x^{(i)}, \kappa_t^{(i)}\)—are estimated to model a given type of transition rate, \(\ln m_{x,t}^{(i)}\). The least square solution to the Eq. 1 is sought; however, this model cannot be fitted by ordinary least squares (OLS) because there are no predictors on the right-hand side. Nevertheless, assuming that \(\epsilon_{x,t}^{(i)}\) is normally distributed, the singular value decomposition (SVD) of the matrix with elements \(\ln(m_{x,t}^{(i)}) - \alpha_x^{(i)}\) estimation is equivalent to the maximum likelihood estimates. Generally a one-factor model is used; hence, in the Lee-Carter model, the matrix \((\hat{\beta}, \hat{\kappa})\) is a function of the leading singular value \((\sigma_1^{(i)})\), the first column \((u_1^{(i)})\) and the first row \((v_1^{(i)})\) of the SVD. Because of lack of identification, Lee and Carter

\(^1\) Online Resource 1 provides detailed descriptions of the quantities obtainable in an MSLT and information about how transition rates are converted into one-year transition probabilities.
proposed using the constraints $\sum_x \hat{\beta}_x^{(i)} = 0$ and $\sum_t \hat{\kappa}_t^{(i)} = 1$ to ensure that the solutions are unique. The latter constraint implies that summing the modeled log transition rate over $t$ and taking its expected value—the age-specific constant parameter $\alpha_x^{(i)}$—is simply the empirical average of the log transition rate at age $x$. The parameter $\kappa_t^{(i)}$ indicates the time-dependent latent process that quantifies the evolution of transition rates over time, whereas $\beta_x^{(i)}$ expresses how large the effect of age is on the transition rate for a unit change in this time index parameter. $\epsilon_{x,t}^{(i)}$s are sets of disturbances. If $x$ is the set of age groups and $t$ is the set of time periods, then the parameter estimates are given by

$$\hat{\alpha}_x^{(i)} = \frac{\sum_{t=1}^T \ln(m_{x,t}^{\epsilon(i)})}{T}$$

$$\hat{\beta}_x^{(i)} = \frac{\mu_x^{(i)}(x)}{\sum_{x \in X} \mu_x^{(i)}(x)}$$

$$\hat{\kappa}_t^{(i)} = \sigma_t^{(i)} \nu_t^{(i)}(t) \sum_{x \in X} \mu_x^{(i)}(x).$$

At each age, the disturbances are assumed to have an independently and identically distributed multivariate normal distribution with mean zero and covariance matrix $\Sigma_x^2$, which takes into account the joint distribution of the disturbances of every type of transition rate: $\epsilon_{x,t}^{(i)} \sim N(0, \Sigma_x^2)$. The maximum likelihood estimate for the covariance parameter is

$$\hat{\Sigma}_x^2_{i,j} = \frac{1}{T-1} \sum_{t=1}^T \left( \hat{\epsilon}_{x,t}^{(i)} - \bar{\epsilon}_x^{(i)} \right) \left( \hat{\epsilon}_{x,t}^{(j)} - \bar{\epsilon}_x^{(j)} \right).$$

In the second step, transition rates are forecast and used to estimate future health expectancies. By modeling future transition rates, $\alpha_x^{(i)}$ and $\beta_x^{(i)}$ are assumed to be constant over time, whereas the values of $\kappa_t^{(i)} = \{ \kappa_1^{(i)}, \kappa_2^{(i)}, \ldots, \kappa_T^{(i)} \}$ are extrapolated using a standard univariate time series model. Eventually, these extrapolated latent factors are inserted into Eq. 1 to obtain future transition rates.

For modeling and extrapolating the estimated values of $\kappa_t^{(i)}$, Lee and Carter tested several autoregressive integrated moving average (ARIMA) time series models. They found that the model of random walk (trajectory of successive random steps) with a drift parameter best described their data. They suggested that different model specifications might be more appropriate for other data sets; however, their random walk model with drift is used almost exclusively in applications. We follow Lee and Carter in adopting their projection model. The time series model on the values of $\kappa_t^{(i)}$ take the following form:
\[ \hat{k}_t^{(i)} = \hat{k}_{t-1}^{(i)} + \theta^{(i)} + \delta_t^{(i)} \]  \hfill (6)

\[ \delta_t^{(i)} \sim N\left(0, \Delta^2_{ij} \right), \]  \hfill (7)

where \( \theta \) is a vector with elements \( \theta^{(i)} \), the drift parameter is of transition type \((i)\), and \( \Delta^2 \) is the variance-covariance matrix taking into account the joint tendency of each transition type \((i)\) over time.

The maximum likelihood estimate of the parameter \( \hat{\theta}^{(i)} \) and the variance-covariance matrix \( \left[ \hat{\Delta}^2 \right]_{ij} \) for the time series model are computed as follows:

\[ \hat{\theta}^{(i)} = \frac{\hat{k}_T^{(i)} - \hat{k}_1^{(i)}}{T - 1} \]  \hfill (8)

\[ \left[ \hat{\Delta}^2 \right]_{ij} = \frac{1}{T - 1} \sum_{t=1}^{T-1} \left( \hat{k}_{t+1}^{(i)} - \hat{k}_t^{(i)} - \hat{\theta}^{(i)} \right) \left( \hat{k}_{t+1}^{(j)} - \hat{k}_t^{(j)} - \hat{\theta}^{(j)} \right), \]  \hfill (9)

where \( i \in \{ \text{tr}, g \} \in I \) and \( j \in \{ \text{tr}, g \} \in J \) are transition types at time \( t \in \{1, 2, \ldots, T\} \), with gender \( g \in \{ \text{male, female} \} \) and with \( \text{tr} \in \{ \text{nd, d, inc} \} \) being the mortality rate of nondisabled, mortality rate of disabled, and the incidence rate, respectively.

Having obtained the parameter estimates of the time series model, one may allow for and take into account parameter uncertainty in the trend itself during the forecasts. In such a case, the trend parameters are assumed to have a multivariate normal distribution with \( \hat{\theta} \sim N\left(\hat{\theta}, V\{\hat{\theta}\}\right) \), where \( \hat{\theta} \) is a vector with the true parameter estimates \( \hat{\theta}^{(i)} \) and where the variance-covariance matrix of the parameter estimates is

\[ V\{\hat{\theta}^{(i,j)}\} = \frac{\left[ \hat{\Delta}^2 \right]_{ij}}{T - 1}. \]  \hfill (10)

To model future transition rates, we use the last-year transition rates as observed in the data set to be the basis for the forecasts. An alternative approach could have been the use of the estimated last-year transition rates, but the advantage of the first method is that it avoids a jump-off bias in the first projected year (De Waegenaere et al. 2010). The transition rates \( s \) year from the base year \( T \) are given by

\[ \hat{m}_{s,T+1}^{(i)} = m_{s,T}^{(i)} \times RF_{s,T+1}^{(i)} + \delta_{s,T+1}^{(i)}, \]  \hfill (11)

where \( RF_{s,T+1}^{(i)} \) is the age-\( x \) reduction factor between time \( T \) and \( T+s \) for type of transition rate \( i \). Forecasts of the reduction factor are obtained by the following equation:

\[ RF_{s,T+1}^{(i)} = \exp\left(\hat{\beta}_x^{(i)} \times \left( \hat{k}^{(i)}_{T+s} - \hat{k}^{(i)}_T \right)\right), \]  \hfill (12)

where \( \hat{\beta}_x^{(i)} \) denotes the estimated \( \beta_x^{(i)} \), and \( \hat{k}^{(i)}_{T+s} \) denotes the forecast reduction factor.
\( s \geq 1 \) periods ahead of \( \hat{\kappa}_{T+s}^{(i)} \), \( \hat{\kappa}_{T+s}^{(i)} \) has the following conditional distribution:

\[
\hat{\kappa}_{T+s}^{(i)} \mid \hat{\kappa}_{T+s-1}^{(i)}, \hat{\Theta}^{(i)} \sim N\left(\hat{\kappa}_{T+s-1}^{(i)} + \hat{\Theta}^{(i)}, \hat{\Sigma}^{(i)}\right).
\] (13)

After simulations of future transition rates are obtained, they can be converted into one-year transition probabilities, taking into account the competition between the rates (see Online Resource 1). For each set of forecast transition probability profiles, a multistate life table can be set up, and corresponding DFLE \( \text{DFLE}_{x,t} \) can be estimated. Furthermore, the several probabilistic simulations yield prediction intervals for the life expectancy estimates, and the simulated health expectancies allow calculating the probability of a specific scenario of compression or expansion of disability.

Application

We applied the method to Dutch population data (that came from several sources) because no single longitudinal data set was available that could have provided all the necessary transition probabilities. Therefore, we used official mortality statistics pertaining to the whole population, prevalence of disability, and estimates of the hazard ratio of the mortality risk between disabled and nondisabled. We made use of the simple relationships among mortality, prevalence, and hazard ratio to obtain state-specific mortality rates in the first step, and to estimate incidence rates given prevalence and mortality rates in the second step (Barendregt et al. 2000).

Mortality

Survival probabilities for Dutch men and women by age (i.e., \( x \in \{55, 56, \ldots, 96, 97+\} \) ) were used, as published at Statistics Netherlands for each year between 1989 and 2007 (i.e., \( T=19 \)). The online database of Statistics Netherlands contains original calculations of one-year mortality probabilities and life tables for the Netherlands. The input data consist of death counts from vital statistics, birth counts, and population numbers.

Prevalence of Disability

Prevalence of disability was estimated using the POLS health and labor survey collected among the community-dwelling population of the Netherlands (CBS 2005). The POLS is an ongoing, annually conducted cross-sectional survey aiming to gather information on a broad range of topics concerning the living situation representative of the Dutch general population. The POLS is sampled on records from a centralized municipal registry and does not include the institutionalized population (less than 2% of men and women younger than 75). Self-reported health data were collected through face-to-face interviews and written questionnaires. The interviewer visited the participants at home, asked for informed consent, and left a written (drop-off) questionnaire. The annual net participation is approximately 10,000 individuals, with response rates of around 60% for the questionnaire. We used POLS surveys conducted between 1989 and 2007 because the current disability questions were first introduced in 1989, and we had access to data until 2007. To correct for
selective nonresponse and to ensure representativeness for the Dutch population, we used POLS sample weights (Stam and Knoops 2009). Data from the health and work module of POLS were available for those aged 12 or older. Table 1 shows the population characteristics by gender.

Disability status was measured by the OECD indicator (McWhinnie 1981) for persons 55 and older. The OECD disability indicator, combining the aspects of basic activities of daily living (ADL) and mobility limitations, measures the ability to perform tasks necessary for both physical functioning and for independent living. In this respect, the OECD indicator measures disability on a less severe level than the ADL disability indicator but measures it on a more severe level than the instrumental activities of daily living (IADL) indicator. The OECD disability indicator uses seven items (conversing, reading small letters, recognizing faces, biting and chewing, carrying objects, walking 400 m, and bending). For each item, respondents were asked whether they were able to perform the activities “without difficulty,” “with minor difficulty,” “with major difficulty,” or “only with help.” Using equipment such as eyeglasses or a hearing aid was not indicative of disability if the respondent did not need help or was able to carry out the activity with little or no difficulty. Disability was defined as having at least one item answered “with major difficulty” or “only with help.” Overall item nonresponse was fairly low, at 14.4%.

Population-level unadjusted prevalence of OECD disability gradually decreased between 1989 and 2007, falling from 23.4% to 17.0% for men and from 38.2% to 28.3% for women. The prevalence of disability for each sex and calendar year was smoothed by logistic regressions using a dummy variable for each sample year. The aim of smoothing was to capture the important patterns in the prevalence of disability while leaving out noise from the sampling design (independent sample every year) of the POLS survey. Logistic regression is a commonly used way to smooth disability prevalence. The Akaike information criterion indicated that a model including squared age and/or interaction variables would have been less appropriate.

Hazard Ratio of Disabled Persons on Death

A unique key for all respondents in the POLS between 1997 and 2006 was provided, which allowed the linking of individuals to the municipal population registries (Reitsma et al. 2003). The available population registries contain annual data on the date of death in the population until December 31, 2007. Records of POLS and population registries were linked deterministically to establish the date of death during the study follow-up period. Those who were not identified in the death registry were considered to be alive at the end of the study follow-up period.

The relative risk of disability on mortality was estimated using the record-linked survival data set with Cox regression models, stratified by survey year, and estimated for men and women separately. The time scale of the survival analyses was defined as a person’s age (Korn et al. 1997). Left truncation was applied to the age range over which the subject was not observed before the inclusion to the POLS survey (Guo 1993). We found no significant age interaction or time trend in the hazard ratios; therefore, we consider them to be constant over age and time. The hazard ratio of disability on mortality was 1.85 (confidence interval (CI): 1.66–2.07) and 1.72 (CI: 1.50–1.97) for men and women, respectively.
Table 1  POLS, study population and prevalence of disability by sex

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<td>37.1</td>
<td>37.9</td>
<td>40.4</td>
<td>34.3</td>
<td>33.4</td>
<td>31.1</td>
<td>33.5</td>
<td>30.1</td>
<td>30.5</td>
<td>27.7</td>
<td>30.5</td>
<td>31.0</td>
<td>31.1</td>
<td>28.8</td>
<td>28.3</td>
</tr>
</tbody>
</table>

Notes: “POLS” denotes the achieved sample size in the POLS survey, and “Response (%)” refers to the (corresponding) achieved response percentages. “Women (%)” denotes the percentage of women in the sample, while the values in the parentheses below the percentages present the number of women in the POLS survey.
Estimating Transition Rates

Because information on mortality rates of nondisabled and disabled populations separately was not available from primary data sources, we decomposed total mortality using the prevalence of disability and the hazard ratio of disability on mortality. We assumed that (1) the age and sex-specific mortality rates in the overall population are the weighted average of mortality rates of nondisabled \(m_{x,t}^{(nd)}\) and disabled \(m_{x,t}^{(d)}\) populations with the proportion of nondisabled and disabled, respectively, as weights; and (2) that the ratio between the mortality rate of disabled and nondisabled people is equal to the hazard ratio. The corresponding age and time-specific incidence rates, \(m_{x,t}^{(inc)}\), can be derived from given mortality rates of the nondisabled and disabled of age \(x\) at time \(t\), and given prevalence of disability at age \(x\) and \(x+1\) at time \(t\), because these quantities are interrelated and mutually define each other. Online Resource 2 presents a formal derivation of these transition rates.

Although our model assumes that only incidence is possible, evidence suggests that people can recover from disability, even at higher ages (Hardy and Gill 2004). Therefore, the probability of incidence in our model can be interpreted as a modified net incidence probability, which corresponds to the number of transitions from nondisabled to disabled state minus the number of transitions from disabled to nondisabled state, relative to the number of nondisabled people.

Figure 1 shows the incidence probabilities and mortality probabilities of the nondisabled for a number of different ages for men and women between 1989 and 2007, where we normalized the transition probabilities to the year 1989. Because our decomposition of total mortality rates assumes that mortality rates of disabled are constant multiples of the mortality rates of nondisabled, where the multiplier is the hazard ratio, the normalized mortality probabilities are identical for these two groups. Consequently, we show the graphs for only the nondisabled.
The panels of Fig. 1 clearly illustrate that over longer periods, the transition probabilities decrease, reflecting the decrease of prevalence of disability, and the increase in life expectancy (LE) over time. The panels of Fig. 1 also show that the decreases in mortality were substantially larger for men, especially at younger age groups (60, 70).

Our estimation of transition rates holds two implicit assumptions. First, our prevalence estimates are based on survey data that do not include institutionalized individuals; hence, our prevalence figures are somewhat underestimated. Second, we assume that the hazard ratio is constant over time, which may not be valid. Sensitivity of our results to these assumptions is discussed explicitly later.

**Fitting Lee-Carter Model on the Transition Rates and Applying the Multistate Method**

We fitted a separate Lee-Carter model on each of the six sets of age-specific transition rates to estimate the model parameters, including $\hat{\xi}_t^{(i)}$. Based on the predicted values of $\hat{\xi}_t^{(i)}$ we estimated six drift parameters and the $6 \times 6$ (men and women together) variance-covariance matrix indicating the size of their joint distribution. The latter allowed for taking into account the joint tendency of the transition rates during the forecasts. By simulating future transition rates, we used the last-year transition rates as observed in 2007 to avoid a jump-off bias. After we obtained the simulated transition rates, we converted them into one-year transition probabilities and set up a multistate life table to derive health expectancy estimates.

**Model Validation**

We used the $R^2$ statistic to measure how large a proportion of the variation in the different transition rates could be explained by the Lee-Carter models. Furthermore, we performed two types of analysis to assess how well the model fit past life expectancy and disability-free life expectancy based on official data published by Statistics Netherlands. In the first analysis, we plotted our life and health expectancy estimates against the official statistics between 1989 and 2007, the period for which we had data. In the second analysis, we backcast LE and DFLE using our model for the years between 1983 and 1988, and compared these estimates with those of the Statistics Netherlands.

**Model Outcomes**

The model can be used to forecast numerous outcomes: (1) transition probabilities, (2) prevalence of disability, (3) total life expectancy ($LE_{55,t}$), (4) total life expectancy of nondisabled and of disabled populations, (5) disability-free life expectancy ($DFLE_{55,t}$), (6) difference between total LE and DFLE ($LE_{55,t} - DFLE_{55,t}$), and (7) the proportion of DFLE in total LE ($DFLE_{55,t} / LE_{55,t}$). Estimating total $LE_{55,t}$ and $DFLE_{55,t}$ enabled us to assess the likelihood of future compression or expansion of disability.
We assessed the role of uncertainty in the projections from three sources: (1) the uncertainty of the parameters for predicting prevalence and hazard ratios; (2) the uncertainty of the evolution of transition profiles over time; and (3) the uncertainty of the trends themselves.

For a reference deterministic model, we assumed that the prevalence of disability and the hazard ratios were known with certainty. Because these values were used to decompose total mortality and to calculate incidence rates, this assumption actually implied that we treated the transition rates as if we had observed them in the whole Dutch population. We further assumed that the future development of transition rates, $\kappa_{T+t_t}^{(l)}$, was also known with certainty. Each year, the transition rates changed according to the drift factor, $\hat{D}^{(l)}$. We refer to this model as the “deterministic model.”

In the first step of our analysis of uncertainty, we relaxed some of the assumptions of the deterministic model: we took into account the fact that the calculation of transition rates was based on estimates of hazard ratios and odds ratios. We applied probabilistic sensitivity analysis to take parameter uncertainty into account, and we drew random hazard ratios and odds ratios 100 times. After each random draw, we obtained a set of transition rates and corresponding DFLE estimates. The simulated variation in the DFLE estimates was summarized by prediction intervals that implicitly reflect the effect of the variability of the Lee-Carter model parameters. We refer to this as Model 1.

In the second step, we relaxed previous assumptions about future realizations of the transition rates. Here, we took into account that future developments of transition rates are uncertain given a fixed trend. We drew 50 random odds ratios and hazard ratios to simulate the variation in the transition rates. Given a particular set of these, and based on which of the trends of evolution was estimated, we simulated the uncertainty in the future evolution of the transition rates 50 times by probabilistic sensitivity analyses. We refer to this as Model 2.

In the third step, we also relaxed the assumption about fixed trends. Based on a particular set of simulated transition rates, where the simulations were done the same way as in step 1 or step 2, we simulated random trend values. Ultimately, conditional on a particular trend value, we simulated the uncertainty in the evolution of future transition rates, just like in step 2. Each part of the simulation was carried out 50 times, and because the simulation contained multiple loops, this resulted in a total number of 125,000 random draws. We refer to this as Model 3.

Results

Parameter Estimation

Parameter estimates of the Lee-Carter model for the different transitions are plotted in Fig. 2. The first column of the graph depicts the empirical average of the age-specific transition rates. The second column shows the age profiles, indicating which rates change rapidly or slowly in response to the time-dependent evolution of the transition rates. This latent evolution is quantified in the third column.

On average, women had higher incidence rates than men; and for both sexes, the incidence rates decreased between 1989 and 2007. Incidence rates decreased
relatively faster than mortality rates (Fig. 2, third panel), which is consistent with the fact that healthy life expectancy increased.

During the period 1989–2007, both types of mortality rates decreased; the decrease was faster for men than for women. Because of our decomposition method, the pace of the decrease was the same for both nondisabled and disabled mortality rates. In absolute terms, however, the mortality rate decreased more for the disabled than for the nondisabled population.

The parameter estimates for the time series models on the values of \( \tilde{\rho}_i \) are given in Table 4 in Online Resource 3.

Figure 3 presents the core results of the model from which life expectancies and health expectancies are derived. The figure depicts age profiles of one-year incidence probability, the mortality probability of the nondisabled, and the prevalence of disability in 1989 and 2007, as well as their expected values in 2030. The graphs clearly show that the likely increase of LE and DFLE will be the combined result of a decreasing disability incidence and a decreasing mortality among both men and women.

Forecast and Validation

We used the \( R^2 \) statistic to measure how large a proportion of the variation in the data was explained by the model. See Online Resource 4 for figures showing the age-specific and overall \( R^2 \) estimates.

An alternative way of assessing model fit is to compare internally obtained results with external statistics. We performed two types of analysis to assess how well the model fits past LE and DFLE measures based on official data published by Statistics Netherlands. In the first analysis, we plotted our life and health expectancy estimates against the official statistics between 1989 and 2007, the period for which we have data (Figs. 4 and 5, period 1989–2007). In the second analysis, we backcast LE and DFLE with our model for the years between 1983 and 1988, and compared these...
estimates with those of the Statistics Netherlands. If the estimates of Statistics Netherlands fall into the prediction intervals of our model, then the model can be considered valid because the model not only predicts in-sample outcomes (LE and DFLE between 1989 and 2007) but also out-of-sample outcomes (LE and DFLE between 1983 and 1988). The results are presented in Figs. 4 and 5.

According to official statistics, LE at age 55 increased faster among men (+3.7 years, from 21.1 to 24.8) than among women (+1.9 years, from 26.8 to 28.7) between 1983 and 2007. Based on estimates of Statistics Netherlands for the period 1989–2007, DFLE increased to approximately the same extent among both men (from 16.1 to 19.9) and women (from 15.8 to 19.1). Statistics Netherlands also published DFLE for years preceding 1989 (1983–1988); however, these time series contain a three-year period (1986–1988) with a considerably different disability questionnaire than the one employed before 1986 and since 1989. We did not use these years in our model, although Statistics Netherlands did publish DFLE estimates for these years, applying a number of adjustment techniques to take into account the breaks in the time series (Lodder and Kardal 2009; Stam and Knoops 2009). These point estimates and confidence intervals are depicted in Figs. 4 and 5.

Fig. 3 Probability of incidence, nondisabled mortality, and prevalence in 1989, 2007, and 2030, men and women. ND = nondisabled. D = disabled
Regarding the model fit in terms of estimated LE and DFLE between 1989 and 2007, it is clear even by visual inspection that fitting the Lee-Carter model on the transition rates result in excellent model fit to reproduce past LE and DFLE as

Fig. 4 Total life expectancy and disability-free life expectancy at age 55, 1983–2030, men. Model 1 allows for uncertainty in prevalence and HR. Model 2 allows for uncertainties of Model 1 and uncertainty in process. Model 3 allows for uncertainties of Model 2 and uncertainty in parameters. Source: CBS: Statistics Netherlands

Fig. 5 Total life expectancy and disability-free life expectancy at age 55, 1983–2030, women. Model 1 allows for uncertainty in prevalence and HR. Model 2 allows for uncertainties of Model 1 and uncertainty in process. Model 3 allows for uncertainties of Model 2 and uncertainty in parameters. Source: CBS: Statistics Netherlands
published by Statistics Netherlands. Concerning the backcast LE and DFLE values, projected prediction intervals of our model contained estimates from Statistics Netherlands; hence, the model can be considered valid for this data set.

Future Projections of Life Expectancy

Figures 4 and 5 show how the various types of uncertainties build up the prediction intervals around the deterministic estimates for future values of total LE and DFLE (period 2008–2030 in the graphs). Tables 2 and 3 detail how LE and DFLE at age 55 are anticipated to increase for men and women until 2030. According to our projections, men’s LE will increase from 24.8 in 2007 to 26.8 years by 2020 and to 28.2 years by 2030. Taking all the uncertainty into account, the 95% prediction interval (PI) lies between 25.3 and 28.0 years by 2020, and between 26.0 and 29.6 years by 2030. These projections correspond to a minimum of 0.5 and 1.2 years and a maximum of 3.2 and 4.8 years of increase in LE by 2020 and 2030, respectively.

The projected increase in LE for women is somewhat smaller than it is for men. Our model predicts that LE is likely to increase from 28.7 in 2007 to 29.8 by 2020 and 30.6 by 2030. However, a decrease in LE has some marginal possibility, resulting in a LE of 28.3 and 28.2 with 2.5% probability by 2020 and 2030, respectively. Conversely, a large increase has some minor potential, too, which would yield a LE of 31.1 by 2020 and 32.6 by 2030.

Tables 2 and 3 present LE estimates for nondisabled and disabled people at age 55 and onward, both for the past and for the future. Between 1990 and 2005, LE of nondisabled men increased from 22.9 (CI: 22.6–23.3) to 25.2 (CI: 24.9–25.4) years, whereas LE of disabled men increased from 17.8 (CI: 17.3–18.3) to 20.2 (CI: 19.7–20.8) years. Further increases are expected in the future. Between 2010 and 2030, LE of nondisabled men is projected to increase from 26.2 (PI: 25.3–26.9) to 28.8 (PI: 26.2–30.7) years, whereas LE of disabled men is forecast to increase from 21.2 (PI: 20.2–22.2) to 24.3 (PI: 21.2–26.9) years.

LE of nondisabled and disabled women also increased between 1990 and 2005. Whereas the former individuals expected to live 28.7 (CI: 28.4–29.3) years in 1990, this expectation increased to 29.7 (CI: 29.3–30.2) by 2005. Corresponding values of the disabled were 24.4 (CI: 24.0–24.8) in 1990 and 25.5 (CI: 25.0–25.8) in 2005. With regard to the future, LE of the nondisabled is forecast to increase between 2010 and 2030, from 30.2 (PI: 29.4–31.1) to 31.6 (PI: 28.9–33.8). A similar increase is anticipated for the disabled, from 26.1 (PI: 25.0–26.9) to 27.6 (PI: 24.4–30.3).

Tables 2 and 3 present estimates of DFLE both in terms of number of years and as a proportion of total LE. DFLE of men is projected to increase from 19.1 (CI: 18.6–19.4) in 2005 to 21.9 years (PI: 18.0–23.5) by 2020 and to 23.4 years (PI: 16.2–25.2) by 2030. DFLE relative to LE is forecast to rise from 78.9% in 2005 to 81.7% and to 82.8% during the same period. Expectations about increases in DFLE for women are similar to those of men. DFLE is expected to increase from 17.7 years (CI: 17.2–18.1) in 2005 to 20.4 years (PI: 15.4–23.3) in 2020 and further to 21.5 years (PI: 13.3–24.9) by 2030. These changes correspond to increases in the DFLE/LE ratio from 62.7% to 68.4% by 2020 and to 70.1% by 2030.
Table 2  Disability-related life expectancy measures for selected years, men

<table>
<thead>
<tr>
<th>Year</th>
<th>Life Expectancy (Total)</th>
<th>Life Expectancy (Nondisabled)</th>
<th>Life Expectancy (Disabled)</th>
<th>Disability-Free Life Expectancy</th>
<th>Life Expectancy With Disability (LwD)</th>
<th>DFLE / LE (%)</th>
<th>Probability of Compression of Disability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(A)</td>
<td>(R)</td>
</tr>
<tr>
<td>1990</td>
<td>21.6</td>
<td>22.9</td>
<td>17.8</td>
<td>17.3–18.3</td>
<td>16.2</td>
<td>5.4</td>
<td>4.8–6.0</td>
</tr>
<tr>
<td>1995</td>
<td>22.1</td>
<td>23.6</td>
<td>18.5</td>
<td>18.0–18.9</td>
<td>15.9</td>
<td>6.2</td>
<td>5.6–6.8</td>
</tr>
<tr>
<td>2000</td>
<td>22.9</td>
<td>23.9</td>
<td>18.9</td>
<td>18.3–19.4</td>
<td>18.1</td>
<td>4.8</td>
<td>4.3–5.3</td>
</tr>
<tr>
<td>2005</td>
<td>24.2</td>
<td>25.2</td>
<td>20.2</td>
<td>19.7–20.8</td>
<td>19.1</td>
<td>5.1</td>
<td>4.8–5.6</td>
</tr>
<tr>
<td>2010</td>
<td>25.3</td>
<td>26.2</td>
<td>21.2</td>
<td>20.2–22.2</td>
<td>20.4</td>
<td>4.9</td>
<td>3.9–6.0</td>
</tr>
<tr>
<td>2015</td>
<td>26.1</td>
<td>26.9</td>
<td>22.1</td>
<td>20.4–23.6</td>
<td>21.2</td>
<td>4.9</td>
<td>3.4–7.4</td>
</tr>
<tr>
<td>2020</td>
<td>26.8</td>
<td>27.6</td>
<td>22.8</td>
<td>20.7–24.8</td>
<td>21.9</td>
<td>4.9</td>
<td>3.0–9.0</td>
</tr>
<tr>
<td>2025</td>
<td>27.6</td>
<td>28.2</td>
<td>23.6</td>
<td>21.0–25.9</td>
<td>22.7</td>
<td>4.9</td>
<td>2.9–10.5</td>
</tr>
<tr>
<td>2030</td>
<td>28.2</td>
<td>28.8</td>
<td>24.3</td>
<td>21.2–26.9</td>
<td>23.4</td>
<td>4.9</td>
<td>2.7–12.0</td>
</tr>
</tbody>
</table>

Notes: For the years 1990–2005, we provide 95% confidence intervals; for the years 2010–2030, we provide 95% prediction intervals based on Model 3, which allows for uncertainty in prevalence and HR, uncertainty in process, and uncertainty in the trend parameters. Size of absolute compression (A): \((\text{LE}_{55} - \text{DFLE}_{55}) - (\text{LE}_{55,2007} - \text{DFLE}_{55,2007}) = \text{LwD}_{55} - \text{LwD}_{55,2007}\); measured in number of years. Size of relative compression (R): \((\text{DFLE}_{55} / \text{LE}_{55}) - (\text{DFLE}_{55,2007} / \text{LE}_{55,2007})\); measured in percentage points. Adding the presented estimates of DFLE and LwD may not reproduce LE exactly because of rounding.

a Absolute compression.
b Relative compression.
Table 3  Disability-related life expectancy measures for selected years, women

<table>
<thead>
<tr>
<th>Year</th>
<th>Life Expectancy (Total)</th>
<th>Life Expectancy (Nondisabled)</th>
<th>Life Expectancy (Disabled)</th>
<th>Disability-Free Life Expectancy</th>
<th>Life Expectancy With Disability (LwD)</th>
<th>DFLE / LE (%)</th>
<th>Probability of Compression of Disability (%)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(A)§</td>
</tr>
<tr>
<td>1990</td>
<td>27.0</td>
<td>28.7</td>
<td>24.4</td>
<td>16.0</td>
<td>11.0</td>
<td>59.3</td>
<td>56.7–62.2</td>
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<td>1995</td>
<td>27.1</td>
<td>29.0</td>
<td>24.7</td>
<td>15.3</td>
<td>11.8</td>
<td>56.3</td>
<td>54.0–58.3</td>
</tr>
<tr>
<td>2000</td>
<td>27.3</td>
<td>28.8</td>
<td>24.5</td>
<td>17.7</td>
<td>9.6</td>
<td>64.8</td>
<td>63.2–66.4</td>
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<tr>
<td>2005</td>
<td>28.2</td>
<td>29.7</td>
<td>25.5</td>
<td>17.7</td>
<td>10.5</td>
<td>62.7</td>
<td>61.0–64.4</td>
</tr>
<tr>
<td>2010</td>
<td>29.0</td>
<td>28.4–29.5</td>
<td>26.1</td>
<td>19.2</td>
<td>9.7</td>
<td>66.5</td>
<td>59.8–72.4</td>
</tr>
<tr>
<td>2015</td>
<td>29.4</td>
<td>28.3–30.4</td>
<td>26.4</td>
<td>19.8</td>
<td>9.6</td>
<td>67.4</td>
<td>55.1–76.3</td>
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<tr>
<td>2020</td>
<td>29.8</td>
<td>28.3–31.1</td>
<td>26.8</td>
<td>20.4</td>
<td>9.4</td>
<td>68.4</td>
<td>51.0–79.2</td>
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<tr>
<td>2025</td>
<td>30.2</td>
<td>28.3–31.9</td>
<td>27.2</td>
<td>20.9</td>
<td>9.3</td>
<td>69.3</td>
<td>46.8–81.2</td>
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<tr>
<td>2030</td>
<td>30.6</td>
<td>28.3–32.6</td>
<td>27.6</td>
<td>21.5</td>
<td>9.2</td>
<td>70.1</td>
<td>42.9–82.8</td>
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</table>

Notes: For the years 1990–2005, we provide 95% confidence intervals; for the years 2010–2030, we provide 95% prediction intervals based on Model 3, which allows for uncertainty in prevalence and HR, uncertainty in process, and uncertainty in the trend parameters. Size of absolute compression (A): (LE$_{55,t}$ – DFLE$_{55,t}$) – (LE$_{55,2007}$ – DFLE$_{55,2007}$) = LwD$_{55,t}$ – LwD$_{55,2007}$; measured in number of years. Size of relative compression (R): (DFLE$_{55,t}$ / LE$_{55,t}$) – (DFLE$_{55,2007}$ / LE$_{55,2007}$); measured in percentage points. Adding the presented estimates of DFLE and LwD may not reproduce LE exactly because of rounding.

§Absolute compression.

§Relative compression.
The jointly simulated DFLE and LE estimates make it possible to calculate the probability that either compression or expansion of disability will occur in the future. Tables 2 and 3 present the likelihood of compression of disability. We expressed compression of disability in terms of both absolute and relative value. In the first case, compression of disability would occur if the increase in DFLE was larger than the increase in total LE: that is, a reduction in the years with disability. If the compression of disability is interpreted in a relative sense, such a compression would occur if the proportion of disability-free life years to total life years would increase over time.

When compression of OECD disability is measured in years, the probability of its occurrence by 2030 is approximately 50% for men and 60% for women. In other words, among women, the number of years lived without OECD disability is more likely to increase slightly faster than the number of years lived in total. The picture is somewhat brighter if compression of disability is measured in a relative sense. According to the projections, it is more likely that disability-free life years as a proportion of total LE would increase; the probability of compression is 63% for men and 67% for women.

**Discussion**

We proposed a theoretical framework for a multistate life table model in which the transition probabilities depend on age and calendar time. We described how to model and project these transition rates by the Lee-Carter method, and illustrated how it could be used to forecast future health expectancies along with prediction intervals. We applied the model to the Dutch population aged 55 and older, and estimated health expectancies between 1989 and 2030. Additionally, we analyzed the changing relationship between DFLE and LE over time, and attached probability distributions to different future scenarios of compression or expansion of disability.

**Explanation**

There are several reasons to believe that DFLE will keep increasing in the future. Favorable trends in tobacco consumption (Draper 2005), dietary habits restricting the intake of saturated fats (Van Kreijl and Knaap 2004), physical exercise (Bemelmans et al. 2004), changes in the composition of the population by socioeconomic status, and advances in medical technology have all contributed to improving individual risk profiles and better health status of the Dutch populations. These trends are likely to continue in the future.

On the other hand, there are unfavorable health trends as well. Particularly worrisome is that the share of the population that is overweight is continuously increasing and that the dietary habits of adolescents are changing adversely (Bemelmans et al. 2004). These trends will have an increased impact on morbidity because diabetes, cardiovascular and musculoskeletal diseases, and various types of cancers have been shown to be associated with obesity (Mokdad et al. 2003). Two demographic trends may also have a negative effect on health expectancy: the increasing instability of social relations and the changing ethnic composition with a higher share of groups with non-Western origin.
Other Studies

Many studies have estimated HE in the past using various study populations, disability measures, and calendar periods. The most extensive work in assessing the evolution of past HE has been conducted for the U.S. population. Crimmins et al. estimated that gains in LE during the 1970s were mainly accompanied by increased time spent with chronic limitations of common activities and by slightly decreased time with severe disability (Crimmins et al. 1989). Later, Crimmins et al. (1997) found that during the 1980s, gains in LE rose along with DFLE for both men and women. In a subsequent study, Crimmins et al. (2009) examined changes in LE with and without ADL and IADL disability, using longitudinal data between 1984 and 2000. They showed that the increase in DFLE at age 70 was the same as the increase in LE. Our results accord with these findings.

In Europe, estimates of LE and DFLE for men and women, based on the European Community Household Panel, were published for 13 European Union member states from 1995 to 2001 (Jagger et al. 2009). Significant increases were found in LE in early (age 16) and late (age 65) adulthood, with considerable heterogeneity in the trends in health expectancy. In nine countries, life expectancy with disability (LwD) increased, whereas four countries showed evidence of decreasing LwD.

Previous studies on trends in health expectancy in the Netherlands (e.g., Perenboom et al. 2004, Picavet and Hoeymans 2002, and Van De Water et al. 1996) used various health status indicators, time periods, and age groups for their analyses and reached in diverse conclusions on the trends. A recent study by the Statistics Netherlands on health expectancy trends at age 65 (Bruggink et al. 2009) used the data set we used; but unlike previous studies, here, morbidity was measured in three different ways: self-rated health, presence of chronic disease, and OECD disability, and health expectancy was estimated for the age of 65. The results show that since the 1980s, health expectancy at age 65 measured in terms of good self-reported health or DFLE has been increasing for men. The increase has been somewhat faster since the early 2000s. Unfortunately, among both men and women, life expectancy without chronic diseases has been decreasing. For women, DFLE increased and years with good self-rated health stagnated.

Sensitivity Analyses

A limitation of the POLS data is that the annual samples do not include the institutionalized population, among whom the prevalence of disability is higher than in the general population. We performed sensitivity analyses to assess the potential bias on the DFLE forecasts caused by this limitation. Information on the number of institutionalized persons for every age and year between 1995 and 2007 is available on the website of Statistics Netherlands (Statline). Using this information, we calculated the age-specific prevalence of institutionalized population for each year and ran a new model using only the period 1995–2007. We assumed that all who were institutionalized were disabled, thereby, assessing the maximum bias that the exclusion of these people may have caused. Results of the sensitivity analyses revealed that our model overestimates DFLE with a maximum of 0.6 years for men and 0.7 years for women between 1995 and 2007. Similar differences were predicted between the
original and the new DFLE forecasts by 2030. Given the uncertainty around these future estimates, the importance of differences can be considered small.

Another limitation of our study comes from the fact that the record-linked POLS data do not have enough power to detect changes in the hazard ratio. We performed additional sensitivity analyses to assess the potential bias that changes in the hazard ratio may have caused. In particular, we assessed the effect of both an annual 1% decrease and 1% increase in the hazard ratio between 1989 and 2007 on the estimates of DFLE. In the first case, the hazard ratio in 2007 was 83% of that in 1989, whereas in the second case, it was 120%. The results of the sensitivity analyses indicate that such changes in the hazard ratio had virtually no effect on the original DFLE estimates. These findings were true for both men and women.

It is important to note that our definition of disability essentially excludes the possibility of detecting a dynamic equilibrium because it does not distinguish between severe and mild disability and because we interpreted future compression of disability in terms of probabilities. A dynamic equilibrium would occur if both incidence and mortality were postponed such that the LwD$_{55,t}$ neither decreased nor increased. Looking at the expected future LwD values for men in Table 2, this is exactly what we found. Correspondingly, the probability of compression is very close to 50%, referring to the situation that an increasing LwD is equally likely as a decreasing LwD. Such a situation in our model seems to indicate a dynamic equilibrium among men.

Model-Related Issues

Every model is a simplification of reality; therefore, certain assumptions are made during its construction. One of the assumptions of the Lee-Carter model is that the expected evolution of the transition rates over time ($\theta(t)$) depends on the first and the last observation of the latent process ($\kappa_1^{(i)}$ and $\kappa_T^{(i)}$) and that the expected evolution of the transition rates is merely an extrapolation of the trend estimated on these two end points. If, for example, the trend of $\kappa_T^{(i)}$ is close to linear, then choosing other end points would not significantly influence the future evolution of the transition rates. Consequently, the uncertainty around the predictions would be relatively small as well. This is true here for mortality rates. However, if the trend in $\kappa_t^{(i)}$ is less linear and the observation window is relatively short, then the estimate of $\theta(t)$ might be sensitive to choosing end points other than $\kappa_1^{(i)}$ and $\kappa_T^{(i)}$. Accordingly, the uncertainty around future evolution would be somewhat larger as well. This is true here for incidence rates.

We assessed the stability of the age-interaction and the trend parameters by defining a different time window during which the parameters were estimated. We eliminated the first three years of the POLS data, resulting in the study period of 1992–2007. We then reestimated the model and found that the parameters were stable. The age-interaction parameters were very close to the original estimates, with an average difference of approximately 5%. The effect of trimming the time window of the analysis had little effect on the results. The deterministic forecasts of life expectancy were essentially the same as at the original forecasts: DFLE was 0.3 years higher by 2030.
We also forecast overall life expectancy based only on mortality rates using the same simple Lee-Carter method that we used for forecasting health expectancy. We then compared these forecasts with those from the multistate life table projections. The projections were very similar, but larger prediction intervals were estimated around the multistate life table projections.

Conclusions

Our findings suggest that the Lee-Carter model is generalizable to multistate life table settings, and can be used to model transition rates connecting nondisabled, disabled, and dead states and to forecast disability-related health expectancies. However, the application of the generalized Lee-Carter model to different data sets may result in poorer model fit if, for example, the time evolution of transition rates is not linear. Nonetheless, the model framework presented here can be used in other countries. Prevalence of OECD disability may be replaced with ADL, IADL disability, subjective well-being, or other prevalence measures, which are good indicators of population health. The approach demonstrated for health expectancies in our study could be used for working life expectancies as well because working life expectancies are based on similar multistate models. Thus, the model framework may be used to forecast population health with various measures of health status. Besides the application of different health indicators, a specific methodological question may appear on the future research agenda: the inclusion of common trends in the forecasts of transition rates (Li and Lee 2005).

References


