Table of Contents



Introduction

2 Relevance of Macro Longevity Risk

- First Pillar: AOW
- Second Pillar: Pension Funds
- 3 Modeling Mortality

Benchmark Model

- The Lee-Carter Model
- Alternative Estimation
- Some Applications and Extensions

5 The AG2022 Model and COVID-19

- Model and Projections
- Closure of the Life Table

Model Risk: A Very Brief Introduction

General Structure



- So far, we have dealt with the Lee & Carter (1992) model and some of its variants. We now look into the AG2022 Model and COVID-19.
- The AG2022 Model consists of three layers (a so-called three-layer Lee-Li model):
 - A layer for the European population.
 - A correction layer for the Dutch population.
 - An extra layer for COVID-19.
- The first two layers are as in AG2020.





- The AG2022 directly builds upon AG2020.
- Surrounding countries selected based upon comparable welfare level.
- AG2020 re-estimated with data EU 2019 added (but data 2020 & 2021 not included).
 - EU data: $D_{x,t}^{(g),EU}$, $E_{x,t}^{(g),EU}$, $t = 1970, \dots, 2019$, $x = 0, \dots, 90$
 - Dutch data: $D_{x,t}^{(g),NL}$, $E_{x,t}^{(g),NL}$, $t = 1970, \dots, 2019$, $x = 0, \dots, 90$
- AG2020 is basis for long-term projections.
- The third layer is due to COVID-19 and is new. It is calibrated using data from 2020 and 2021.

AG2020 Model Re-estimated, $t \leq 2019$



Number of deaths (D^(g)_{x,t}) modeled assuming a Poisson-distribution with expectation equal to exposure (E^(g)_{x,t}) times force of mortality (μ^{(g),pre-covid}_{x,t}):

$$D_{x,t}^{(g)} \mid E_{x,t}^{(g)} \sim \mathcal{P}\left(E_{x,t}^{(g)} \mu_{x,t}^{(g), pre-covid}
ight)$$

• The long-term mortality trend is estimated based on the European reference group:

$$\ln \mu_{x,t}^{(g),pre-covid,EU} = A_x^{(g)} + B_x^{(g)} K_t^{(g)}$$

• For the Netherlands mortality is estimated conditional on the force of mortality of the European reference group:

$$\ln \mu_{x,t}^{(g),pre-covid} = A_x^{(g)} + B_x^{(g)} K_t^{(g)} + \alpha_x^{(g)} + \beta_x^{(g)} \kappa_t^{(g)}$$

• All parameters are estimated by maximizing the corresponding likelihood functions.

Christoph Hambel (TiSEM)

AG2020 Model Re-estimated, $t \leq 2019$



Estimation









AG2020 Model – Simulation

The European period effects, K_t^(g), are assumed to follow a random walk with drift (as in Lee-Carter):

$$\Delta K_t^{(g)} = \theta^{(g)} + \varepsilon_t^{(g)}$$

 The Dutch period effects, κ^(g)_t, are assumed to follow a first-order autoregressive process with constant:

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

- The error terms are assumed to follow a multivariate normal distribution with mean vector 0 and covariance matrix *C*.
- This combination of assumptions results in coherent projections:
 - In the long run the difference between the Dutch and the European death probabilities converges to zero, but:
 - In the short run the Dutch and European death probabilities might deviate.

AR(1)-Process





Third Layer: COVID-19



• Clear impacts of COVID-19 in both 2020 and 2021.

• Age effect in AG2022 differs from age effect in AG2020.

Christoph Hambel (TiSEM)

Life Insurance

Third Layer: COVID-19



- Data from 2020 and 2021 cannot be used for normal update.
- Change to weekly data:
 - Customized data needed, plus interpolation and extrapolation.
 - Seasonal effect.
 - New age- and time effect.



Third Layer: COVID-19



- To describe the deviation in mortality in 2020 and 2021 relative to what is expected on the basis of data before 2020, we introduce a new age effect B_x^(g) and new (week-based) timeseries R_{w,2020}^(g) for 2020 and R_{w,2021}^(g) for 2021.
- The seasonal effect determined earlier is also added.
- Three factors:
 - the pre-pandemic estimate for a given year (an AG2020 model update with datapoints until 2019),
 - a seasonal effect for a given week,
 - a new factor representing the impact of the altered circumstances since the pandemic:

$$\ln \mu_{x,t}^{(g)} = \ln \mu_{x,t}^{(g), pre-covid} + \ln \phi_{w,t} + \mathfrak{B}_x^{(g)} \mathfrak{K}_{w,t}^{(g)}$$

• The time effect of COVID-19 $\Re_{w,t}^{(g)}$ varies significantly across weeks.







- Using weekly data allows the estimation of age effects based on more than 2 (annual) data points.
- No effect until age 55, constant from age 90.

Christoph Hambel (TiSEM)

Life Insurance







- Time series for difference in mortality (whether or not due to COVID) relative to AG2020 model (with update 2019 data).
- Aggregating week effects $\mathfrak{K}_{w,t}^{(g)}$ gives estimate of the impact $\mathfrak{X}_t^{(g)}$ for the whole year (dashed lines).

Christoph Hambel (TiSEM)



- Estimating the impact for a whole year is the starting point for projecting future years.
- For the course of the projection further assumptions are needed.
- Choice CSO: disappearing (exponentially), i.e.,

$$\mathfrak{X}_{t}^{(g)} = \mathfrak{X}_{2021}^{(g)} \eta^{t-2021}, \qquad t \ge 2021$$

with $\eta = 1/2$, which implies that the half-life of the impact equals one year.

• This assumption determines the 'best estimates' for all future values of the time series in the model.

Third Layer: Projection Model













- Problem: The AG2022 model uses mortality data for x = 0,...,90. If x ≥ 91, the data becomes rather noisy, because the population older than 90 is small.
- To deal with this issue, the AG2020 model used a popular method to extrapolate mortality rates for older ages the *Kannisto closing method*.
- For the ages $x \in \{91, \dots, 120\}$, $\widehat{\mu}_{x, \mathcal{T}+t}^{(g)}$ is determined as

$$\widehat{\mu}_{x,T+t}^{(g)} = L\Big(\sum_{k=80}^{90} w_k(x) L^{-1}(\widehat{\mu}_{k,T+t}^{(g)})\Big),$$

where $L(z) = \frac{1}{1+e^{-z}}$ and $L^{-1}(z) = \ln(\frac{z}{1-z})$ and some weight function w_k (see Assingment).





Issues with Kannisto



- The Kannisto method was standard in the AG-models and has been standard in many other forecasting models to deal with sparse data points in older cohorts.
- This method has some drawbacks:
 - Not all ages show improved mortality over time. For higher ages mortality rises monotonously to a positive and limit value that is known with certainty, $\lim_{t\to\infty} \hat{q}_{x,T+t}^{(m)} = 0.6321, \ x \ge 101$. As a result, life expectancy also converges to a limit value known with certainty $\lim_{t\to\infty} e_{0,t}^{(m)} = 102.08$.
 - Because the limit values are known with certainty, uncertainty decreases (smaller confidence intervals) over time, while we expect increasing uncertainty (wider confidence intervals).
- The new method in AG2022 addresses this issue and closes the life table without knowing limit values with certainty.

Issues with Kannisto







- Extrapolate $\ln(B_x^g)$ linearly
- <u>Interpretation</u>: all ages benefit from decreasing trend in K_t

• Determine A_{χ}^{g} such that in the last sample period (2019) the same EU death probabilities result as in case of Kannisto





 A_x^g

0.2

0.1

- 0.1 - 0.2 - 0.3 - 0.4 - 0.5 - 0.6

0

 α_x^g

50





 <u>Interpretation</u>: for age 120 no difference between NL and EU.



• Determine β_x^g such that in the last sample period (2019) the same NL death probabilities result as in case of Kannisto.



Christoph Hambel (TiSEM)

100







- The new closing method does not have the undesirable characteristics, which we observe in the application of Kannisto per projection year.
- There is no turning point at a certain age: also, at higher ages the death probabilities keep decreasing.
- The life expectancy does not have a limit whose value is known in advance.
- The confidence intervals do not become smaller over time.

