Assessing the impact of the COVID-19 shock on a stochastic multi-population mortality model

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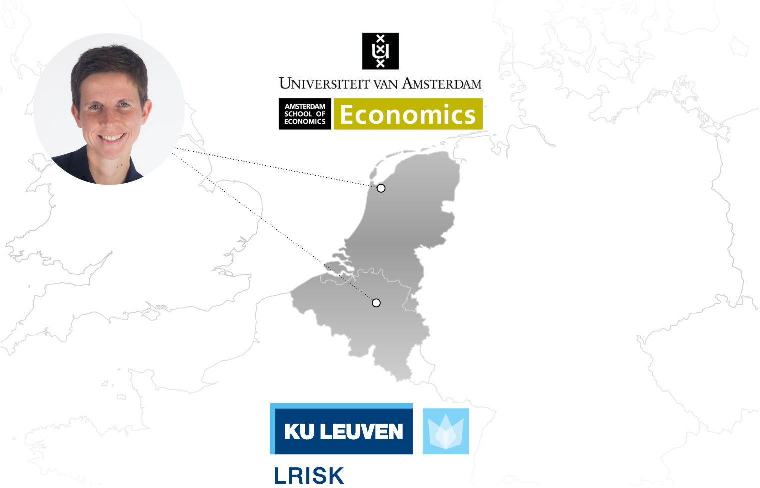
LRisk - KU Leuven and ASE - University of Amsterdam

September 27, 2022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LRISK

Our people

The Research Centre for Longevity Risk (RCLR) is part of the University of Amsterdam. Prof. Dr. Torsten Kleinow is the director of RCLR and together with co-director Prof. Dr. Katrien Antonio, they are responsible for all the centre's research programmes. The directors are supported by management team members Prof. Dr. Michel Vellekoop and Frank van Berkum.

The research team consists of PhD students, postdoctoral researchers and other senior researchers of the Amsterdam School of Economics. Additional appointments will continue to be made in 2022.

Prof. Dr. Torsten Kleinow

Prof. Dr. Katrien Antonio

Prof. Dr. Michel Vellekoop

Presenter + Authors

Katrien Antonio

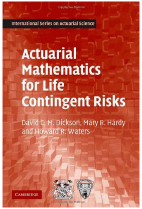
Sander Devriendt *

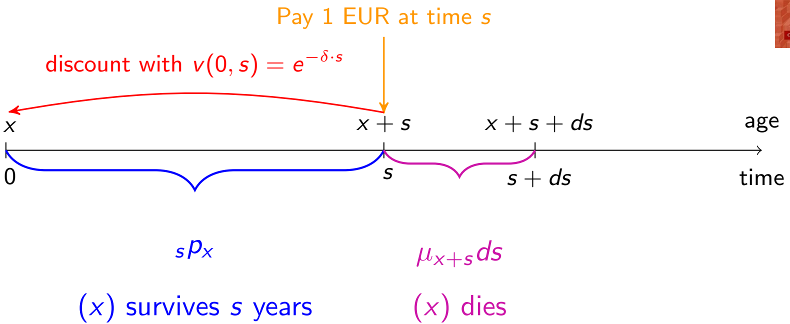
Jens Robben

(*) This presentation reflects the personal views of the author and not the views of his employer.

Life insurance mathematics 101

Whole life insurance





If T_x, the future lifetime of (x), takes value s, then present value of 1 EUR at $t = s$ is $e^{-\delta \cdot s}$.

Interest goes to (distribution of) $Z = v^{T_x} = e^{-\delta \cdot T_x}$.

Survival probabilities

Period vs cohort

Consider (x), a policyholder aged x in year t, with future lifetime $T_{x,t}$.

Period approach:

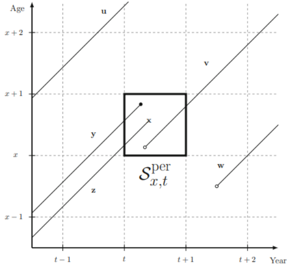
$$ {}_kp_{x,t} \;=\; Pr(T_{x,t} \geq k) = p_{x,t} \cdot p_{x+1,t} \cdot \ldots \cdot p_{x+k-1,t} $$

Cohort approach:

$$ {}_kp_{x,t} \;=\; Pr(T_{x,t} \geq k) = p_{x,t} \cdot p_{x+1,t+1} \cdot \ldots \cdot p_{x+k-1,t+k-1} $$

Need for mortality projections (beyond most recent t) in the cohort approach!

Mortality rate and force of mortality



Exact age definition.

$q_{x,t}$ is called the mortality rate:

$$q_{x,t} = 1 - p_{x,t} = 1 - \exp\left(-\mu_{x,t}\right)$$ (with piecewise constant hazard rate $\mu_{x,t}$),

where $\mu_{x,t}$ is the force of mortality or hazard rate.

Research goals

Professional actuarial associations and their mortality projection models

Actuarial associations (like IA|BE in Belgium, KAG in the Netherlands, Institute and Faculty of Actuaries in UK) publish mortality projection models:

- industry standard at national population level (‘pop’)
- insurance companies or pension funds then estimate portfolio correction factors (‘pf’), e.g.

$$\mu_{x,t,g,\ell}^{pf} \quad = \quad \mu_{x,t,g}^{pop} \cdot \exp\left(f(\boldsymbol{x}_\ell)\right),$$

  for age x, period t, gender g and risk profile ℓ (with covariates $\boldsymbol{x}_\ell$).

I am/was involved in the design of KAG 2014, IA|BE 2015 and IA|BE 2020 (published in November 2020).

KAG updates every 2 years, IA|BE every 5 years, CMI in the UK every year.

Research goals

Pandemic data points in 2020 and 2021, including mortality shocks

Today, I will focus on:

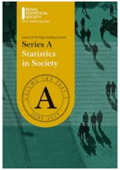
(1) the basic principles of a stochastic multi-population mortality projection model of type Li& Lee (cfr. IA|BE 2015 and 2020, KAG 2014 - 2020 and 2022)

(2) the impact of pandemic data points (as in 2020 and 2021) on the parameters calibrated for such a model

(3) adjustments in the model specification, the calibration and the time dynamics that were recently proposed in response the (2).

References

Stochastic mortality models at population and portfolio level



- Antonio, Devriendt et al. (2017, European Actuarial Journal). Producing the Dutch and Belgian mortality projections: a stochastic multi-population standard

  with applications on e.g. calculating life expectancies, cash flow valuation for stylized portfolios.

- Van Berkum, Antonio & Vellekoop (2020, JRSS A). Quantifying longevity gaps using micro-level lifetime data

  capture portfolio-specific mortality with national population model as baseline.

Both papers are available via open access.

References

COVID-19 impact analysis and adjustments

- Robben, Antonio & Devriendt (2022, Risks). Assessing the impact of the COVID-19 shock on a stochastic multi-population mortality model.

- Koninklijk Actuarieel Genootschap (2022). Prognosetafel AG 2022 - langer leven in onzekere tijden.

  and the accompanying working paper

  Van Berkum, Melenberg & Vellekoop (2022). Estimating the impact of the COVID-19 pandemic using granular mortality data

All the above papers are available via open access.

Foundations of the IA|BE 2020 stochastic mortality projection model for the Belgian population

The basic principles of IA|BE 2015 and IA|BE 2020

The mortality project of IA|BE opts for:

- biological reasonableness, state of the art (but not necessarily *novel*)
- good performance on in sample statistical measures as well as out-of-time back-tests
- ability to generate future scenarios of mortality ('simulation generator')
- reproducibility and full transparency, use of open data.

More detailed discussion in Antonio, Devriendt et al. (2017, EAJ), KAG 2014, 2016, 2018 and 2020, IA|BE 2015 and 2020.

A general class of models ('LifeMetrics models'):

$$\log \mu_{x,t} \quad = \quad \beta_x^{(1)} \kappa_t^{(1)} \gamma_{t-x}^{(1)} + \ldots + \beta_x^{(N)} \kappa_t^{(N)} \gamma_{t-x}^{(N)}$$

or

$$\text{logit } q_{x,t} \quad = \quad \beta_x^{(1)} \kappa_t^{(1)} \gamma_{t-x}^{(1)} + \ldots + \beta_x^{(N)} \kappa_t^{(N)} \gamma_{t-x}^{(N)}$$

where

- $\beta_x^{(k)}$ = age effect for component k
- $\kappa_t^{(k)}$ = period effect for component k
- $\gamma_{t-x}^{(k)}$ = cohort effect for component k.

From single to multi-population mortality models

Multi-population models specify (for the log of the force of mortality) a $M_{\text{com}}+M_{\text{country}}$, where M_{com} is common and M_{country} is country-specific.

The augmented common factor model by Li & Lee (2005, Demography):

- across a set of countries:

$$\ln \mu_{x,t}^{(i)} = \underbrace{A_x}_{\text{common}} + \underbrace{\alpha_x^{(i)}}_{\text{country}} + \underbrace{B_x \cdot K_t}_{\text{common}} + \underbrace{\beta_x^{(i)} \cdot \kappa_t^{(i)}}_{\text{country}},$$

  for a specific country (i)

- twice a Lee & Carter (1992, JASA) specification.

“Collect and include new data points, re-calibrate the model parameters, and - if necessary - incorporate any methodological changes.”

Starting point is the IA|BE 2015 model, documentation of all assumptions, calibration and simulation details is part of our mission.

Antonio, Devriendt et al. (2017, European Actuarial Journal). Producing the Dutch and Belgian mortality projections: a stochastic multi-population standard.

Data collection

We select European countries with GDP per capita above the average of the Euro area (in 2018, Worldbank data).

This results in a set of 14 countries:

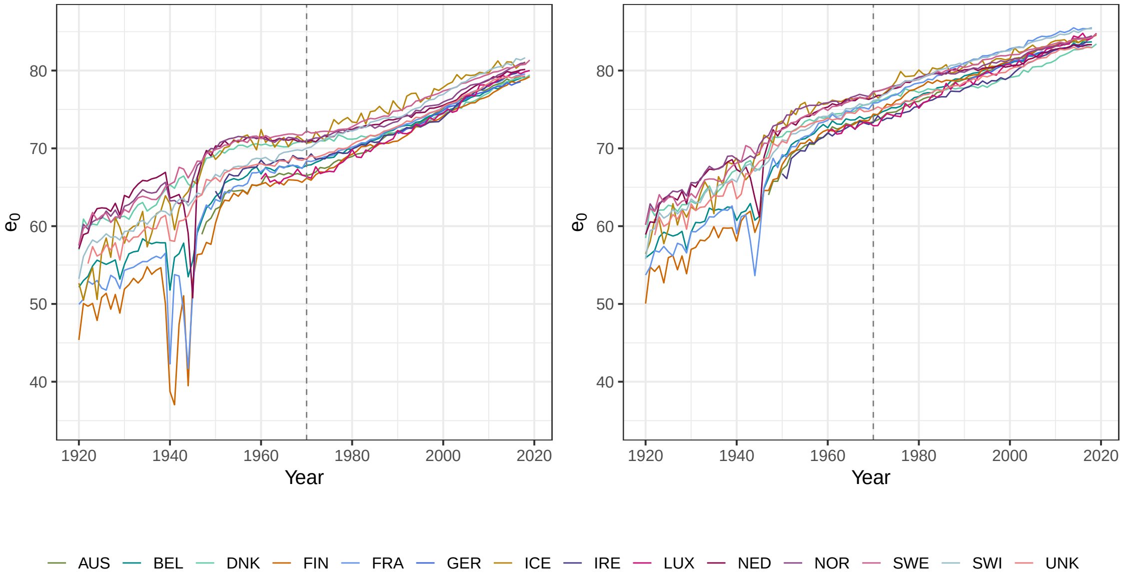
> Belgium, The Netherlands, Luxembourg, Germany, France, UK, Ireland, Iceland, Norway, Sweden, Finland, Denmark, Switzerland, Austria.

For these countries we obtain data on deaths and exposures from 1970 until 2018 from HMD (www.mortality.org) and Eurostat (https://ec.europa.eu/eurostat).

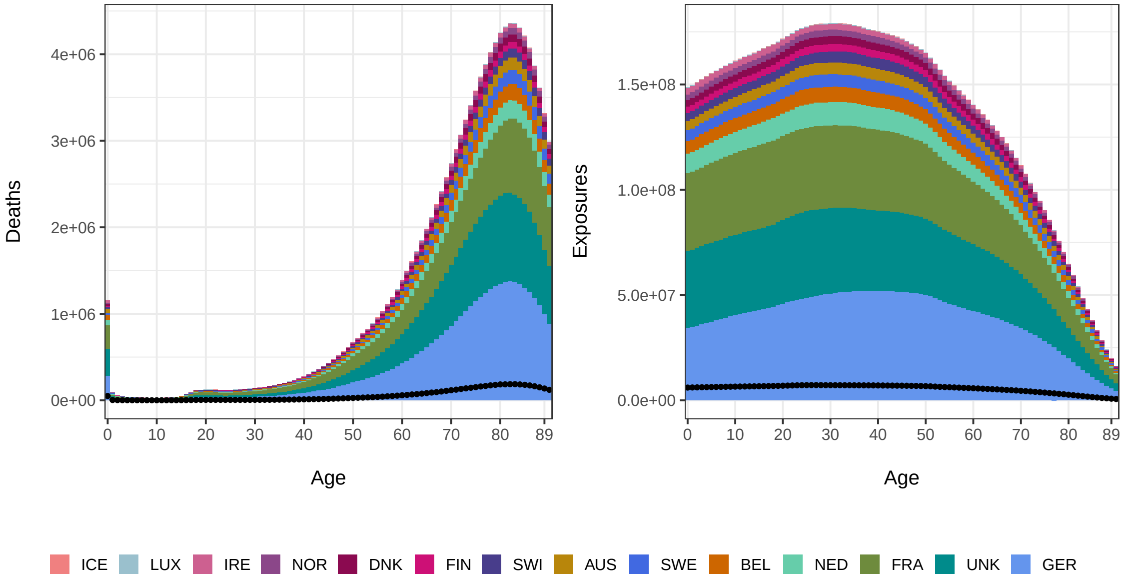
For Belgium, we add deaths and exposures in 2019 from Statbel (https://statbel.fgov.be/en).

A more data driven selection of the countries is discussed in Devriendt, Antonio & Vellekoop (2021) on *Regularized multi-population mortality modelling*.

The data - evolution in period life expectancy (source: HMD)



The data - (combined male and female) deaths and exposures



Model specification

and calibration

Lee & Carter model for EU mortality and country-specific deviation:

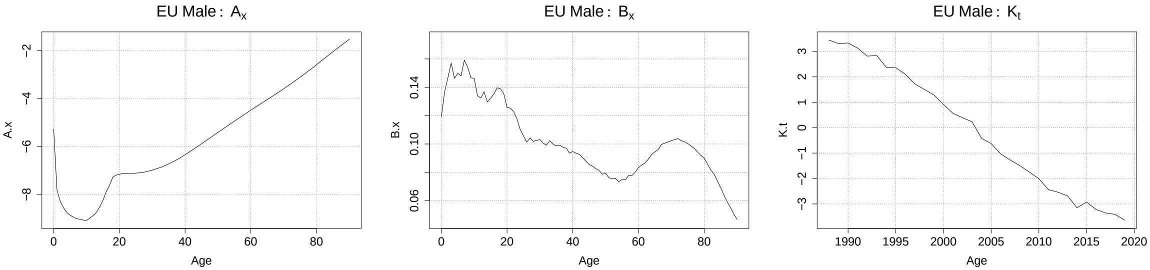
$$\begin{aligned} \ln \mu_{x,t}^{(\text{BEL})} &= \ln \mu_{x,t}^{(\text{EU})} + \ln \tilde{\mu}_{x,t}^{(\text{BEL})} \\ \ln \mu_{x,t}^{(\text{EU})} &= A_x + B_x K_t \\ \ln \tilde{\mu}_{x,t}^{(\text{BEL})} &= \alpha_x + \beta_x \kappa_t \end{aligned}$$

with constraints

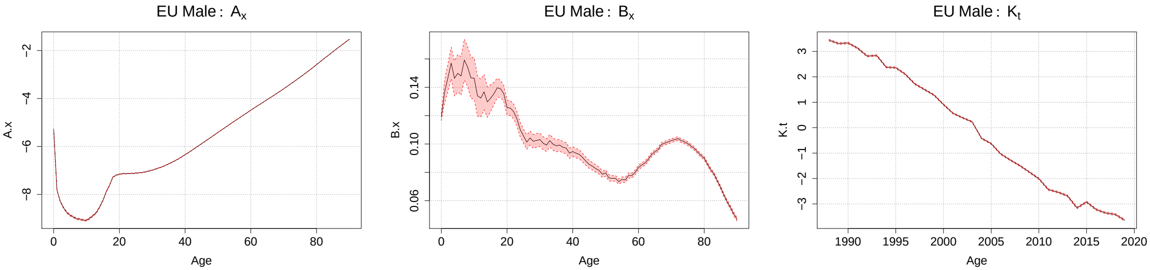
$$\sum_t K_t = \sum_t \kappa_t = 0 \text{ and } \sum_x B_x^2 = \sum_x \beta_x^2 = 1.$$

We use a Poisson assumption for the number of deaths and Maximum Likelihood Estimation (MLE) for estimating the parameters.

IA|BE 2020: males, fitted parameters, EU level

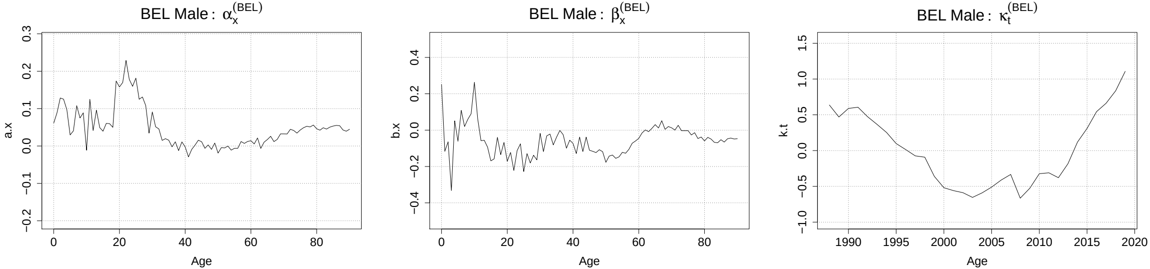


Note: calibration period 1988 - 2018 extensively motivated in Antonio, Devriendt and Robben (2020).

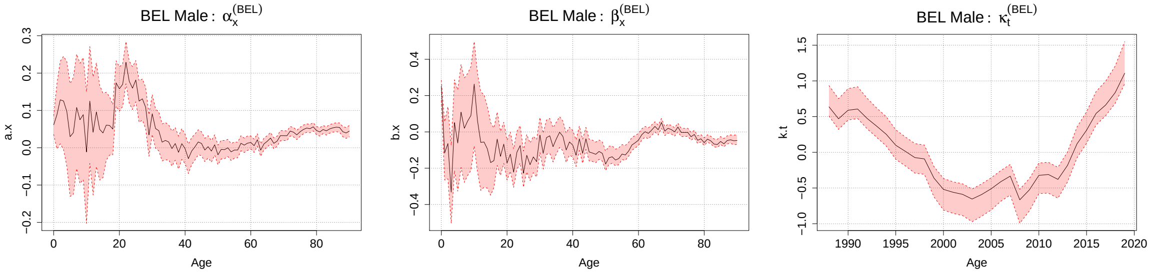


Poisson bootstrap used to add parameter uncertainty (99% pointwise intervals, based on 10 000 simulations).

Note: calibration period 1988 - 2018 extensively motivated in Antonio, Devriendt and Robben (2020).



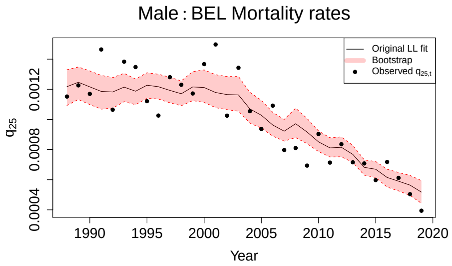
Note: calibration period 1988 - 2019 extensively motivated in Antonio, Devriendt and Robben (2020).

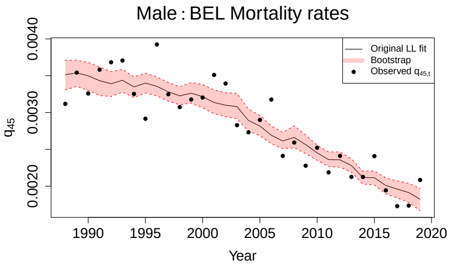


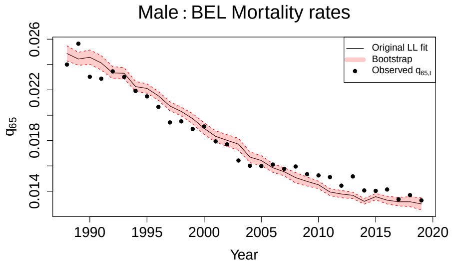
Poisson bootstrap used to add parameter uncertainty (99% pointwise intervals, based on 10 000 simulations).

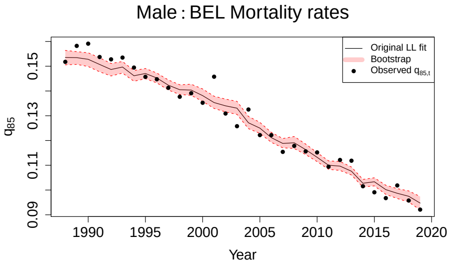
Note: calibration period 1988 - 2019 extensively motivated in Antonio, Devriendt and Robben (2020).

IA|BE 2020: males, in sample $q_{x,t}$ for $x = 25, 45, 65, 85$









Time dynamics

in the IA|BE 2020 model

Bivariate time series model for (estimated) K_t and κ_t (per gender):

$$\begin{aligned} K_{t+1} &= K_t + \theta + \epsilon_{t+1} \\ \kappa_{t+1} &= c + \phi \cdot \kappa_t + \delta_{t+1}. \end{aligned}$$

We combine $(\epsilon_t^{(M)}, \delta_t^{(M)}, \epsilon_t^{(F)}, \delta_t^{(F)})$ and assume i.i.d 4-variate normally distributed noise terms with mean (0,0,0,0) and covariance matrix $\boldsymbol{C}$.

Estimate with MLE for $\boldsymbol{C}$.

To use IA|BE 2020 as a scenario generator, we simulate noise terms and obtain projections for $\mu_{x,t}^{(\text{BEL})}$ and $q_{x,t}^{(\text{BEL})}$ (for future t).

From IA|BE 2015 to IA|BE 2020: differences in time dynamics

IA|BE 2020 incorporates correlation between K_t the European trend and $\kappa_t^{(\text{BEL})}$ the country-specific deviation from this trend

- for males and females, jointly (new!)
- hence, a (new!) 4-variate distribution for error terms $(\epsilon_t^{(\text{M})}, \delta_t^{(\text{M})}, \epsilon_t^{(\text{F})}, \delta_t^{(\text{F})})$.

From IA|BE 2015 to IA|BE 2020: differences in time dynamics

IA|BE 2020 uses AR(1) with intercept (new!):

- AR(1) parameter in the κ_t process no longer depends on the linear identifiability constraint imposed on κ_t
- κ_t may converge to a non-zero value, thus an extra gap, besides the age effect α_x, between the long term projected mortality rates for Belgium and Europe
- stability of the AR(1) process and sensitivity analysis with respect to AR(k) process extensively investigated.

For each future scenario i and with t running from $t_{\text{max}} = 2019$ to T (e.g. 2060):

1. start with the published $(K^M_{t_{\text{max}}}, \kappa^M_{t_{\text{max}}}, K^F_{t_{\text{max}}}, \kappa^F_{t_{\text{max}}})$ and time series parameter estimates

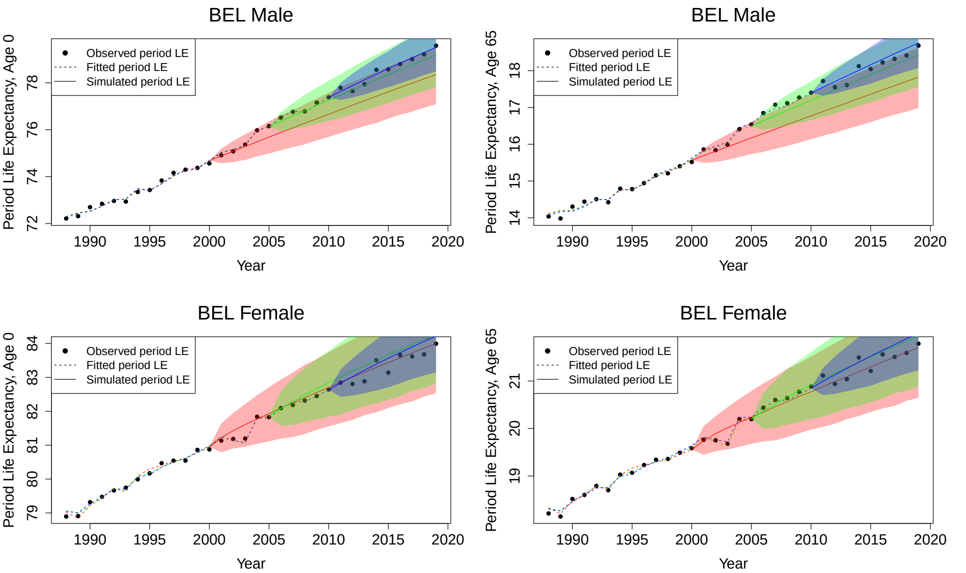
   simulate error terms $(\epsilon^M_t, \delta^M_t, \epsilon^F_t, \delta^F_t)$ and retrieve future $(K^{M,i}_t, \kappa^{M,i}_t, K^{F,i}_t, \kappa^{F,i}_t)$ from the time series specifications

2. combine with the published age specific parameters (A_x, B_x, α_x and β_x) and obtain future $\mu^i_{x,t}$ or $q^i_{x,t}$

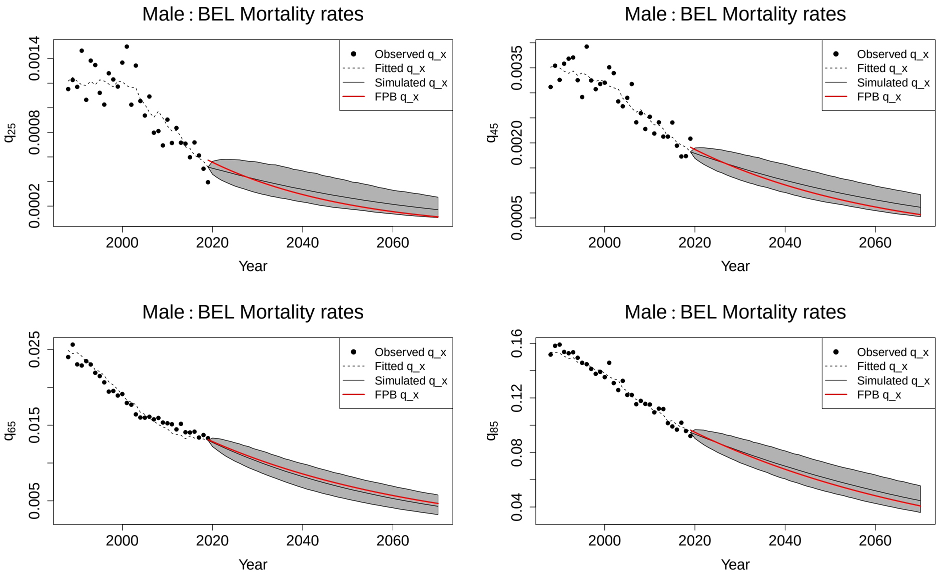
3. close each generated period table (i, t) for old ages, say $x \in \{91, \ldots, 120\}$, using law of Kannistö (1992) calibrated on ages $\{80, 81, \ldots, 90\}$.

Results, including back-tests

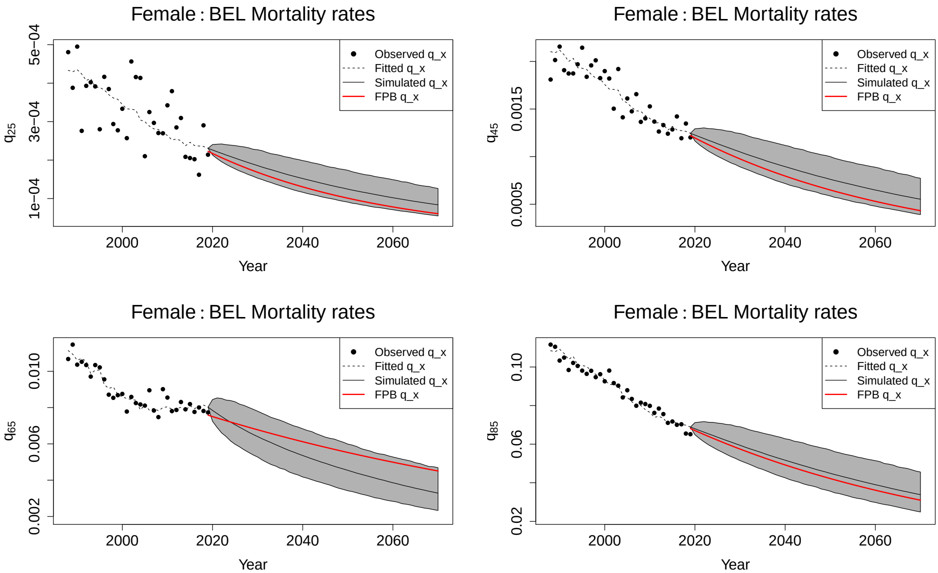
IA|BE 2020: back-test period LE



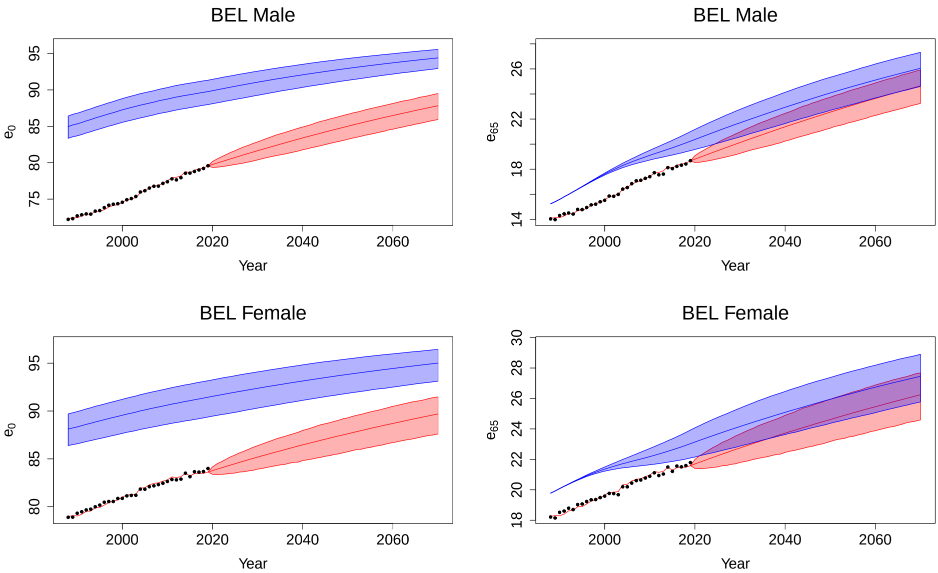
IA|BE 2020: mortality rates $q_{x,t}$



IA|BE 2020: mortality rates $q_{x,t}$



IA|BE 2020: period and cohort life expectancy



year		males		females	
		0	65	0	65
2020	Best Est.	89.91	20.38	91.54	23.14
	[$q_{0.5}$; q_{50}; $q_{99.5}$]	[88.11;89.89;91.46]	[19.57;20.37;21.17]	[89.46;91.53;93.25]	[22.15;23.14;24.07]
	FPB	(90.07;90.25)	(20.11;20.56)	(91.28;91.53)	(22.92;23.38)
2040	Best Est.	92.08	22.94	93.15	25.09
	[$q_{0.5}$; q_{50}; $q_{99.5}$]	[90.35;92.08;93.52]	[21.65;22.94;24.14]	[91.12;93.14;94.82]	[23.63;25.09;26.46]
	FPB	(92.09;92.36)	(22.80;23.26)	(92.80;93.08)	(24.82;25.28)
2060	Best Est.	93.73	25.11	94.45	26.74
	[$q_{0.5}$; q_{50}; $q_{99.5}$]	[92.18;93.72;94.97]	[23.69;25.11;26.39]	[92.50;94.45;95.97]	[25.06;26.74;28.18]
	FPB	(93.62;93.90)	(25.00;25.48)	(94.06;94.34)	(26.45;26.92)

Multi-population model of type Li & Lee calibrated on $t \in \{1988, \ldots, 2018\}$ and $t \in \{1988, \ldots, 2019\}$ for Belgian data and $x \in \{0, 1, \ldots, 90\}$.

COVID-19 impact analysis and adjustments to the Li & Lee multipopulation model and the proposed time dynamics

We will now focus on:

- Robben, Antonio & Devriendt (Risks, 2022) published early January 2022, written mid 2021, using only the pandemic data point 2020
- Prognosetafel AG 2022 (from www.ag-ai.nl) and the working paper by Van Berkum, Melenberg & Vellekoop, both published on September 13, 2022, using the pandemic data points 2020 and 2021.

An important note on data collection

To assess the impact of the COVID-19 pandemic on our proposed stochastic mortality model:

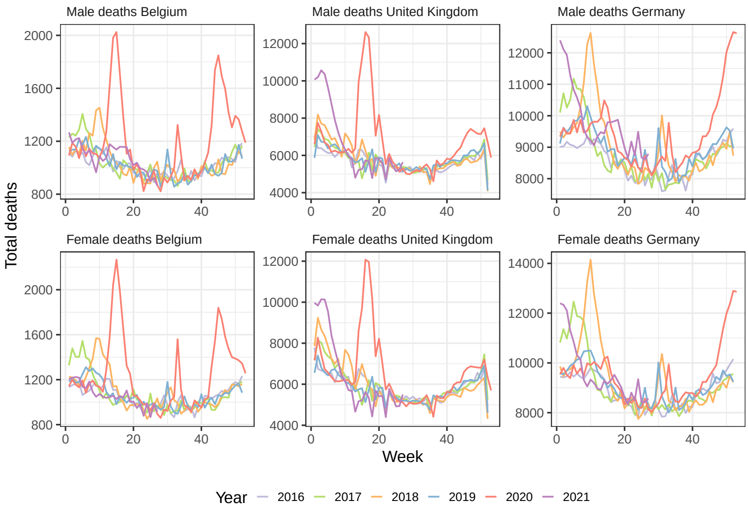
- extract death counts $d_{x,t}$ and exposures $E_{x,t}$ for individual ages up to and including years 2020 and 2021
- however, publication of these statistics by national statistics institutes takes time!
- alternative sources:

  Eurostat and STMF ('Short Term Mortality Fluctuations') publish weekly statistics, in age buckets

  or acquiring customized (granular) data from National Statistical Institutes ('maatwerk').

See Robben, Antonio & Devriendt (2022). Assessing the impact of the COVID-19 shock on a stochastic multi-population mortality model. Risks, 10(2), 26.

Weekly death counts, Eurostat and STMF

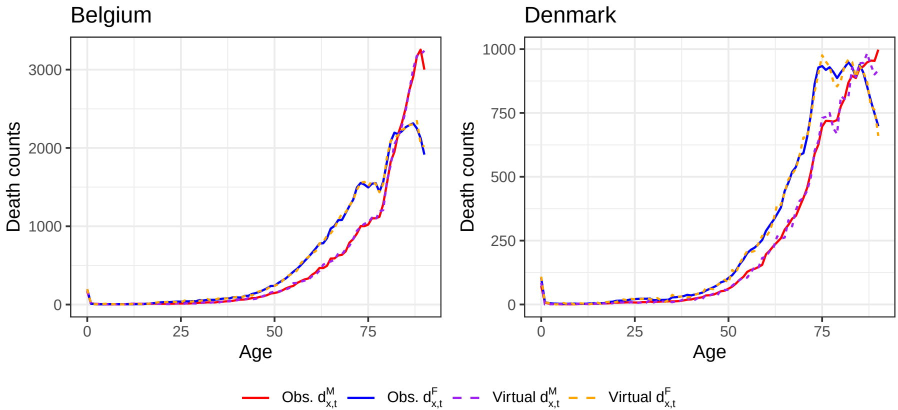


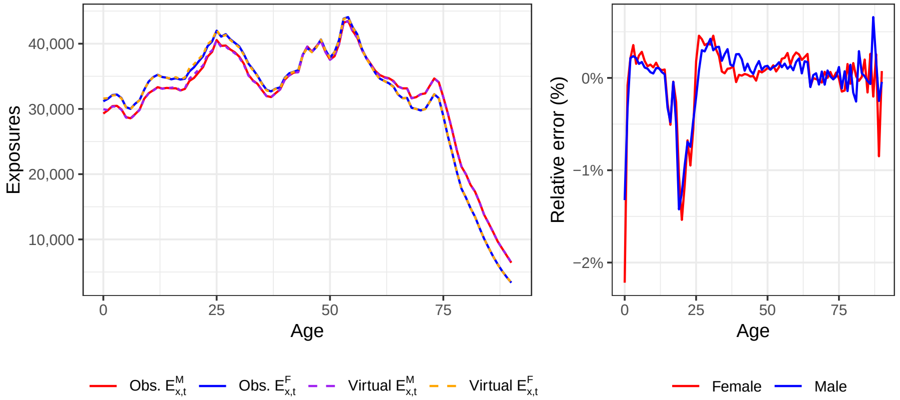
Transform weekly data registered in age buckets to annualized, age-specific observations

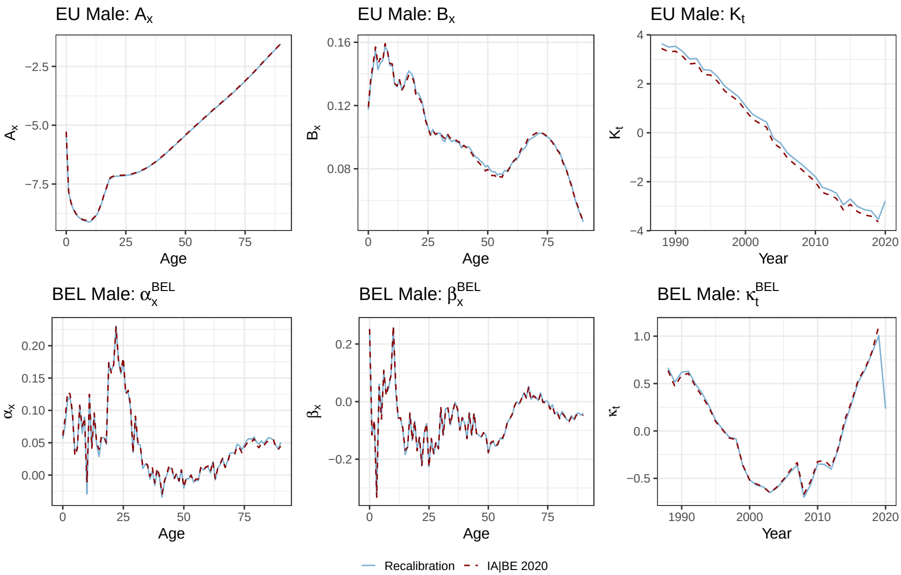
1. We use weekly exposures and death counts in age buckets from STMF (by HMD) and Eurostat, for the 13 EU countries from IA|BE 2020, Ireland is not included (no data).

2. We design and apply a technical protocol to transform the weekly mortality data in age buckets to yearly mortality data for individual ages.

   We verify our protocol on the 2020 data for Belgium and Denmark (published at the moment of writing the paper).

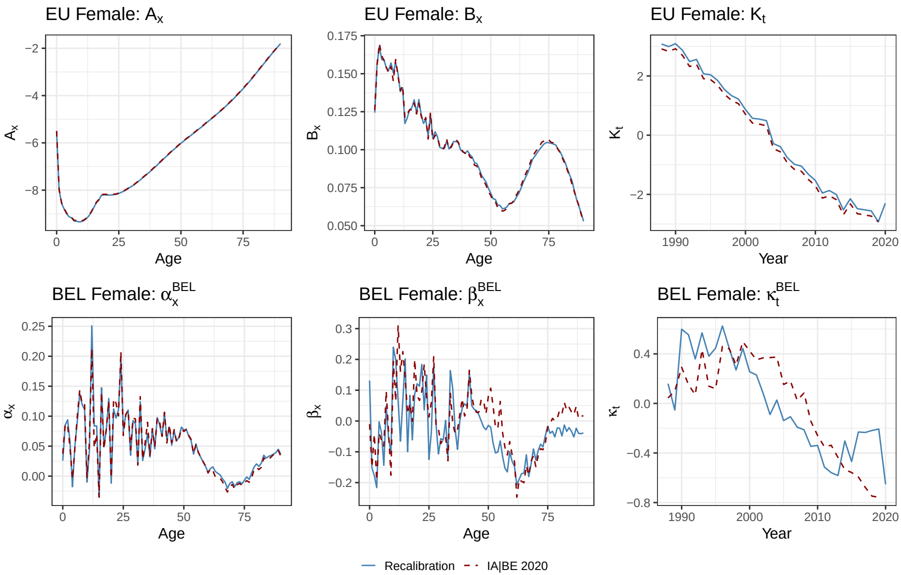

Belgium
Denmark
Death counts
Age
0
1000
2000
3000
0
25
50
75
0
250
500
750
1000
Obs. $d^M_{x,t}$
Obs. $d^F_{x,t}$
Virtual $d^M_{x,t}$
Virtual $d^F_{x,t}$

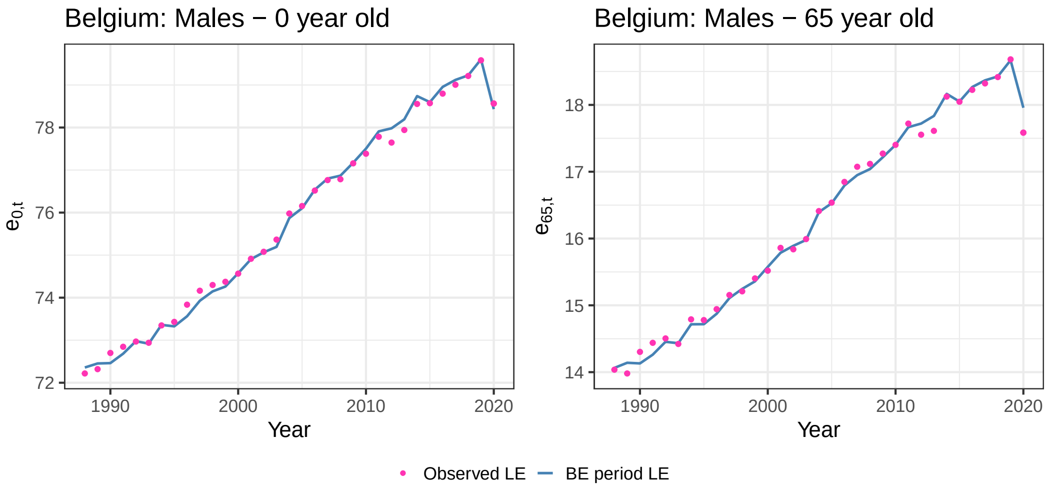

40,000
30,000
20,000
10,000
Exposures
0
25
50
75
Age
Obs. $E^M_{x,t}$
Obs. $E^F_{x,t}$
Virtual $E^M_{x,t}$
Virtual $E^F_{x,t}$
0%
−1%
−2%
Relative error (%)
0
25
50
75
Age
Female
Male

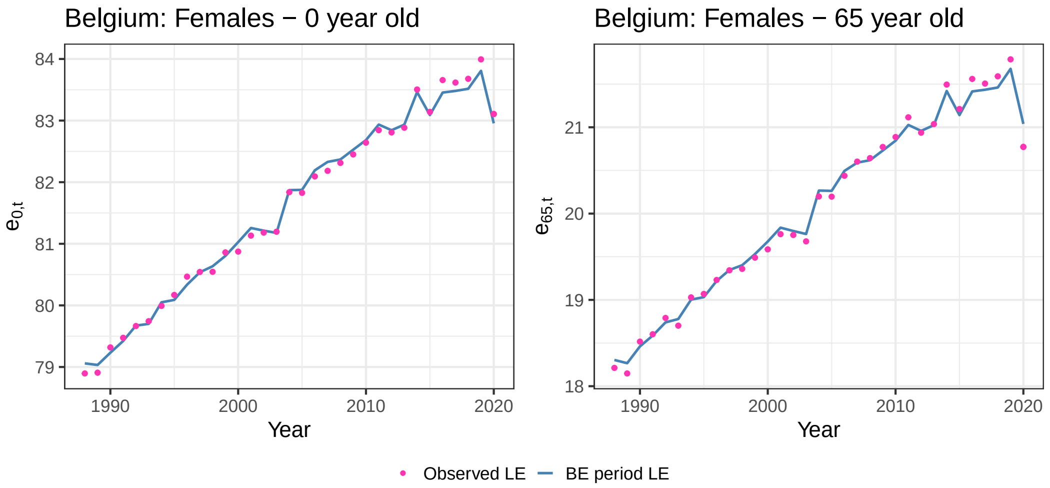


EU Male: A_x
EU Male: B_x
EU Male: K_t
BEL Male: α_x^{BEL}
BEL Male: β_x^{BEL}
BEL Male: κ_t^{BEL}
Age
Year
Recalibration
IA|BE 2020

Pandemic impact on calibrated parameters - recalibrating IA|BE 2020




Belgium: Males − 0 year old
Belgium: Males − 65 year old
$e_{0,t}$
$e_{65,t}$
Year
Year
72
74
76
78
14
15
16
17
18
1990
2000
2010
2020
Observed LE
BE period LE


Belgium: Females − 0 year old
Belgium: Females − 65 year old
$e_{0,t}$
$e_{65,t}$
84
83
82
81
80
79
21
20
19
18
1990
2000
2010
2020
Year
Observed LE
BE period LE

Cohort life expectancy in 2020		Males		Females	
		0	65	0	65
IA|BE 2020	Best. Est.	89.91	20.38	91.54	23.14
	$[q_{0.5}; q_{50}; q_{99.5}]$	[88.11; 89.89; 91.46]	[19.57; 20.37; 21.17]	[89.46; 91.53; 93.25]	[22.15; 23.14; 24.07]
Recalibration	Best. Est.	87.64	19.26	89.67	22.21
	$[q_{0.5}; q_{50}; q_{99.5}]$	[83.94; 87.63; 90.51]	[17.99; 19.25; 20.53]	[85.98; 89.65; 92.60]	[20.81; 22.20; 23.55]

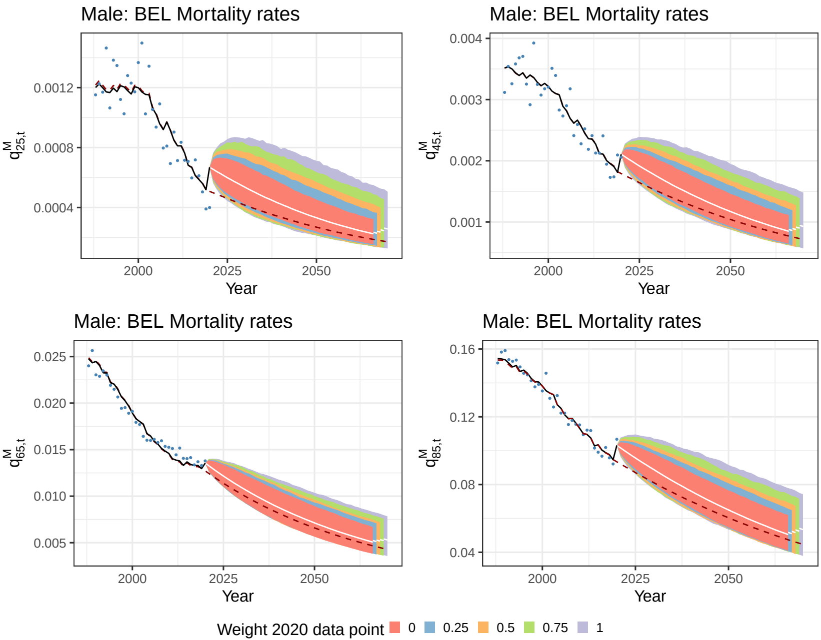
No expert judgement made about the 2020 observation; re-calibrated along the principles of IA|BE 2020.

Robben, Antonio & Devriendt (2022, Risks) investigate how to limit the impact of the 2020 data point (if wanted):

- by intervening in the likelihood to calibrate the time series models
- via a weighted time series likelihood

$$l(\boldsymbol{\Psi}, \boldsymbol{C}) \;=\; -\frac{1}{2}\sum_{t=1989}^{2020} w_t \cdot \left(4\log 2\pi + \log|\boldsymbol{C}| + tr\left[\boldsymbol{C}^{-1}(\boldsymbol{Y}_t - \boldsymbol{X}_t\boldsymbol{\Psi})(\boldsymbol{Y}_t - \boldsymbol{X}_t\boldsymbol{\Psi})^t\right]\right),$$

where $w_t = 1$ for $t < 2020$ (pre-COVID) and 5 possible scenarios are investigated for w_{2020}, i.e. $w_{2020} \in \{0, 0.25, 0.50, 0.75, 1\}$.

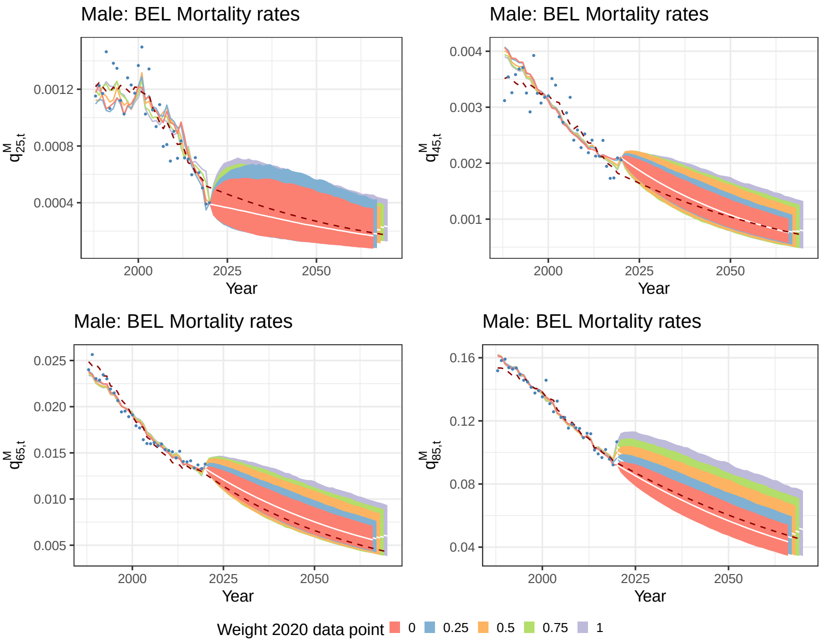

Male: BEL Mortality rates
Male: BEL Mortality rates
Male: BEL Mortality rates
Male: BEL Mortality rates
$q^M_{25,t}$
$q^M_{45,t}$
$q^M_{65,t}$
$q^M_{85,t}$
Year
Weight 2020 data point
0
0.25
0.5
0.75
1

Robben, Antonio & Devriendt (2022, Risks) investigate how to limit the impact of the 2020 data point (if wanted):

- via the calibration strategy, with a Lee & Miller (2001) inspired modification

$$
\begin{aligned}
\ln \mu_{x,t}^{\text{BEL}} &= \ln \mu_{x,t}^{\text{EU}} + \ln \tilde{\mu}_{x,t}^{\text{BEL}} \\
\ln \mu_{x,t}^{\text{EU}} &= \underbrace{\lambda_{2020} \cdot \log m_{x,2020}^{\text{EU}} + (1-\lambda_{2020}) \cdot \log m_{x,2019}^{\text{EU}}}_{\text{adjusted } A_x} + B_x(K_t - K_{2020}) \\
\ln \tilde{\mu}_{x,t}^{\text{BEL}} &= \underbrace{\lambda_{2020} \cdot \log \tilde{m}_{x,2020}^{\text{BEL}} + (1-\lambda_{2020}) \cdot \log \tilde{m}_{x,2019}^{\text{BEL}}}_{\text{adjusted } \alpha_x} + \beta_x(\kappa_t - \kappa_{2020}),
\end{aligned}
$$

where $\lambda_{2020} \in \{0, 0.25, 0.50, 0.75, 1\}$ is the weight assigned to the observed central death rates in 2020.



Male: BEL Mortality rates
0.0004
0.0008
0.0012
$q^M_{25,t}$
Male: BEL Mortality rates
0.001
0.002
0.003
0.004
$q^M_{45,t}$
Male: BEL Mortality rates
0.005
0.010
0.015
0.020
0.025
$q^M_{65,t}$
Male: BEL Mortality rates
0.04
0.08
0.12
0.16
$q^M_{85,t}$
2000
2025
2050
Year
Weight 2020 data point
0
0.25
0.5
0.75
1

KAG 2022 interventions in model specification

KAG 2022 proposes a three-layer Li & Lee model:

$$\begin{aligned}\ln \mu_{x,t}^{(\text{NL})} &= \ln \mu_{x,t}^{(\text{pre-COVID, NL})} + \left(\tilde{\mathcal{B}}_x \Upsilon_t\right) \\ &= A_x + B_x K_t + \alpha_x + \beta_x \kappa_t + \tilde{\mathcal{B}}_x \Upsilon_t,\end{aligned}$$

calibrated for male and female data, respectively.

Here:

- the pre-COVID baseline mortality is calibrated on data up to (and including) 2019
- Υ_t for $t = 2020$ and $t = 2021$ capture the time effect of the pandemic
- the $\tilde{\mathcal{B}}_x$ express age-specific differences in pandemic impact.

KAG 2022 interventions in model specification

To calibrate the COVID-19 impact, expressed as $\tilde{\mathcal{B}}_x \Upsilon_t$, focus on weekly Dutch data:

$$D_{x,w,t} \quad \sim \quad \text{POI}\left(E_{x,w,t} \cdot \mu_{x,w,t}\right),$$

for ages $x \in \{55, \ldots, 90\}$ and $t \in \{2020, 2021\}$, where

$$\mu_{x,w,t} \quad = \quad \mu_{x,t}^{\text{(pre-COVID, NL)}} \cdot \underbrace{\phi_{w,t}}_{\text{yearly seasonal effect}} \cdot \overbrace{\exp\left(\mathcal{B}_x \mathcal{K}_{w,t}\right)}^{\text{COVID impact}},$$

and $\sum_{x=55}^{90} \mathcal{B}_x = 1$.

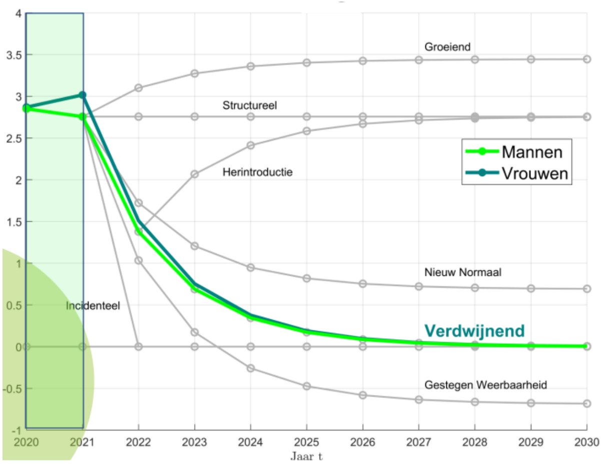
A transformation is then proposed to step:

- from calibrated $\mathcal{B}_x$ to $\tilde{\mathcal{B}}_x$ for $x \in \{55, \dots, 90\}$
- from weekly $\mathcal{K}_{w,t}$ to yearly Υ_t for $t \in \{2020, 2021\}$.

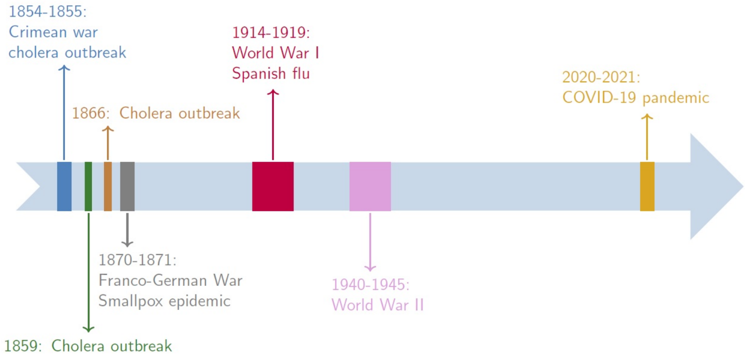
Hereto, KAG 2022 assumes

- the one-year annual survival probabilities in 2020 and 2021 equal the product of the weekly survival probabilities in these years $\Rightarrow \Upsilon_t$
- survival over 2020 and 2021 should be equal to surviving over all weeks in these years $\Rightarrow$ $\tilde{\mathcal{B}}_x$.

KAG 2022 scenarios for future impact of COVID-19 via the Υ_t's

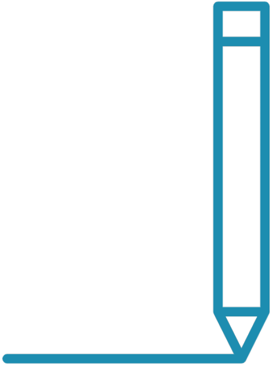


Picture from Presentatie Prognosetafel AG2022, future scenarios for the Υ_t.



Ongoing work:

- age-dependent mortality shocks in a stochastic multi-population mortality projection model of type Li & Lee with multiple age-time components
- regime switch process to switch between a high volatility regime (prone to mortality shocks) and a low volatility regime.



That's a wrap!

That's a wrap!

IA|BE 2020 is still our best estimate for future long-term mortality.

Cfr. CMI 2020 in the UK: *'We put no weight on the data for 2020.'*

At this moment, scenario-thinking + some methodological interventions are necessary to quantify the long-term impact of COVID-19 on mortality.

Papers and code available via the hyperlinks in the sheets or from my website and Github.

Thank you for your attention!