MILLIMAN WHITE PAPER

Impact of COVID-19 on best estimate mortality assumptions

Adjustment of COVID-19 mortality data points

Impact on the calibration of mortality models

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Following the COVID-19 pandemic which killed more than 7 million people worldwide, the mortality data relative to the years 2020 to 2022 is not directly usable for updating the calibration of stochastic mortality models or Solvency II internal model calibrations for mortality and longevity risks.

In this paper, several approaches are presented to adjust COVID-19 mortality data points prior to the calibration of mortality models. We then discuss their impact on mortality projections and shocks.

Various national and statistical institutes have recorded the number of deaths attributable to COVID-19. These deaths correspond to the excess mortality caused by the pandemic, where excess mortality is the difference between the mortality that occurred and the expected mortality. These COVID-19 death data are highly dependent on how deaths are counted and correspond only to the direct effect of the pandemic on mortality. This direct effect may be overestimated in some countries, especially those with intensive testing and high sensitisation and/or incentives for COVID-19 diagnoses, or underestimated in other countries, especially in Africa.[1] In addition to the COVID-19 direct effects, which are the deaths caused by the virus, there are also indirect effects such as the decrease in the number of deaths due to other viruses such as influenza, or the postponement of some surgical operations.

Insurers and reinsurers have several options to update the calibration of their mortality and longevity models considering the COVID-19 experience. One option is to change the model calibration process, e.g., by introducing a weighting mechanism that allows less weight to be placed on years with unusual mortality experience. For instance, the 2022 CMI (Continuous Mortality Investigation) Core Model considers such a mechanism and puts a 0% weight on the 2020 and 2021 mortality data years, a 25% weight on the year 2022, and a 100% weight on all other years included in the calibration period.[2]

Data adjustment options can also be used to determine a reference mortality level without the short-term effects of the COVID-19 pandemic, and this option will be explored in the rest of our paper. Note that the long-term effects of COVID-19 on the non-pandemic mortality and, in particular, long COVID are also not considered in our approach. The most robust and reliable approaches to quantify the excess mortality due to short-term risk factors such as COVID-19 are based on estimating weekly excess mortality, unlike those only based on official COVID-19 death counts. They make it possible to exclude both positive and negative indirect effects of COVID-19, e.g., the postponements of surgical operations or the decrease in the number of seasonal influenza cases. This kind of adjustment is useful for different applications, such as avoiding double counting in internal models where it is taken into account in the pandemic module (along with its consequences), or to avoid distortions on forecasts for insured portfolio mortality since the models are not designed to capture such one-off/irregular effects.

In the next section, we present a methodology to adjust COVID-19 mortality data points prior to the calibration of mortality models. The data required and the modelling framework are described first, and then the theory behind the adjustment methods will be explained. The results for some countries for which Human Mortality Database (HMD) data are available are presented, followed by the results of a study of mortality rates in the Netherlands. Finally, we present alternative calibration strategies to model mortality considering the COVID-19 experience.

Note that the models and projections do not take into account other effects on mortality, such as the evolution of neurodegenerative diseases or the opioid crisis, which are not the focus of the work presented here. These effects can be studied by modelling mortality by cause of death.[3]

Methodology

DATA

The study is based on the use of the following mortality databases:

- **The Human Mortality Database:**[4] The HMD is a joint initiative of the Department of Demography at the University of California at Berkeley in the United States and the Max Planck Institute for Demographic Research in Rostock in Germany. It was created in 2000 with the objective of bringing together detailed population mortality data and to serve as a reference for anyone interested in human longevity. It contains data for almost 40 countries or areas in the form of periodic tables by year, age and sex, and also in the form of cohort tables.
- **The Short-Term Mortality Fluctuations (STMF) data series:**[5] This data resource has been created to provide data for scientific analysis of all-cause mortality fluctuations by week within each calendar year. The decision to add this new resource to the HMD was triggered by the COVID-19 pandemic. An additional motivation for this HMD extension was increasing importance of short-term or seasonal mortality fluctuations that are driven by temporary hazards such as influenza epidemics and temperature extremes, as well as man-made or natural disasters. The STMF provides open access to detailed data on mortality by week, sex and aggregated age group. The data series contains death counts, death rates and original input data used to produce these output indicators. Availability of weekly mortality data depends on the country. For the United States, for example, the data is available from the year 2015.
- **The demography of COVID-19 deaths database:**[6] It contains daily cumulative death counts attributable to COVID-19 broken down by sex, age, country and date of occurrence of the death, along with associated documentation, which includes the exact data sources. It also points out issues of quality and coverage of the data.
- **Statistics Netherlands:** The Dutch mortality data is not available in the HMD for the year 2020, so we used mortality data from Statistics Netherlands, a Dutch governmental institution that gathers statistical information about the Netherlands.

OPTIONS TO ADJUST COVID-19 DATA POINTS

In this section, we present some adjustment options to determine a reference mortality level for the year 2020 without the short-term effects of the COVID-19 pandemic. The objective of these methods is to obtain a reference level of mortality, called standardised death rates (SDRs), for a given index year y, where $y = 2020$ in our case.

The following adjustment methods are applied to the annual mortality rates:

- **Adjusting the data by removing the COVID-19 deaths:** The COVID-19 deaths counted by the French Institute for Demographic Studies (INED) and available for several countries are removed from the total number of deaths in the year 2020. This method only enables mortality data to be corrected for the direct effects of COVID-19, without taking into consideration the indirect effects (negative and positive).
- **Replacing the mortality rates of the index year 2020** by the average of the annual mortality rates over the last previous N years. Mortality rates have a generally decreasing trend over time that is not accounted for in this method. By averaging historical death rates, the method remains dependent on past fluctuations.

The following adjustment methods are applied to weekly mortality data.[7]

- **Week-specific averages:** The weekly reference rate for week w is the average of the mortality rates for the N years prior to the index year y in week w.
- **Week-specific trends:** The weekly reference rate for week w is determined by performing a linear regression of the mortality rates of the N previous years on week w.
- **Week-specific lower quartiles:** The weekly reference rate for week w is determined by averaging the quartile mortality rates of the N previous years over the week w. Therefore, the week-specific lower quartiles for week i, $x_i^{Q_1}$ are defined by:

$$x_i^{Q_1} = \frac{\sum_{j \in L_i} x_{ij}}{|L_i|} \quad L_i := \{j \in P : x_{ij} \leq quantile(\{x_{ij} : j \in P\}, 0.25)\}$$

  With:

  - x_{ij}: The mortality rate for week i in year j
  - P: Contains the N previous years in the selected reference period

- **Yearly average-week:** This denotes the expected level of mortality if every week had the same average level of mortality in the year. The yearly average-week $\bar{x}$ is defined by:

$$\bar{x} = \frac{\sum_{i \in W} \overline{x_i}}{|W|}$$

  Where:

  - $\overline{x_i}$ equals the arithmetical mean over the years in the selected period and is given by $\overline{x_i} = \frac{\sum_{j \in P} x_{i,j}}{|P|}$, where the set P contains all years in the selected reference period and $|P|$ denotes the number of elements in the set P.
  - W is the set of available weeks in the target year.

    Thus, $\bar{x}$ denotes the expected level of mortality if every week had the same average level of mortality in the year.

- **Summer average-week:** This measure $\bar{x}^*$ is similar to the above-mentioned yearly average-week measure, i.e., $\bar{x}$ but excludes from the calculation the winter weeks that tend to have higher mortality in general in comparison to summer weeks. For countries and regions in the Northern Hemisphere, winter season is defined as weeks from calendar week 1 to week 12 and from week 48 to week 52 included. For those situated in the Southern Hemisphere, winter season is defined as weeks from calendar week 22 to week 38 included. Thus, generally, the value of $\bar{x}^*$ is expected to be lower than $\bar{x}$. The formula for the summer average-week is given by:

$$\bar{x}^* = \frac{\sum_{i \in W^*} \overline{x_i}}{|W^*|}$$

  with W^* denoting the set of non-winter weeks, i.e., available weeks between calendar weeks 13 and 47 for the Northern Hemisphere and weeks 1 to 21 and 39 to 52 in the Southern Hemisphere.

  In addition to the adjustment methods just presented, Shkolnikov et al. developed in their 2022 paper alternative methods to address the need to determine the excess mortality caused by COVID-19.[8] They use an alternative retrospective baseline derived from the lowest weekly death rates achieved in previous years and a within-year baseline based on the average of the 13 lowest weekly death rates within the same year. These baselines express normative levels of the lowest feasible target death rates. The excess death rates calculated from these baselines are not distorted by past mortality peaks and do not treat non-pandemic winter mortality excesses as inevitable.

- **The alternative retrospective baseline method:** It is derived from the lowest weekly mortality rates achieved in the previous years. The baseline weekly death rate referring to past N years $SDR^{B}_{\text{aretro}}(y,w)$ is defined as:

$$SDR^{B}_{\text{aretro}}(y,w) = \hat{a}_w + \hat{\beta} \cdot y$$

  With:

  - w: The week number.
  - y: The index year.
  - $\hat{\beta}$: An estimate of the slope of the linear regression of the annual SDR on year t: $SDR(t) = \beta \cdot t + \varepsilon_t, y - N \leq t \leq y - 1$.
  - $\hat{a}_w$: Weekly effects defined as: $\hat{a}_w = \min_t 2\,(SDR(t\,,w) - \hat{\beta} \cdot t)$ with $\min_t 2$ denoting the second-lowest $SDR(t,w)$ value for week w among years t running from $y - N$ to $y - 1$. Note that the use of the second minimum is a commonly used approach to reduce the probability of outliers (David & Nagaraja, 2003).[9]

  The $SDR^{B}_{\text{aretro}}(y,w)$ indicates a target level of mortality referring to the lowest weekly death rates in the recent past, i.e., the past N years. The baseline weekly death rates based on the previous minimal values are insensitive to past mortality peaks. This makes an important difference from more conventional metrics involving annual averaging of past weekly death rates.

- **The alternative within-year baseline method:** It is based on weekly mortality rates in the index year. This method is independent of peaks in historical mortality rates. To calculate the baseline mortality, the method is based on the lowest weekly mortality rates in the index year y:

$$SDR^{B}_{wy}(y) = \frac{1}{13} \sum_{w \in Q_1} S\,DR(y,w)$$

  Where the set Q_1 includes the 13 weeks (a quarter of a year) that constitute the lower quartile of the 52 or 53 $SDR(y,w)$ values in year y. It determines a lower baseline of mortality in the index year y and highlights the amount of mortality to be eliminated to reach the average level of the lowest and not necessarily consecutive 13 mortality weeks.

CALIBRATION METHODS AND MORTALITY PROJECTIONS

The widely used Lee-Carter model is used to model mortality. The model is constructed as follows:

$$ln(\mu_{x,t}) = \alpha_x + \beta_x \kappa_t$$

With:

- $\mu_{x,t}$: Mortality rate at age x in year t
- α_x: Static age structure
- β_x: Sensitivity parameter at age x in relation to the evolution over time
- κ_t: Temporal evolution of mortality, modeled by an ARIMA process

In order to quantify the impact of the 2020 COVID-19 mortality shock on the calibration of the Lee-Carter model, we calibrate the Lee-Carter model on real data up to 2019 in a first step, then up to the year 2020 in a second step. We then compare its parameters and mortality forecasts to different calibration strategies using adjusted mortality data.

Results

IMPACT OF COVID-19 DISEASE ON MODELLING RESULTS

The global COVID-19 pandemic has had an impact on mortality, which can be quantified as discussed above. Health situations varied from country to country depending on the spread of the virus and the health policy in each country. The statistics of the pandemic have shown that not all individuals in the population were equally affected by the virus. The elderly and those with pre-existing conditions were the most vulnerable, and deaths due to COVID-19 were generally concentrated in the 60+ age group.

The following graphs show the mortality rates for 2019 and 2020 in the United States, France and Japan. These three countries have different mortality profiles because they have been impacted differently by the pandemic. Among these 3 countries, the United States is the country that has been the most impacted by COVID-19 in terms of 2020 mortality, followed by France and then Japan, where the mortality continued to decrease in 2020 as shown by the Figure 3 below.

FIGURE 1: MORTALITY RATES IN THE USA, TOTAL POPULATION

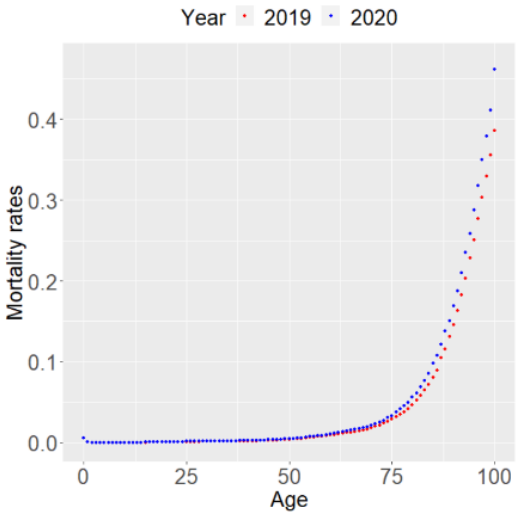


FIGURE 2: MORTALITY RATES IN FRANCE, TOTAL POPULATION

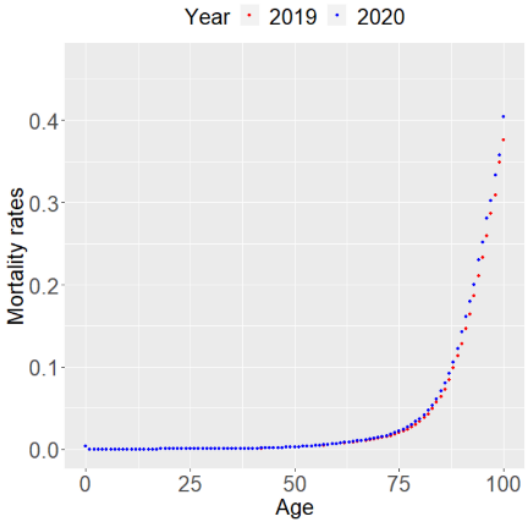
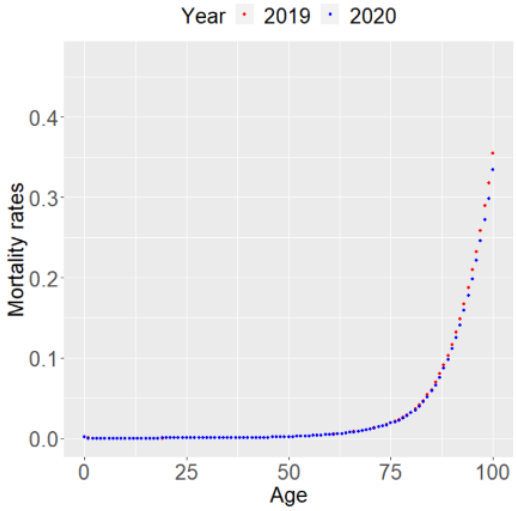


FIGURE 3: MORTALITY RATES IN JAPAN, TOTAL POPULATION



The Lee-Carter model κ_t time series forecasts are based on a random walk with drift specified as follows:

$$\kappa_t = \kappa_{t-1} + \delta + \sigma\epsilon_t$$

Where the ϵ_t are independent and identically distributed (IID) standard normal realisations (centered, unit variance), δ is the so-called trend, and σ is the volatility parameter.

The Lee-Carter model allows for the calculation of projected life expectancies at age x:

$$e_x(t) = \sum_{u=1}^{110-x} p_{u,x}\,(t)$$

With:

$$p_{u,x}(t) = \prod_{k=0}^{u-1}[1 - m(x+k, t+k)]$$

Each Lee-Carter model is calibrated on mortality data up to 2019 in a first step, then up to the year 2020 (without using any data adjustment method) in a second step.

FIGURE 4: TREND RELATIVE DIFFERENCES BETWEEN THE TWO STEPS

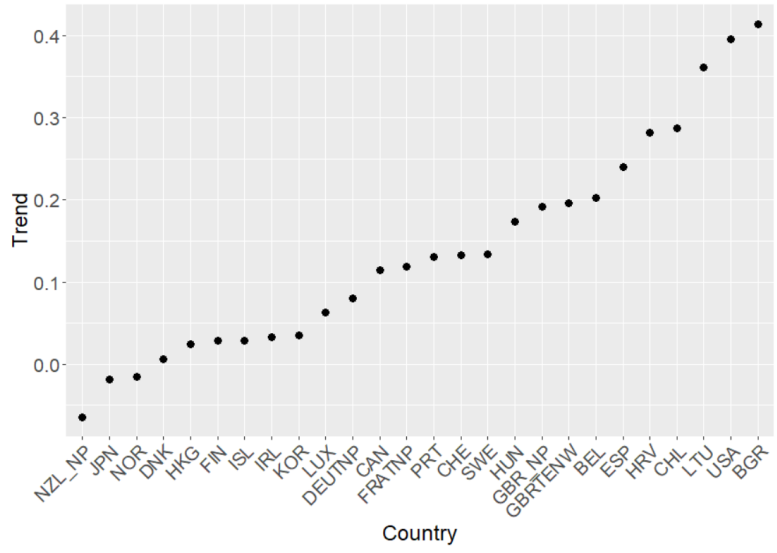
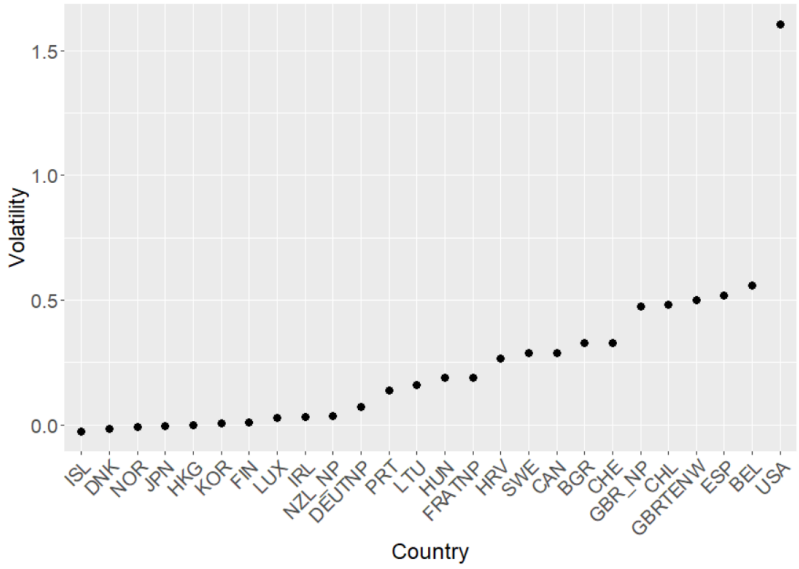


FIGURE 5: VOLATILITY RELATIVE DIFFERENCES BETWEEN THE TWO STEPS



The graphs show the relative increase in trend δ and volatility σ following the inclusion of the 2020 raw mortality data point in the calibration data. The countries are ordered according to the relative deviation observed, which is consistent with the number of COVID-19 deaths recorded in each country. The larger the number of COVID-19 deaths, the greater the trend and volatility are impacting the mortality projections.

The projected life expectancy of the total population in 2030 at age 60 with the 2019 and 2020 Lee-Carter models is compared measuring the impact of incorporating the year 2020 into the model. First, the countries show large differences in pre-pandemic life expectancies. In particular, Japan has the longest average life expectancy among G7 countries, primarily due to remarkably low mortality rates from ischemic heart disease and cancer (particularly breast and prostate).[10] Adding the 2020 mortality data in the calibration period of the Lee-Carter model results in a decrease in the resulting life expectancy of almost two years for the United States, while there is very little influence on that of Japan. Indeed, despite early exposure, its dense and aging population, and little social distancing measures, Japan reported low infection and low death from COVID-19.

FIGURE 6: LIFE EXPECTANCIES RESULTING FROM THE LEE-CARTER MODEL

Country	Age	2019	2020
USA	47	35.78	33.53
	67	17.71	16.34
	87	4.14	3.97
France	47	39.43	38.49
	67	20.23	19.56
	87	4.58	4.43
Japan	47	40.69	40.80
	67	20.85	20.92
	87	4.83	4.85
The Netherlands	47	37.75	37.00
	67	18.34	17.84
	87	3.97	3.86

EXCESS MORTALITY ATTRIBUTED TO COVID-19

The adjustment methods presented previously are applied over the period 2005 to 2020 when weekly and annual data are available. The excess age-standardised death rates (ESDR) are the differences between the observed age-standardised death rates and the baseline age-standardised death rates determined by the adjustment method:

$$ESDR(y,w) = SDR(y,w) - SDR_{baseline}(y,w)$$

The annual baseline and observed SDRs, as well as the annual ESDRs, are obtained by averaging the weekly SDRs and ESDRs within respective years. Such a simple calculation is correct because STMF uses the same population exposure for every week within each calendar year.

Note that although the year 2020 stands out due to the increase in mortality during the COVID-19 pandemic, high excess mortality is seen also in earlier years, as shown by the Figure 7 in the case of the alternative within-year adjustment method.

FIGURE 7: EXCESS MORTALITY PER 100,000 INHABITANTS DETERMINED WITH THE ALTERNATIVE WITHIN-YEAR METHOD

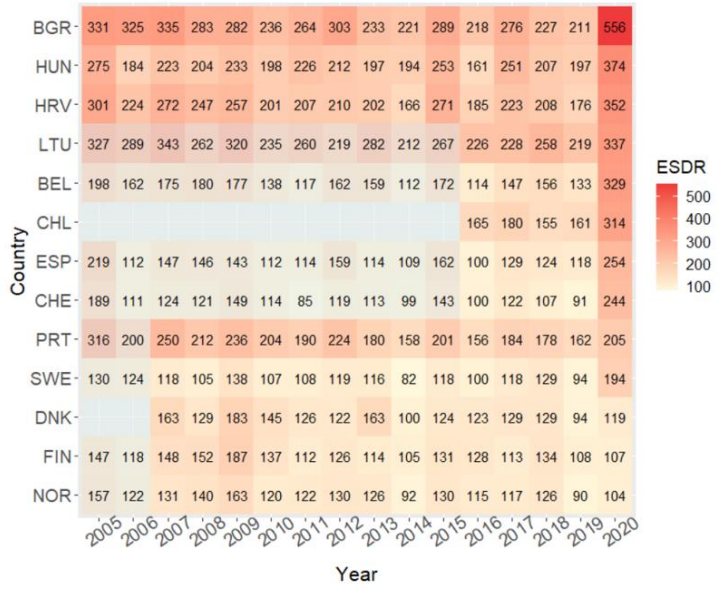


FIGURE 8: EXCESS MORTALITY PER 100,000 INHABITANTS IN 2020 USING THE ADJUSTMENT METHODS

	USA	France
Official recorded COVID-19 deaths	107	96
Average historical annual mortality	131	132
Week-specific average	161	90
Week-specific lower quartiles	178	124
Week-specific trends	106	130
Alternative within-year	134	193
Alternative retrospective	205	125

For the USA and France, most of the adjustment methods lead to a higher excess mortality in 2020 than the official recorded COVID-19 deaths. This result was expected as these methods produce a total excess mortality that also includes the indirect effects of COVID-19. Note that the results from these methods are not homogeneous. In particular, the week-specific lower quartiles, alternative within-year and alternative retrospective methods lead to higher excess mortality results than the average historical annual mortality, week-specific average and week-specific trends methods.

MORTALITY MODEL CALIBRATION

In the following, the mortality models are calibrated with data up to the year 2020. We then analyse the impact of using adjusted mortality data for the year 2020 on the calibration of mortality models, in terms of projected mortality rates and life expectancies.

The figures below show the projection of mortality rates at age 70 in the United States with and without adjusted mortality data. The adjusted mortality rates in 2020 are consistent with historical mortality rates. Besides, the width of the confidence intervals of the Lee-Carter mortality projections is reduced when using adjusted data, due to a lower volatility σ.

FIGURE 9: WITHOUT ADJUSTED MORTALITY DATA

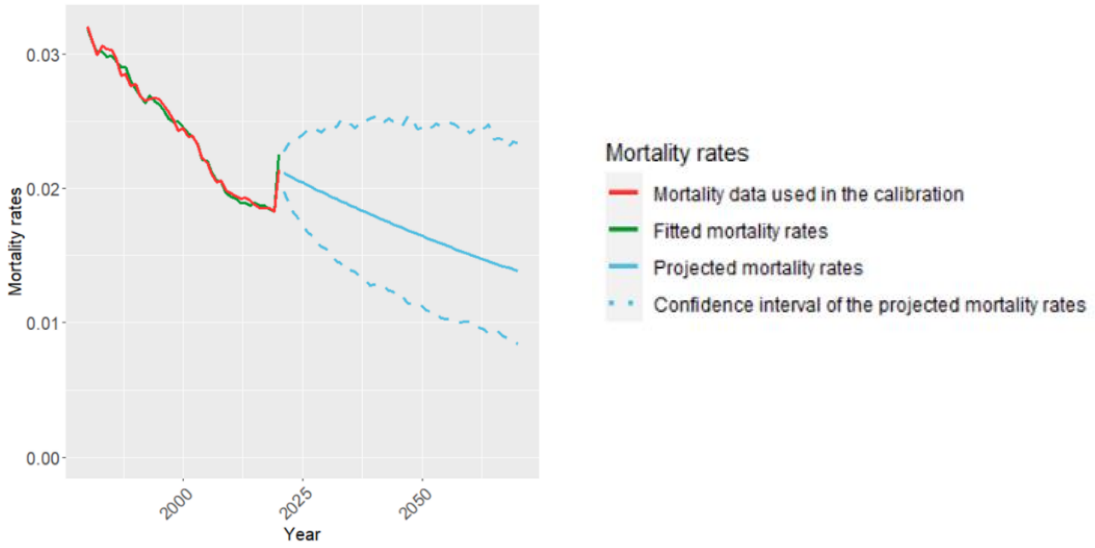


FIGURE 10: WITH ADJUSTED MORTALITY DATA: WEEK-SPECIFIC LOWER QUARTILES METHOD

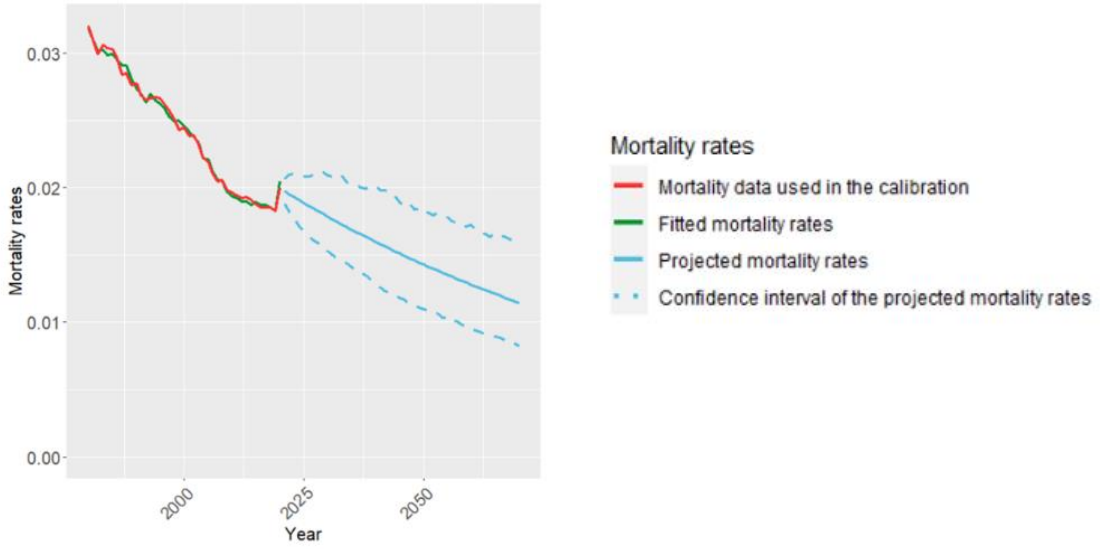


FIGURE 11: WITH ADJUSTED MORTALITY DATA: ALTERNATIVE WITHIN-YEAR METHOD

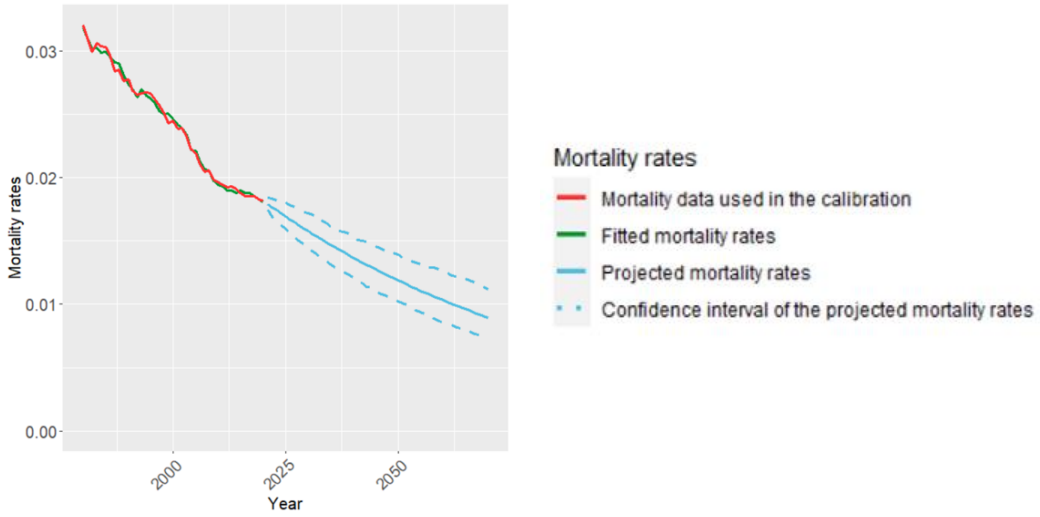
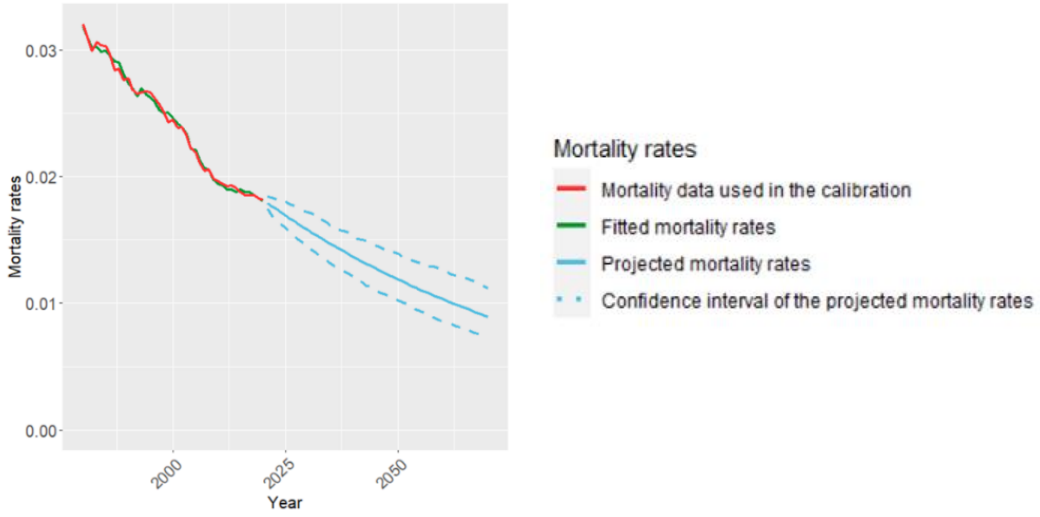


FIGURE 12: WITH ADJUSTED MORTALITY DATA: REMOVING THE OFFICIAL RECORDED 2020 COVID-19 DEATHS



Life expectancies

The inclusion of the unadjusted mortality data for the year 2020 in the calibration period of the Lee-Carter model results in a significant reduction in life expectancies. Figure 13 below presents the results when considering adjusted mortality data for the United States, France and the Netherlands for three ages representing age groups impacted differently by the pandemic. The week-specific lower quartiles and alternative within-year methods are the ones that lead to the highest life expectancies across all countries.

FIGURE 13: LIFE EXPECTANCIES OBTAINED USING THE LEE-CARTER MODEL CALIBRATED WITH ADJUSTED MORTALITY DATA

Country	Age	2020 week-specific lower quartiles	2020 alternative within-year	2020 Average historical annual mortality
USA	47	35.78	34.55	35.47
	67	17.72	16.96	17.52
	87	4.16	4.05	4.12
France	47	38.49	40.10	38.93
	67	19.56	20.71	19.88
	87	4.43	4.70	4.50
The Netherlands	47	38.33	38.86	37.55
	67	18.70	19.07	18.20
	87	4.00	4.09	3.92

MORTALITY SHOCKS

Methodology

The method for calculating mortality shocks is based on a method which follows that used by the European Insurance and Occupational Pensions Authority (EIOPA) and is divided into three main steps.[11]

Step 1: Projection of the future mortality rates at a one-year horizon. The number of simulations is fixed at 5,000, and the future mortality rates are projected with the Lee-Carter model.

Step 2: Life expectancies are calculated for each attained age given the survival function determined by the simulated mortality tables. The 0.5th percentile realisations of the cohort life expectancies are then computed.

Because mortality sensitivity can be captured by changes in life expectancies, such optimal stresses can be determined by analysing their impact on life expectancies. For each age, the optimal mortality shock is defined as the stress which matches the shocked central life expectancy with the 0.5th percentile of the not shocked life expectancy. The age-dependent shocked life expectancy is formulated as:

$$e_x^h(t) = \frac{1}{2} + \sum_{k=1}^{+\infty} \prod_{s=0}^{k-1} \left(1 - (1+h) q_{x+s}(t+s)\right)$$

We propose to determine the mortality shocks with the Lee-Carter model calibrated on the historical mortality rates including the adjustment of the data for the year 2020. We then compare the impact of the COVID-19 data adjustment on the mortality shocks.

Step 3: For each age, the optimal mortality shocks are defined as the shocks that minimise the distance between the life expectancy in the central scenario and the quantile realisation.

$$h_{\inf}(x) = \underset{h \in]-1,1[}{\operatorname{argmin}} \left(e_x^h(t) - e_x^{0.5\%}(t) \right)^2$$

Caveat

Note that the COVID-19 event brings additional uncertainty about future non-pandemic mortality due to the long-term effects of COVID-19, such as long COVID. As this is not considered in our approach, it would be necessary to add an extra buffer to the mortality shock obtained in order to take this uncertainty into account. Note that the methodology to be used for the determination of this additional adjustment is not the scope of this article.

Results

As expected, considering adjusted mortality data leads to lower mortality shocks, more in line with those obtained by excluding the year 2020 in the calibration period. Note that the results vary according to the adjusting method. Also note that by using adjusted mortality data, we exclude in our mortality assumptions the direct short-term effects of COVID-19.

The obtained mortality shocks for France and the United States are presented below, as well as in the figures showing the average mortality shocks by age group.

FIGURE 14: MORTALITY SHOCKS – FRANCE

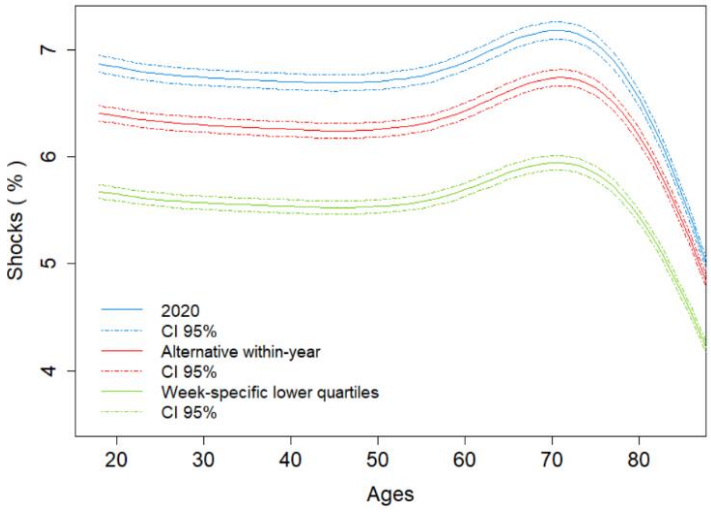
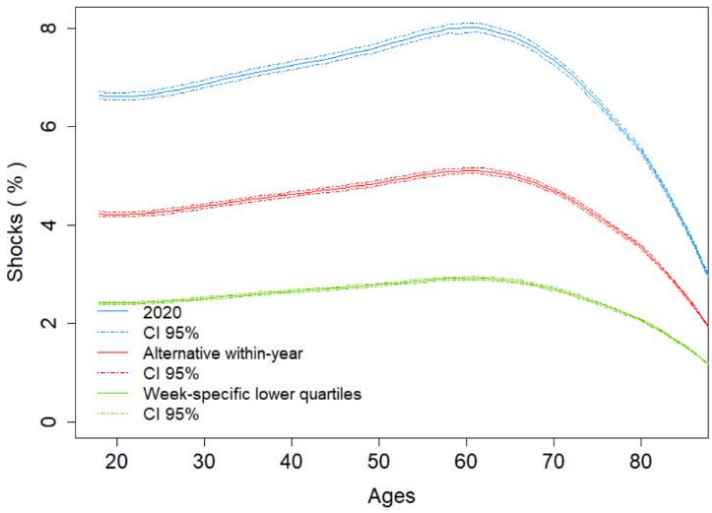


FIGURE 15: MORTALITY SHOCKS – USA



It can be observed that the mortality shocks vary depending on which data adjustment method is considered. For the United States, calibrating the Lee-Carter model using unadjusted 2020 mortality data leads to much higher mortality shock values than calibrating it using mortality data up to 2019. Higher shocks are also obtained when adjusting the 2020 mortality data with the alternative within-year adjustment method. However, applying the historical average or the week-specific lower quartiles adjustment methods leads to much lower mortality shocks.

Overall, these adjustment methods lead to mortality shocks closer to those obtained by excluding the 2020 year in the calibration period of the Lee-Carter model.

FIGURE 16: AVERAGE MORTALITY SHOCKS BY AGE GROUP

United States

Last year in the calibration period	Adjustment method	18-35	36-55	56-80	80-94
2019	No adjustment	2.62	2.88	2.80	1.30
2020	No adjustment	6.90	7.59	7.39	3.36
2020	Historical average	2.64	2.90	2.83	1.34
2020	Alternative within-year	4.31	4.75	4.63	2.13
2020	Week-specific lower quartiles	2.47	2.72	2.66	1.28

France

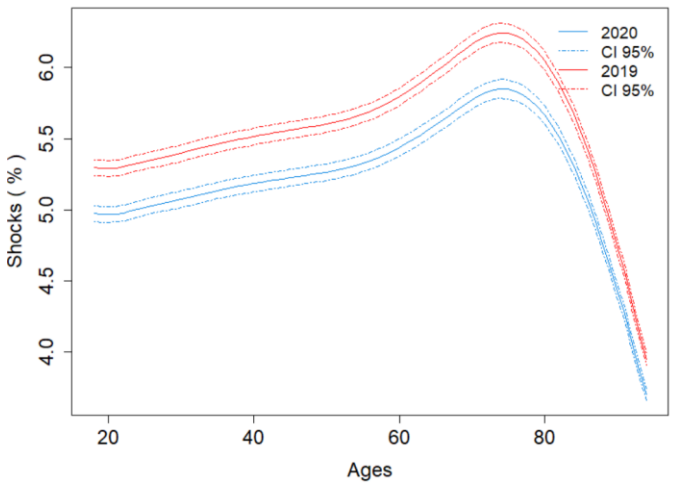
Last year in the calibration period	Adjustment method	18-35	36-55	56-80	80-94
2019	No adjustment	5.97	5.90	6.16	4.57
2020	No adjustment	6.77	6.70	6.97	5.13
2020	Historical average	5.94	5.88	6.13	4.55
2020	Alternative within-year	6.32	6.25	6.54	4.95
2020	Week-specific lower quartiles	5.59	5.53	5.77	4.32

The Netherlands

Last year in the calibration period	Adjustment method	18-35	36-55	56-80	80-94
2019	No adjustment	4.24	4.34	3.98	1.88
2020	No adjustment	4.85	4.96	4.52	2.00
2020	Historical average	4.10	4.21	3.86	1.65
2020	Alternative within-year	6.13	6.33	5.85	2.81
2020	Week-specific lower quartiles	4.59	4.69	4.29	1.90

For Japan, calibrating the Lee-Carter model using unadjusted 2020 mortality data gives slightly lower mortality shock values than calibrating it using mortality data up to 2019. This is due to the fact that the excess mortality due to COVID-19 in 2020 is very low and mortality continued to improve in Japan in 2020. This is why the 2020 adjustment for countries with a similar profile does not seem necessary.

FIGURE 17: MORTALITY SHOCKS - JAPAN



Qualitative comparison with AG2022

GENERAL DESCRIPTION OF AG2022

The Royal Dutch Actuarial Association (AG) has also taken COVID-19 into account, using a slightly different approach, in their latest Projection Life Table AG2022, which estimates expected developments in survival rates and life expectancy in the Netherlands.[12] The aim of this section is to describe the AG's approach, and to compare it with the approach that has been previously described.

The AG model is based on mortality rates in European countries with comparable levels of prosperity. It is assumed that the Dutch mortality rates will follow the European mortality rates in the long term but may deviate from them in the short term. Average gross domestic product (GDP) is used as a criterion for the country selection, which has led to the selection of, in addition to the Netherlands, Belgium, Denmark, Finland, France, Germany, Ireland, Iceland, Luxembourg, Norway, Sweden, the United Kingdom and Switzerland.

The model used to project mortality rates is based on the stochastic Li-Lee multi-population model, which consists of two parts: pre-COVID mortality rates and excess mortality rates for 2020 and 2021. The first part of the model provides estimated pre-COVID mortality rates for Europe and the Netherlands, based on maximum likelihood estimation for ages x up to 90, years t=1983, …, 2019, and per gender g:

$$ln\left(\mu_x{}^{g,pre-cov,EU}(t)\right) = A_x{}^g + B_x{}^g K_t{}^g \quad (1)$$

$$ln\left(\mu_x{}^{g,pre-cov,NL}(t)\right) = A_x{}^g + B_x{}^g K_t{}^g + \alpha_x{}^g + \beta_x{}^g \kappa_t{}^g \quad (2)$$

With:

- $\mu_x{}^{g,pre-cov,EU}$: European pre-covid mortality rate at age x in year t for gender g
- $A_x{}^g$: European static age structure for gender g
- $B_x{}^g$: European sensitivity parameter at age x for gender g in relation to the evolution over time
- $K_t{}^g$: European time evolution of mortality for gender g
- $\alpha_x{}^g, \beta_x{}^g, \kappa_t{}^g$: Dutch deviation compared to the European variables $A_x{}^g, B_x{}^g, K_t{}^g$

The model then projects time series for $t \geq 2020$ by fitting a random walk with drift and a first-order autoregressive process with one constant to the extended data set:

$$K_t{}^g = K_{t-1}{}^g + \theta^g + \epsilon_t{}^g \quad (3)$$

$$\kappa_t{}^g = a^g \kappa_{t-1}{}^g + c^g + \delta_t{}^g \quad (4)$$

$$\left(\epsilon_t{}^M, \epsilon_t{}^F, \delta_t{}^M, \delta_t{}^F\right) \sim i.i.d.N(\mathbf{0}, \boldsymbol{C}), \quad (5)$$

where θ^g is the estimated drift of the time effects of Europe, c^g is the estimated constant term of the Dutch deviation, a^g is the estimated AR(1) autoregressive term of the time effects of the Dutch deviation, $\epsilon_t{}^g$ and $\delta_t{}^g$ are error terms.

The model is calibrated using data up to 2019, and it is only used for ages up to 90 years due to limited observations for higher ages. For ages above 90 years, a closure mechanism is used.

Unlike in the previous Projection Life Table AG2020, excess mortality caused by COVID-19 is taken into account in AG2022. However, only Dutch data is used for excess mortality rates in 2020 and 2021 due to varying COVID-19 approaches across Europe and limited age-specific data at the European level. To estimate the COVID-19 effect, weekly Statistics Netherlands mortality data (formerly Dutch Central Agency for Statistics (CBS)) from 2020 and 2021, categorised by age and gender, are used. The excess mortality effect is determined by adjusting for seasonality and combining a *time effect* ($\mathfrak{X}_t{}^g$) with an *age effect* ($\widetilde{\mathfrak{B}}_x{}^g$), resulting in a surcharge on estimated mortality. Mortality probability projections for ages under 55 are not influenced by COVID-19 (i.e., $\widetilde{\mathfrak{B}}_x{}^g = 0 \; for \; x < 55$), as limited excess mortality was visible for these ages in the data.

The weekly data for 2020 and 2021 are aggregated to a single value capturing the effects for the whole year (i.e., ${\mathfrak{X}_{2020}}^{g}$ and ${\mathfrak{X}_{2021}}^{g}$), which are determined such that the survival probabilities over the full year equal the product of survival probabilities per week. The final annual forecast is made for ages x from 0 to 90, with normalisation done by ensuring that the sum of the resulting annual age effects for ages above 55 is equal to 1 ($\sum_{x=55}^{90} {\widetilde{\mathfrak{B}}_x}^{g} = 1$). This leads to equation (6), in which equation (2) is extended by the inclusion of excess mortality through the time and age effect (i.e., ${\mathfrak{X}_t}^{g}$ and ${\widetilde{\mathfrak{B}}_x}^{g}$).

$$ln\left({\mu_x}^{g,NL}(t)\right) = {A_x}^{g} + {B_x}^{g}\,{K_t}^{g} + {\alpha_x}^{g} + {\beta_x}^{g}\,{\kappa_t}^{g} + {\widetilde{\mathfrak{B}}_x}^{g}\,{\mathfrak{X}_t}^{g} \quad (6)$$

Several potential future scenarios were considered by the AG. They decided to select a scenario in which the COVID-19 impact on survival rates diminishes over time, with little to no lasting effect on life expectancy. The model assumes that COVID-19's impact on life expectancy disappears after several years, returning to pre-pandemic levels, with a half-life of one year used to determine the remaining impact:

$${\mathfrak{X}_t}^{g} = {\mathfrak{X}_{2021}}^{g}\eta^{t-2021} \text{ with } t \geq 2022 \text{ and } \eta = \frac{1}{2}. \quad (7)$$

DIFFERENCES AND SIMILARITIES

AG2022 and the modelling in this paper differ in their approach to modelling, but they also share some similarities.

The methods differ in the following ways:

- AG2022 takes into account the European mortality trend for the long term (based on data up to 2019) using the Li-Lee model, while this paper does not consider multi-population mortality experience as the Lee-Carter model is used.
- This paper uses weekly data from 2020 by five- or 10-year age groups from INED, while AG2022 uses more detailed weekly data available per age from the CBS.
- AG2022 uses a closure measure for ages above 90 years due to limited observations, whereas this paper uses the available data.
- AG2022 incorporates a temporary COVID-19 effect for ages 55 and above based on excess mortality in 2020 and 2021, while this paper acknowledges excess mortality is concentrated in the 60+ age group but does not restrict this in the modelling.
- AG2022 assumes that COVID-19's impact on life expectancy disappears after several years (returning to pre-pandemic levels), with a half-life of one year, while the data adjustment methodologies presented in this paper assume that COVID-19 should not impact future mortality at all.
- AG2022 aggregates weekly data for 2020 and 2021 to a single value capturing the effects for the whole year, whereas this paper considers different methods on weekly rates.

On the other hand, the methods share the following similarities:

- Both methods assume the same scenario for the best estimate mortality rates, in which the pandemic does not impact long-term mortality rates.
- Both methods use weekly data for the years 2020 and 2021 to determine excess mortality.
- Both methods make an adjustment for seasonality in the weekly data.

EXAMPLES OF IMPACT

We won't provide a full quantitative comparison of the different methods here, though we would like to provide a general idea of the impact that using a different methodology for incorporating COVID-19-related effects might have on the life expectancy numbers.

For example, Figure 18 below shows the life expectancy for 65-year-olds at different start years, for a number of methodologies. Especially in the female case, we can observe that the AG2022 model shows a substantial increase in life expectancy a few years after the pandemic. A Lee-Carter (LC) model fitted on the 2020 data shows a similar starting point, though with a slower increase. The latter is also true for the model in which a data adjustment has been applied, albeit with a higher starting point.

FIGURE 18: COMPARISON OF LIFE EXPECTANCY FOR 65-YEAR-OLDS USING DIFFERENT METHODOLOGIES AT VARIOUS STARTING YEARS

MALE

	Realisation	AG2020	AG2022	LC 2019	LC 2020 no correction	2020 historical average	2020 Week-specific lower quartiles	2020 Alternative within-year
2019	18.8	18.7	18.7	19.0	18.4	18.7	19.4	19.9
2020	18.1	18.8	18.1	19.1	18.5	18.8	19.5	20.0
2021	18.2	18.9	18.2	19.2	18.6	18.9	19.6	20.1
2022		19.0	18.7	19.3	18.7	19.0	19.7	20.2
2023		19.1	18.9	19.5	18.8	19.1	19.8	20.3
2024		19.2	19.1	19.6	18.9	19.2	19.9	20.4
2025		19.3	19.3	19.7	19.0	19.3	20.1	20.6

FEMALE

	Realisation	AG2020	AG2022	LC 2019	LC 2020 no correction	2020 historical average	2020 Week-specific lower quartiles	2020 Alternative within-year
2019	21.3	21.3	21.3	21.0	20.6	21.0	21.7	22.0
2020	20.7	21.4	20.8	21.1	20.7	21.1	21.8	22.1
2021	20.8	21.5	20.8	21.2	20.7	21.1	21.8	22.2
2022		21.6	21.3	21.2	20.8	21.2	21.9	22.3
2023		21.7	21.6	21.3	20.8	21.2	22.0	22.4
2024		21.8	21.7	21.3	20.9	21.3	22.0	22.4
2025		21.9	21.9	21.4	21.0	21.4	22.1	22.5

Alternative methods

Other calibration strategies are possible in order to take into account a pandemic experience when modelling mortality, such as:

- Performing an outlier analysis on the fitted period effects ($\boldsymbol{\kappa_t}$) of the Lee-Carter model in order to identify extreme mortality changes and remove their influence on the model. Lee and Carter followed this idea in 1992, but they only identified the 1918 Spanish flu as an outlier and then applied an intervention model to remove its effect.[13] Li and Chan proposed in 2007 a more systematic approach, applying established techniques from time series outlier analysis.[14] Such an approach is appropriate if the aim of the modeller is to predict future non-pandemic mortality based on past mortality data. That is why it is reasonable to remove all pandemic events from the calibration data of the Lee-Carter model.
- Including a jump process in the time series model for the Lee-Carter period effects. Jumps can be transitory or permanent, and their severity can be assumed to follow different distributions (e.g., normal, truncated normal, Pareto, beta). For example, Chen and Cox proposed in 2009 an extension of the Lee-Carter period effect model with transitory jumps via the following relationship: $\boldsymbol{\kappa_{t+1} = \kappa_t + \mu + e_{t+1} + N_{t+1}Y_{t+1} - N_tY_t}$ where the jump indicator $\boldsymbol{N_t}$ follows a Bernoulli distribution and the jump severity $\boldsymbol{Y_t}$ is normally distributed.[15] Such an approach is appropriate if the aim of the modeler is to predict both future non-pandemic and pandemic mortality based on past mortality data. There are alternative methods, as well.[16]
- Introducing weights on mortality data, as it is the case for the latest version of the CMI (Continuous Mortality Investigation) model. Unlike the previous versions of the CMI model which considered 0% weight to the 2020/2021 mortality data, the CMI proposes to set a 25% weight for mortality data in 2022. Note that in the coming years, the CMI plans to steadily increase the weight on mortality data for future years as a clearer indication of mortality trends emerges. Note that such an approach allows the modellers the flexibility to modify mortality projections tailored to their own views and purpose.

Conclusion

In order to project future mortality via stochastic mortality models by avoiding distortions caused by the COVID-19 experience, mortality data adjustment methods can be used. Using indirect approaches instead of direct ones using the official COVID-19 death counts makes it possible to exclude indirect effects of COVID-19. These methods are particularly relevant within economic capital models (e.g., to avoid double counting with pandemic risk measured apart), as well as to derive long-term mortality trends without instabilities from a one-off pandemic experience, combined with the context of mitigation measures and economic crisis.

In the case of an adjustment of the 2020 calibration mortality data for a country where the COVID-19 excess deaths is significant, the mortality projections and the resulting mortality shocks are:

- Significantly lower than those obtained by calibrating the model on non-adjusted mortality data
- More in line with what would have been obtained by calibrating the models using mortality data up to 2019

In addition, note that HMD 2021 data is now available for more and more countries. As 2021 is also affected by excess mortality due to COVID-19, it is also necessary to adjust this year of data. We could therefore apply the same adjustment methods for 2021, using adjusted 2020 data in the case of adjustment methods based on past mortality data. Each of the presented adjustment methodologies should be checked separately for 2021 in order to choose the ones that suit the best.

Also note that other data adjustment methods are possible. For instance, in France, observed deaths in 2022 significantly exceeded those expected in the absence of a COVID-19 pandemic or other unusual events such as flu episodes or extreme heat.[17] Thus, it would be interesting to consider mortality scenarios for the years 2020 and beyond assuming that COVID-19 had never occurred, taking into consideration all the other particularities of these years affecting mortality, e.g., influenza episodes or extreme heat.

Finally, other methods can be used to take into account COVID-19 experience when calibrating mortality models:

- Using refined versions of mortality models as the extension of the Lee-Carter period effect model with transitory jumps proposed by Chen and Cox in 2009[18]
- Introducing weights on mortality calibration data as it is the case for the latest version of the CMI model

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