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Modeling and Forecasting Health Expectancy

Theoretical Framework and Application

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MODELING AND FORECASTING HEALTH EXPECTANCY;

THEORETICAL FRAMEWORK AND APPLICATION

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 less life years spent with ill-health. Therefore it is useful to complement forecasts of life expectancy with forecasts of health expectancies. 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 multi-state life table methods (MSLT). In our paper we present a theoretical framework for a MSLT model, in which the transition probabilities depend on age and calendar time. The goal of our study was 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

BACKGROUND

Life expectancy

Over the last decades improving mortality conditions have resulted in increases in the length of human life and subsequent population ageing in western countries. The continuous rise of life expectancy (LE) 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 OECD countries (OECD 2009). The old-age dependency ratio, a commonly used indicator of demographic pressure on social security, has been increasing for decades, and is expected to rise further in these countries. Since these developments have considerable consequences for the sustainability of two fundamental institutions of social security, 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, Blake and Dowd 2008; MacMinn, Brockett and Blake 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 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, biomedical and life-style arguments, but even 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

which 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, Blake and Dowd 2006; De Waegenaere, Melenberg and Stevens 2010; Dowd, Blake and Cairns 2010; Lee and Carter 1992). One of the advantages of such stochastic extrapolative models is that probabilities can be attached to a full range of different scenarios, yielding probabilistic prediction intervals for the forecasts. 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). In many cases however, it is not sufficient to form expectations on future life expectancy alone. For example, if a further raise of retirement age is being considered, it is more appropriate to estimate how long people will be able to work in the future, 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 useful to form expectations not only on how long people are expected to live, but also on how healthy they will be in the future.

Health expectancy and compression of morbidity

Health expectancy (or expected healthy life years, HE) 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 ill-health, and is increasingly used to complement the conventional measure of life expectancy (Robine and Jagger 2003). Health expectancy, in its most frequently employed form, is a functional health status measure, yielding the disability-free life expectancy (DFLE) and the life expectancy with disability (LwD) measures. 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 DFLE and LE over time: compression of morbidity, expansion of morbidity and the so-called dynamic equilibrium theory. Compression of morbidity, proposed by Fries (Fries 1980), postulates that survival and morbidity curves will become more and more rectangularized and closer to each other in the future, as a result of strategies that effectively eliminate premature morbidity and mortality. Supporters of the more pessimistic expansion theory (Olshansky et al. 1991) assert that increases in LE 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 theory emphasizes the link between morbidity and mortality. Supporters of the dynamic equilibrium hypothesis claim 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 (Manton 1982). Compression (expansion) of morbidity can be measured in absolute values: increases in healthy life expectancy are larger (smaller) than increases in total life expectancy; or as a proportion: healthy life expectancy over total life expectancy is increasing (decreasing). Alternatively, one can refer to absolute compression of morbidity as decreasing number of years with ill-health, and to relative compression of morbidity as decreasing proportion of years with ill-health over total number of life-years.

Although there is a clear rationale for forecasting HE, studies with such objective are rare. 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 to forecasting LE based on mortality alone, forecasting HE is more complicated because of the additional dimensions in the models.

Modeling and forecasting health expectancy

There are two commonly used methods to estimate health expectancy: Sullivan's method and the multi-state life table (MSLT) method. They require different kinds of data and can yield different results (Barendregt, Bonneux and Van der Maas 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 MSLT method models the prevalence of disability as the result of several transitions (e.g. incidence, mortality and possibly remission) (Rogers, Rogers and Belanger 1990). Although an MSLT has larger data requirements since it needs age-specific estimates of multiple transitions, it has several advantages. Most importantly, it acknowledges the fact that the stock of disability/ill health is the result of different processes. Accordingly, one can interpret trends in HE as a result of developments in the underlying transition rates. Using the MSLT method it is possible to decompose the population LE into a weighed average of the LE of non-disabled and the LE of disabled people.

To our knowledge, there has been only a recent study that forecast LE and a form of health expectancy. The authors employed Sullivan's method to forecast active life expectancy (ALE) for a number of years during the twenty-first century until 2080 for the U.S. (Manton, Gu and Lamb 2006), and for which they used future life tables estimated by the Social Security Administration (SSA) and two scenarios on the expected rate of disability decline (1.7% and

0.8% per annum). The disability status was measured as loss of ability to perform activities related to mobility and life-maintaining activities. Their projections indicated that both absolute and relative compression of disability is expected to occur in the U.S. Other studies forecasting HE - either Sullivan or MSLT - are virtually non-existent.

Purpose of our study

Our study had two goals. The first was to build a theoretical framework for a multi-state 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 MSLT methods to obtain forecasts of life expectancy (LE), disability-free life expectancy (DFLE), LE of non-disabled and LE of disabled people. In addition, 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.

A key concept in our work is the idea that the stochastic extrapolative models developed to forecast total LE could be used to forecast HE. 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. Theoretically there is no reason to assume that stochastic extrapolative models would predict any kind of transition rates worse than they do mortality rates: this is entirely an empirical question. In any case, developments of future transition rates can be viewed as realizations of stochastic

processes, like in case of mortality. For example if an MSLT is based on incidence rates and two state-specific mortality rates, and these transition rates change over calendar time, then the same argument holds for incidence and state-specific mortality as it does for overall mortality. Consequently 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: non-disabled, disabled, and dead. Three possible transitions between these states were allowed: healthy persons may experience onset of disability or they may die, while disabled person may die[1]. A crucial element in our model is that transition probabilities do not only depend on age but also on calendar year, and that they are treated as stochastic time series, which can be forecasted by extending the Lee-Carter model (Lee and Carter 1992). Lee and Carter modeled future mortality rates of the U.S. population using an extrapolative method in which the mortality depended on three effects, a deterministic age effect, a stochastic period effect and an interaction between those two effects. The virtue of their approach was that it combined a simple demographic model with standard time series methods to forecast past mortality, and that it proved to perform well in practice. Because the Lee-Carter model was very parsimonious in the number of parameters required it was not subject to unstable parameter estimates like in many other models. The method of Lee and Carter as developed for mortality rates can be readily generalized to other types of transition rates. In the following subsection we will describe how the Lee-Carter method can be used to forecast multiple transitions in

[1] Detailed descriptions of the quantities obtainable in an MSLT and information about how transition rates are converted into 1-year transition probabilities have been put in Appendix A.

order to forecast HE. In particular, we pay attention as to how the joint tendency of the stochastic period effects of each transition type can be modeled.

Forecasting transition rates and health expectancy with the Lee-Carter model

The Lee Carter model takes the following form:

$$\ln m_{x,t}^{(i)} = \alpha_x^{(i)} + \beta_x^{(i)} \kappa_t^{(i)} + \varepsilon_{x,t}^{(i)} \ . \qquad (1)$$

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

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

In the first step, parameters of equation (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 equation (1) is sought, however this model cannot be fitted by Ordinary Least Squares, because there are no predictors on the right hand side. Nevertheless, assuming that $\varepsilon_{x,t}^{(i)}$ 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, $\hat{\beta}_x \hat{\kappa}_t$, is a function of the leading singular value, $\sigma_1^{(i)}$, the first column, $u_1^{(i)}$, and the first row, $\left[v_1^{(i)}\right]^T$, of the SVD. Due to lack of identification Lee and Carter proposed to use the constraints: $\sum_x \hat{\beta}_x^{(i)} = 0$ and $\sum_t \hat{\kappa}_t^{(i)} = 1$ in order 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. The $\beta_x^{(i)}$ profiles express which age-specific rate change rapidly or slowly in response to changes in $\kappa_t^{(i)}$. $\varepsilon_{x,t}^{(i)}$'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:

$$\hat{\alpha}_x^{(i)} = \frac{\sum_{t=1}^{T} \ln(m_{x,t}^{(i)})}{T} \tag{2}$$

$$\hat{\beta}_x^{(i)} = \frac{u_1^{(i)}(x)}{\sum_{x \in X} u_1^{(i)}(x)} \tag{3}$$

$$\hat{\kappa}_t^{(i)} = \sigma_1^{(i)} v_1^{(i)}(t) \sum_{x \in X} u_1^{(i)}(x) \tag{4}$$

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

$$\left[\hat{\Sigma}_x^2\right]_{ij} = \frac{1}{T-1}\sum_{t=1}^{T}\left(\hat{\varepsilon}_{x,t}^{(i)} - \bar{\varepsilon}_x^{(i)}\right)\left(\hat{\varepsilon}_{x,t}^{(j)} - \bar{\varepsilon}_x^{(j)}\right). \quad (5)$$

In the second step, transition rates are forecasted 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 $\kappa_t^{(i)} = \left[\kappa_1^{(i)}, \kappa_2^{(i)}, ..., \kappa_t^{(i)}\right]^T$ are extrapolated using a standard univariate time-series model. Eventually these extrapolated latent factors are inserted into equation (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, and they found that the model of random walk (trajectory of successive random steps) with a drift parameter described their data the best. 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 $\hat{\kappa}_t^{(i)}$ take the following form:

$$\hat{\kappa}_t^{(i)} = \hat{\kappa}_{t-1}^{(i)} + \theta^{(i)} + \delta_t^{(i)} \quad (6)$$

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

where θ is a vector with elements $\theta^{(i)}$, the drift parameter of transition type (*i*), and Δ^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:

$$\hat{\theta}^{(i)} = \frac{\hat{\kappa}_T^{(i)} - \hat{\kappa}_1^{(i)}}{T-1} \tag{8}$$

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

where $i = (tr, g) \in I$ and $j = (tr, g) \in J$ are transition types at time $t \in \{1,2,\ldots,T\}$ with gender $g \in \{male, female\}$ and $tr \in \{nd, d, inc\}$, the mortality rate of non-disabled, 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 $\dot{\theta} \sim N\left(\hat{\theta}, V\left\{\hat{\theta}\right\}\right)$, 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:

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

To model future transition rates we use the last year transition rates as observed in the dataset in order to avoid a jump-off bias. Hence, the estimation errors in the final data year are artificially set to zero. The transition rates *s* year from the base year *T* are given by:

$$\hat{m}_{x,T+1}^{(i)} = m_{x,T}^{(i)} \times RF_{x,T+1}^{(i)} + \hat{\varepsilon}_{x,T+1}^{(i)} \tag{11}$$

where $RF_{x,T,s}^{(i)}$ 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:

$$RF_{x,T,s}^{(i)} = \exp\left(\hat{\beta}_x^{(i)} \times \left(\hat{\kappa}_{T+s}^{(i)} - \hat{\kappa}_T^{(i)}\right)\right), \tag{12}$$

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

$$\hat{\kappa}_{T+s}^{(i)} \left| \hat{\kappa}_{T+s-1}^{(i)}, \dot{\theta}^{(i)} \sim N\left(\hat{\kappa}_{T+s-1}^{(i)} + \dot{\theta}^{(i)}, \hat{\Delta}^2\right) \right. . \tag{13}$$

Once simulations of future transition rates are obtained, they can be converted into one-year transition probabilities taking into account the competition between the rates (Appendix A). For each set of forecasted transition probability profiles an MSLT can be set up and corresponding $DFLE_{x,t}$ can be estimated. Furthermore, the several probabilistic simulations yield prediction intervals for the life expectancy estimates, and the simulated HE values allow calculating the probability of a specific scenario of compression or expansion of disability.

Application

We applied the method to Dutch population data which came from several sources because there was no single longitudinal data set 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 non-disabled. We made use of the simple relationships between 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, Baan and Bonneux 2000).

Mortality. Survival probabilities for Dutch men and women by age (i.e., $x \in \{55.5,56.5,\ldots,96.5,97.5+\}$) were used, as published at Statistics Netherlands (CBS: Centraal Bureau voor de Statistiek) 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 provide 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. Self-reported health data was collected by 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 until 2007 because the current disability questions were first introduced in 1989 and we had access to data until 2007. To correct for selective non-response 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 Organization for Economic Co-operation and Development (OECD) indicator (McWhinnie 1981), in persons aged 55 years and older. The OECD disability indicator uses 7 items (conversing, reading small letters, recognizing faces, biting, carrying objects, walking 400ms, bending). For each item respondents were asked if 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 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'.

Population-level unadjusted prevalence of OECD disability gradually decreased between 1989 and 2007. For men, it fell from 23.4% to 17.0%, whereas for women it declined from 38.2% to 28.3% . The prevalence of disability for each sex and calendar year was smoothed by logistic regressions using a dummy variable for each sample year. Logistic regression is commonly used way to smooth disability prevalence. The

Akaike Information Criteria 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 dataset 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, Graubard and Midthune 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 did not find significant age-interaction and time trend in the hazard ratios therefore we considered them as being constant over age and time. Hazard ratio of disability on mortality was 1.85 (CI: 1.66, 2.07) and 1.72 (CI: 1.50, 1.97) for men and women, respectively.

[Table 1 around here]

Estimating transition rates. Because information on mortality rates of non-disabled 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 non-disabled, $m^{(nd)}_{x,t}$, and disabled populations, $m^{(d)}_{x,t}$, with the proportion of non-disabled and disabled respectively as weights, and 2) that the ratio between the mortality rate of disabled and non-disabled people is equal to the hazard ratio. The corresponding age and time-specific incidence rates, $m^{(inc)}_{x,t}$, could be derived from given mortality rates of the non-disabled and disabled of age *x* at time *t*, and given prevalence of disabled population at age *x* and *x+1* at time *t*, because these quantities are interrelated and mutually define each other. Appendix B presents a formal derivation of these transition rates.

Although our model assumes that only incidence is possible, there is evidence 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 non-disabled to disabled state minus the number of transitions from disabled to non-disabled state, relative to the number of non-disabled people.

Figure 1 shows the incidence probabilities and mortality probabilities of the non-disabled 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 non-disabled, where the multiplier is the hazard ratio, the normalized mortality probabilities are identical for these two groups. Consequently, we only show the graphs for the non-disabled. The figures clearly illustrate that over longer periods, the transition probabilities decrease, reflecting the decrease of prevalence of disability, and the increase in LE over time. The figures also show that the decreases in mortality were substantially larger for men, especially at younger age groups (60, 70).

[Figure 1 around here]

Fitting Lee-Carter model on the transition rates and applying the MSLT 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 $\hat{\kappa}_t^{(i)}$. Based on the predicted values of $\hat{\kappa}_t^{(i)}$ we estimated six drift parameters and the 6-by-6 (men and women together) variance-covariance matrix indicating the size of their joint distribution. This latter one 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. Once we obtained the simulated transition rates we converted them into one-year transition probabilities, and set up a MSLT to get HE estimates.

Model validation. We used the R^2 statistic to measure how large 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 fitted past life expectancy and disability-free life expectancy based on official sources

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 on that we had data. In the second analysis, we back-cast LE and DFLE by 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: i) transition probabilities, ii) prevalence of disability, iii) total life expectancy ($LE_{55,T}$), iv) total life expectancy of non-disabled and of disabled v) disability-free life expectancy ($DFLE_{55,T}$), vi) difference between total LE and DFLE ($LE_{55,T}$ - $DFLE_{55,T}$) vii) 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 a number of sources: first, the uncertainty of the parameters for predicting prevalence and hazard ratios; second, the uncertainty of the evolution of transition profiles over time; and third, 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. Since these two ingredients 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,

$\kappa_{T+s}^{(i)}$, was also known with certainty. Each year the transition rates changed according to the drift factor, $\hat{\theta}^{(i)}$. 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 HE estimates. The simulated variation in the HE estimates was summarized by prediction intervals. We refer to this model as 'Model [1]'

In the second step we relaxed the assumptions we made 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 the trend 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 model as 'Model [2]'.

In the third step, we also relaxed the assumption about fixed trends. We simulated random sets of transition rates, based on a particular set of transition rates we simulated random trends, and conditional on a particular realization of the trend, we simulated the uncertainty in the evolution of future transition rates. Each part of the simulation was carried out 50 times, and since the simulation contained multiple loops

this resulted in a total number of 125,000 random draws. We refer to this model as 'Model [3]'.

RESULTS

Parameter estimation

Parameter estimates of the Lee-Carter model for the different transitions are plotted in Figure 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 (Figure 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. Due to our decomposition method the pace of the decrease was the same for both non-disabled and disabled mortality rates. In absolute terms however, mortality rate of disabled people decreased more than non-disabled mortality rates.

The parameter estimates for the time series models on the values of $\hat{\kappa}_t^{(i)}$ are given in Table 4 in Appendix C.

[Figure 2 around here]

Figure 3 presents the core results of the model from which life- and health expectancies are derived. We depicted age profiles of one-year incidence probability, mortality probability of non-disabled, and prevalence of disability in 1989, 2007 and their expected value 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.

[Figure 3 around here]

Forecast and validation

We used the R^2 statistic to measure how large proportion of the variation in the data was explained by the model. We refer the reader to Appendix D for figures which shows 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 sources 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 on that we had data (Figure 4-5, period 1989-2007). In the second analysis, we back-cast LE and DFLE by 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). We presented the results in Figure 4 and Figure 5.

According to official statistics, LE at 55.5 increased faster among men (+3.7 years, from 21.1 to 24.8) than it did 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 with 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 3-year period (1986-1988) with a considerably different disability questionnaire as compared to the one employed before 1986 and since 1989. We decided not to use these years in our model whereas 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 Figure 4 and Figure 5.

Regarding the model fit in terms of estimated LE and DFLE between 1989 and 2007, it is clear even by visual inspection that fitting Lee-Carter model on the transition rates result in excellent model fit to reproduce past life expectancy and disability-free life expectancy as published by Statistics Netherlands. Concerning the back-cast LE and DFLE values, projected prediction intervals of our model contained estimates from CBS, hence the model can be considered valid for this data set.

[Figure 4 around here]

[Figure 5 around here]

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 55.5 is 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 lies between 25.3 and 28.0 years by 2020, and 26.0 and 29.6 years by 2030. These projections correspond to a minimum of 0.5 and 1.2, or 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 and 30.6 by 2020 and 2030, respectively. 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 and 32.6 by 2020 and 2030, respectively.

Tables 2 and 3 present LE estimates for non-disabled and disabled people at age 55.5 and onwards, both for the past and for the future. Between 1990 and 2005 LE of non-disabled 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 non-disabled 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 forecasted to rise from 21.2 (PI: 20.2-22.2) to 24.3 (PI: 21.2-26.9) years.

LE of non-disabled 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 non-disabled is forecasted to increase between 2010 and 2030, from 30.2 (PI: 29.4-31.1) to 31.6 (PI: 28.9-33.8). This increase is anticipated to be approximately the same 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 (PI: 18.0-23.5) and 23.4 (PI: 16.2-25.2) years by 2020 and 2030, respectively. DFLE relative to LE is forecasted 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. It is anticipated that DFLE will increase from 17.7 (CI: 17.2-18.1) to 20.4 (PI: 15.4-23.3) years between 2005 and 2020, and further to 21.5 (PI: 13.3-24.9) years 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.

The jointly simulated DFLE and LE estimates made 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, then 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, then 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, 67% for women.

[Table 2 around here]

[Table 3 around here]

DISCUSSION

We proposed a theoretical framework for a multi-state life table model, in which the transition probabilities depended 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 including 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 why 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 socio-economic 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 contrary, there are unfavorable health trends as well. Particularly worrying is the fact that the share of overweight population is continuously increasing, and that the dietary habits of adolescents change adversely. In the Netherlands the proportion of the population that is obese has doubled in the last two decades, and it is expected that the number of obese persons will increase by 50% by 2020 (Bemelmans et al. 2004). These trends will have an increased impact on morbidity, as diabetes, cardiovascular and musculoskeletal diseases, as well as various types of cancers have been shown to be associated with obesity (Mokdad et al. 2003). Another reason to expect expansion of disabled life years is that more effective (life saving) treatment options are available for those who are already ill and vulnerable, including those at older ages. Two demographic trends may also have a negative effect on health expectancy: the increasing instability of social relations and the changing ethnic composition with higher share of groups with non-western origin.

The large number of conflicting trends affecting the future development of health expectancy is, in itself, an indication of uncertainty. One of the biggest advantages of our model is that it quantifies this uncertainty because the model not only takes into account the fact that the trend in the transition rates itself is uncertain but also the fact that future realizations of the trend are uncertain.

Other studies

Many studies have estimated HEs 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 increasing time spent with chronic limitations of common activities and by slight decreasing time with severe disability (Crimmins, Saito and Ingegneri 1989). Later, Crimmins et al. found that during the 1980s gains in LE rose along with DFLE for both men and women (Crimmins, Saito and Ingegneri 1997). In 2009 Crimmins et al. examined changes in LE with and without ADL and iADL disability using longitudinal data between 1984 and 2000 (Crimmins et al. 2009). 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 were published for 13 European Union member states from 1995 until 2001 based on the European Community Household Panel (Jagger et al. 2009). Significant increases were found in LE at early (age 16) and late (age 65) adulthood with considerable heterogeneity in the trends in health expectancy. In nine countries expansion of disability was the prevailing trend, whereas four countries had evidence of compression of disability.

For the Netherlands, van de Water et al. studied trends in HE between 1983 and 1990 (Van De Water, Boshuizen and Perenboom 1996). Their study indicated of a rise (decline) in the healthy life percentage of men (women), where health status was defined by self-rated health status. Perenboom et al. assessed trends in DFLE and LwD according to levels of severity between 1989 and 2000 (Perenboom et al. 2004). At an aggregated level, for both and women at age 65, a decrease in DFLE and an increase in LwD were observed. These trends were caused by the fact that increases in mild disability were larger than the declines in severe disability. Trends in visual, hearing, mobility and ADL disability prevalence between 1990 and 1998 in the Netherlands were studied in Picavet et al. (Picavet and Hoeymans 2002). They found fairly stable disability prevalences during the study period.

In 2009 the Statistics Netherlands published trends on HE estimates for the period 1981-2007 (Bruggink et al. 2009). Morbidity was measured in three different ways: self-rated health, presence of chronic disease and physical limitation (OECD disability). Since the 1980s HE 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, LE without chronic diseases at age 65 has been decreasing. For women, DFLE increased and HE 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 was 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 everybody who was institutionalized was disabled thereby we assessed the maximum bias that exclusion of these people may have caused. Results of the sensitivity analyses revealed that our model overestimates DFLE with a maximum of 0.6 year for men and 0.7 year 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 did 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 our estimates of DFLE. In the first case the HR in 2007 was 83% of the HR in 1989, whereas in the second case it was 120%. The results of the sensitivity analyses indicated that such changes in the hazard ratio virtually had no effect on the original DFLE estimates. These findings were true for men as well as for women.

It is important to note that our definition of disability essentially excludes the possibility of detecting a dynamic equilibrium, because we did not make distinction 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 (column LwD), this is exactly what we find.

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. Whether which interval of the LwD distribution should indicate a dynamic equilibrium, we believe is an arbitrary choice and may depend on the variation of the LwD. Nevertheless, a stable life expectancy with OECD disability 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 the construction of the model. One of the assumption of the Lee-Carter model is that the expected evolution of the transition rates over time, $\theta^{(i)}$, 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. Therefore, 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. We see this situation at mortality rates. However, if the trend in $\kappa_t^{(i)}$ is less linear and the observation window is relatively short, then the estimate of $\theta^{(i)}$ might be sensitive on choosing other end points than $\kappa_1^{(i)}$ and $\kappa_T^{(i)}$. Accordingly, the uncertainty around future evolution would be somewhat larger as well. We see such situation at incidence rates.

Once a model has been developed and its parameters have been estimated, it is important to consider whether it is a good model or not. For stochastic mortality forecast models Cairns et al. (Cairns et al. 2007) proposed a checklist of criteria against which a model can be

evaluated. Among many technical criteria concerning how projections are carried out, the checklist includes that the mortality rates should be positive, the model should be consistent with historical data, the parameter estimates and the model forecasts should be robust and long-term trends should be biologically plausible. We believe that our model fulfils all these requirements. Regarding historical trends and biological reasonability we have given a short summary of explanations above.

Conclusions

Our finding suggest that the Lee-Carter model is generalizable to multi-state life table settings, and can be used to model transition rates connecting non-disabled, 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, for example if the time-evolution of transition rates is not linear. Nonetheless, we consider that the model framework presented here can be used in other settings, for example for 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, since working life expectancies are based on similar MSLTs. Thus the model framework may be used to forecast population health where the health status is measured in various ways.

APPENDIX A

The original (mortality or actuarial) life table is a transition model in which observed death rates, within age interval, are the basis of probabilities of dying, and in which the main parameter of interest is the expectation of life. A multi-state life table model is an extension of the original life table method. In a MSLT not only 'alive' and the absorbing 'dead' states are distinguished but there is at least one additional state, typically between 'perfectly healthy' and 'dead', for example 'disabled'. In contrast to a mortality table, an MSLT not only shows, for each age, what the probability is that a person of that age will die before his next birthday, but rather it shows what the probability is that a person of that age will move from one state to another. Correspondingly, an MSLT not only shows the remaining life expectancy and the proportion of the original birth cohorts still alive at different ages, but rather it shows the remaining life expectancy and proportion of people still alive in a given state. Furthermore, the population-average LE can be decomposed into a weighted average of health expectancies, indicating the number of years people are expected to live in each health state.

Conversion of rates into probabilities taking into account competing risks

In an MSLT the possible transitions are expressed by the matrix, $M^{g}_{x,t}$, standing for the transition rates between the several states. The matrix $M^{g}_{x,t}$ refers to the chance of moving from the i^{th} state to the j^{th} state in infinitesimal time. However, instead of infinitesimal time intervals, one typically works with longer periods, like one year. In such a case one refers to the transition probability matrix $Q^{g}_{x,t}$, whose q_{ij} element indicate the transition probability that a person at age *x* at time *t* is in the i^{th} state and in the j^{th} state one year later. Assuming that the

exposure is linear in age, one can convert the transition rates into the appropriate transition probabilities.

1. Transition rates

$M^{g}_{x,t}$ is the matrix of transition rates at age x and time t

$$M^{g}_{x,t} = \begin{bmatrix} m^{(inc,g)}_{x,t} + m^{(nd,g)}_{x,t} & -m^{(rec,g)}_{x,t} \\ -m^{(inc,g)}_{x,t} & m^{(rec,g)}_{x,t} + m^{(d,g)}_{x,t} \end{bmatrix} \quad (1)$$

where *rec* represents the transition from disabled to non-disabled

2. Transition probabilities

Using linear approximation: that is, all transitions (incidence, deaths) occur in the middle of the interval.

$$Q^{g}_{x,t} = \frac{I - \frac{1}{2}M^{g}_{x,t}}{I + \frac{1}{2}M^{g}_{x,t}} = \begin{bmatrix} 1 - \left(q^{(inc,g)}_{x,t} + q^{(nd,g)}_{x,t}\right) & q^{(rec,g)}_{x,t} \\ q^{(inc,g)}_{x,t} & 1 - \left(q^{(rec,g)}_{x,t} + q^{(d,g)}_{x,t}\right) \end{bmatrix} \quad (2)$$

$Q^{g}_{x,t}$ is the transition-probability matrix, consisting of elements $q_{ij}(x,t)$ which represents the 1-year probability that an individual with gender *g* alive at age *x* and time *t* will be in state j at age *x+1*, and $\boldsymbol{I}$ is a 2x2 identity matrix.

$$q_{x,t}^{(inc,g)} = \frac{m_{x,t}^{(inc,g)}}{\left(1+\frac{m_{x,t}^{(inc,g)}}{2}+\frac{m_{x,t}^{(nd,g)}}{2}\right)\left(1+\frac{m_{x,t}^{(d,g)}}{2}\right)} \quad (3)$$

$$q_{x,t}^{(nd,g)} = \frac{m_{x,t}^{(inc,g)}+m_{x,t}^{(nd,g)}}{\left(1+\frac{m_{x,t}^{(inc,g)}}{2}+\frac{m_{x,t}^{(nd,g)}}{2}\right)} - \frac{m_{x,t}^{(inc,g)}}{\left(1+\frac{m_{x,t}^{(inc,g)}}{2}+\frac{m_{x,t}^{(nd,g)}}{2}\right)\left(1+\frac{m_{x,t}^{(d,g)}}{2}\right)} \quad (4)$$

$$q_{x,t}^{(d,g)} = \frac{m_{x,t}^{(d,g)}}{\left(1+\frac{m_{x,t}^{(d,g)}}{2}\right)} \quad (5)$$

Note: in our model, recovery is set to zero, and incidence is considered as net incidence (real incidence minus real recovery).

Calculating number of non-disabled and disabled alive

1. Number of persons alive

$l_{x,t}^{g}$ is the sum of the number of non-disabled ($l_{x,t}^{(nd,g)}$) and disabled ($l_{x,t}^{(d,g)}$) individuals alive at age x and at time t:

$$l_{x,t}^{g} = \begin{bmatrix} l_{x,t}^{(nd,g)} \\ l_{x,t}^{(d,g)} \end{bmatrix} \quad (6)$$

$l^{g}_{x+1,t+1}$ is the sum the number of aged *x+1* individuals with gender *g* alive at time *t+1*, expressed as a function of the number of individuals alive and transition probabilities at age *x* and at time *t* ($l^{(nd,g)}_{x,t}, l^{(d,g)}_{x,t}, q^{(.tr,g)}_{x,t}$).

$$l^{g}_{x+1,t+1} = \begin{bmatrix} l^{(nd,g)}_{x+1,t+1} \\ l^{(d,g)}_{x+1,t+1} \end{bmatrix} = \begin{bmatrix} l^{(nd,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(nd,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(inc,g)}_{x,t} \\ l^{(d,g)}_{x,t} - l^{(d,g)}_{x,t} q^{(d,g)}_{x,t} + l^{(nd,g)}_{x,t} q^{(inc,g)}_{x,t} \end{bmatrix} \tag{7}$$

2. Prevalence of disabled

$p^{g}_{x,t}$ is the prevalence matrix, consisting of elements $p^{(nd,g)}_{x,t}$ and $p^{d,g}_{x,t}$ which represent the proportion of gender *g* specific population without (*nd*) and with (*d*) disability at age *x* and at time *t*.

$$p^{g}_{x,t} = \begin{bmatrix} p^{(nd,g)}_{x,t} \\ p^{(d,g)}_{x,t} \end{bmatrix} = \begin{bmatrix} \dfrac{l^{(nd,g)}_{x,t}}{l^{(nd,g)}_{x,t} + l^{(d,g)}_{x,t}} \\ \dfrac{l^{(d,g)}_{x,t}}{l^{(nd,g)}_{x,t} + l^{(d,g)}_{x,t}} \end{bmatrix} \tag{8}$$

$p^{g}_{x+1,t+1}$ is the gender *g* specific prevalence matrix, expressed as a function of the number of individuals alive and transition probabilities at age *x* and at time *t* ($l^{(nd,g)}_{x,t}, l^{(d,g)}_{x,t}, q^{(tr,g.)}_{x,t}$).

$$p^{g}_{x+1,t+1} = \begin{bmatrix} \dfrac{l^{(nd,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(nd,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(inc,g)}_{x,t}}{l^{(nd,g)}_{x,t} + l^{(d,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(nd,g)}_{x,t} - l^{(d,g)}_{x,t} q^{(d,g)}_{x,t}} \\ \dfrac{l^{(d,g)}_{x,t} - l^{(d,g)}_{x,t} q^{(d,g)}_{x,t} + l^{(nd,g)}_{x,t} q^{(inc,g)}_{x,t}}{l^{(nd,g)}_{x,t} + l^{(d,g)}_{x,t} - l^{(nd,g)}_{x,t} q^{(nd,g)}_{x,t} - l^{(d,g)}_{x,t} q^{(d,g)}_{x,t}} \end{bmatrix} \tag{9}$$

Calculating life expectancy of non-disabled and disabled

$L^{g}_{x,t}$ denotes the gender *g* specific average number of non-disabled and disabled aged *x* individuals alive at time *t*

$$L^{g}_{x,t} = \begin{cases} \left[\dfrac{l^{(nd,g)}_{x,t} + l^{(nd,g)}_{x+1,t+1}}{2} \right] & \text{if } x < \omega, \\ \left[\dfrac{l^{(d,g)}_{x,t} + l^{(d),g}_{x+1,t+1}}{2} \right] & \\ \left[\dfrac{l^{(nd,g)}_{MA,t}}{M^{(nd,g)}_{MA,t}} \right] & \text{if } x = \omega, \\ \left[\dfrac{l^{(d,g)}_{MA,t}}{M^{(d,g)}_{MA,t}} \right] & \end{cases} \tag{10}$$

where ω is the maximum attainable age.

$T^{g}_{x,t}$ denotes the cumulative average number of non-disabled and disabled aged *x* individuals alive at time *t*

$$T^{g}_{x,t} = \begin{bmatrix} \sum_{s>0} \dfrac{l^{(nd,g)}_{x+s,t+s} + l^{(nd,g)}_{x+1+s,t+s}}{2} \\ \sum_{s>0} \dfrac{l^{(d,g)}_{x+s,t+s} + l^{(d,g)}_{x+1+s,t+s}}{2} \end{bmatrix} \tag{11}$$

Gender *g* specific life expectancy of non-disabled and disabled are calculated as

$$e^{g}_{x,t} = \begin{bmatrix} \dfrac{T^{(nd,g)}_{x.t}}{l^{(nd,g)}_{x,t}} \\ \dfrac{T^{(d,g)}_{x.t}}{l^{(d,g)}_{x,t}} \end{bmatrix} \tag{12}$$

Disability-free life expectancy (DFLE) and life expectancy with disability (LwD) are calculated as

$$\begin{bmatrix} DFLE_{x,t}^{(g)} \\ LwD_{x,t}^{(g)} \end{bmatrix} = \begin{bmatrix} \frac{T_{x.t}^{(nd,g)}}{l_{x,t}^{(g)}} \\ \frac{T_{x.t}^{(d,g)}}{l_{x,t}^{(g)}} \end{bmatrix} \quad (13).$$

APPENDIX B

Estimating transition rates

Because information about mortality rates of non-disabled and disabled was not available from primary data sources we decomposed total mortality using the prevalence of disability and the hazard ratio of disability on mortality as follows:

$$\tilde{m}_{x,t}^{(nd,g)} = \frac{m_{x,t}^{(g)}}{\hat{HR}_{x}^{g} \times \hat{p}_{x,t}^{(d,g)} + \left(1 - \hat{p}_{x,t}^{(d,g)}\right)} \quad (1)$$

$$\tilde{m}_{x,t}^{(d,g)} = \tilde{m}_{x,t}^{(nd,g)} \times \hat{HR}_{x}^{g} \quad (2)$$

where $m_{x,t}^{g}$, $\tilde{m}_{x,t}^{(nd,g)}$, $\tilde{m}_{x,t}^{(d,g)}$, $\hat{HR}_{x}^{g}$ and $\hat{p}_{x,t}^{(d,g)}$ indicate the gender-*g* specific population mortality rate, estimated mortality rate of non-disabled and disabled, the estimated hazard ratio and smoothed prevalence of disability at age *x* and time *t*, respectively.

The converted transition, $q_{x,t}^{(nd,g)}$ ($q_{x,t}^{(d,g)}$), show the probability that a person is non-disabled (disabled) at age *x* at time *t* and is dead at age *x+1* at time *t*. Such formulation of the model implies the period-age approach, which is often used when the main point of interest is the change of transition probabilities over a certain period of time, e.g. calendar years. With the period-age approach it is implicitly assumed that a person of age *x* at time *t* will have the same transition probability at age *x+1* at time *t+1* (assumption) as a person who is of age *x+1* at time *t* (reality). Making such assumption is unavoidably done by estimating period life expectancies.

Estimating incidence rates

Given the prevalence of disabled populations $p_{x,t}^{(d,g)}$, $p_{x+1,t}^{(d,g)}$ of age *x* and *x+1* at time *t*, the mortality rate of non-disabled $m_{x,t}^{(nd,g)}$ and disabled $m_{x,t}^{(d,g)}$ of age *x* at time *t*, it is possible to calculate the corresponding incidence rate, $m_{x,t}^{(inc,g)}$, since these quantities are interrelated and mutually define each other. The prevalence of disabled population of age *x+1* at time *t* is expressed as the proportion of those who are disabled to those who are alive. However, this fraction is dependent on the number of transitions during age *x*. That is, the prevalence at age *x+1* is a function of the number of people alive ($l_{x,t}^{g}$), the prevalence of disabled and the transition probabilities at age *x* and at time *t*:

$$p_{x+1,t}^{(d,g)} = \frac{l_{x,t}^{g} p_{x,t}^{(d,g)} - l_{x,t}^{g} p_{x,t}^{(d,g)} q_{x,t}^{(d,g)} + l_{x,t}^{g}(1-p_{x,t}^{(d,g)}) q_{x,t}^{(inc,g)}}{l_{x,t}^{g} - l_{x,t}^{g}(1-p_{x,t}^{(d,g)}) q_{x,t}^{(nd,g)} - l_{x,t}^{g} p_{x,t}^{(d,g)} q_{x,t}^{(d,g)}} \tag{3}$$

Expressing transition probabilities as functions of the transition rates, the incidence rate can be obtained by the following formula after rearranging (3):

$$A^{g} = \frac{\hat{p}_{x+1,t}^{(d,g)}}{1-\hat{p}_{x,t}^{(d,g)}} - \frac{\hat{p}_{x+1,t}^{(d,g)} \hat{p}_{x,t}^{(d,g)} \tilde{q}_{x,t}^{(d,g)}}{1-\hat{p}_{x,t}^{(d,g)}} - \frac{\hat{p}_{x,t}^{(d,g)}}{1-\hat{p}_{x,t}^{(d,g)}} + \frac{\hat{p}_{x,t}^{(d,g)} \tilde{q}_{x,t}^{(d,g)}}{1-\hat{p}_{x,t}^{(d,g)}} \tag{4}$$

$$\hat{m}_{x,t}^{(inc,g)} = \frac{A^{g}\left(1+\frac{\tilde{m}_{x,t}^{(nd,g)}}{2}\right)\left(1+\frac{\tilde{m}_{x,t}^{(d,g)}}{2}\right) - \hat{p}_{x+1,t}^{(d,g)} \tilde{m}_{x,t}^{(mrn,g)}\left(1+\frac{\tilde{m}_{x,t}^{(d,g)}}{2}\right)}{1+p_{x+1,t}^{(d,g)}\left(1+\frac{\tilde{m}_{x,t}^{(d,g)}}{2}\right) - \hat{p}_{x+1,t}^{(d,g)} - \frac{A^{g}}{2}\left(1+\frac{\tilde{m}_{x,t}^{(d,g)}}{2}\right)}. \tag{5}$$

Then $q_{x,t}^{(inc,g)}$ shows the probability that a person is non-disabled at age *x* at time *t* and disabled at age *x+1* at time *t*. Although our model assumes that only incidence is possible, there is evidence that people can recover from disability even at higher ages. 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 non-disabled to disabled state minus the number of transitions from disabled to non-disabled state, relative to the number of non-disabled people.

APPENDIX C

Table 4. Parameter Estimates in the Time Trends of the Lee-Carter Model

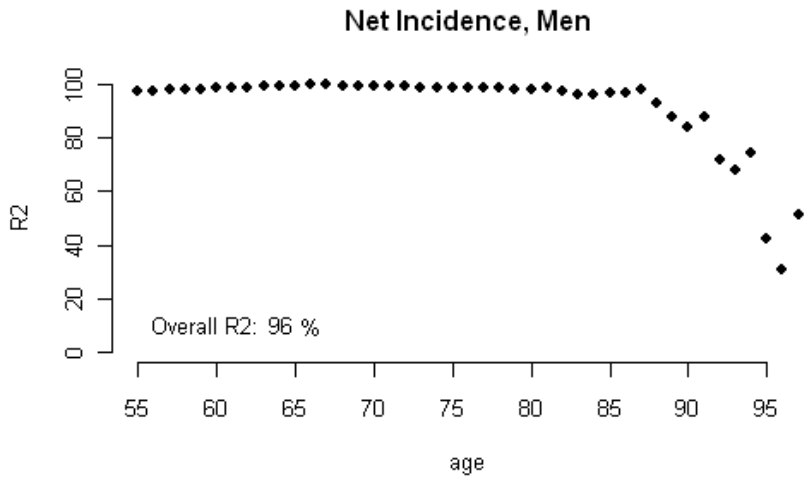
Transition type, i = {tr,g}	Best estimate trend $\theta^{(i)}$	Standard deviation trend $\sqrt{V\{\hat{\theta}^{(i,i)}\}}$	Standard deviation innovations $\sqrt{[\Delta^2]_{i,i}}$	Correlation: $\frac{[\Delta^2]_{i,j}}{\sqrt{[\Delta^2]_{i,i}}\sqrt{[\Delta^2]_{j,j}}} = \frac{V\{\hat{\theta}^{(i,j)}\}}{\sqrt{V\{\hat{\theta}^{(i,j)}\}}\sqrt{V\{\hat{\theta}^{(i,j)}\}}}$					
				j = (nd , m)	j = (nd , f)	j = (d , m)	j = (d , f)	j = (inc , m)	j = (inc , f)
(nd , m)	-0.669	0.040	0.844	1	0.748	1	0.748	-0.638	-0.322
(nd , f)	-0.376	0.048	0.929		1	0.748	1	-0.247	-0.544
(d , m)	-0.669	0.040	0.844			1	0.748	-0.638	-0.322
(d , f)	-0.376	0.048	0.929				1	-0.247	-0.544
(inc , m)	-0.825	0.607	3.306					1	0.399
(inc , f)	-0.590	0.347	2.499						1

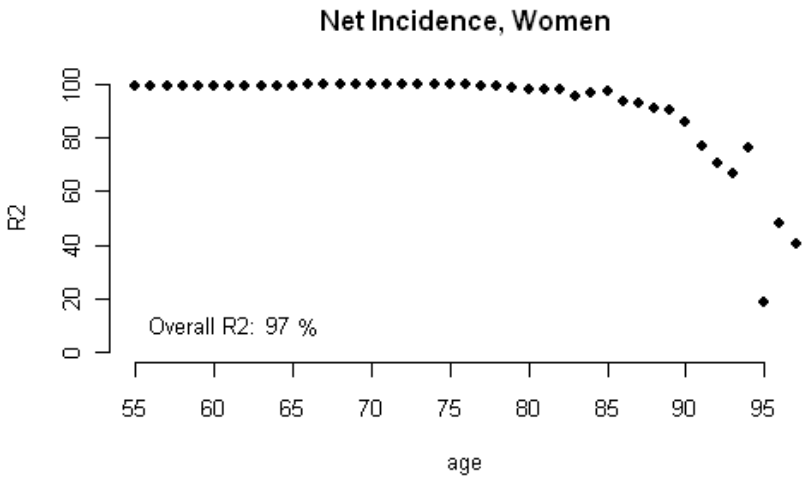
Note:
nd = mortality of non-disabled, d = mortality of disabled, inc= incidence, m = male, f = female

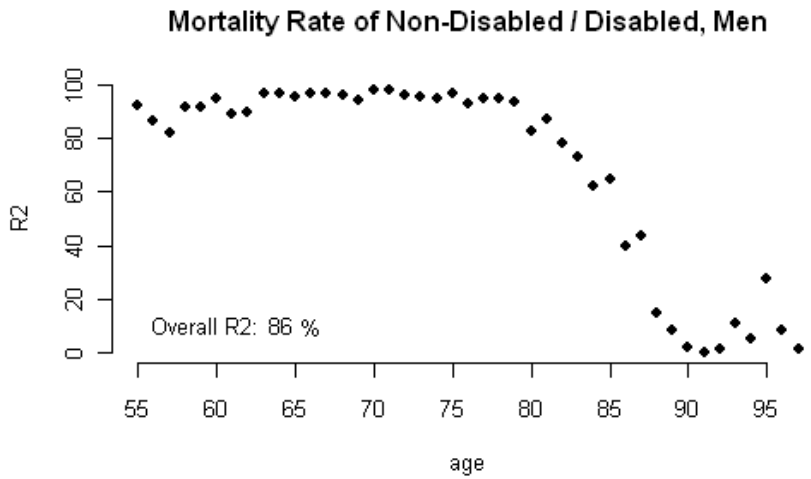
APPENDIX D

Fit of transition rates, age-specific and overall R^2

The R^2 statistic can be used to measure how large proportion of the variation in the data is explained by the model. R^2 can be calculated for each age separately, R_x^2, or for the entire age-profile of a certain type of transition rate, R^2. In most of the transition rates above 80% of the age-specific variation is explained by the model until the age of 85. Up till the age of 60 and after the age of 85 the model fit was somewhat lower. A possible explanation is that the number of transitions (incident cases, deaths) at younger ages is low compared to the size of the exposed populations; therefore there is a larger variation in the transition rates at these ages. After the age 80 the model fit started to decrease. This could be explained by the large number of transitions relative to the small size of exposed populations; therefore the transition rates were less stable at higher ages. Even though the age-specific model fits were quite poor at very high ages, the overall fit of the models can be considered as very good (≈ 70-95%).


Net Incidence, Men
R2
0
20
40
60
80
100
Overall R2: 96 %
55
60
65
70
75
80
85
90
95
age


Net Incidence, Women
R2
0
20
40
60
80
100
Overall R2: 97 %
55
60
65
70
75
80
85
90
95
age


Mortality Rate of Non-Disabled / Disabled, Men
R2
0
20
40
60
80
100
Overall R2: 86 %
55
60
65
70
75
80
85
90
95
age

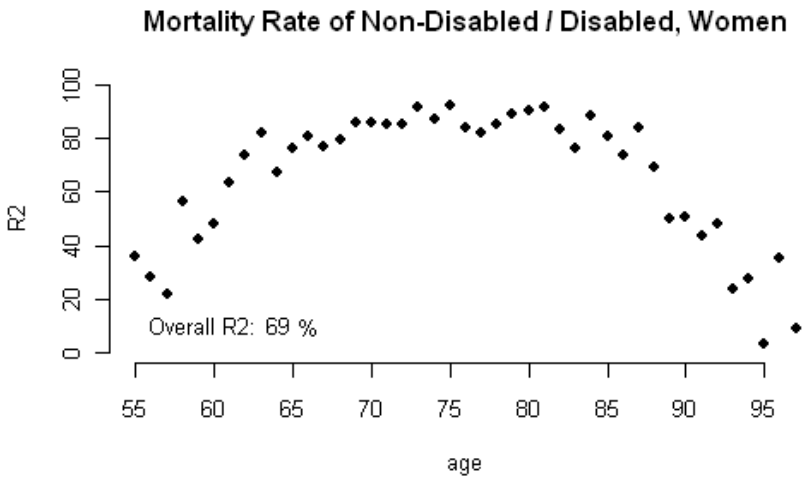

Mortality Rate of Non-Disabled / Disabled, Women
R2
0
20
40
60
80
100
Overall R2: 69 %
55
60
65
70
75
80
85
90
95
age

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Table 1. POLS, Study Population and Prevalence of Disability by Sex

Survey response	Year																		
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
	Survey																		
POLS	8,284	7,342	6,942	8,763	8,408	8,823	9,352	8,738	10,898	9,323	9,877	9,922	9,676	9,745	9,876	11,117	10,378	9,607	8,741
Response (%)	58.5	56.3	56.7	56.7	55.0	56.1	58.6	56.6	59.4	58.1	55.9	55.0	61.8	61.2	58.3	61.3	65.0	66.4	63.9
Women (%)	50.8 (4,208)	50.5 (3,706)	51.2 (3,555)	51.1 (4,475)	51.0 (4,290)	50.9 (4,489)	51.5 (4,814)	51.3 (4,484)	50.7 (5,530)	51.2 (4,774)	50.8 (5,013)	50.7 (5,026)	50.8 (4,915)	51.7 (5,034)	50.7 (5,006)	51.1 (5,681)	51.1 (5,303)	51.0 (4,902)	51.7 (4,520)
	Study population - men																		
55+	855	762	754	894	905	879	991	937	1,113	945	1,033	1,078	1,055	1,121	1,204	1,341	1,278	1,236	1,088
Disabled (%)	23.4%	23.6%	23.5%	25.4%	24.4%	25.4%	26.6%	20.0%	19.8%	17.8%	17.8%	19.4%	19.7%	19.3%	18.4%	21.0%	18.6%	20.1%	17.0%
	Study population - women																		
55+	998	928	922	1,094	1,090	1,101	1,166	1,095	1,204	1,044	1,130	1,119	1,132	1,216	1,301	1,442	1,395	1,362	1,232
Disabled (%)	38.2%	37.4%	38.4%	38.0%	37.1%	37.9%	40.4%	34.3%	33.4%	31.1%	33.5%	30.1%	30.5%	27.7%	30.5%	31.0%	31.1%	28.8%	28.3%

Table 2. Disability-Related Life Expectancy Measures for Selected Years, Men

Year	Life Expectancy (Total)		Life Expectancy (Non-disabled)		Life Expectancy (Disabled)		Disability-Free Life expectancy		Life Expectancy with Disability (LwD)		DFLE / LE (%)		Probability of Compression of Disability (%) (A)	(R)
1990	21.6	-	22.9	22.6 - 23.3	17.8	17.3 - 18.3	16.2	15.6-16.8	5.4	4.8-6.0	74.8	72.1 - 77.6	-	-
1995	22.1	-	23.6	23.2 - 24.0	18.5	18.0 - 18.9	15.9	15.3-16.5	6.2	5.6-6.8	71.8	69.3 – 74.5	-	-
2000	22.9	-	23.9	23.6 - 24.2	18.9	18.3 - 19.4	18.1	17.6-18.6	4.8	4.3-5.3	79.0	77.0 – 81.1	-	-
2005	24.2	-	25.2	24.9 – 25.4	20.2	19.7 - 20.8	19.1	18.6-19.4	5.1	4.8-5.6	78.9	77.0 – 80.3	-	-
2010	25.3	24.7 - 25.8	26.2	25.3 - 26.9	21.2	20.2 - 22.2	20.4	19.1 - 21.3	4.9	3.9-6.0	80.6	75.3 - 84.8	48.9	55.3
2015	26.1	25.0 - 27.0	26.9	25.5 - 28.1	22.1	20.4 - 23.6	21.2	18.6 - 22.5	4.9	3.4-7.4	81.1	70.9 - 86.7	48.9	58.7
2020	26.8	25.3 - 28.0	27.6	25.7 - 29.1	22.8	20.7 - 24.8	21.9	18.0 - 23.5	4.9	3.0-9.0	81.7	66.6 - 88.3	49.2	60.6
2025	27.6	25.7 - 28.4	28.2	26.0 - 29.9	23.6	21.0 - 25.9	22.7	17.2 - 24.4	4.9	2.9-10.5	82.2	62.2 - 89.2	49.8	62.0
2030	28.2	26.0 - 29.6	28.8	26.2 - 30.7	24.3	21.2 - 26.9	23.4	16.2 - 25.2	4.9	2.7-12.0	82.8	57.6 - 89.8	50.3	63.1

Notes:

[a] For the years between 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.

[b] Size of absolute compression: (LE55, T – DFLE55,T) – (LE55, 2007 –DFLE55,2007) = LwD55,T – LwD55,2007; measured in number of years
[c] Size of relative compression: (DFLE55,T / LE55, T) – (DFLE55,2007 / LE55,2007); measured in percentage points
[d] A is an abbreviation for absolute, R is an abbreviation for relative

Adding the presented estimates of DFLE and LwD may not reproduce LE exactly because of rounding

Table 3. Disability-Related Life Expectancy Measures for Selected Years, Women

Year	Life Expectancy (Total)		Life Expectancy (Non-disabled)		Life Expectancy (Disabled)		Disability-Free Life expectancy		Life Expectancy with Disability (LwD)		DFLE / LE (%)		Probability of Compression of Disability (%) (A)	(R)
1990	27.0	-	28.7	28.4-29.3	24.4	24.0-24.8	16.0	15.3-16.8	11.0	10.2-11.7	59.3	56.7-62.2	-	-
1995	27.1	-	29.0	28.6-29.5	24.7	24.2-25.0	15.3	14.6-15.8	11.8	11.3-12.5	56.3	54.0-58.3	-	-
2000	27.3	-	28.8	28.5-29.3	24.5	24.0-24.9	17.7	17.3-18.2	9.6	9.1-10	64.8	63.2-66.4	-	-
2005	28.2	-	29.7	29.3-30.2	25.5	25.0-25.8	17.7	17.2-18.1	10.5	10.1-11.2	62.7	61.0-64.4	-	-
2010	29.0	28.4-29.5	30.2	29.4-31.1	26.1	25.0-26.9	19.2	17.4-20.9	9.7	7.9-11.7	66.5	59.8-72.4	56.2	60.5
2015	29.4	28.3-30.4	30.6	29.3-31.9	26.4	24.8-27.7	19.8	16.3-22.2	9.6	6.8-13.3	67.4	55.1-76.3	57.4	63.6
2020	29.8	28.3-31.1	30.9	29.1-32.6	26.8	24.6-28.7	20.4	15.4-23.3	9.4	6.1-14.8	68.4	51.0-79.2	58.1	65.1
2025	30.2	28.3-31.9	31.3	29.0-33.2	27.2	24.5-29.5	20.9	14.3-24.1	9.3	5.5-16.4	69.3	46.8-81.2	58.8	66.2
2030	30.6	28.3-32.6	31.6	28.9-33.8	27.6	24.4-30.3	21.5	13.3-24.9	9.2	5.0-17.9	70.1	42.9-82.8	59.2	67.0

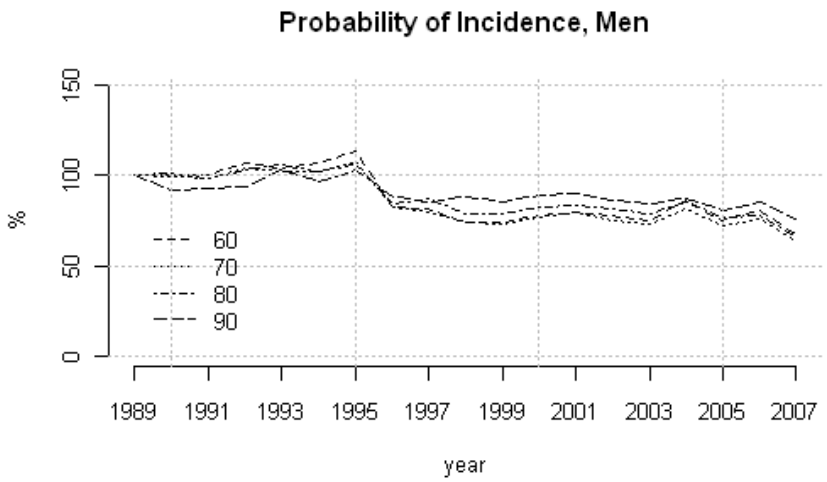
Notes:

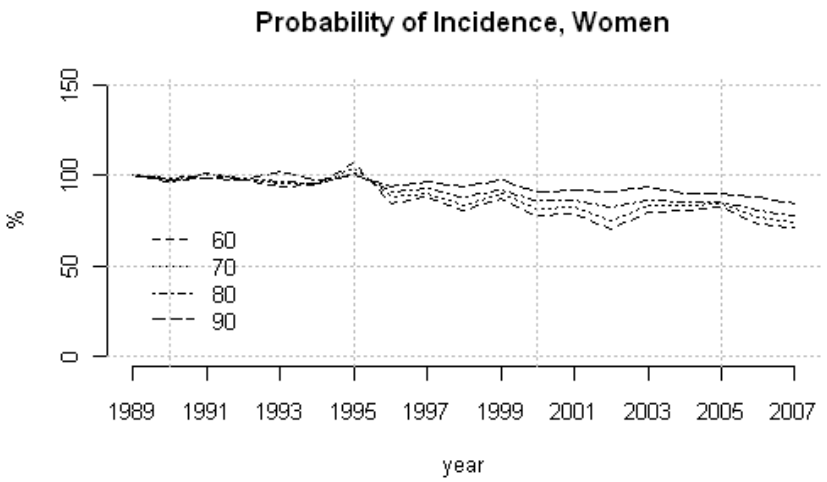
[a] For the years between 1990-2005 we provide 95% confidence intervals; for the years 2010-2030 we provide 95% prediction intervals based on Model [3] which allows for uncertainty in prevalence and HR, uncertainty in process and uncertainty in the trend parameters.

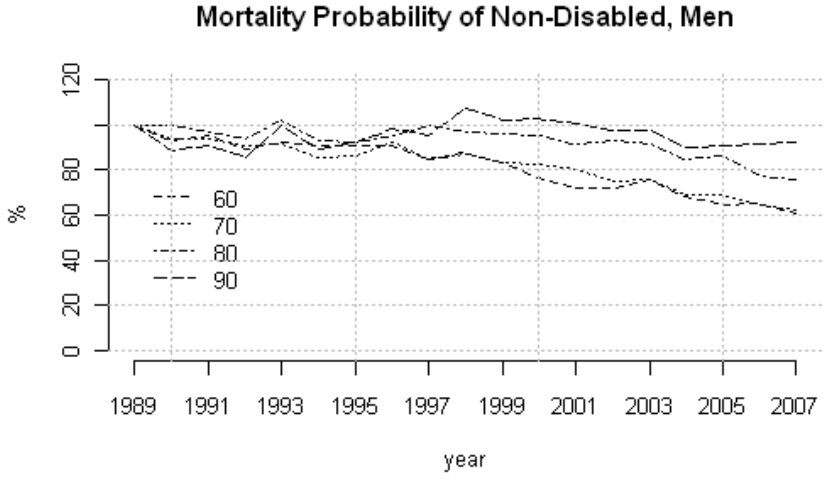
[b] Size of absolute compression: (LE55, T – DFLE55,T) – (LE55, 2007 –DFLE55,2007) = LwD55,T – LwD55,2007; measured in number of years)
[c] Size of relative compression: (DFLE55,T / LE55, T) – (DFLE55,2007 / LE55,2007); measured in percentage points
[d] A is an abbreviation for absolute, R is an abbreviation for relative

Adding the presented estimates of DFLE and LwD may not reproduce LE exactly because of rounding

Figure 1. Normalized Transition Probabilities at Age 60, 70, 80 and 90, 1989-2007







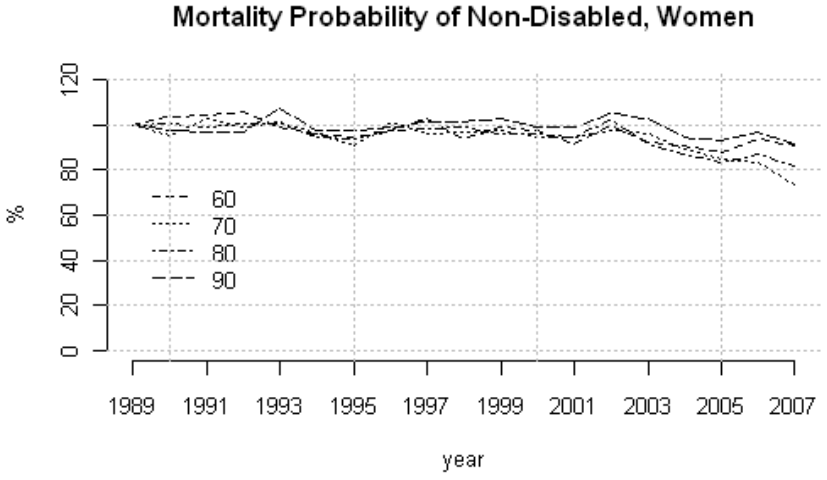


Figure 2. Parameter Estimates of the Lee-Carter Model

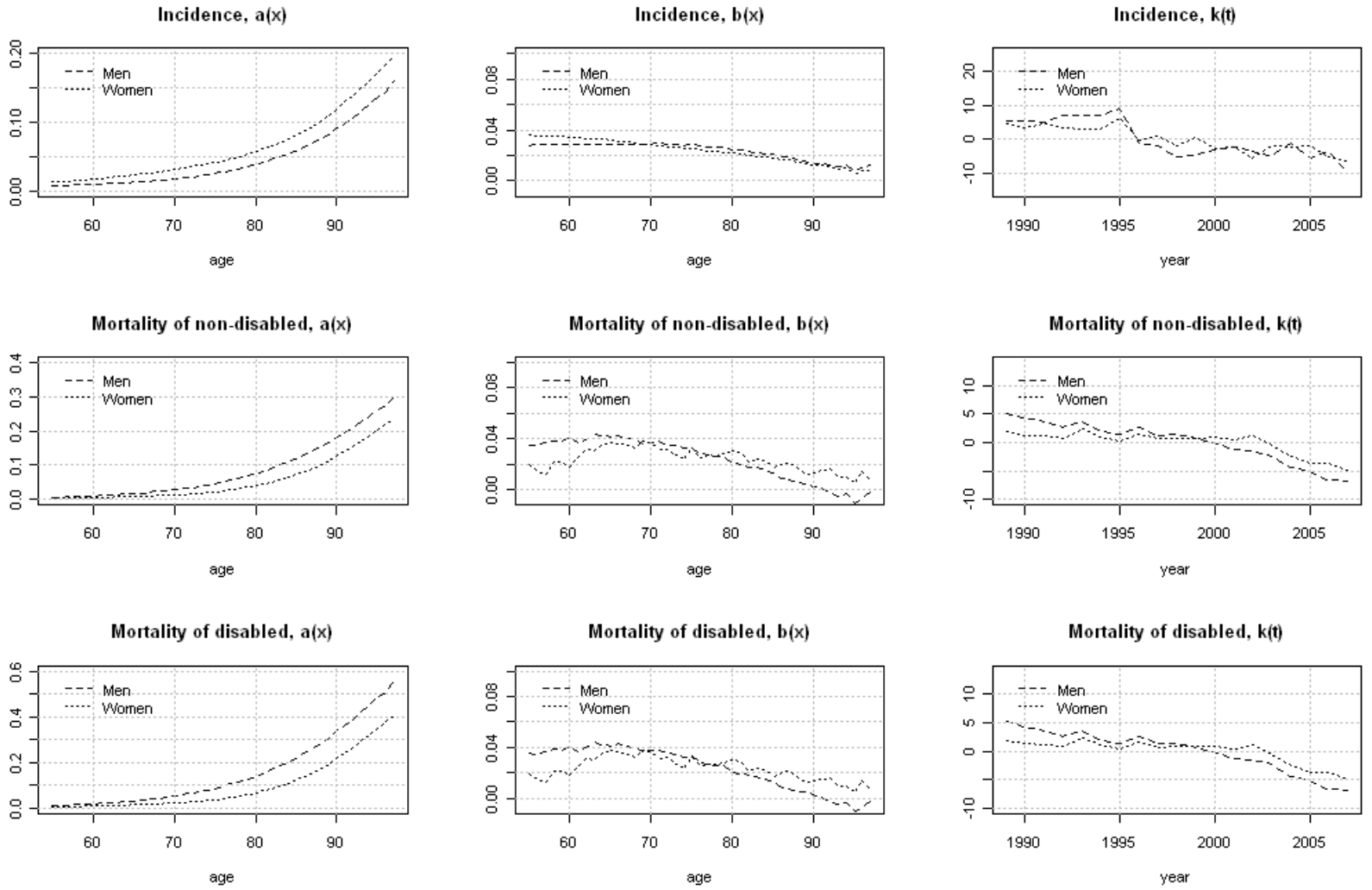
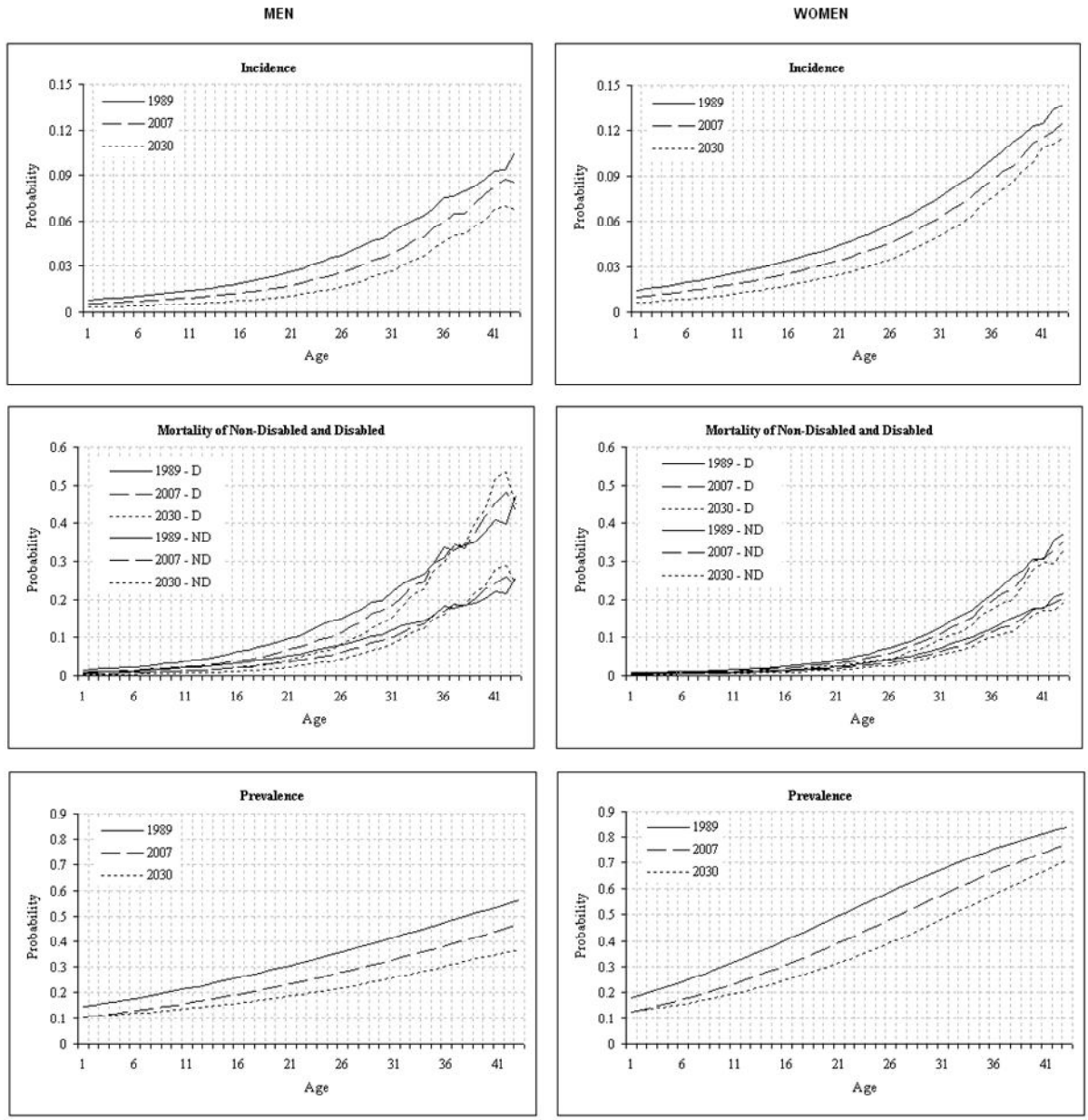
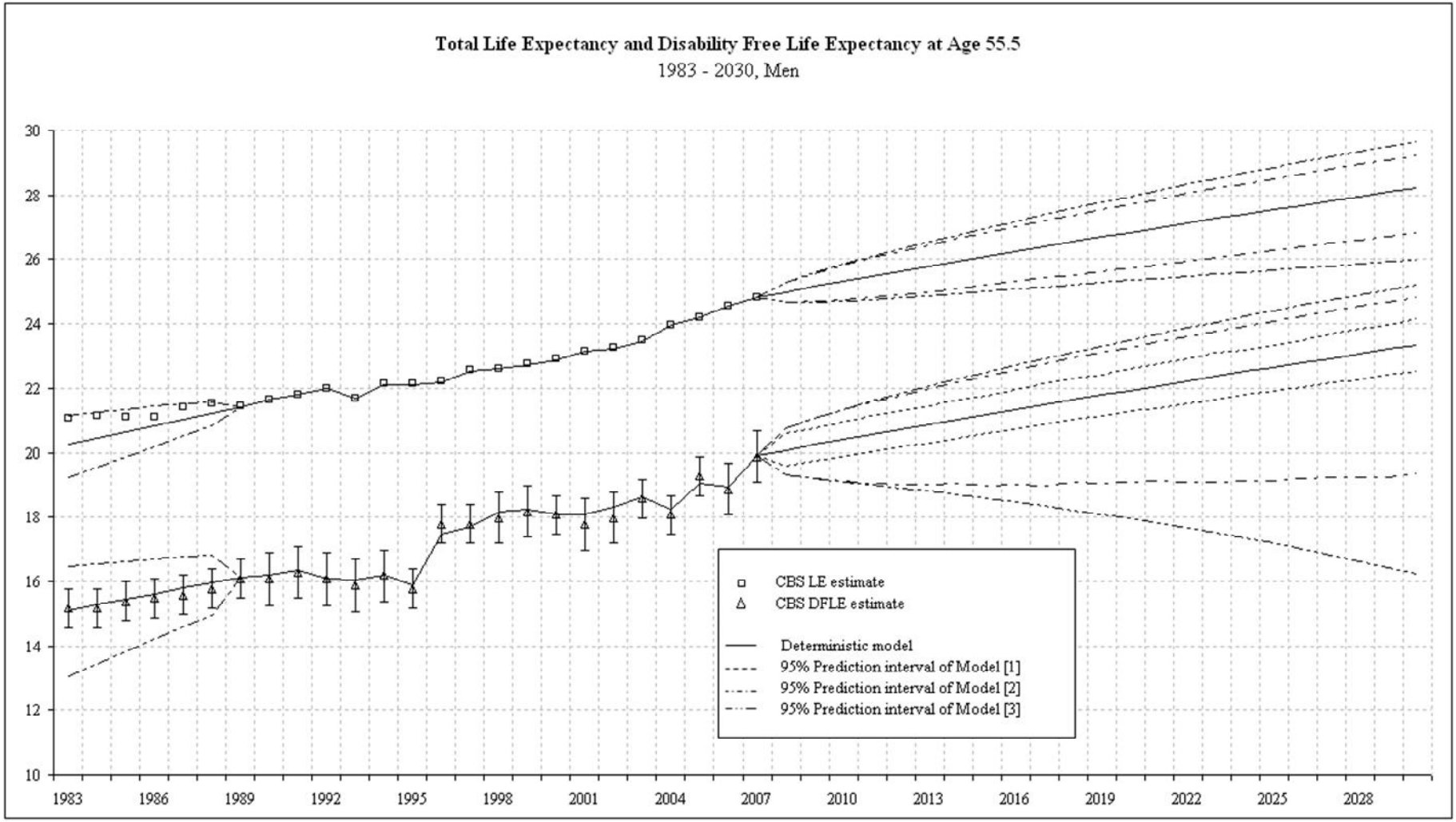


Figure 3. Probability of Incidence, Non-Disabled Mortality and Prevalence in 1989, 2007 and 2030, Men and Women



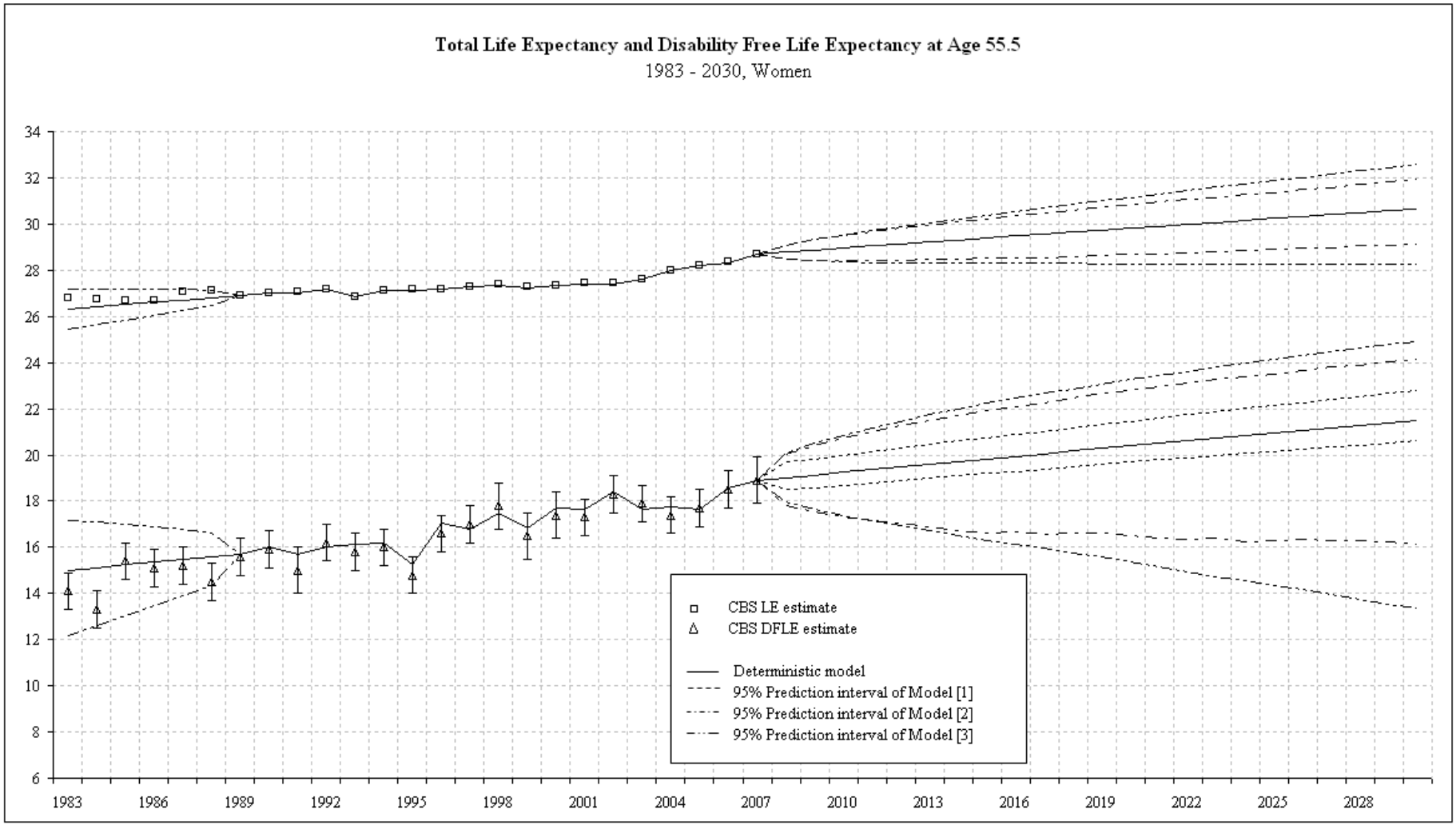
Notes:
ND indicates non-disabled
D indicates disabled

Figure 4. Total Life Expectancy and Disability Free Life Expectancy at Age 55.5, 1983-2030, Men



Notes: 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. CBS: Statistics Netherlands.

Figure 5. Total Life Expectancy and Disability Free Life Expectancy at Age 55.5, 1983-2030, Women



Notes: 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. CBS: Statistics Netherlands.