Changes and trends in mortalities in relation to COVID-19

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Introduction and objectives

Source of uncertainty:

- Insurers' and pension funds' dependence on demographics. Demographics are sensitive to pandemics, (extreme) weather
- Some developed countries: mortality improvement seems to plateau

Objectives:

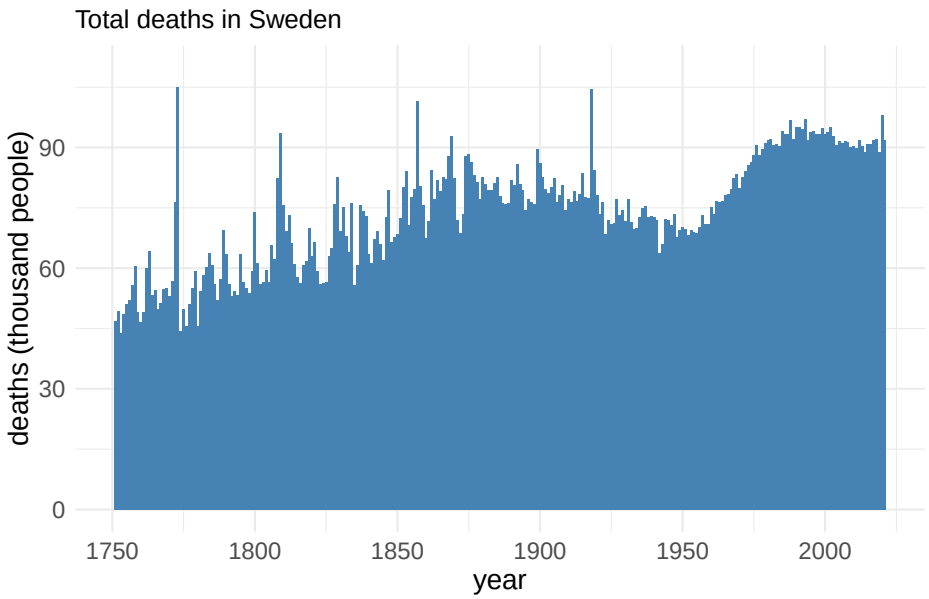
- Changes in mortalities over calendar years, effects during Covid, comparison and proximity of countries
- Quality of models from the perspective of variance over time, ranking based on excess mortality
- Effect on reinsurance calculations, in particular, longevity swap net cash flow variances and capital

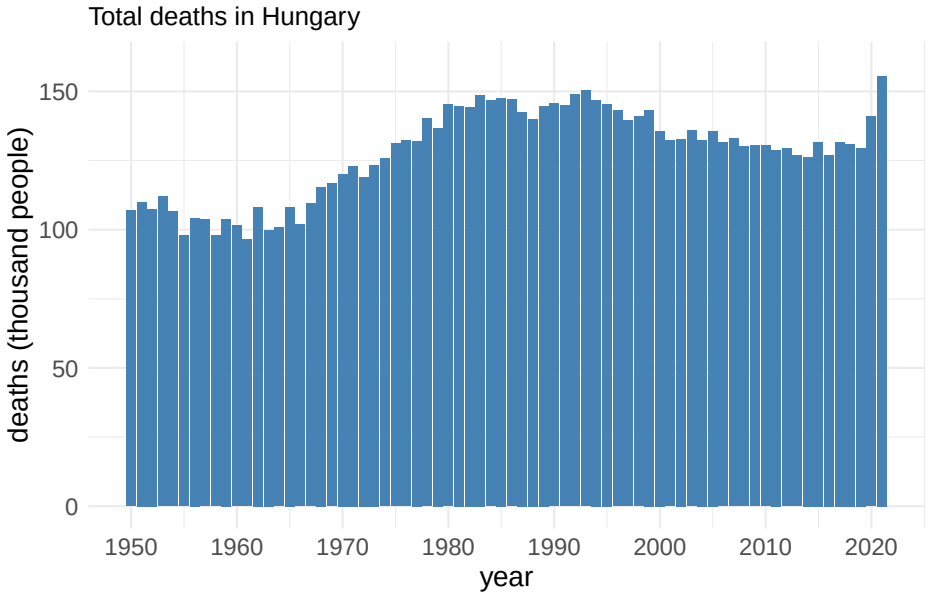
Data:

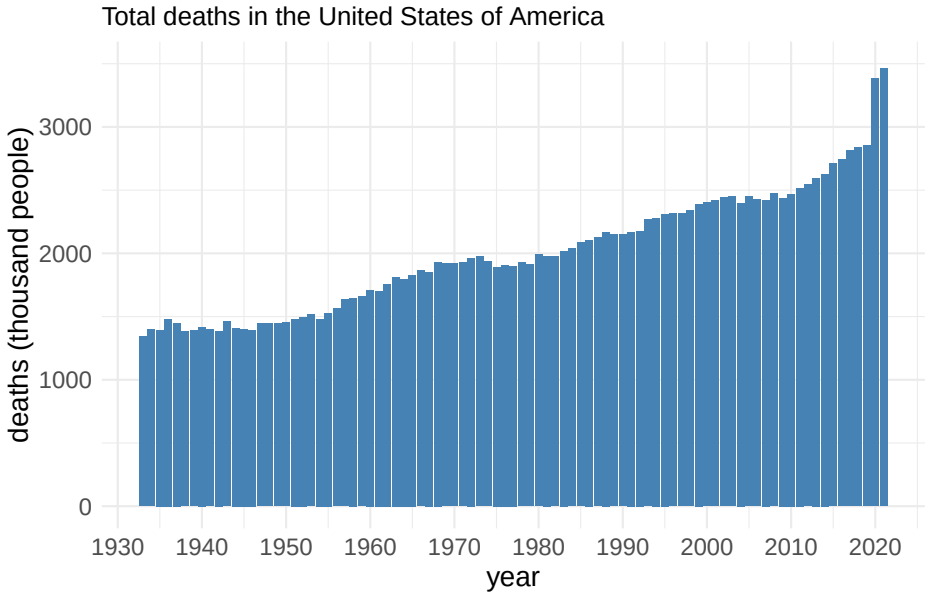
- Human Mortality Database (https://www.mortality.org), 41 countries with births, deaths, population size, exposure-to-risk, life tables
- Eurostat (https://ec.europa.eu/eurostat) and their publication. European countries. Death counts by gender and birth year, population by gender and birth year as of 1 January every year. A bit more recent data than HMD

Insufficiency of pure death counts

- Death counts per calendar year: USA, Sweden, Hungary
- The total death count has been mostly increasing on a yearly basis
- Not sufficiently explanatory to only look at these (because of population composition change, migration, seasonal effects, etc.)

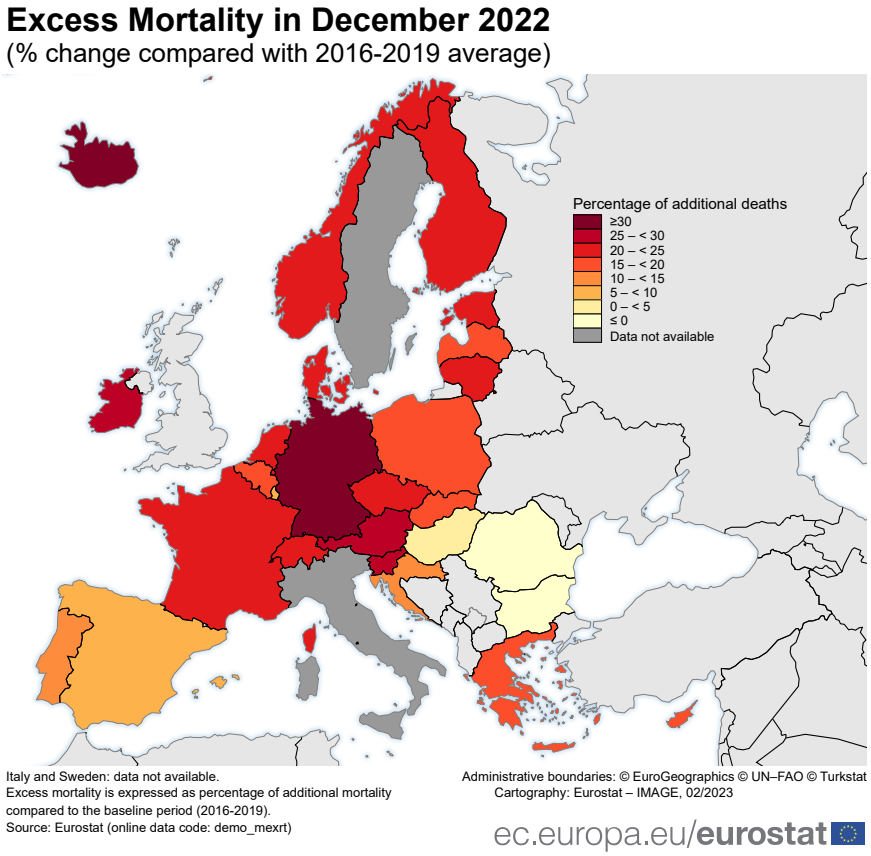






Insufficiency of pure death counts

- News from Eurostat: Excess mortality rose sharply to 19% in December 2022.
- Applied method: average 2016-2019 December deaths compared with December 2020-2022 numbers



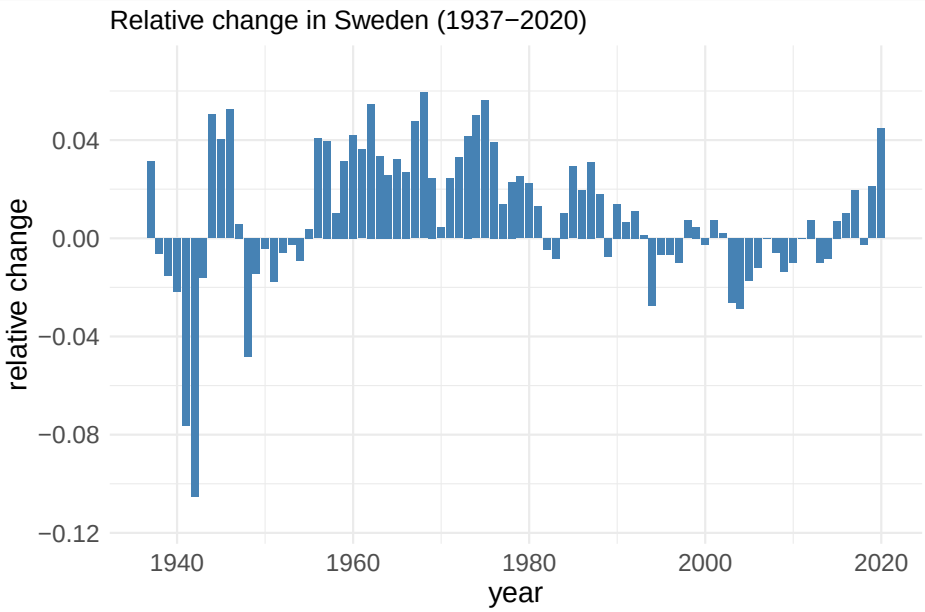
Source dataset: demo_mexrt

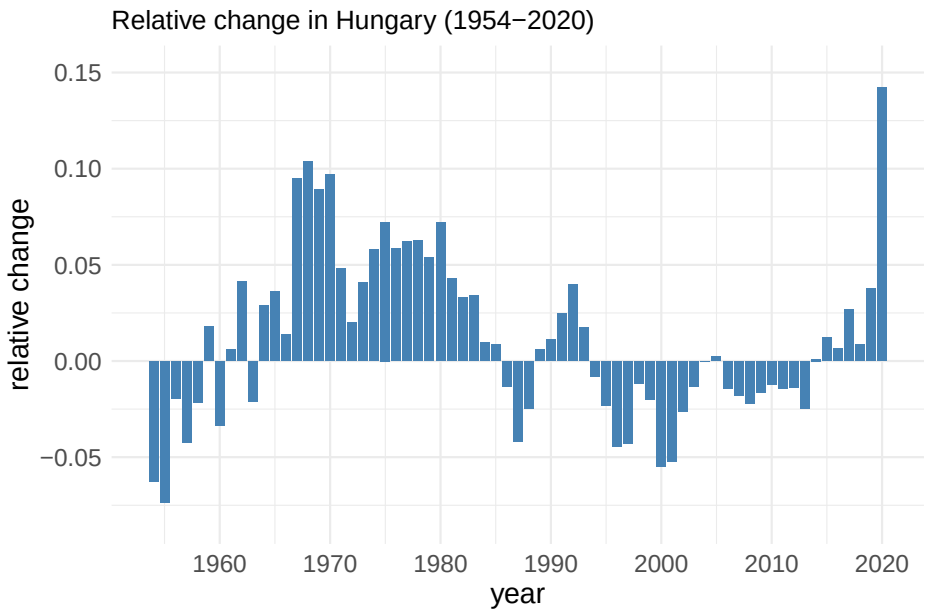
In December 2022, excess mortality continued to vary across the EU members. Romania and Bulgaria (both -6%) recorded values lower than the national monthly average for 2016-19, while Hungary (+3%), Luxembourg, Spain and Malta (all +10%) had excess mortality rates less than half the EU average.

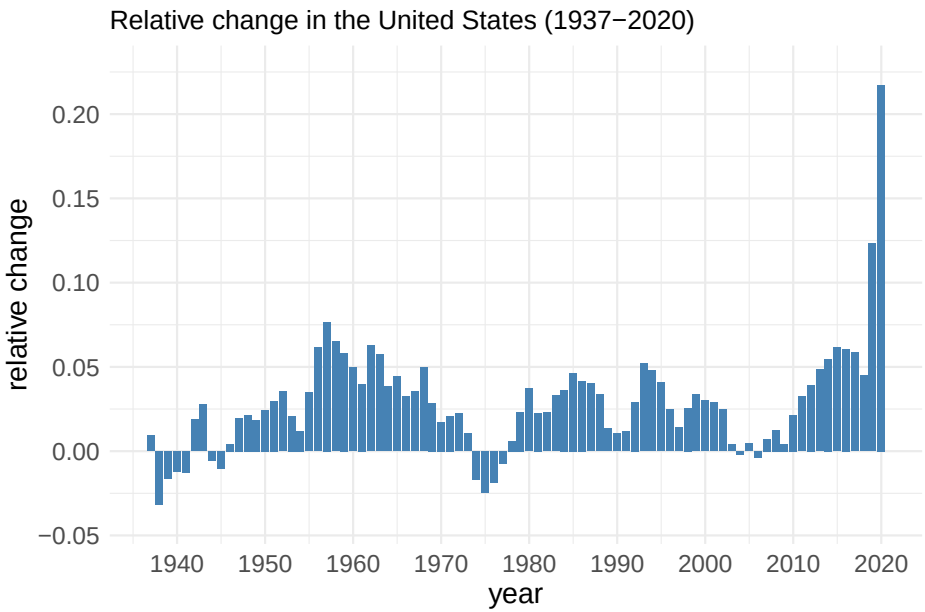
Conversely, the highest rate was recorded in Germany (+37%). Other countries with rates over +20% were Austria (+27%), Slovenia (+26 %), Ireland and France (both +25%), Czechia, the Netherlands and Estonia (all +23 %), Denmark (+22%), and Finland and Lithuania (both +21%).

Looking at pure death counts on the long run

- Apply the method of Eurostat for multiple years: $D_{tot}(t)$ is the total number of deaths in year t, then the graphs show $\frac{2\sum_{t=y}^{y+1} D_{tot}(t)}{\sum_{t=y-4}^{y-1} D_{tot}(t)} - 1$ for $y = \ldots, 2020$.







Relative change

Definition (relative change)

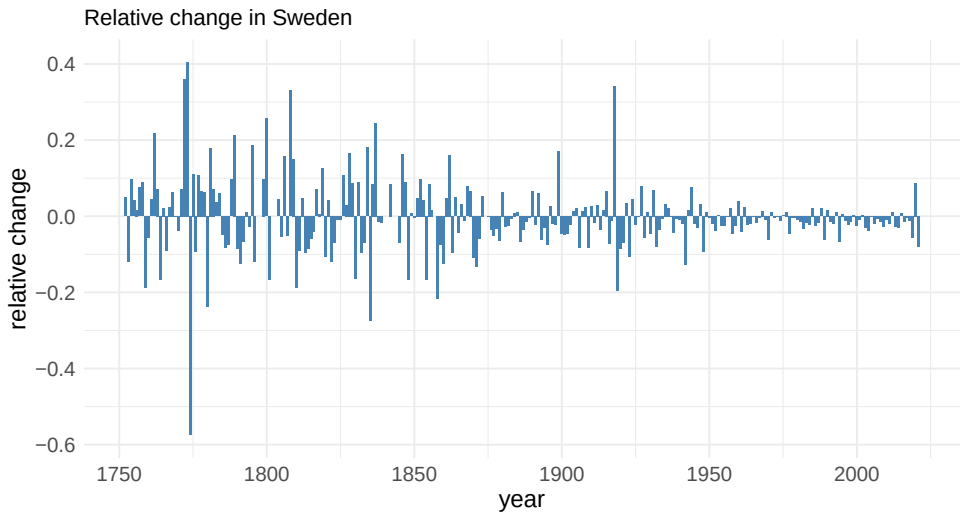
The relative change rc_i of a population in calendar year i is defined as follows:

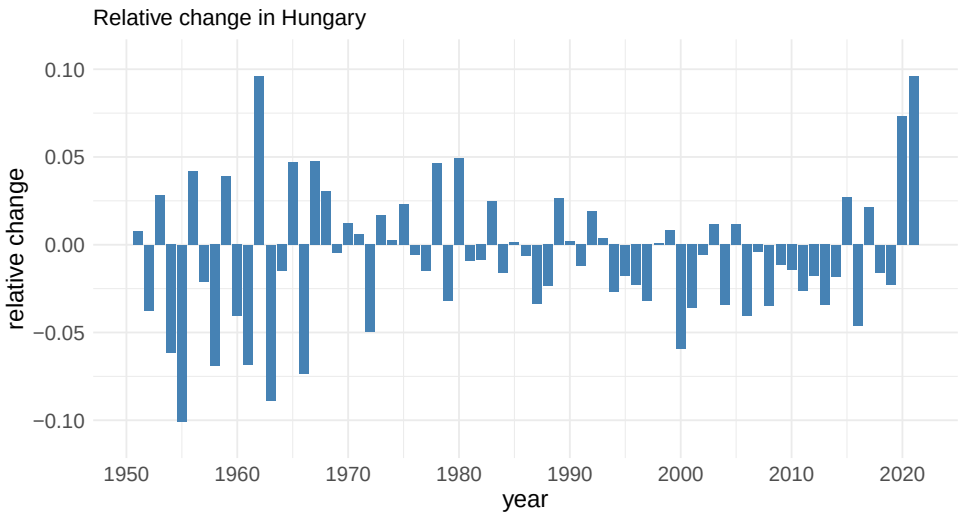
- $t_{i,g,j}$: exposure-to-risk of gender g at age j in calendar year i
- $d_{i,g,j}$: death count of gender g at age j in calendar year i
- $md_{i,g,j} = t_{i,g,j} \cdot \frac{d_{i-1,g,j}}{t_{i-1,g,j}}$: expected count of deaths for gender g and age j in calendar year i (assuming an unchanged death/exposure-to-risk rate)
- $d_i = \sum_{g,j} d_{i,g,j}$: death count in year i
- $md_i = \sum_{g,j} md_{i,g,j}$: *expected* death count in year i
- $rc_i = \frac{d_i - md_i}{md_i}$: relative change in year i

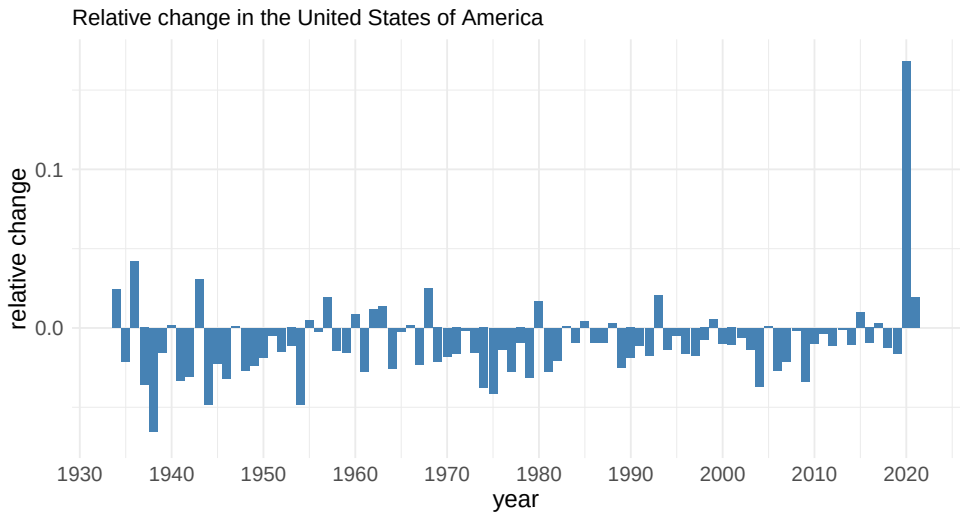
Relative change

Assumptions:

- Figures reflect population on 1 Jan instead of exposure-to-risk
- Deaths of new born children based on previous year
- Aggregate values above age 99







Proximity measures

Definition (excess mortality log correlation)

Take country A and B, N set of observed calendar years, and relative changes $rc_{ctr,i}$, with $ctr \in \{A, B\}$ and $i \in N$. The excess mortality log correlation is
$\rho^{\log}_{A,B} = corr(\log(rc_{A,\cdot}), \log(rc_{B,\cdot}))$

(We can similarly define
$\rho_{A,B} = corr(rc_{A,\cdot}, rc_{B,\cdot})$.)

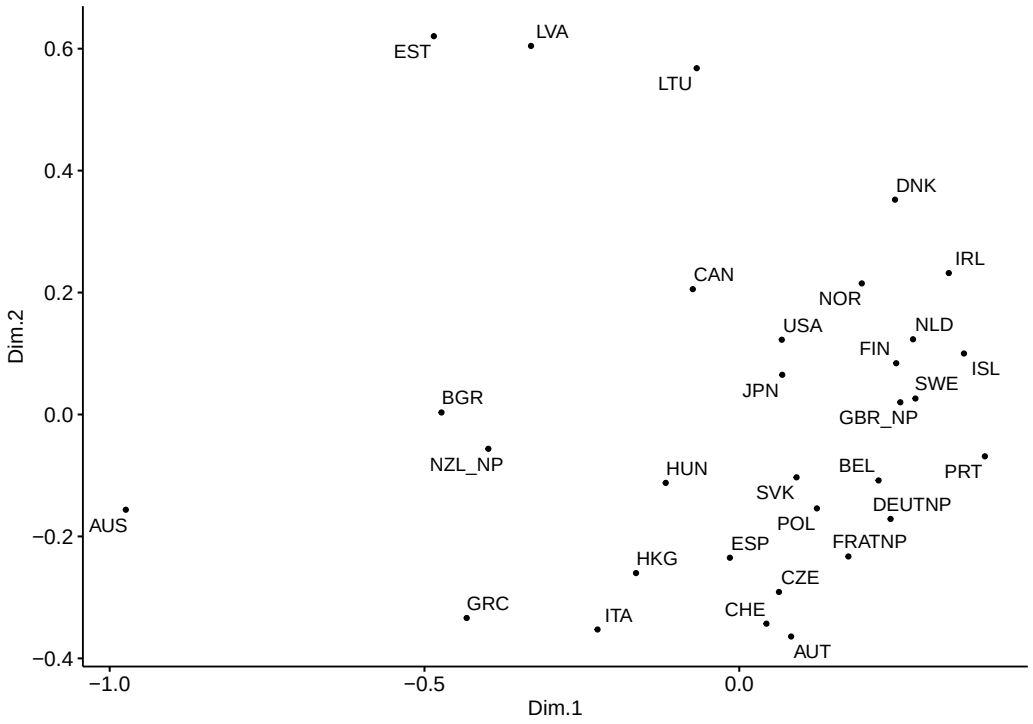


Figure: Excess mortality log correlations visualised by means of multidimensional scaling. Data stems from changes between 1991-2019.

Relative change based on multiple years' average

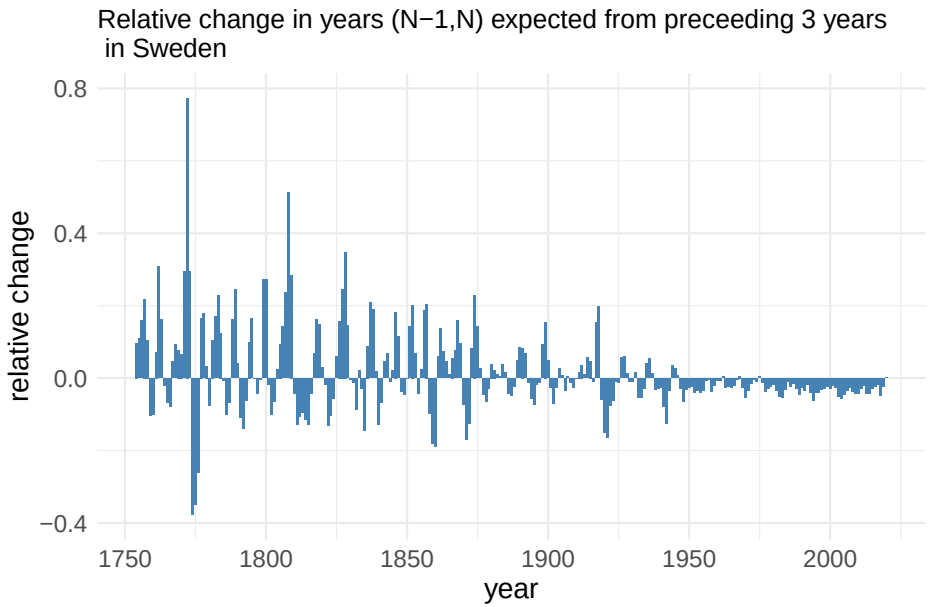
Potential definitions of excess mortality - actual death count compared with:

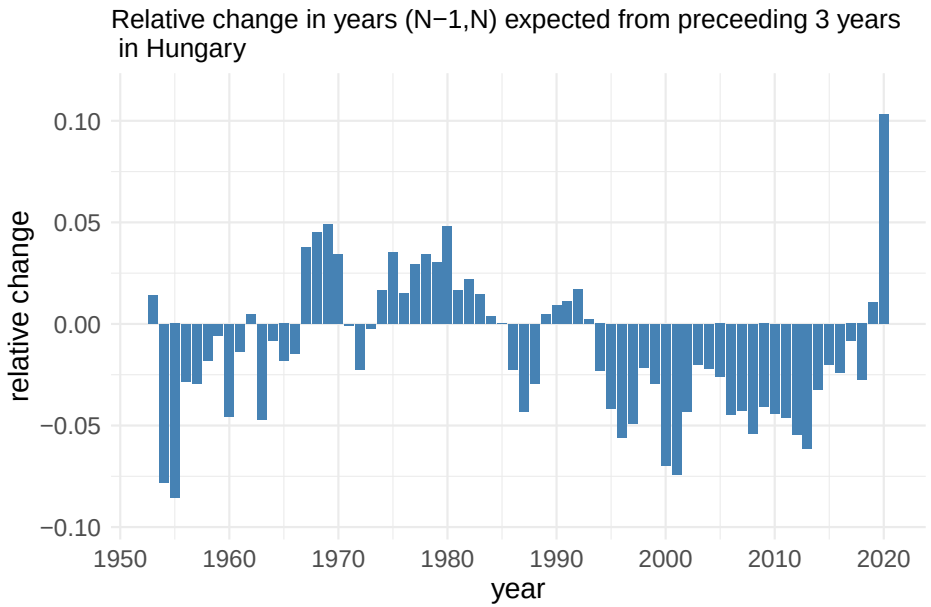
- the death of previous year's/years' average (age/gender segregation)
- fitted mortality forecast
- taking into account weather conditions and other factors

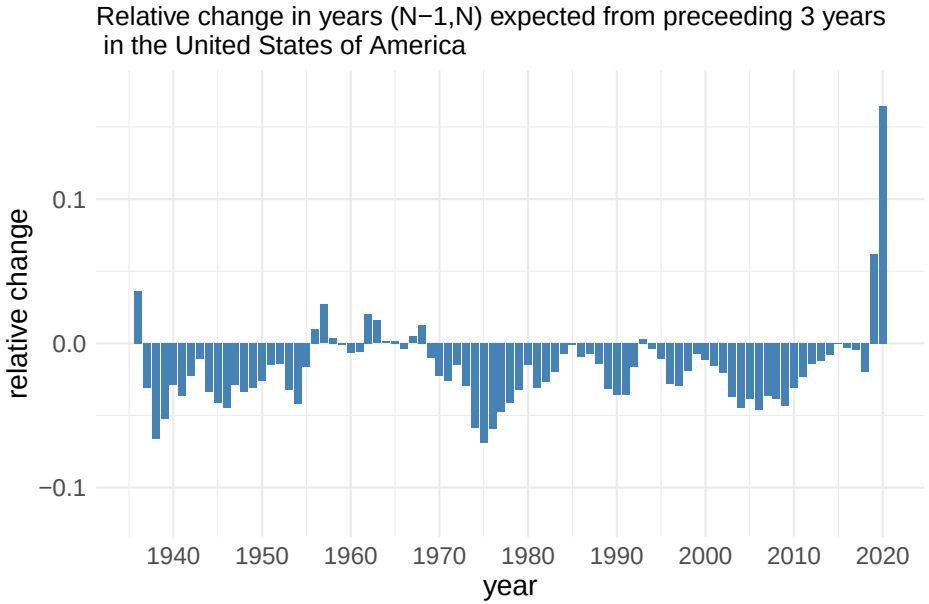
Now look at

- the relative changes for '20-'21 based on '17-'19
- which was the last year that would justify a death rate at least as bad as the one observed in '20-'21

Relative change based on multiple years' average







Relative change based on multiple years' average

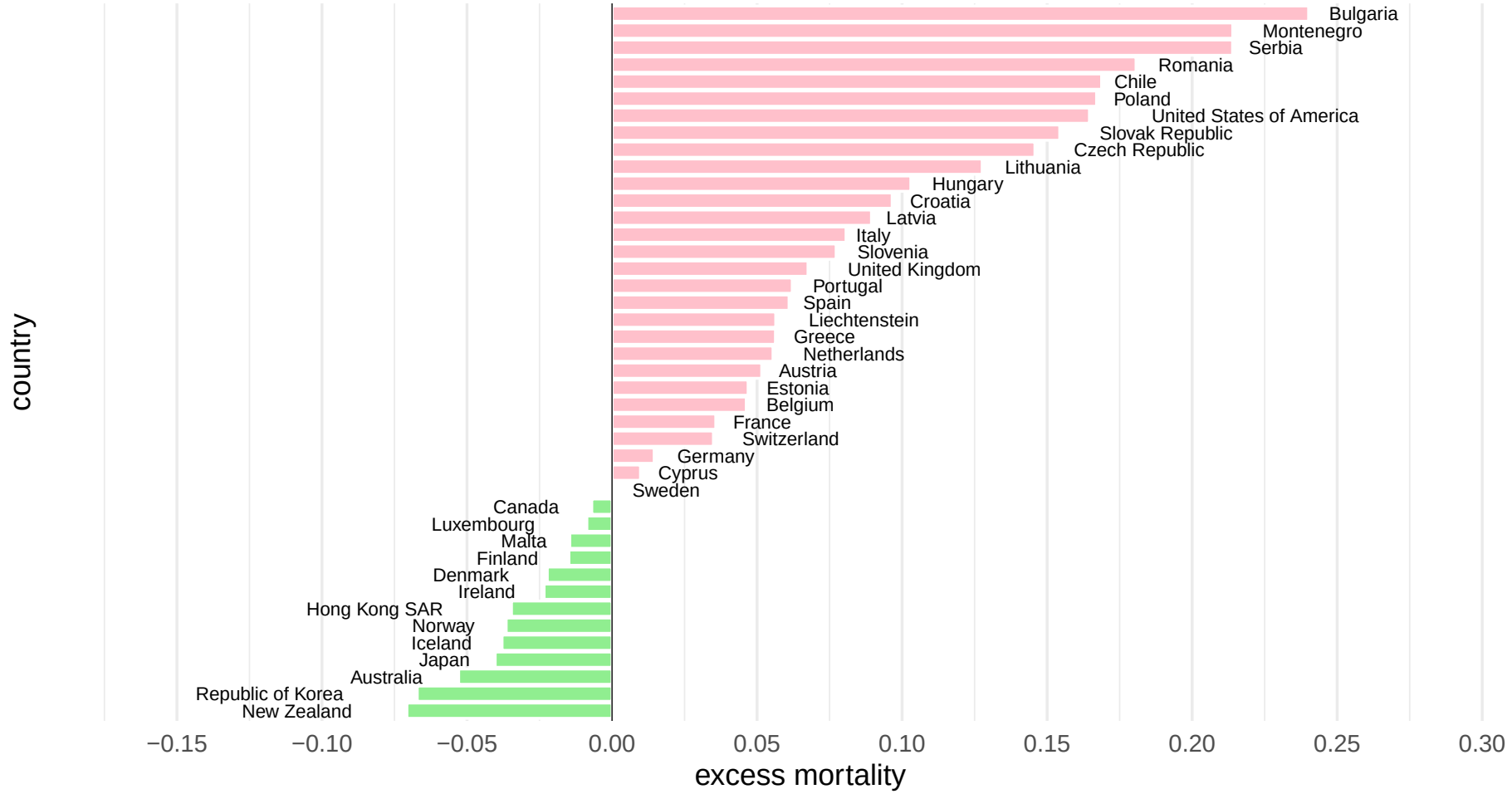


Figure: Relative change in 2020-2021 compared to mortality expectations based on death rates of 2017-2019.

Relative change based on multiple years' average

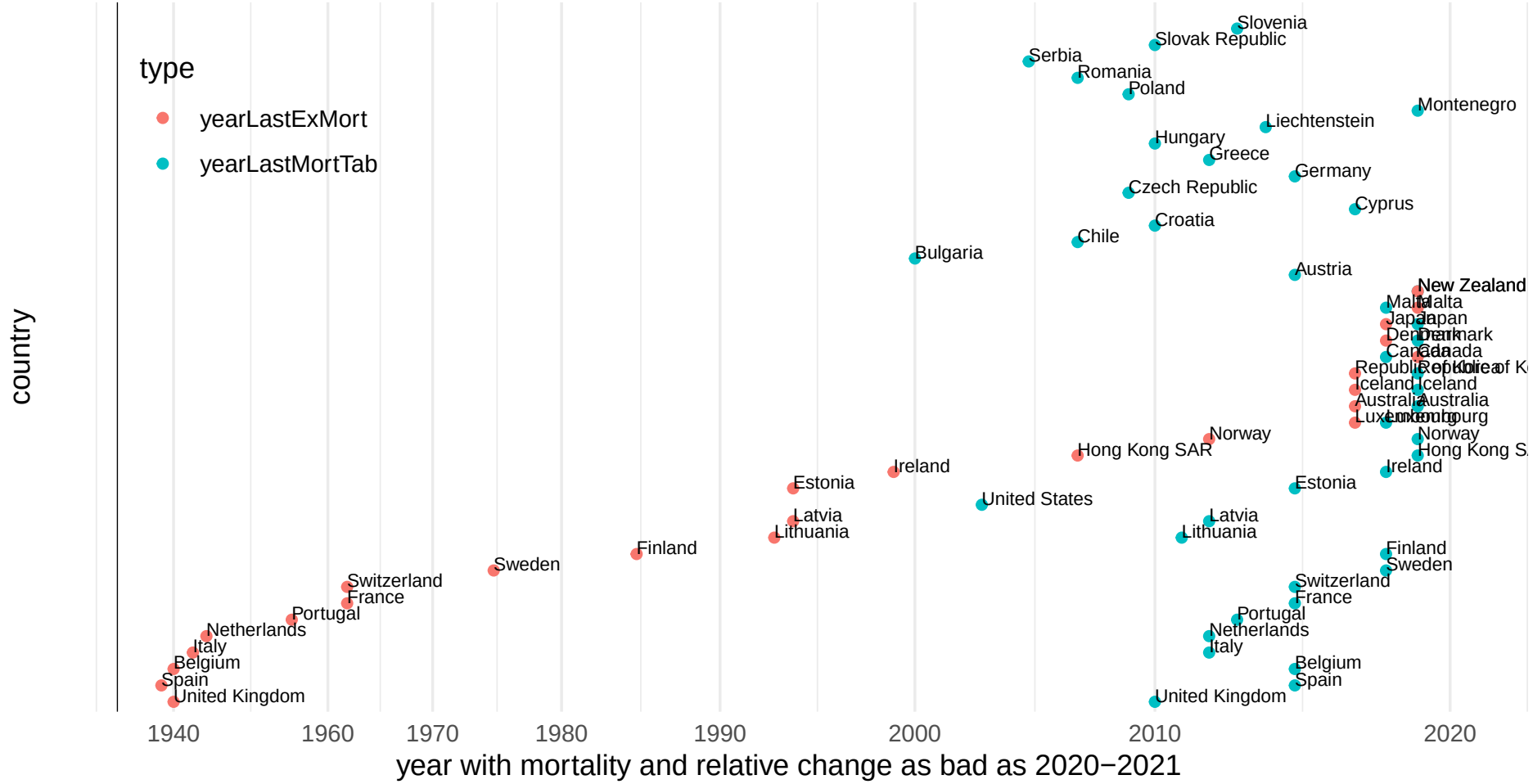


Figure: Which was historically the last year when (green) mortality rates underperformed 2020-2021 and (red) the relative change was as high as in 2020-2021?

Relative change by gender and age

1. We observed the relative change between 1991-2019 by gender: $corr(rc_{male}, rc_{female})$ falls in $(0.80, 0.89)$
2. We bucketed average observed mortalities from 2017-2019 by age and compared them with the 2020 and 2021 mortalities separately. (Calculated with exposure-to-risk.) - This has shown significant differences between cohorts.

		2020				2021			
	Age	BEL	CZE	FIN	USA	BEL	CZE	FIN	USA
	0-20	0.83	0.89	1.08	1.04	0.92	0.91	0.95	1.09
	21-40	0.99	1.02	1.00	1.24	0.99	1.07	0.90	1.40
M	41-60	1.04	1.03	1.03	1.18	1.00	1.21	0.99	1.32
	61-80	1.10	1.12	0.97	1.17	1.03	1.27	1.00	1.19
	81-100	1.15	1.17	0.97	1.15	0.98	1.18	0.99	1.10
	All males	1.11	1.12	0.98	1.17	1.00	1.23	0.99	1.19
	Age	BEL	CZE	FIN	USA	BEL	CZE	FIN	USA
	0-20	0.99	0.81	0.80	0.99	0.89	0.85	0.94	1.08
	21-40	0.91	1.10	1.01	1.19	1.05	1.25	0.99	1.37
F	41-60	0.99	1.06	0.94	1.14	0.95	1.20	0.97	1.28
	61-80	1.10	1.08	0.98	1.15	1.02	1.22	0.99	1.19
	81-100	1.15	1.11	0.98	1.15	0.93	1.10	0.99	1.08
	All females	1.12	1.10	0.98	1.15	0.96	1.15	0.99	1.15

Figure: Relative change by gender and age group in 2020-2021, relative to average mortalities in 2017-2019.

Excess mortality and Lee-Carter

- Calibration of LC: 1980-2019 mortalities
- Relative change observed for year 2020 compared to 2019
- $\hat{F}_g$ is the empirical distribution by Lee-Carter from $10,000$ scenarios for gender g

	AUS	BEL	CAN	CHL	FRATNP	DEUTNP	JPN	KOR	ESP	GBR_NP	USA
Female, observed excess mortality	-5.2%	15.3%	3.9%	9.2%	6.5%	2.3%	-4.3%	-1.9%	16.7%	11.1%	16.4%
Male, observed excess mortality	-4.2%	14.9%	5.3%	13.9%	7.9%	3.2%	-2.9%	-2.2%	15.7%	13.6%	18.0%
Female, quantiles from the LC model											
50%	-1.3%	-1.4%	-1.1%	-1.2%	-1.4%	-1.4%	-1.9%	-3.5%	-1.6%	-1.2%	-0.8%
75%	0.3%	0.3%	-0.2%	0.8%	0.5%	0.1%	-0.3%	-2.1%	0.3%	0.5%	0.1%
90%	1.9%	1.8%	0.6%	2.7%	2.2%	1.4%	1.2%	-0.9%	2.0%	2.0%	1.0%
95%	2.8%	2.7%	1.1%	3.9%	3.2%	2.3%	2.1%	-0.2%	3.2%	2.9%	1.6%
99%	4.5%	4.6%	2.0%	6.0%	5.3%	3.9%	3.7%	1.2%	5.1%	4.8%	2.5%
Male, quantiles from the LC model											
50%	-1.9%	-1.8%	-1.4%	-1.5%	-1.8%	-1.8%	-1.8%	-3.6%	-1.5%	-1.8%	-1.3%
75%	-0.4%	-0.5%	-0.4%	0.2%	-0.6%	-0.6%	-0.5%	-2.6%	0.0%	-0.6%	-0.5%
90%	0.9%	0.7%	0.4%	1.8%	0.5%	0.5%	0.7%	-1.8%	1.4%	0.5%	0.2%
95%	1.7%	1.5%	0.9%	2.7%	1.2%	1.1%	1.4%	-1.4%	2.3%	1.1%	0.6%
99%	3.1%	2.8%	1.9%	4.4%	2.4%	2.3%	2.8%	-0.4%	3.9%	2.4%	1.5%
Female, F^hat(x_real)	0.0517	1.0000	1.0000	0.9993	0.9969	0.9494	0.1547	0.7931	1.0000	1.0000	1.0000
Male, F^hat(x_real)	0.1271	1.0000	1.0000	1.0000	1.0000	0.9978	0.2756	0.8535	1.0000	1.0000	1.0000

A Model of C.H. Skiadas

The population's health state depending on age is characterized by a **stochastic process** $S(t)$:

$$S(t) = S(0) + \int_0^t \mu(s)ds + \int_0^t \sigma(s)dW(s)$$

Paths represent individuals, health changes with the age t. $S(0)$ is health at birth. Death occurs when the health state decreases below, say, 0. Therefore, we are interested in the **first hitting time** of 0 of an Ito process. Supposing $\sigma(s) = 1$, its density can be approximated as

$$g(0,t;c,0) = \frac{|c + (b-1)(lt)^b|}{\sqrt{2\pi t^3}} exp(-\frac{(c-(lt)^b)^2}{2t}),$$

where the parameters: the universal b, the birth year dependent $S(0) = c$ and the age cohort dependent l are linked by the **health state function**:

$$H(t) = E(S(t)) = \int_{t_0}^t \mu(s)ds = c - (lt)^b$$

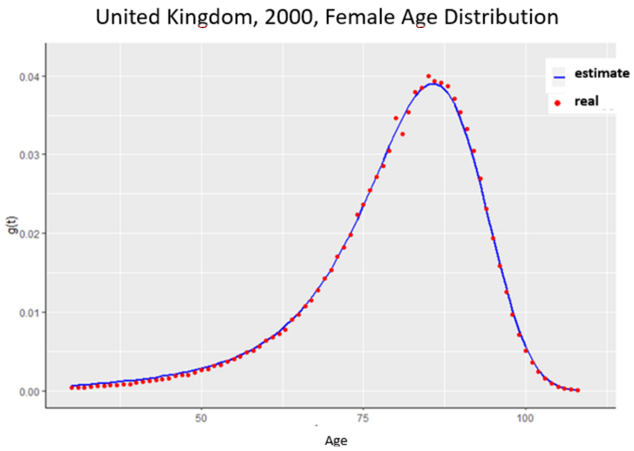
Our model differs that of Skiadas' in the birth year dependence of the initial health c.

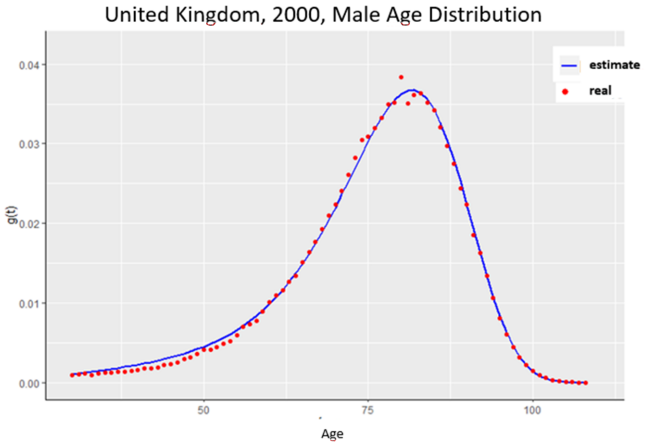
Maximum Likelihood Estimation in the Skiadas Model

For estimating the parameters for a given year

- Janssen and Skiadas use a **squared error minimizing iterative algorithm**
- Alternatively, we determined the more superior **maximum likelihood estimator**

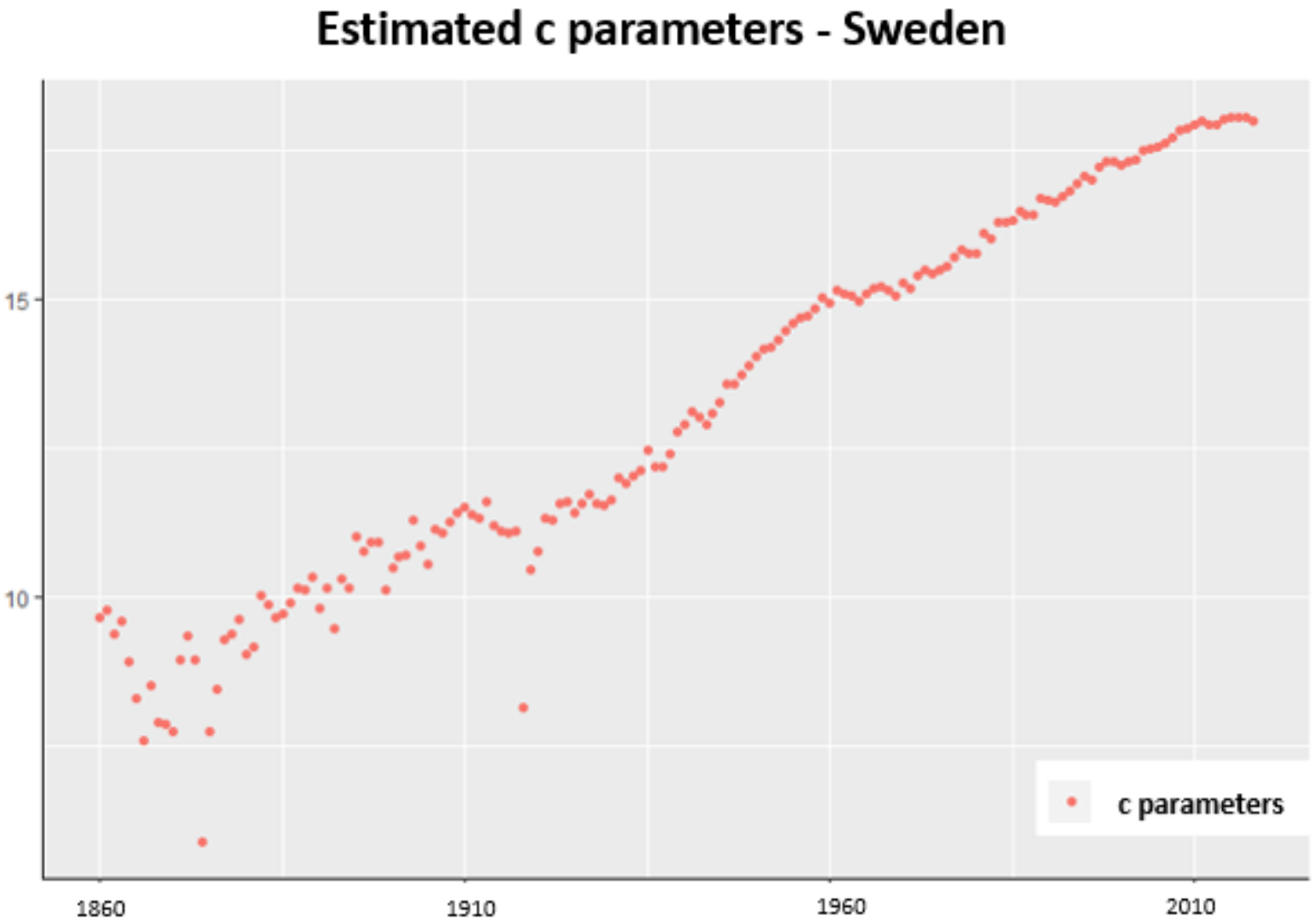
The obtained fit is spectacular:





Supposing available data for a set of consecutive calendar years and ages, the parameters b and l do not change with the years, unlike c. Thus, the parameters c_i characterize the effects specific to the i -th calendar year. For example, if there was a war or a serious epidemic, we would expect a lower value for c_i.

Parameter c in Sweden



The drop of the c parameter spectacularly signifies the Spanish flu's effect.

Reinsurance and longevity hedge

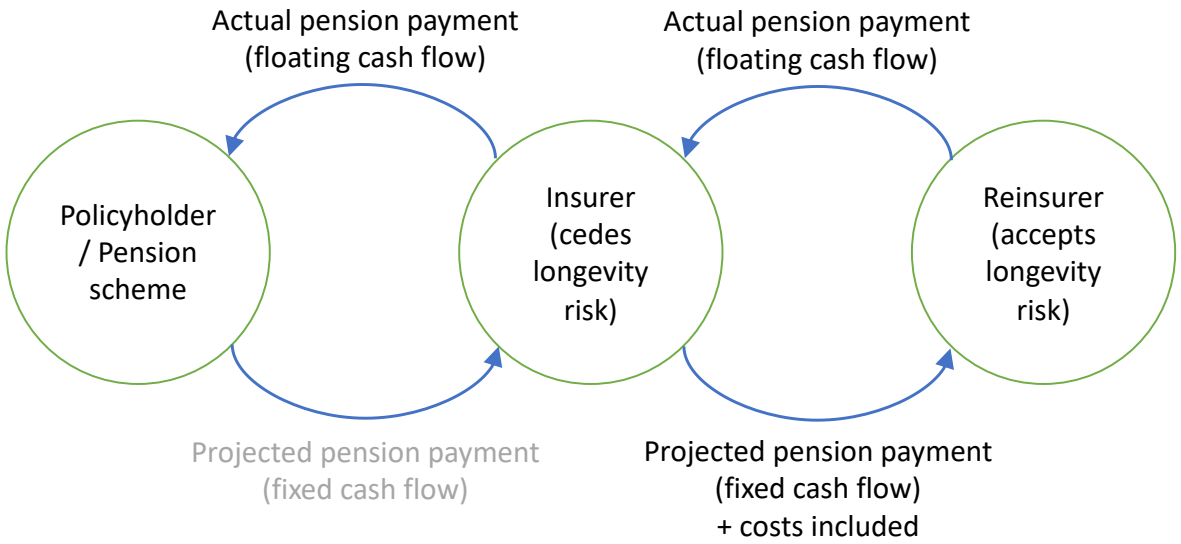


Figure: Basic structure and cash flows of a longevity swap

Reinsurance and longevity hedge

The net cash flows of the deal are determined by the realised and anticipated mortalities. We look at the longevity swaps of a reinsurer in multiple (m) countries simultaneously with 2 models:

1. Model 1: $\log m(x,t,c) = \log m(x,t-1,c) + \xi_c \; \forall c, \forall t > T$ with $(\xi_{c_1}, \ldots, \xi_{c_m})^\intercal \sim N(\underline{\mu}, \Sigma)$, where Σ is the covariance of the countries' error terms. Calibration is based on the historical log excess mortality (relative change) observations.
2. Model 2: Li-Lee model, an extension of Lee-Carter to multiple populations. $\log m(x,t,c) = \log m(x,T,c) + B(x)(K(t) - K(T)) + b(x,c)(k(t,c) - k(T,c))$. Calibration is based on each country's death rate history simultaneously. $B(x)K(t)$ is a common factor representing long-term trend and random fluctuations, $b(x,c)k(t,c)$ the short-term changes in population c.

where

1. $m_{x,t,c}$ = death rate of age x at time t in country c

Reinsurance and longevity hedge

Simulation of model 1:

- 100 policies between age 62-75, paying yearly 100 (similar in each country)
- 5000 mortality scenarios
- 2.5% fixed yearly reinsurance loading
- Year-end 2022 Dutch EIOPA curve for discounting

Variance of reinsurance profits:

- $(Var(A_1), \ldots, Var(A_m))\Sigma(1, \ldots, 1)^\intercal$ is a good estimation of the combined variance

Country	Variance Profit	Mean Profit	Var. (prof./fixed)	Mean (prof./fixed)
NOR	7,120,575	1,233	0.0004	0.009
USA	6,408,389	1,520	0.0005	0.013
HUN	5,483,999	4,224	0.0005	0.039
CZE	2,045,870	3,546	0.0001	0.030
Combined	41,509,865	10,522	0.0002	0.022

Table: Mean and variance of reinsurance profits

Reinsurance and longevity hedge

- The widely applied combined VaR estimation from individual VaRs and covariance (*) $\sqrt{\underline{VaR}^{\intercal}\Sigma\underline{VaR}}$ significantly misestimates the real VaR

Country	VaR-95%	VaR-99.5%
NOR	-3,276	-5,888
USA	-2,795	-5,209
HUN	294	-1,829
CZE	1,220	-219
Combined	-109	-6,444
Calc. from indiv. (*)	-4,777	-10,377

Table: Value-at-risk of reinsurance losses

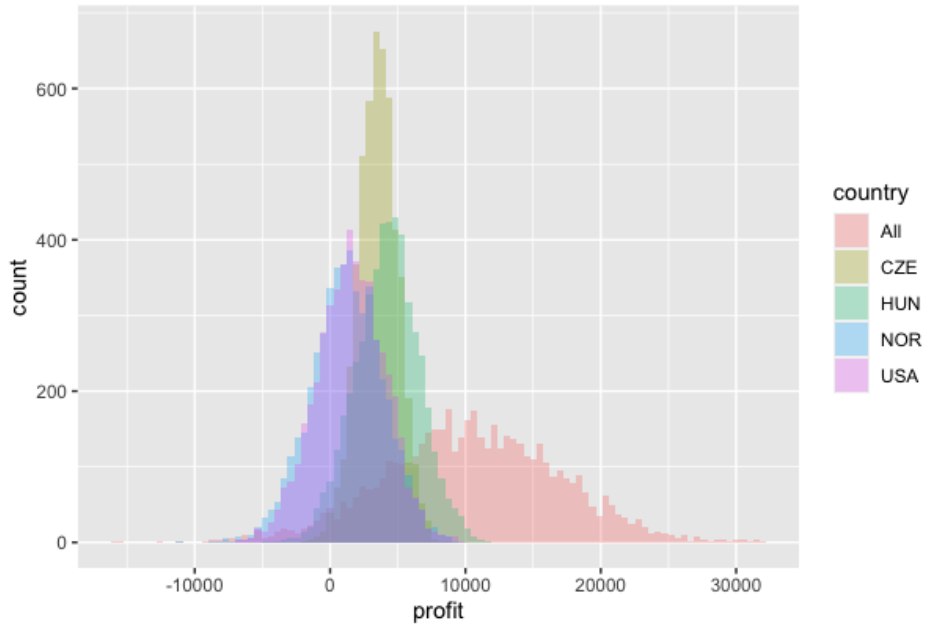


Figure: Histogram of reinsurance profits (5000 scenarios).

Reinsurance and longevity hedge

Simulation of model 2 (Li-Lee):

- As in model 1: 100 policies, age 62-75, paying yearly 100, 2000 mortality scenarios, 1.0% fixed yearly reinsurance loading, same discounting

Country	Variance Profit	Mean Profit	Var. (prof./fixed)	Mean (prof./fixed)
BEL	3,204,585	1,263	0.0002	0.0096
NLD	8,301,777	1,047	0.0005	0.0082
NOR	3,049,907	1,293	0.0002	0.0096
SWE	2,863,631	1,296	0.0002	0.0096
FRA	4,983,739	1,295	0.0003	0.0093
Combined	22,624,343	6,194	0.0001	0.0093

Table: Mean and variance of reinsurance profits

Reinsurance and longevity hedge

Country	VaR-95%	VaR-99.5%
BEL	-1,644	-3,081
NLD	-3,743	-6,425
NOR	-1,525	-3,131
SWE	-1,504	-2,845
FRATNP	-2,340	-4,237
Combined	-1,794	-5,476
Calc. from indiv. (*)	$\rho = -0.265$	$\rho = -0.187$

Table: Value-at-risk of reinsurance losses

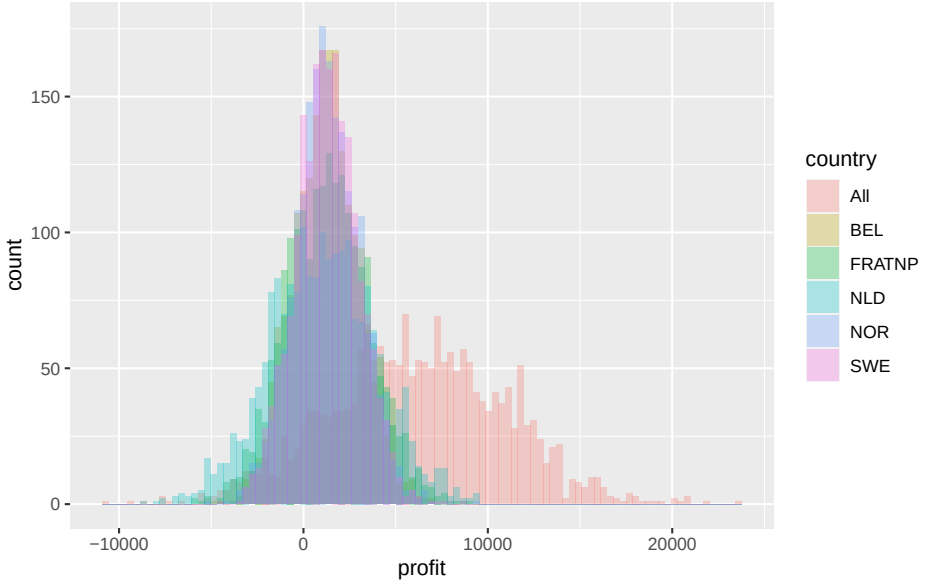


Figure: Histogram of reinsurance profits (2000 scenarios).

Conclusion

- We have seen:
  1. the relative change in mortalities and proximity measures,
  2. compared countries and looked at Lee-Carter's prediction as opposed to observed variance and,
  3. looked at a longevity hedge construction, related variance and value-at-risk of reinsurance profits.
- To explore:
  1. Why are the relative changes so different per age bucket, for instance, during a pandemic? (Not a typical actuarial question.)
  2. From reinsurance perspective, it is crucial that mortality trends vary per country and show dependency between countries. How improvements and deteriorations are linked together between insured populations of different regions?
  3. If mortalities improve/deteriorate in a single country, is it also true that the same happens to the insured population?

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