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EDITORIAL

AAS Thematic issue: "Mortality: from Lee–Carter to AI"

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Exactly 11 years ago, Sweeting (2011) noted in his Editorial that "*Even with the uncertainties around the choices of models and parameters, [stochastic mortality modeling] can be used to give a probabilistic assessment of the range of outcomes*". A quick read through past issues of *Annals of Actuarial Science* shows us that mortality modelling is still a *hot* topic in actuarial science, as evidenced in the multiple papers that have aimed at innovating towards the most suitable mathematical frameworks and model specifications.

The past three decades have been characterised by a myriad of developments, Li & Lee (2005), Cairns *et al*. (2006), Renshaw & Haberman (2006) to cite a few, raising the need for a useful overview in both modelling and forecasting. Booth & Tickle (2008), in their exhaustive work, review the main methodological developments in (stochastic) mortality modelling from 1980 onwards focusing not only on Lee–Carter or GLM-based methodologies but also on parametric models and old-age mortality. In the same vein, Li (2014) focuses exclusively on simulation strategies. After sticking to a Lee & Carter (1992) model, and given the explosion of scientific papers focusing on how to best account for forecasting uncertainty, Li (2014) asks the simple question: *What is the best performing simulation strategy?* The answer is: it depends on the model fit; furthermore the choice of forecasting procedure matters. Clearly, attention has to be put into how the base model fits the data before focusing on the forecast. If there are unusual patterns in the residuals caused, e.g. by a non-captured cohort effect, the results produced by different simulation techniques could vary substantially.

There is consensus about residuals needing to be pattern-free for a model to be well performing. This observation motivated Renshaw & Haberman (2006) to generalize the classical Lee & Carter (1992) model, adding a cohort component. They show that adding such a cohort effect renders the residual plots pattern-free. However, since cohort is directly related to age and period, identifiability issues arise due to the collinearity between these three parameters. This could be particularly problematic when projecting future mortality rates. Hunt & Blake (2020) focus on this particular issue. They highlight that some identifiability constraints are arbitrary and have an impact on the trend of particular parameters. Hence, they propose to determine which features of the parameters are data driven or choice driven. Based only on the data-driven trends, a selection for the time series should be done, ensuring that the forecast does not depend on arbitrary choices.

Another way of studying mortality is not by extrapolating aggregate trends with a suitable model, but by studying the underlying causes of death. This allows for an analysis of causal mortality, as well as the dependence between different competing causes. Indeed, if you die from cardiovascular disease, you simply cannot have also died in a car accident. Alai *et al*. (2015) present a multinomial logistic framework to incorporate cause of death into mortality analysis. As others in the literature, they obtain estimates that are more conservative with regard to longevity, finding lower long-term increase than average. This stems from a failure to exploit information obtained from the aggregate trend and only relying on cause-of-death dependent mortality forecasts (Wilmoth 1995). Recent contributions to reconcile forecasting to account for this phenomenon could increase popularity of these models (Li *et al.* 2019). Indeed, only a model of this sort allows us to study the effect of eliminating a cause, that is, answering the question "*What if a medical treatment is found for cancer?*".

The reader soon realises that there are plenty of choices to be made in estimation and forecasting and that they require careful consideration. Aiming to integrate these decisions, Fung *et al.* (2017) propose a Bayesian model to estimate and forecast under a unified framework, which, despite an increase in model complexity, provides better performing model fits. This work contributes to the recent rise of interest in Bayesian-based approaches to mortality modelling, see, e.g., Antonio *et al.* (2015) for a useful overview of the literature.

Li & Lee (2005) presented an extension of the Lee & Carter (1992) model by studying mortality within a multi-population context, whereby countries with similar economic performance are expected to have similar long-term mortality trends. Existing frameworks produced sometimes diverging long-term trends. Building on this work, already applied in the practical context to build life tables in countries like Belgium and The Netherlands (Antonio *et al.* 2017), recent contributions have been made in the pages of our journal. First, on the model choice, Li & Lee's framework follows closely the common and country-specific parameter choice as given by Lee & Carter (1992). To overcome this restriction, Richman & Wüthrich (2021) use neural networks to choose an optimal model structure. Their model, fit to various countries, provides a very good forecasting performance and has the clear advantage that no ex-ante choices on structure need to be made. Second, on an application to study heterogeneity in mortality (Wen *et al.* 2021), the seminal work of Li & Lee (2005) studied mortality between different countries. However, Wen *et al.* (2021) exploit the multi-population setting to say something about the mortality per socio-economic group. This is of particular interest as various public pension reforms are based on the *representative agent*, whereas in reality big differences arise between socio-economic groups. Wen *et al.* (2021) study different specifications of the multi-population model to conclude that models that incorporate a group-specific time trend outperform models with a common global period effect, suggesting that both the base mortality and long-term trend differ per socio-economic category.

A final contribution that I would like to highlight is that of Spreeuw & Owadally (2013) on the dependence of joint lives. Most actuarial research, including of course the papers I discuss in this Editorial, focuses on mortality for a given gender, country or cause. However, the random remaining lifetime is always studied as an isolated independent individual event when over 60% of people in the UK, and most western countries, live in a couple. The authors show, using a North American life insurance data set, that mortality rates significantly increase after the death of the partner but that the dependence is only short term. As researchers and insurers, we need to keep in mind this *broken-heart* phenomenon and adjust our modelling accordingly.

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