“Tackling non-communicable diseases by a forecasting model for critical illness cover”

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SECTION 1. Macroeconomic processes and regional economies management

Maria Russolillo (Italy)

Tackling non-communicable diseases by a forecasting model for critical illness cover

Abstract

Non-communicable diseases are the most frequent causes of death in most countries in the Americas, the Eastern Mediterranean, Europe, South-East Asia, and the Western Pacific. In the African Region, there are still more deaths from infectious diseases than NCDs. WHO projections show that NCDs will be responsible for a significantly increased total number of deaths in the next decade (WHO, 2014). In this context, the market of illness insurance is strongly being developed, allowing policyholders to reduce the financial impact of diseases. Indeed, critical illness insurance typically provides a payment of a lump sum in the event of the person insured suffering a condition covered under the policy. In other words, the insured receives a fixed sum on the diagnosis of a specified list of critical illnesses. The contract terms may also be structured to pay out regular income cash-flows on the policyholder. In general, since the policy face amount has to be paid on diagnosis, the incidence rates or diagnosis rates have to be accurately estimated. The research is here developed around the following focal and original points:

- the estimation of the diagnosis rates by means of an analysis by cause of death for obtaining cause-specific diagnosis rates: in particular, the author modeli the probability of death by cause as a proxy of the estimate of the diagnosis rates;
- the cause-specific death rates are modelled by a *stratified* stochastic model for avoiding the durable problem in literature of the dependence among different causes of death;
- a fair valuation framework is adopted for pricing a specific product of critical illness insurance.

The analysis is completed by empirical findings.

Keywords: critical illness, diagnosis rates, Lee-Carter model, stratified sampling.
JEL Classification: C02, G22, J11.

Introduction

Today, non-communicable diseases (NCDs) like cancers, cardiovascular diseases, chronic respiratory diseases, and diabetes, are the major killers in most of the countries. Despite real-life case studies around us, and the oft-repeated reports and statistics being flung our way, many continue to be ill-prepared for illness when it strikes us or our family members, especially on major illnesses. When calamities strike, we fall back on savings and personal finances to fund treatment needs. Costs for treatment vary widely depending on location, tests, procedures and hospital. It takes several years to make up for what patients lose in terms of monetary loss if they dip into personal savings to cover expenses. According to the World Health Organization statistic (WHO, 2014), there is a 10% of probability that a person between 30 and 70 years could die of any of the four non-communicable diseases in Italy. Getting a critical illness insurance cover, then, seems to be an obvious choice. But few people opt for health insurance, and of that barely a fraction gets the additional critical illness cover. Basic healthcare insurance does not cover critical illness, and even if it did, the amount is too small to cover any major medical treatment. Critical illness is a very important pure health cover and should be included in a person's portfolio to guard one from any such eventualities. Underwriting a critical illness coverage allows the insured to receive a lump payment which can be used to pay any ongoing financial commitments such as a mortgage, loans, in event of critical illness. Furthermore, the coverage can be used for any specialist medical treatment, upon diagnosis of any critical illness outlined in the policy.

For the insurance company management perspective, it is essential to avoid mismatch between the actual settled claims with expected diagnosed claims, by accurately evaluating the diagnosis rates, in order to measure the actual future outflows.

In the critical illness insurance, the claims that it expects to be settled in the years arise from diagnoses. In other words, they are tightly related to the diagnosis rates.

When a critical illness claim is incurred, the insurer has to settle the payment. In this order of ideas, it is very relevant to determine the diagnosis rates. The aim of the paper is to propose a methodology for deriving the diagnosis rates by resorting to an analysis by cause. The layout of the paper is the following. Section 1 describes the critical illness market. In Section 2, we describe the Lee-Carter

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model in its Poisson version; in Section 3, we propose the adjusted stratified Lee-Carter model; Section 4 shows the details of a typical contract of critical illness insurance; in Section 5, some numerical results are presented. Concluding remarks are offered in Final Section.

1. The critical illness market

The 20th century witnessed a high decline in the mortality level of populations, namely, in more developed countries. The positive evolution of mortality implied a substantial increase in the life expectancy, stimulated, in the first times, by the infant and youth mortality reduction and, in the last years, also by the reduction in the mortality rates of the old generations. The increasing survival in higher ages associated to the smaller number of births implies more and more aged populations. A higher longevity has direct impact on the costs of the social security public systems and on the health care expenditures for individuals, families, seniors, and small businesses.

The critical illness market, in particular, in UK, growth up to 1999 was followed by a plateau in 2000 and 2001. Sales peaked in 2002, when over one million accelerated critical illness policies were sold (CMI, 2010). According to the 2012 U.S. Critical Illness Insurance Market Survey (GenRe, 2012), participants report $147.5 million in new premium sales for the year 2011. Critical illness insurance typically provides the insured a fixed sum on the diagnosis of a specified list of critical illnesses. In particular, in our research, we propose to express the diagnosis rates for the specific illness by estimating the cause-specific mortality probabilities.

According to the WHO, a "right" detection of the causes of death is vital for forecasting more accurately mortality. Booth and Tickle (2008) provide an overview of mortality projection by cause of death. Girosi and King (2008) proposed a Bayesian model to use information on causes of death to estimate more accurately mortality. Furthermore, the U.S. Social Security Administration carries out projections by cause of death, as described in "Board of Trustees of the Federal Old-age and Survivors Insurance and Disability Trust Funds Report" by Social Security and Medicare Boards of Trustees (2009).

There are two types of critical illness covers (from herein, CIC): acceleration of death benefits and standalone. Experience suggests that the products under accelerated CIC, where the benefit is provided upon death or diagnosis of a critical illness, whichever occurs first, is more popular than standalone. The insurance of accelerated critical illness (CI) risk is often in the actuarial practise aligned with the associated mortality risk. The reason for this is, essentially, a practical one, because there may be insufficient opportunity to acquire the medical evidence that allows the critical illness claim definition. Consequently, as the death is believed to occur shortly after a critical illness event, the insurer, generally, insists on insuring the associated mortality risk on the same basis. In these terms, the diagnosis rates for the specific illness can be measured by the cause-specific mortality probabilities.

2. The model

Mortality forecasts are used in a wide variety of academic fields, and for global and national health policy making, medical and pharmaceutical research, and social security and retirement planning. In the last decades, several mortality forecasting methodologies have been developed: Biomedical Process-based, Expert-based, Structural Modeling (Explanatory or Econometric), Decomposition and Disaggregation, Trend Modeling (Extrapolation). As it is known, Extrapolation methods fail to account for future structural change. Anyway, there are many justifications for using Extrapolation methods, as, for example, the complexity and stability of historical trends. Extrapolation may be the most reliable approach in terms of forecast accuracy. As Keyfitz said: "…we cannot afford to be ashamed of extrapolating the observed regularities of the past" (Keyfitz, 1982). But there is a trade-off between model fit and forecast accuracy: in-sample errors may not be a good guide to forecast errors.

Extrapolation methods have had significant development in the last few years: the basic Lee-Carter model (LC from now on) has been extended and, among its extensions, we can remember, for example, the log-bilinear Poisson version (Renshaw and Haberman, 2003a,b,c), the age-period-cohort version (Renshaw & Haberman, 2006) or the stratified LC model (Butt and Haberman, 2010, etc.).

In order to develop forecasts of future mortality rates, it is necessary to transform the raw or crude mortality data into appropriate mortality rates, probabilities and other metrics suitable for valuation and risk management. To this aim, the LC model is one of the most popular theoretical frameworks. It belongs to the extrapolative stochastic methods assuming that the observed historical trends of human mortality improvement will persist into the future.

In the LC modelling approach, the age effects are assumed to be constant in time, and the time-variant period effects are projected forward using autoregressive time series models. Thus, the period

factors are extrapolated in time by a stochastic ARIMA process (e.g., random walk with drift) in order to make forecasts of the future force of mortality and, implicitly, future life expectancy.

In its original formulation, the LC model is expressed as:

$$\log\left(m_{xt}\right) = \alpha_x + \beta_x \kappa_t + \varepsilon_{xt}, \quad (1)$$

where the logarithm of a time series of age-specific death rates m_{xt} is expressed as the sum of age-specific parameters, α_x indicating the age-specific pattern of mortality and a component given by the product of a time varying parameter κ_t, reflecting the general level of mortality and the parameter β_x, measuring the sensitivity of mortality at each age to changes in the general level of mortality.

In this paper, we resort to an alternative model version: the so-called log-bilinear Poisson version of the Lee-Carter model (Renshaw and Haberman, 2003c), which is based on an iterative method applied to the deviance function. This approach assumes that the age and period-specific number of deaths D_{xt} are independent realizations from a Poisson distribution with parameter:

$$E\left(D_{xt}\right) = e_{xt} \exp \eta_{xt} \text{ where } \eta_{xt} = \alpha_x + \beta_x \kappa_t.$$

Because the predictor η_{xt} is non-linear in the parameters, it cannot be implemented as a GLM. However, adapting the iterative fitting method due to Goodman (1979), as described in Brouhns et al. (2002), it is possible to optimize the Poisson likelihood by monitoring the associated deviance (Renshaw and Haberman, 2003c).

3. The adjusted model

In this Section, we introduce a significant handling to the stratified Lee-Carter model (from herein, SLC) proposed by Butt and Haberman (2010). It allows for taking into account the valuable information by the main causes of death improving the forecasting performance. Simultaneously, the methodology we present overcomes the problem of dependence between causes, which represent competing risks.

In particular, the key points which enhance the powerfulness of the model concern the stratified probabilistic sampling and the multivariate random walk. The first one allows for determining the weight of the cause of death, according to the proportional allocation scheme. It is consistent with the heterogeneity of the population under consideration. In other words, the effectiveness of the sampling is increased by the organization in homogenous groups. The second one captures the correlation between the subpopulations composed by the different causes of death.

The longevity phenomenon is explored by age, period and cause of death, where the extra variate $h = 1, 2, \ldots, H$ corresponds to the $h - th$ subpopulation identified by $h - th$ cause of death which denotes the stratum $h - th$. In practise, the whole region of interest is split into H disjoint subset, the so-called strata:

$$\bigcup_{h=1}^{H} Z_h = Z.$$

The following notation is introduced:

$i = 1, 2, \ldots, N_h$ size of the $h - th$ stratum,

$N = \sum_{h=1}^{H} N_h$ size of the population,

$n_h = \frac{N_h}{N}$ size of the $h - th$ sample,

$f_h = \frac{n_h}{N_h}$ sampling ratio in the $h - th$ stratum.

In order to quantify the differences in the mortality experience of population subgroups differentiated by an additional measurable covariate (other than age and period), this model assumes a direct additive effect of an observable factor on the log mortality rates across all ages and calendar time periods. In this way, the classical Lee-Carter relationship, when it is introduced a Poisson error structure, becomes the following:

$$\log\left(d_{xth}\right) = \alpha_x + \alpha_h + B_x K_t + \varepsilon_{xth}, \quad (2)$$

where d_{xth} represents number of deaths, α_x is referred to the whole population, while α_h measures the relative differences between the age-specific mortality profiles on the log scale of the population subgroups defined by the extra variate (Butt et al., 2010). The model here assumes that mortality rates for h populations are driven by a common stochastic factor. In other words, the trend of changes in mortality is the same for each subpopulation, that is, the time-varying index of the whole population K_t, as the sensitivity of mortality at each age to changes in the general level of mortality expressed by B_x. To estimate the parameter values, it is necessary to compose a matrix so built:

$$\sum_{h=1}^{H} f_h \left[\ln\left(m_{xth}\right) - \alpha_{xh}\right], \quad (3)$$

where f_h is the stratified sampling ratio, m_{xth} represents the central mortality rates for each cause of death h and $\alpha_{xh} = \alpha_x + \alpha_h$ characterized by the sum of specific parameters, respectively, for the whole population and for the subpopulation related to the cause of death h.

The fitting of the parameters is obtained by optimizing the Poisson likelihood of the associated deviance of the residuals of the matrix in formula (3).

To capture the correlation between the subpopulations subdivided by cause of death, the K_t follows a multivariate random walk with drift:

$$K_t = d + K_{t-1} + \varepsilon_t,$$

$$K_t = \left(k_{t1}, k_{t2}, ..., k_{tH}\right),$$

$$d = \left(d_1, d_2, ..., d_H\right)^T,$$

$$\varepsilon_t \approx N\left(0, \Omega\right).$$

In this contribution, we propose a variant of the SLC model, in order to obtain accurate survival projections, capturing the heterogeneity in mortality trend given by different causes of death.

In this framework, we determine the cause-specific death probabilities q^h, where the index h denotes a specific cause which approximates the diagnosis rate for that cause.

4. The critical illness insurance

According to Swiss Re Term & Health Watch (2008), the critical illness insurance has largely developed. In 2007, sales for a particular contractual option, the so-called *Accelerated Critical Illness*, accounted for over 90% of all critical illness plans taken up in the UK.

The critical illness cover pays a lump sum amount or critical illness benefit in the event of the life assured getting diagnosed with any of the critical illnesses covered by the policy during the period of coverage. The policy contract guarantees a benefit only on diagnosis of a pre-determined list. The number of diseases named in the contract varies from insurer to insurer, but cancer, stroke, coronary artery bypass, major organ failure, paralysis, etc, are, generally, covered.

Generally, the benefit payment is due only if the life assured survives a certain period after being diagnosed with the critical illness.

There are two main contractual options: the *Standalone Cover* and the *Accelerated Cover*.

In the first case, the critical illness cover is separated from the life cover. Standalone Illness Cover guarantees a predetermined lump sum if the assured is diagnosed with a specified illness during the term of the policy.

In the second one, if the death of the person named on the policy occurred or the assured is diagnosed with a specified illness indicated in the contract, the Accelerated Illness Cover provides a lump sum payment. Nevertheless, if the assured is diagnosed with a specified illness, the insurer pays over the critical illness benefit. Furthermore, in case the assured recovers from the illness and dies during the contract period, the life company pays out the remaining life cover benefit. We consider a critical illness cover.

Let us indicate by k_x the healthy curtate future lifetime of the insured aged x at issue.

The cash flow scheme related to the policy at time s is the following, in the case of anticipated annual premiums:

$$X_s = \begin{cases} {}_{/m}P_{x,s+1} & k_x \geq s \qquad 0 \leq s \leq m-1 \\ 0 & k_x \geq s \qquad s \geq m \\ B_s = F & s-1 \leq k_x \leq s \qquad 1 \leq s \leq n \end{cases},$$

with $s = 1, 2, ..., n$ $P_{n+1} = 0$ and $X_0 = P_1$

where ${}_{/m}P_{x,s+1}$ is the premium amount payable up to time m, and B_s is the critical illness benefit equal to the facial amount F.

In light of a fair valuation of the policy (as in Coppola et al., 2009), the critical illness cover stochastic flow of the portfolio f_s at time s, $s > t$ by a trading strategy can be expressed as follows:

$$f_0 = -c\,{}_{/m}P_{x,1} \text{ if } s = 0,$$

$$f_s = -{}_{/m}P_{x,s+1}Y_s + B_s Y_s^u, \qquad \text{if } s = 1, 2, ..., n$$

where y_s is the number of healthy assured among the survivors or briefly we call healthy survivors at time s; Y_s^u is the number of unhealthy assured among the survivors or briefly we call unhealthy survivors at time s, in particular, having $Y_s^u = Y_s - y_s$, in which Y_s is the number of the healthy and unhealthy survivors at time s.

We formulate the stochastic provision at time t in its fair value form, replicating the stochastic flow F_s at time s as in the below mathematical representation:

$$V_t = E\left\{L_t / \Im_t\right\} = E\left\{\sum_{s=t+1}^{n}\left[-{}_{/m}P_{x,s+1}y_s + B_s y_s^u + \right.\right. \\ \left.\left. + B_s\left(Y_s - Y_{s-1}\right)\right]v\left(t,s\right) / \Im_t\right\}, \tag{4}$$

where L_t is the stochastic loss in t of the portfolio of c contracts in-force and $\Im$ is represented by the filtration $\left\{\Im_t\right\} \subset \Im$, containing the information flow at time t. On the basis of the conditional expectation calculus, we can write:

$$\sum_{s=t+1}^{n}\left[-{}_{/m}P_{x,s+1}\ c\ \ {}_{t}p_{x}\ \ {}_{s-t}p_{x+t}+B_{s}cq_{x}^{h}\ \right]E\left[v(t,s)/\Im_{t}\right], \quad (5)$$

where ${}_tp_x$ is the survival probability of assured aged x up to time t, q_x^h is the $h-th$ death or diagnosis of a critical illness rate of assured aged x, whichever occurs first, and $v(t,s)$ is the stochastic present value at time t of one monetary unit at time s.

5. Numerical analysis

This Section is devoted to obtain mortality projections and to measure their impact on the solvency of a particular insurance product, the critical illness cover, according to different alternatives:

- the aggregation of the causes of death or all-causes death rates in the Poisson Lee-Carter setting (aggregated scheme);
- the decomposition of the causes of death or specific-causes death rates in the Poisson Lee-Carter setting (decomposed scheme);
- the ASLC (adjusted stratified Lee-Carter) model (stratified scheme).

5.1. Mortality data for analysis. The population data are characterized by the Italian total population from 1950 up to 2006 from 0 up to 110 years, collected from Human Mortality Database. The death rates above age 100 have been aggregated in an open age group 100+ (aggregated scheme).

Mortality experience is made up by the cross-tabulated mortality rates (*mu*) and the central exposures (*e*) by individual ages (*x*) and calendar years (*t*) sequence classified by cause of death. In particular, the World Health Organization (WHO) taxonomy has been slightly modified by including some classes of similar features (decomposed and stratified schemes).

In the case of the decomposed and stratified schemes, the mortality experience is cross-classified by an additional covariate, a sort of grouping factor, the cause of death, where the dataset is best represented by a three dimensional matrix (i.e., array). In other words, we use cross-classified data by age, period and factor *g*.

Figure 1 shows the parameter values of the Poisson LC by considering the entire Italian total population.

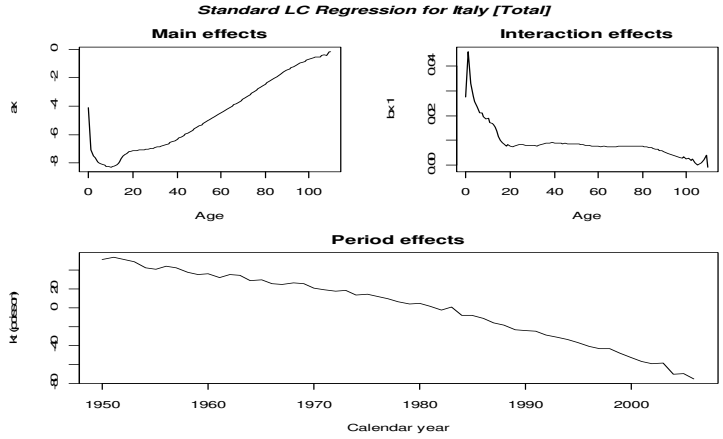

Fig. 1. Poisson Lee-Carter parameters' model – aggregation by causes of death, Italian total population

The α_x's clearly increase in x, reflecting higher mortality at older ages, as expected. The β_x's decrease with age, remaining positive. The k_t's exhibit a regular behavior. In Figure 2, we report the forecasted k_t's which represent the overall mortality index, used for calculating the central death rates m_{xt}.

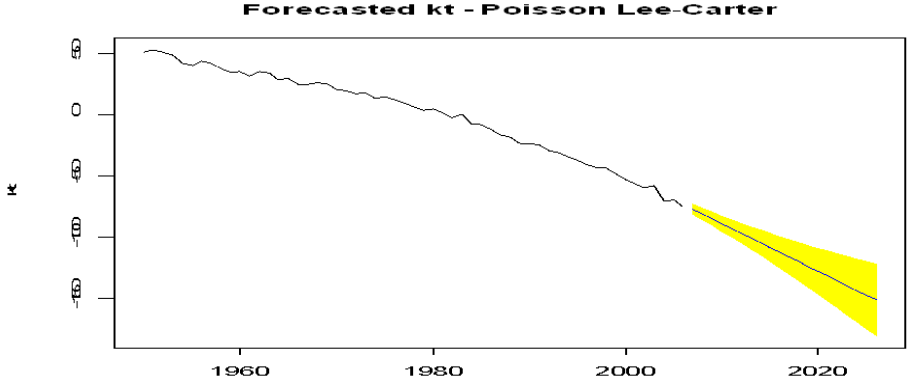

Fig. 2. Poisson Lee-Carter forecasted k_t – aggregation by causes of death, Italian total population

Table 1 shows the k_t prediction intervals for $h = 1,\ldots, 20$ periods ahead at level of 95%.

Table 1. Confidence intervals for forecasted k_t – aggregation by causes of death, Italian total population

h year ahead	Point forecast	Lo 95	Hi 95
2007	77.22736	81.96754	72.48718
2008	81.13388	86.31559	75.95217
2009	85.04041	90.81710	79.26372
2010	88.94694	95.46257	82.43130
2011	92.85346	100.23749	85.46943
2012	96.75999	105.12692	88.39307
2013	100.66652	110.11755	91.21549
2014	104.57304	115.19837	93.94772
2015	108.47957	120.36048	96.59866
2016	112.38610	125.59675	99.17545
2017	116.29263	130.90144	101.68381
2018	120.19915	136.26988	104.12842
2019	124.10568	141.69824	106.51312
2020	128.01221	147.18329	108.84113
2021	131.91873	152.72232	111.11515
2022	135.82526	158.31300	113.33752
2023	139.73179	163.95331	115.51026
2024	143.63831	169.64148	117.63515
2025	147.54484	175.37593	119.71375
2026	151.45137	181.15524	121.74749

The plots in Figure 3 illustrate the logarithm of death rates for different causes of death ranging from 1979 to 2003.

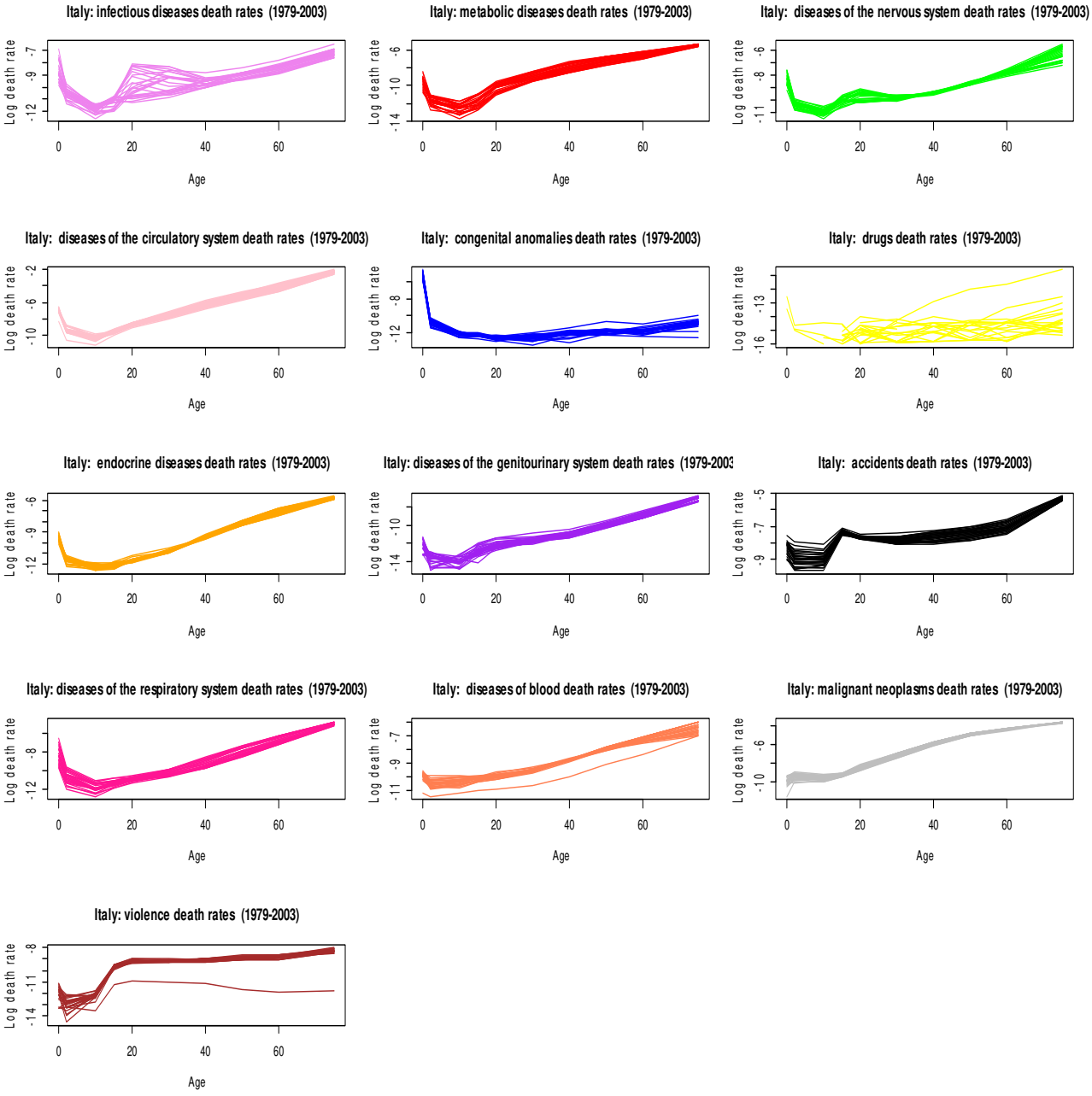

Fig. 3. Log death rates – decomposition by causes of death, Italian total population

In Figure 4, we can observe projected mortality obtained by the aforementioned decomposition.

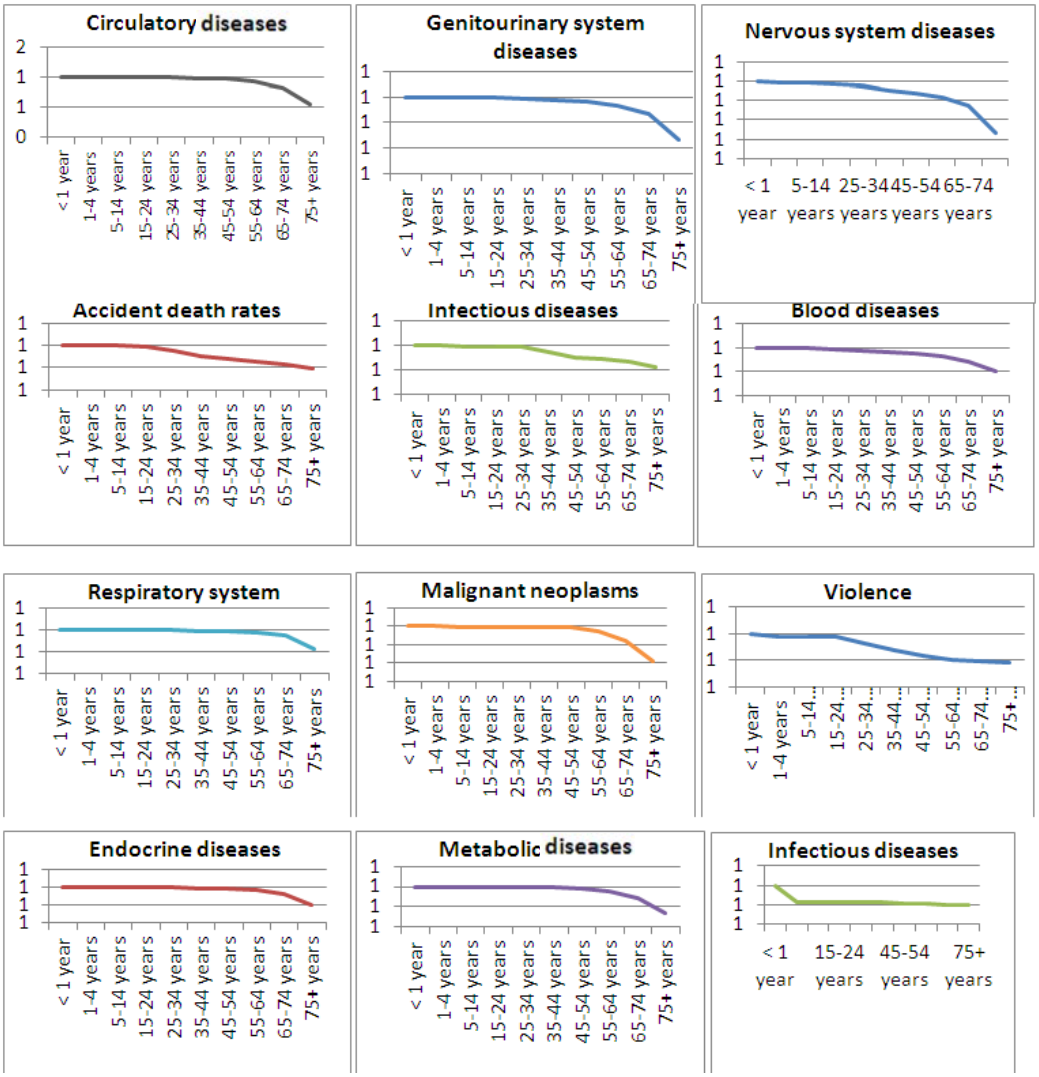

Fig. 4. Forecasted central death rates – decomposition by causes of death, Italian total population

In order to forecast the mortality death rates according to the stratified scheme, we create an artificially stratified mortality experience with a Poisson error structure. In particular, taking the mortality experience of the Italian whole population (male and female all-causes death rates) as the base dataset, we can produce a randomly stratified mortality data. The plots illustrated in Figure 5 represent the randomized data with respect to the (artificial) additional effect (X) showing entirely indistinguishable central exposures and log mortality profiles.

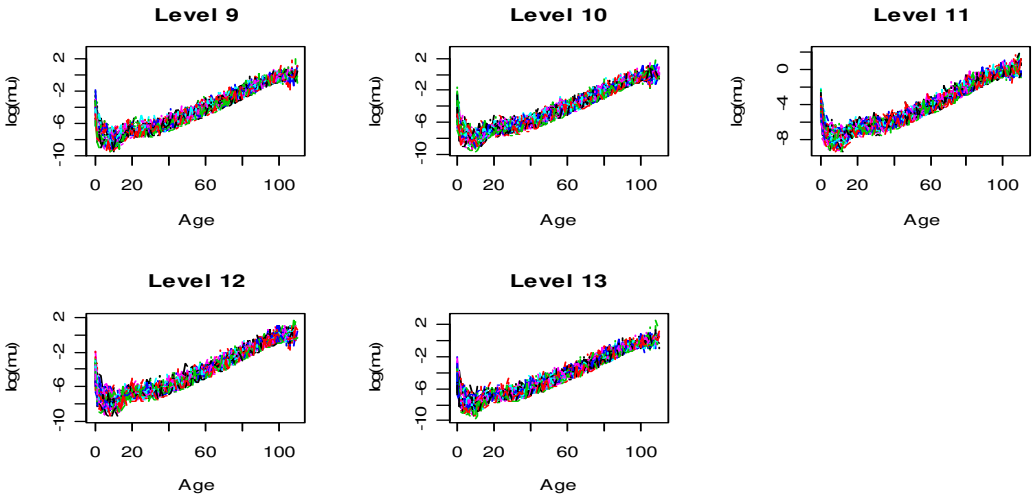

Fig. 5. Artificial log death rates – ASLC model

The estimation of the evolution of k_t by means the ASLC model is reported in Figure 6.

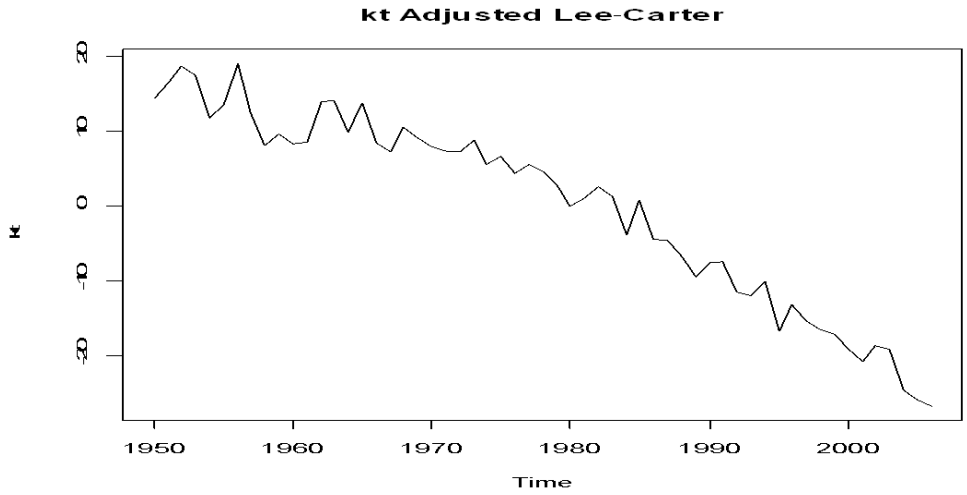

Fig. 6. Poisson Lee-Carter adjusted k_t – ASLC, Italian total population

We note that the sub grouping of the dataset can be carried out by more than one additional covariate, where covariate is represented by a, b, c, d, e, f as reported in Table 2.

Table 2. Measure of α_h, ASLC model

Measure of α_h						
BASE	*a*	*b*	*c*	*d*	*e*	*f*
0	0.5176268	1.1997733	-0.7470632	2.4947570	0.4841734	0.4037400

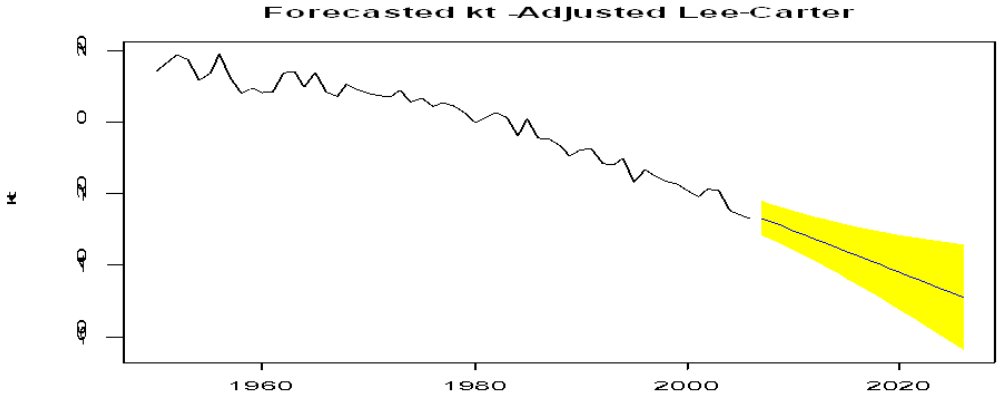

Fig. 7. Poisson Lee-Carter forecasted k_t –- ASLC, Italian total population

Figure 7 shows the forecasted k_t by implementing the ASLC model. Table 3 shows the k_t prediction intervals for h periods ahead at level of 95% in the case of ASLC.

Table 3. Confidence intervals for forecasted k_t – ASLC, Italian total population

h year ahead	Point forecast	Lo 95	Hi 95
2007	26.79760	31.63181	21.96338
2008	27.96818	32.98668	22.94967
2009	29.13876	34.38667	23.89085
2010	30.30934	35.83250	24.78618
2011	31.47992	37.32369	25.63615
2012	32.65050	38.85885	26.44215
2013	33.82108	40.43601	27.20616
2014	34.99166	42.05287	27.93045
2015	36.16224	43.70704	28.61745
2016	37.33282	45.39614	29.26951
2017	38.50340	47.11794	29.88887
2018	39.67399	48.87036	30.47761
2019	40.84457	50.65153	31.03760
2020	42.01515	52.45976	31.57053
2021	43.18573	54.29354	32.07791
2022	44.35631	56.15153	32.56108
2023	45.52689	58.03255	33.02123
2024	46.69747	59.93553	33.45941
2025	47.86805	61.85952	33.87658
2026	49.03863	63.80369	34.27357

We calculate the impact of the different kind of projections on the temporal profile of the mathematical provision of the insurance company balance-sheet. We take into account a critical illness cover issued at 2012, with maturity 2022 (10 years). The contract is characterized by a unitary amount and a benefit equal to 100.

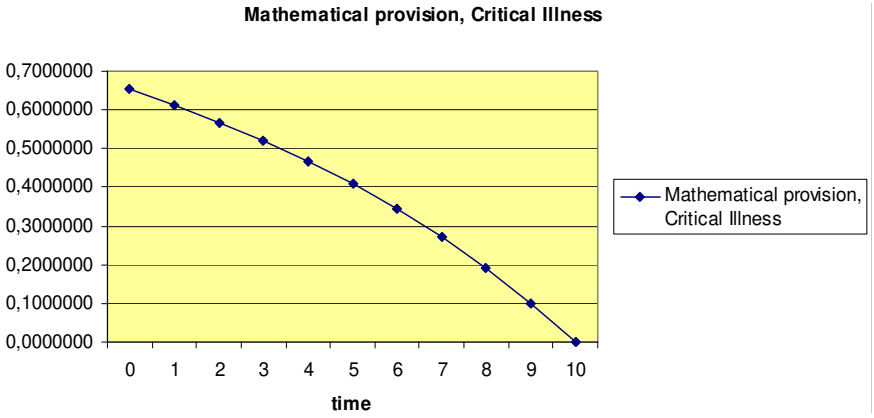

Fig. 8. Mathematical provision critical illness cover, 10 years – Poisson LC aggregation by causes of death

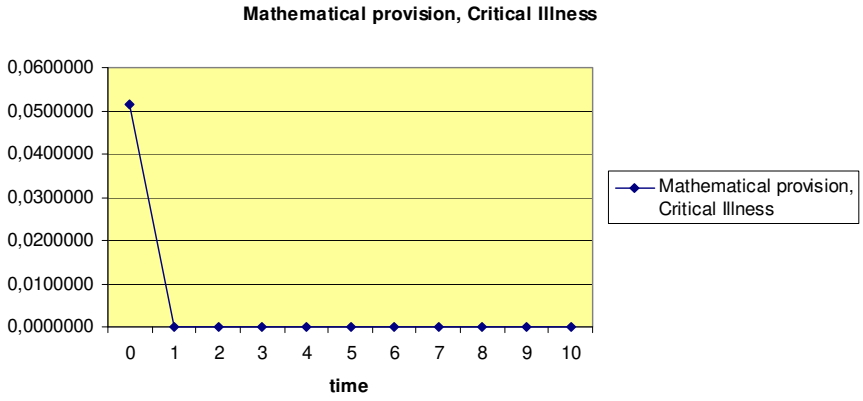

Fig. 9. Mathematical provision critical illness cover, 10 years – Poisson LC decomposition by cause (circulator system)

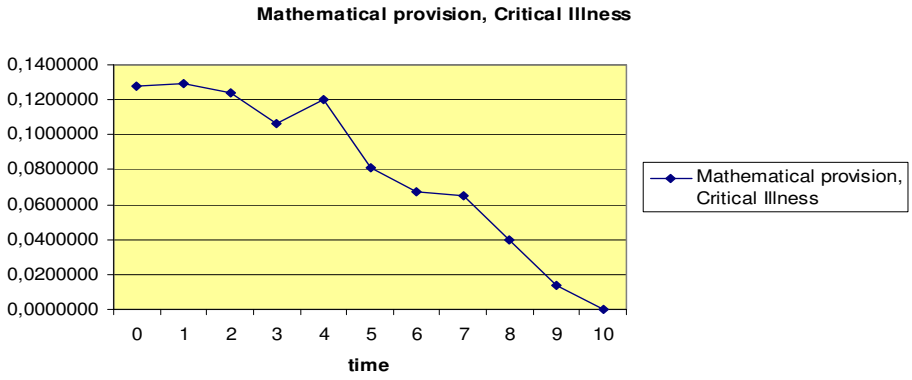

Fig. 10. Mathematical provision critical illness cover, 10 years – Poisson LC ASLC

The difference between ASLC and aggregation is significant.

Conclusions

Many demographers consider the causes of death as the key factors needed in mortality modelling (Gutterman et al., 1998; Tabeau et al., 1999). Systematic changes in causes of death represent common trends in longevity which should be included in mortality risk models. Nevertheless, the mortality has, generally, been analyzed by using extrapolative models neglecting the influence of the causes of death, in an aggregate projection setting. In order to take into account important insights on underlying socio-economic factors provided by causes of death, many authors try to model cause-specific mortality models (Foreman et al., 2012). However, there are evidences that the decomposition by cause of death leads to conservative forecasts. In particular, model parameters for causes of death are often less stable in respect of aggregate mortality model, as remarked by Wilmoth (1995). Furthermore, the disaggregation by cause of death involves problems associated with the lack of independence among causes (Booth et al., 2008) and difficulty related to the coding of the data on the basis of different international rules. Especially, the issue of independence contradicts the presence of multiple causes which, instead, should require to incorporate the interrelations under consideration in the theoretical models. Over the last decades, to surmount this issue, an independence assumption has been postulated.

In this context, we proposed a forecasting model we called adjusted stratified Lee-Carter model which assumes a direct additive effect of an observable factor, i.e., the cause of death, on the log mortality rates across all ages and calendar time periods.

The main advantages of our proposal are the following:

- it includes the dependence between cause of death representing competing risks throughout the differentiation of the population in subgroups by an additional measurable covariate;
- by stratifying, it allows for leading an aggregate analysis on the population, avoiding the problem of instable estimates connected to the decomposition by cause of death;
- it is based on a model like Lee and Carter type structure belonging to a trend modelling class, so that it preserves their main prerogatives, as the most reliable in terms of forecast accuracy.

Further extension of the research will be performed in terms of the impact on different kind of insurance portfolios.

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