# CHANGES IN AGE PATTERNS OF MORTALITY DECLINE, THE IMPACT OF COVID-19, AND NOVEL FORECASTING METHODS

Péter Vékás, Ph.D. (Corvinus University of Budapest)

# Structure

1. **Changes in age patterns of mortality decline**
2. Measuring rotation
3. Modeling rotation

4. Impact of COVID-19 on rotation
5. Impact of COVID-19 on trend and volatility

6. Novel forecasting methods

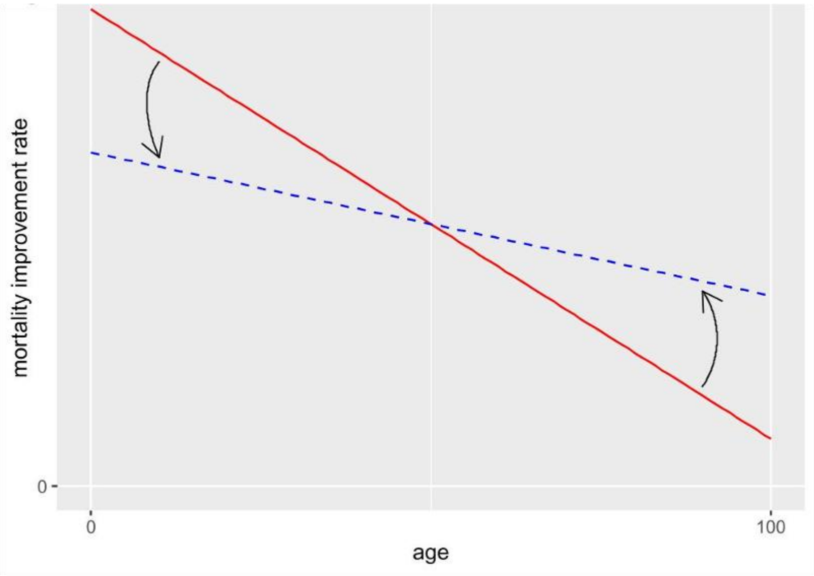
# Mortality improvement rates

- Mortality improvement rates ($m$: mortality rate, $x$: age, $t$: year, $c$: country, $g$: gender):

$$r_{xt}^{cg} = \ln m_{xt}^{cg} - \ln m_{x,t+1}^{cg}$$

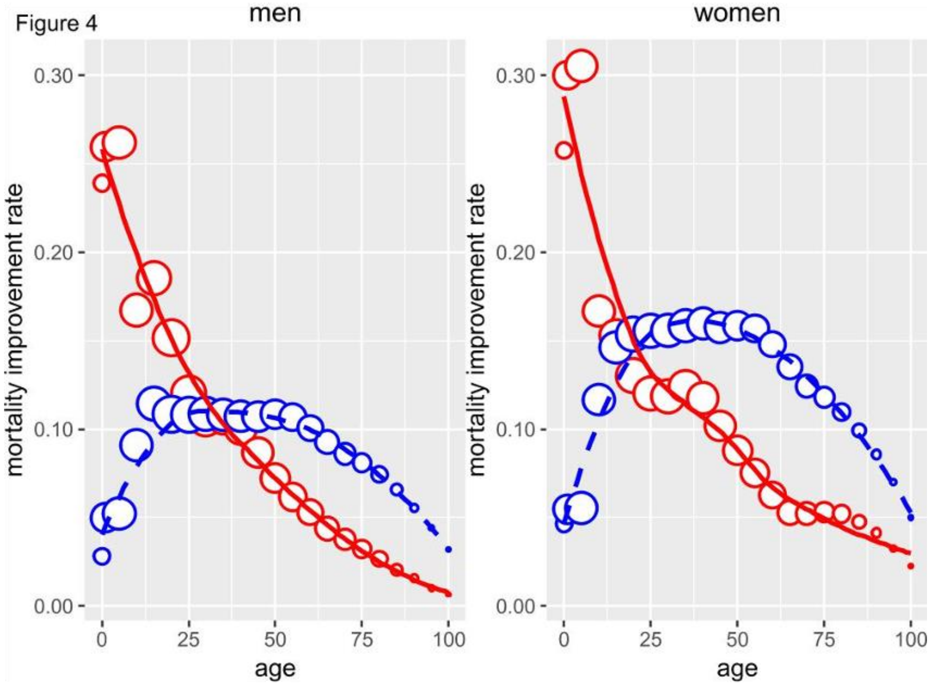
- These depend heavily on all four parameters.
- Higher for infants and children than for seniors.
- Typically decreasing in time for infants and children, and increasing in time for seniors.

# Rotation of mortality decline




- Decline tends to slow down in younger ages and speed up in older ages in the long run.
- Li, Lee and Gerland (2013) call this the ‘rotation’ of the age pattern of mortality decline.
- Observed mostly in developed countries.

# Example: Cyprus (1955 and 2015)



# Drivers of rotation

- Decline tapering off for infants and children:
  - Little room for improvement in vaccination rates (~100%)
  - Death due to child starvation largely eliminated
  - Premature infant incubators
  - Improved sanitation, access to clean water, better care during pregnancy and childbirth
  - Decrease in infant mortality in Hungary between 1950 and 2020: by factor of 27
- Accelerating decline for seniors:
  - Progress in treating chronic diseases
  - Advancements in surgical techniques and costly medical technology

# Rotation in the literature

- Kannisto et al. (1994): accelerating mortality decline in ages 80 to 99 between 1950 and 1989 in 27 countries.
- Horiuchi and Wilmoth (1995): rotation in Sweden.
- Lee and Miller (2001): comparison of average rates of mortality decline by age in 1st and 2nd halves of 20th century.
- Carter and Prskawetz (2001): Lee–Carter models on Austrian data using sliding time windows.
- Rau et al. (2008) and Christensen et al. (2009): acceleration of mortality decline in ages 80+ since 1950 in some countries out of 30.
- Vékás (2020): measure of rotation, evidence for rotation since 1950 in several EU countries.

# Practical significance

- Differences between rotated and unrotated forecasts: minor in short run, but huge in long run!
- Ignoring rotation leads to underestimation of old-aged population and overestimation of young-aged population.
- This exacerbates longevity risk in life insurance, pensions and social security.
- For long-term forecasts, assessing rotation is crucial.
- If present, it should be modeled appropriately.

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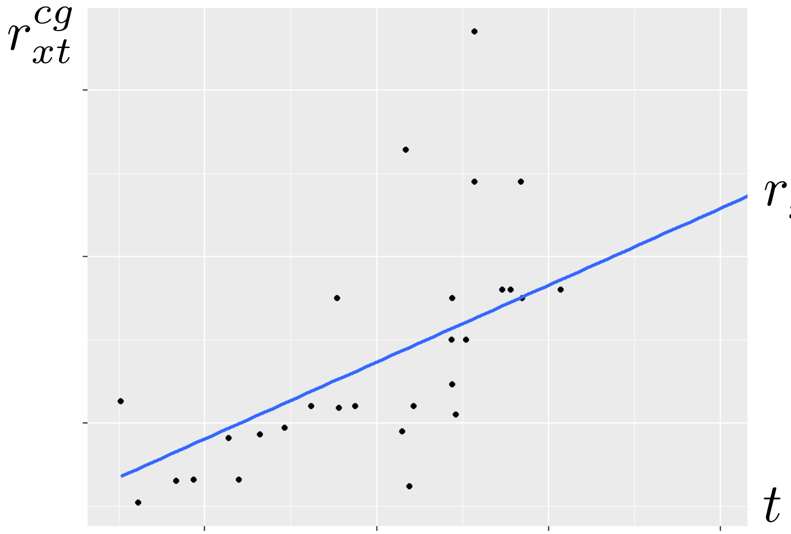
# Measuring rotation (Vékás, 2020)

- Acceleration rate: slope of linear trend of mortality improvement rates



$$r_{xt}^{cg} = \alpha_x^{cg} + \beta_x^{cg} t + \varepsilon_{xt}^{cg}$$

# Measuring rotation (Vékás, 2020)

- $\rho$ measure of rotation:

  Spearman's $\rho$ rank correlation coefficient between acceleration and age, weighted by population counts

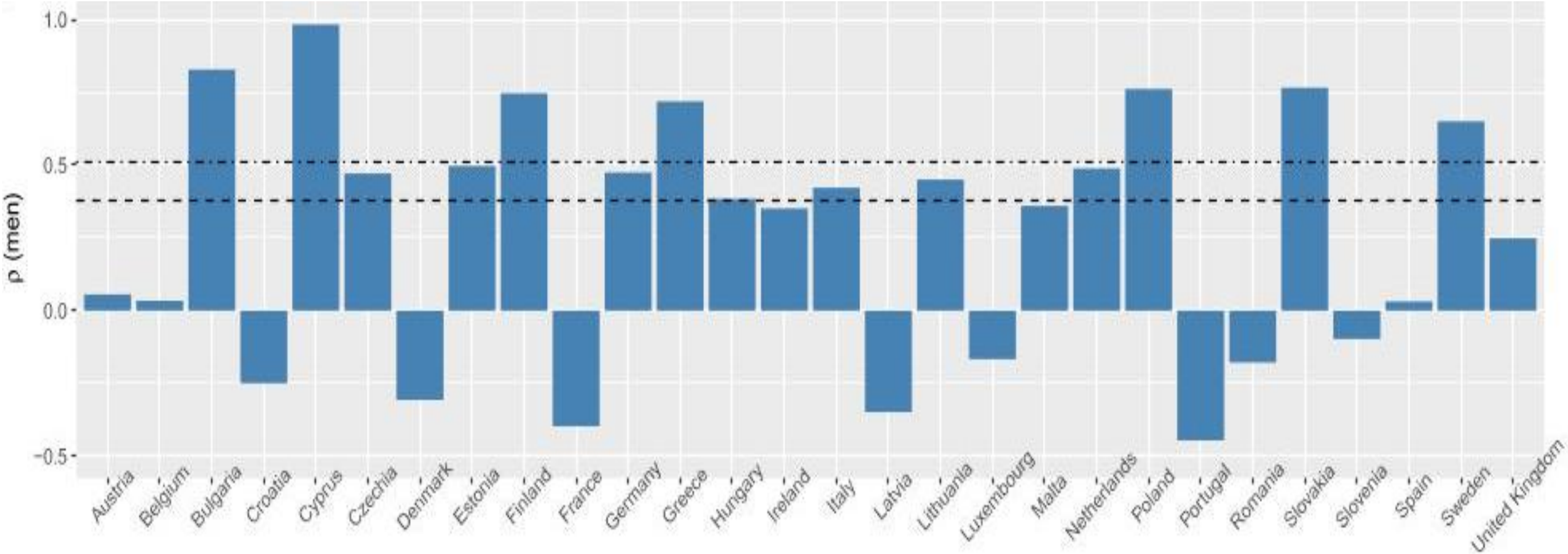
- $\rho = 1$ if and only if acceleration is a strictly increasing function of age
- *t* test of rotation:

  $H_0$: $\rho = 0$

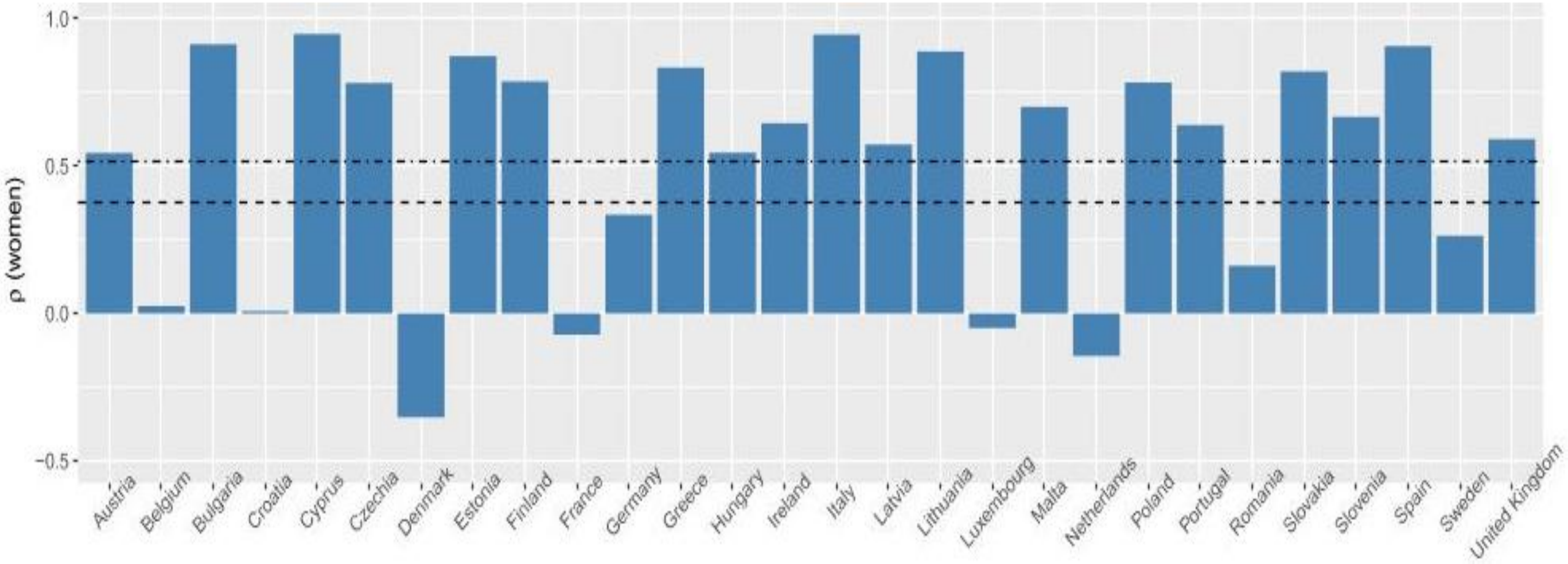
# Rotation in EU – Data

- UN World Population Prospects 2017,  28 European Union member states
- Mortality rates, life expectancies at birth and population counts
- 22 age groups
- Separately by gender
- 13 periods (1950−1955 up to 2010−2015)

# Rotation in EU – Results (men)



# Rotation in EU – Results (women)



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# Lee−Carter model including rotation

- Original Lee−Carter (1992) model:

$$\ln m_{xt} = a_x + b_x k_t + \varepsilon_{xt}$$

- As $k_t$ declines over time, coefficients $b_x$ determine rates of improvement by age. These are independent of time!
- Model variant of Li, Lee and Gerland (2013) including rotation, used by UN in long-term projections:

$$\ln m_{xt} = a_x + B(x,t)k_t + \varepsilon_{xt}$$

- Improvement rates are weighted means of initial (from LC model) and hypothetical limiting values:

$$B(x,t) = (1 - w_s(t))b_0(x) + w_s(t)b_u(x)$$

# Lee−Carter model with rotation

- „Raw” weights increase linearly from 0 to 1 after LC period life expectancy at birth reaches a hypothetical threshold until it reaches a hypothetical maximum:

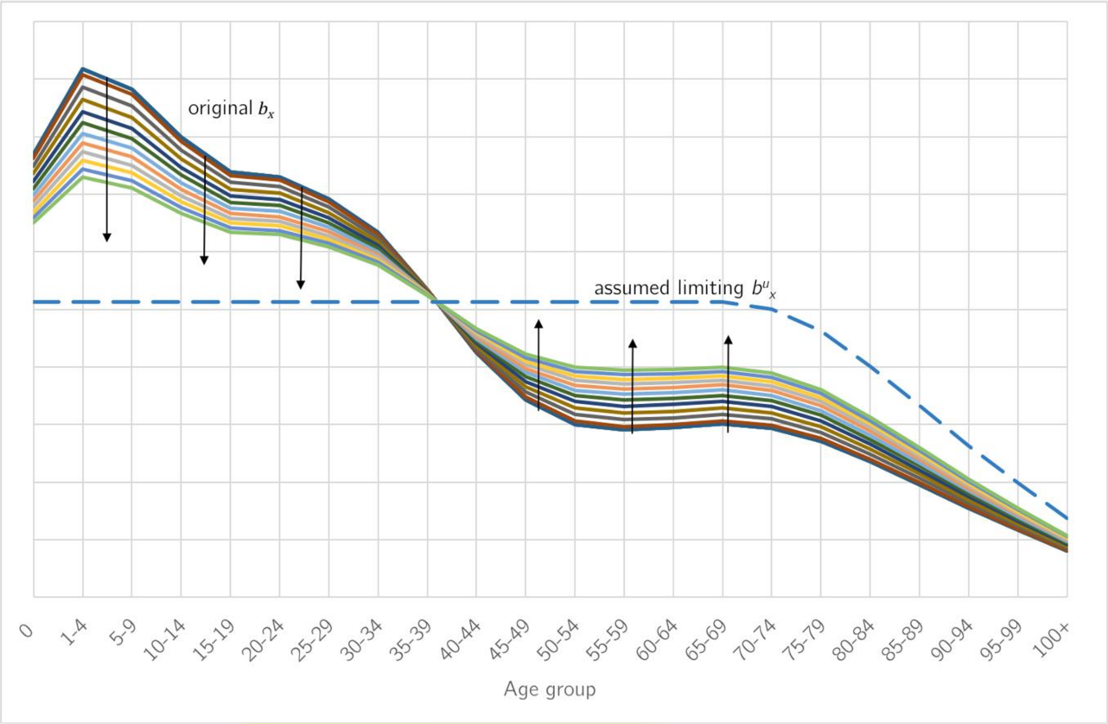
$$w(t) = \frac{e_0(t) - e_0^{start}}{e_0^u - e_0^{start}}$$

- “Smooth” weights computed from “raw” weights (zero if life expectancy at birth is below 80 years), and exponent *p* governs speed of rotation:

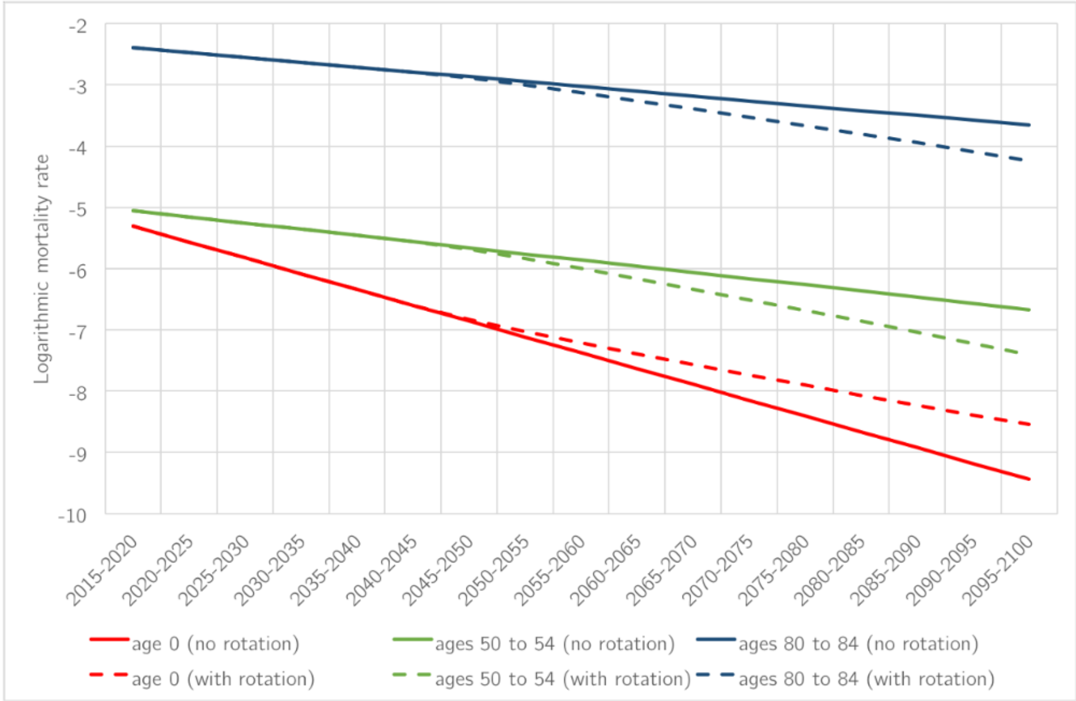
$$w_s(t) = \left\{0.5\left[1 + \sin\left[\frac{\pi}{2}(2w(t) - 1)\right]\right]\right\}^p$$

- Two hyperparameters not optimized by authors: they assume threshold $e_0^{start} = 80$ years and exponent $p = 0.5$.

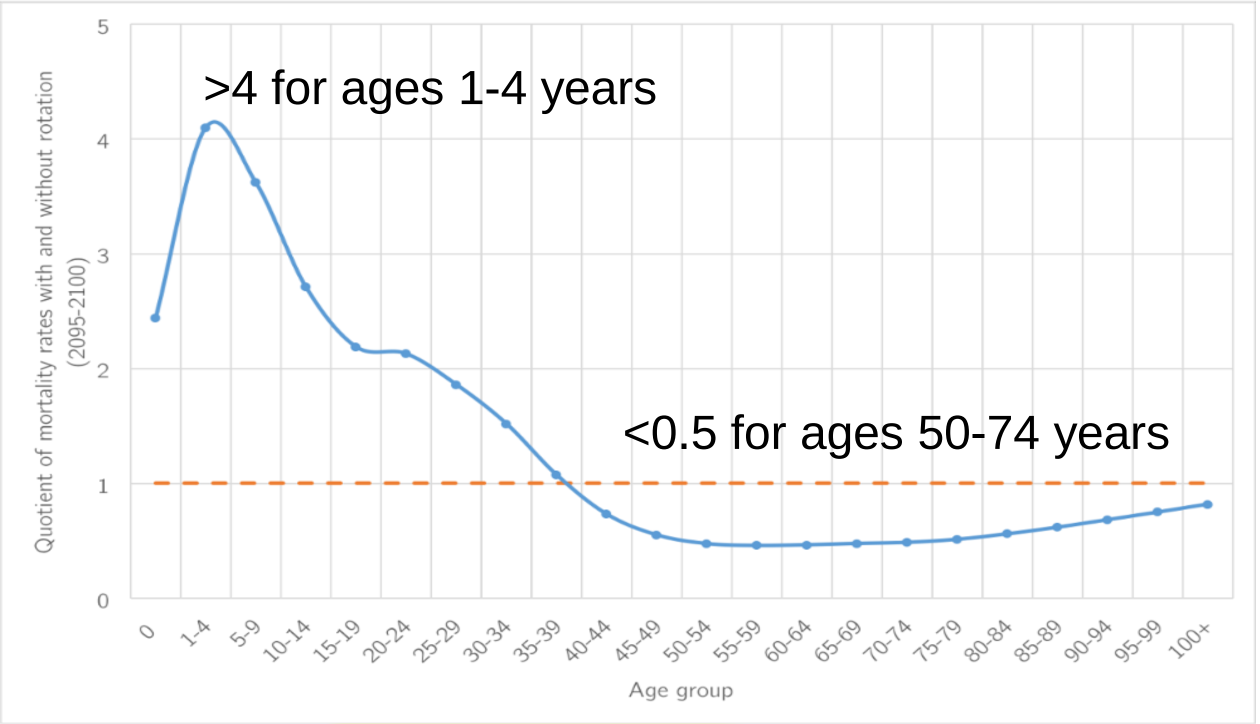
# Rotation of B(x,t)



# Rotated and unrotated forecasts



# Rotated/unrotated forecasts in 2100



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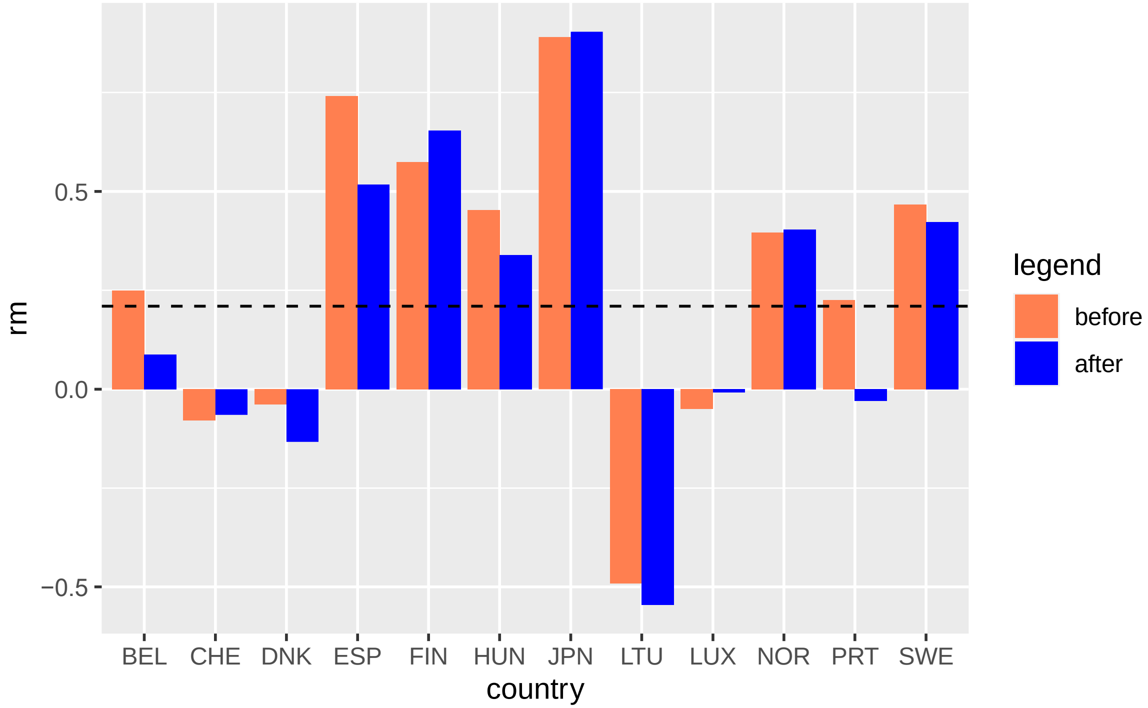
# Impact of COVID-19 on rotation

- The pandemic has changed the picture significantly since it emerged in early 2020.
- Seniors were more susceptible to die, which has moderated rotation.
- Impact of COVID-19 assessed by comparing rotation measures including and excluding data from 2020 (and 2021, if available).
- Mortality data still scarce for 2022.

# Impact of COVID-19 on rotation – Data

- Human Mortality Database (www.mortality.org)
- Mortality rates and population counts from all 42 countries
- 1x1 data from 1950 up to last available year
- Ages 0 to 100 years
- Separately for males and females

# Impact – men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before
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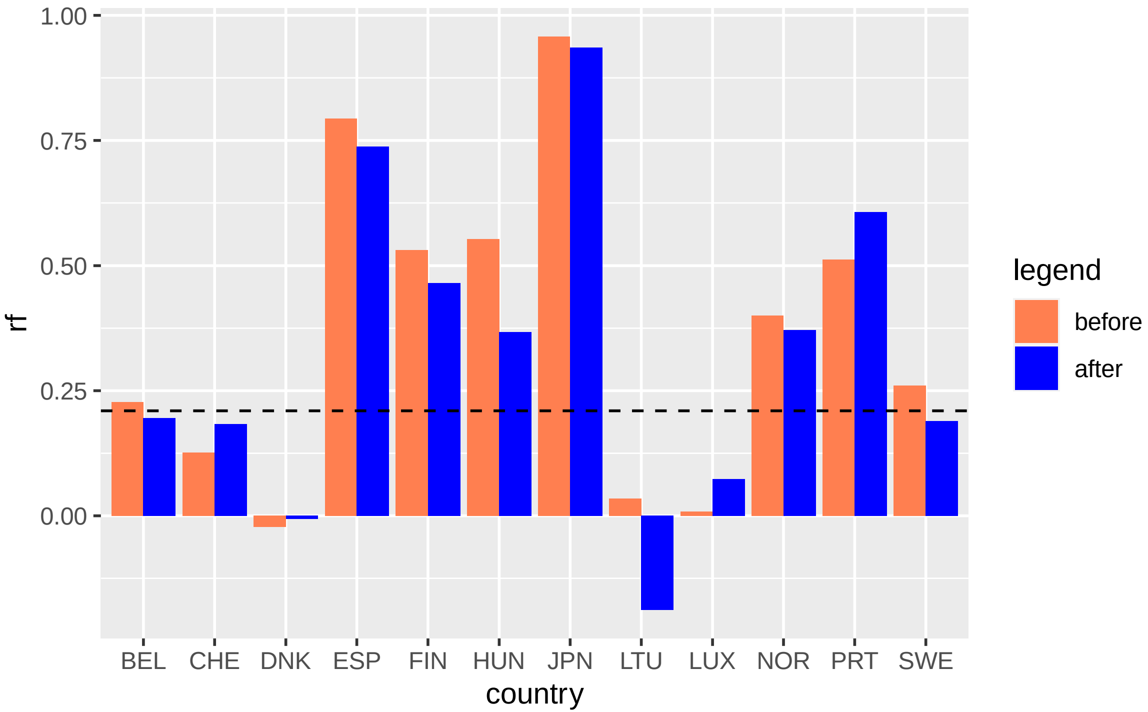
# Impact – women



# Mean rotation including and excluding 2020

| Period | Male | Female | Total |
|---|---|---|---|
| 1950 to 2019 | 0.28 | 0.37 | 0.32 |
| 1950 to 2020 | 0.21 | 0.33 | 0.27 |

# Rotation has taken a hit

- COVID has decreased rotation for males in 5 out of 8, and for females in 7 out of 8 countries where there had been significant rotation.
- It has completely wiped out trends of 70 years in some countries!
- As seen earlier, rotation strongly impacts long-term forecasts. Even minor changes lead to huge differences in long run!
- Important to be aware of and consider options to model COVID-19.

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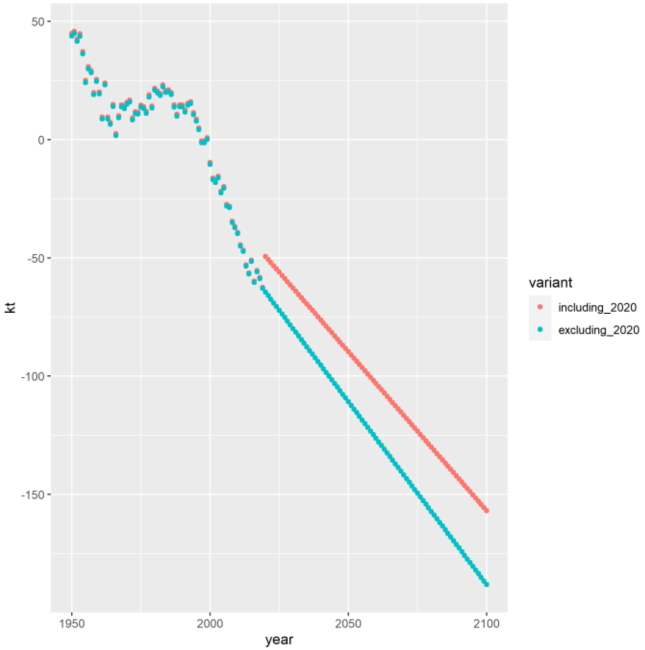
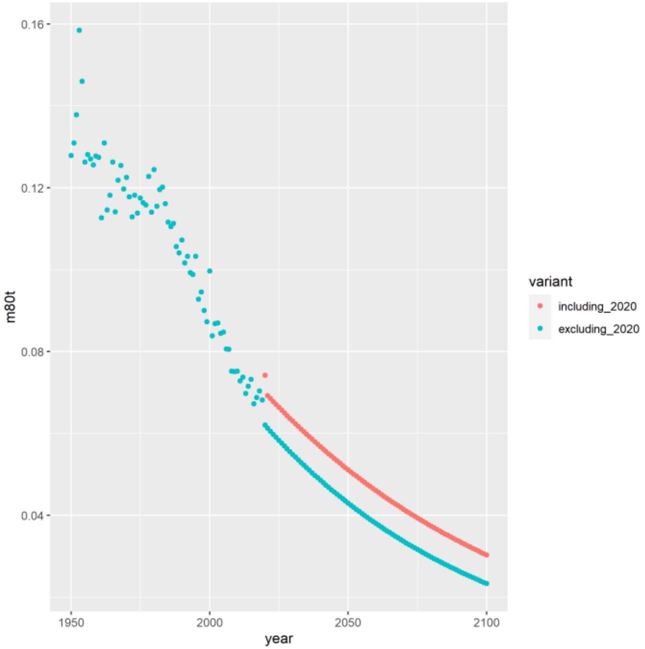
# How (not) to incorporate data from COVID years into forecasts?

1. Treat them as outliers
   - Remove them from training data (use years only up to 2019)
   - Add dummy variables representing years of COVID-19 to time series forecasting model: how Lee and Carter (1992) handled Spanish flu
   - Leave them in training data, but remove COVID-19 deaths
2. Treat them as meaningful
   - Leave them as they are
   - Assume (e.g., exponential) decay of shock

# Impact of inclusion vs exclusion of 2020 on $k_t$ in Hungary



# Impact of inclusion vs exclusion of 2020 on $m_{80t}$ in Hungary



# Impact of inclusion vs exclusion of 2020 on mortality

- Death rate of 80-year-olds only **9%** higher in 2020 than in 2019.
- Yet due to cumulative behavior, LC forecasts it to be **30%** higher in 2100 if including COVID year 2020 in training period.
- No data for 2021 yet: joint impact of 2020 and 2021 will be even **much higher**!

- Conclusion: long-term mortality forecasts **extremely sensitive** to how we handle COVID years.
- Pricing of products affected by mortality risk **extremely sensitive** to how we handle COVID years.

# Impact of inclusion vs exclusion of 2020 on longevity

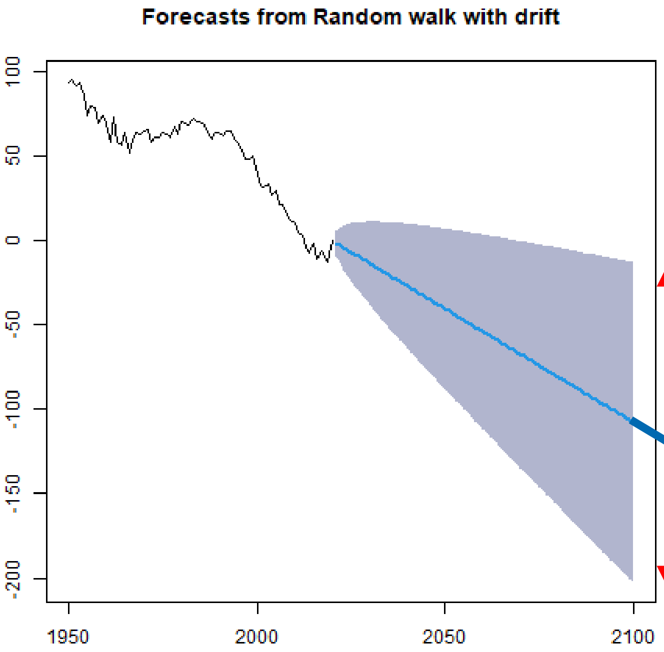
- Cohort life expectancy at age 65 is 18.4 years if excluding and 17.5 years if including 2020 in training data.
- Difference: **0.9 years, or 5%**.
- No data for 2021 yet: joint impact of 2020 and 2021 will be **much higher**!

- Conclusion: Pricing of products affected by longevity risk **fairly sensitive** to how we treat COVID years.

# How (not) to incorporate data from COVID years into forecasts?

- Removing COVID years: more prudent for annuities and pensions.
- Including them: more prudent for term life and endowment products.
- Milliman White Paper (September 2023): Impact of COVID-19 on best estimate mortality assumptions
  - Replacing 2020 mortality by average of previous $N$ years
  - Jump process in model of $k_t$ (Chen and Cox, 2009)
  - Subjective weighting of years (UK CMI: 2020/21: 0%, 2022: 25%).

# Slope and volatility of forecasts




$$k_t = k_{t-1} + \theta + \sigma\varepsilon_t$$

$$\varepsilon_t \sim \mathcal{N}(0,1)$$

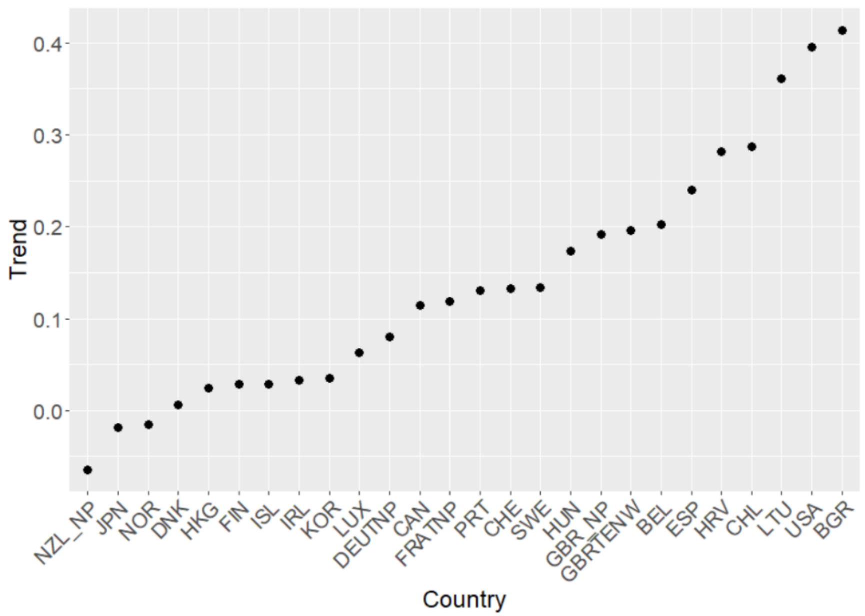
volatility proportional to $\sigma$

slope $\theta$

(slope of $\ln m_{xt}$: $b_x\theta$)

# Impact of excluding 2020 on slope by country

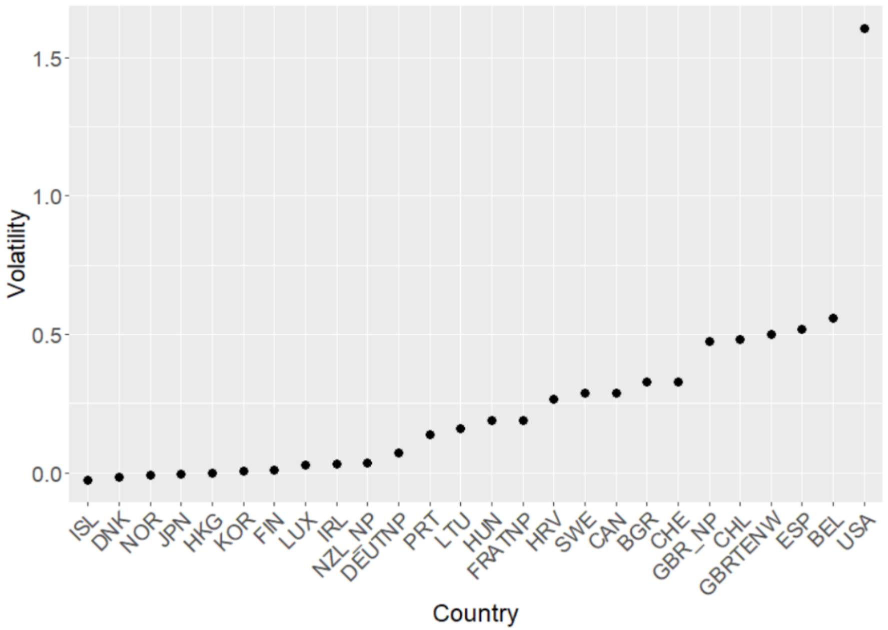
FIGURE 4: TREND RELATIVE DIFFERENCES BETWEEN THE TWO STEPS




Source: Auter et al. (2023). Milliman White Paper.

# Impact of excluding 2020 on volatility by country

FIGURE 5: VOLATILITY RELATIVE DIFFERENCES BETWEEN THE TWO STEPS




Source: Auter et al. (2023). Milliman White Paper.

# How (not) to incorporate data from COVID years into forecasts?

- Trend and volatility most affected by excluding 2020 in countries with high deaths tolls.

- Unexplored long-term impact:
  - Mutations,
  - Long COVID.

- Epidemiologists can hopefully keep providing updated assumptions.

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6. **Novel forecasting methods (ongoing joint work with László Kovács and Ronald Richman)**

# Applications of AI in actuarial work

- Mortality forecasting
- Reserve calculations
- Lapse models
- Non-life premium calculation
- Fraud detection
- Underwriting
- etc.

# AI for mortality forecasting

- Recurrent neural networks (Richman and Wüthrich, 2019)
- Feedforward neural networks for multiple populations (Richman and Wüthrich, 2021)
- Lee−Carter + Long-Short Term Memory networks (Nigri et al., 2019)
- Bootstrap confidence intervals for LC-LSTM (Marino, Levantesi and Nigri, 2021)
- Convolutional neural networks (Perla et al., 2021, Schnürch and Korn, 2022)
- Tree-based models (Levantesi and Pizzorusso, 2019, Levantesi and Nigri, 2020)
- etc.

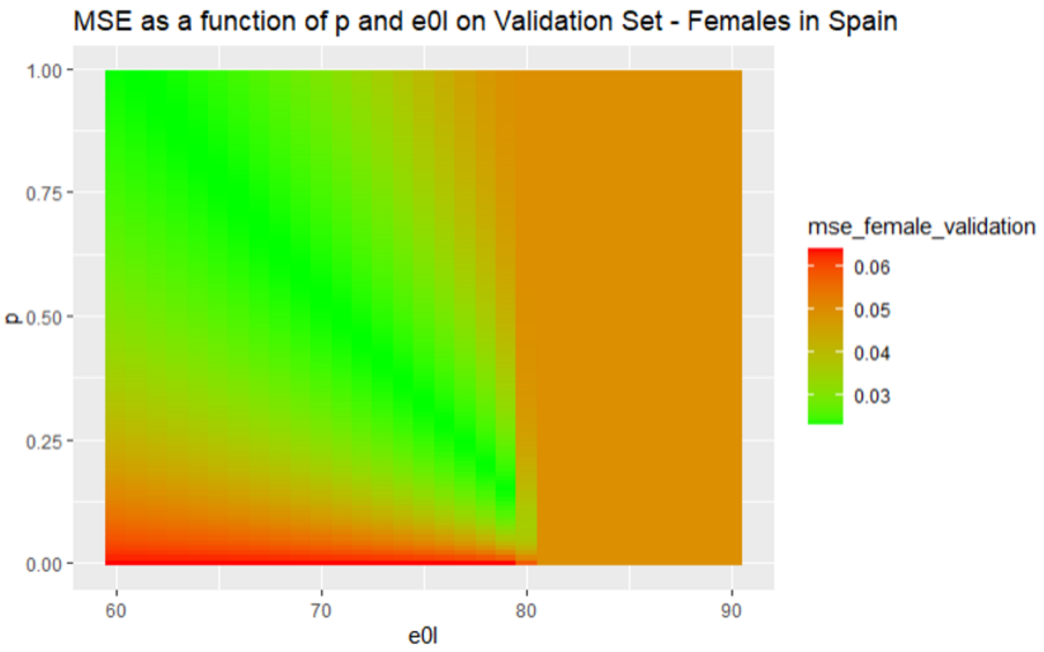
# AI methods to capture long-term rotation

- Kovács, L., Richman, R. and Vékás, P.: AI in Longevity Risk Management – Improved Long-Term Forecasts by Machine Learning (coming soon).
- Sponsored by AFIR-ERM section of IAA.
- Four methods proposed:
  - Hyperparameter tuning of LC model including rotation,
  - Generalized additive model on LC residuals,
  - Deep feedforward neural network,
  - Stacking ensemble of previous three.

# Demographic data

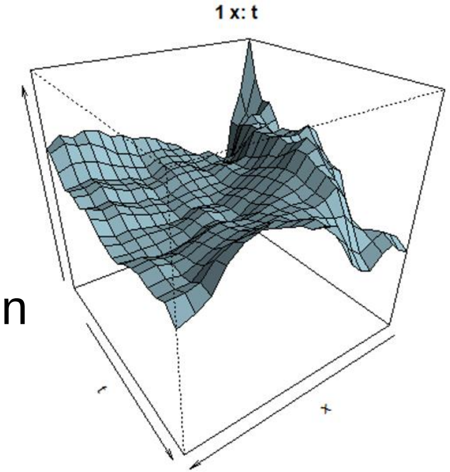
- Data from Human Mortality Database (HMD) for 38 countries for 1950-2018
- Training, validation and test periods:
  - Train: 1950-1990
  - Validation: 1990-1999
  - Test: 2000-2018
- Models fit in two rounds:
  - Fit on Train and test on Validation – hyperparameter tuning
  - Fit best models on Train + Validation and test on Test – measuring out-of-sample performance

# Hyperparameter tuning of rotated LC model



# GAM on LC residuals

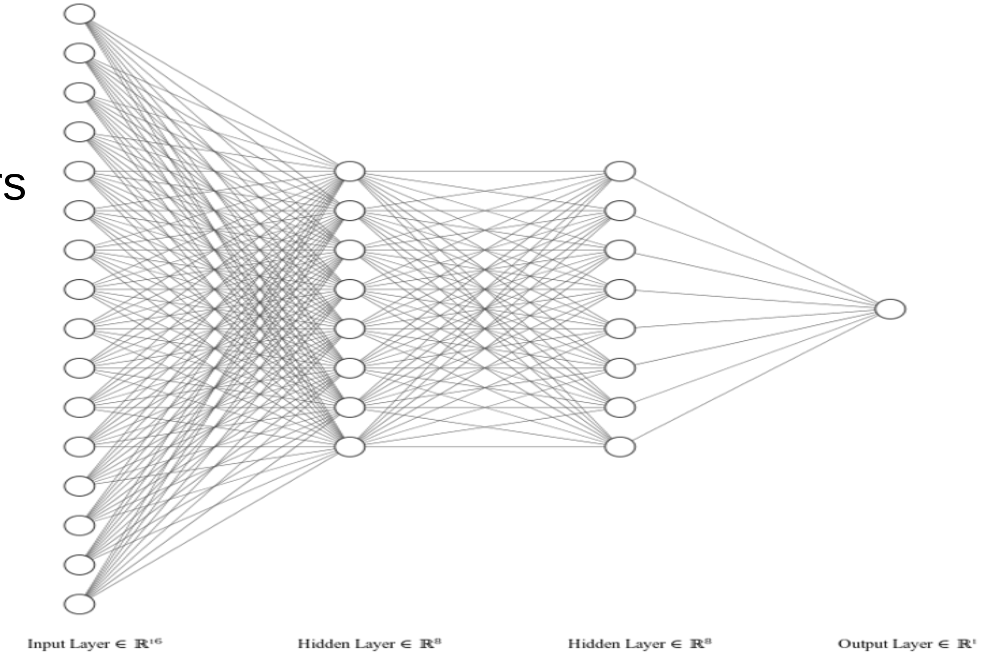
- LC residuals are not IID if there is rotation.
- We can extract meaningful information from them by fitting bivariate spline functions (piecewise polynomials) of *x* and *t* to them.
- Hyperparameters: number of knots of splines, and spline fitting method (several available in *mgcv* package of R).



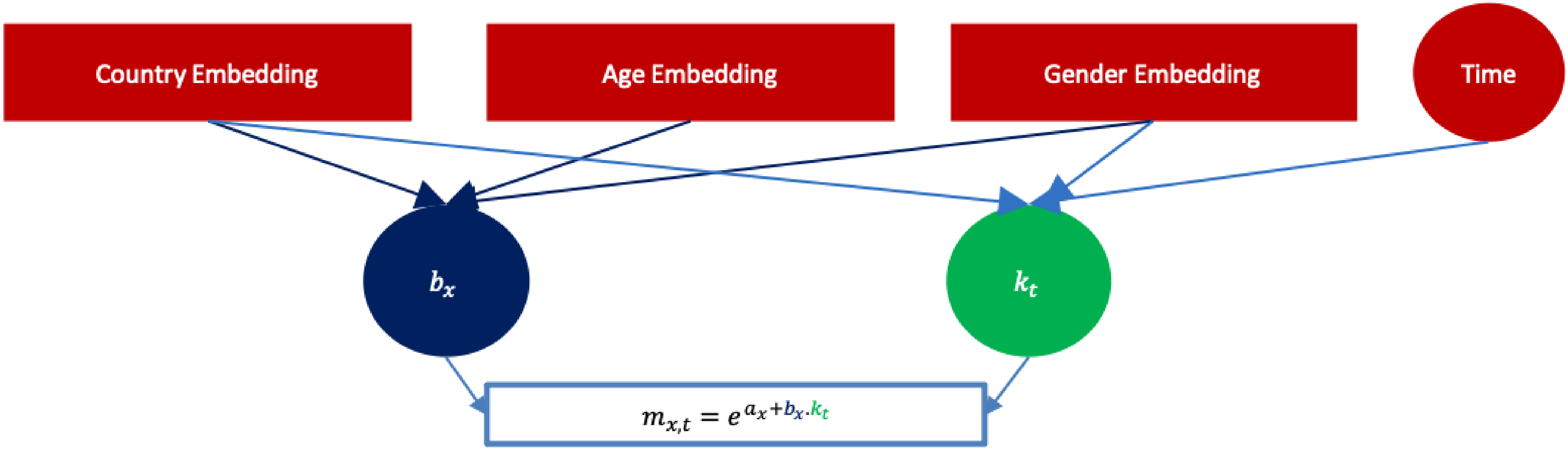

$h(x, t)$ fitted on
Spanish female population

# Deep feedforward network

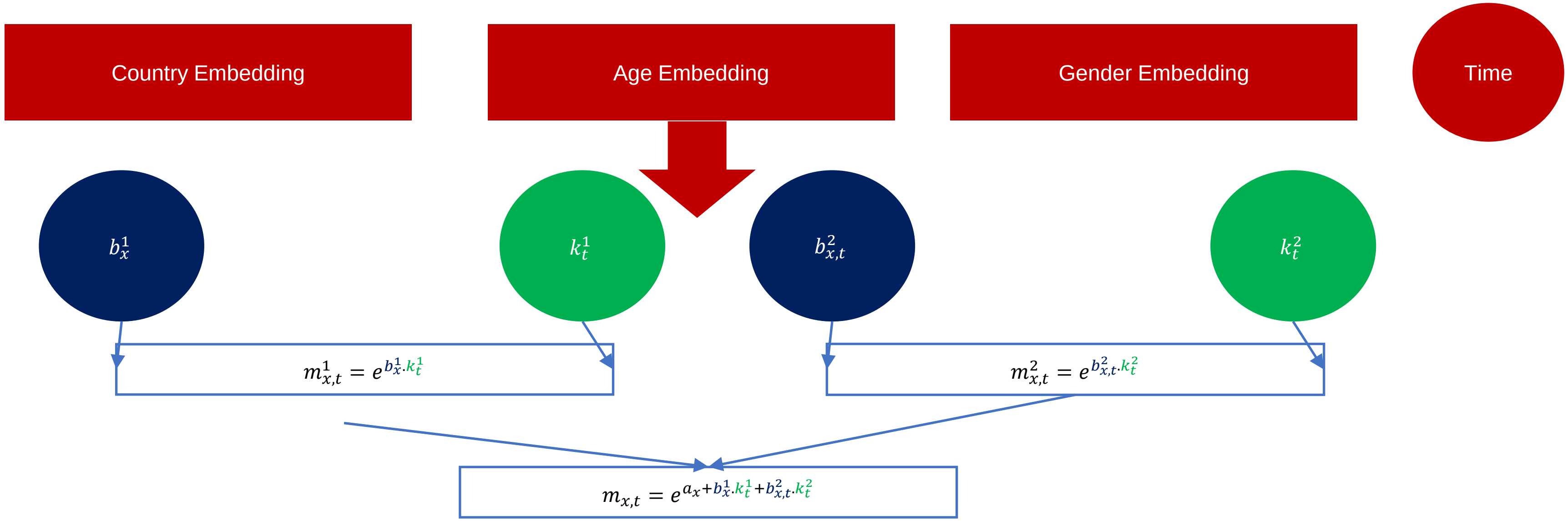
- Inputs: country, gender, age embeddings, and year (numeric)
- Outputs: parameters of LC model (hypernetwork: outputs parameters of another model)
- Boosting: adding second network that captures rotation



# Basic LC network



# Boosted LC network



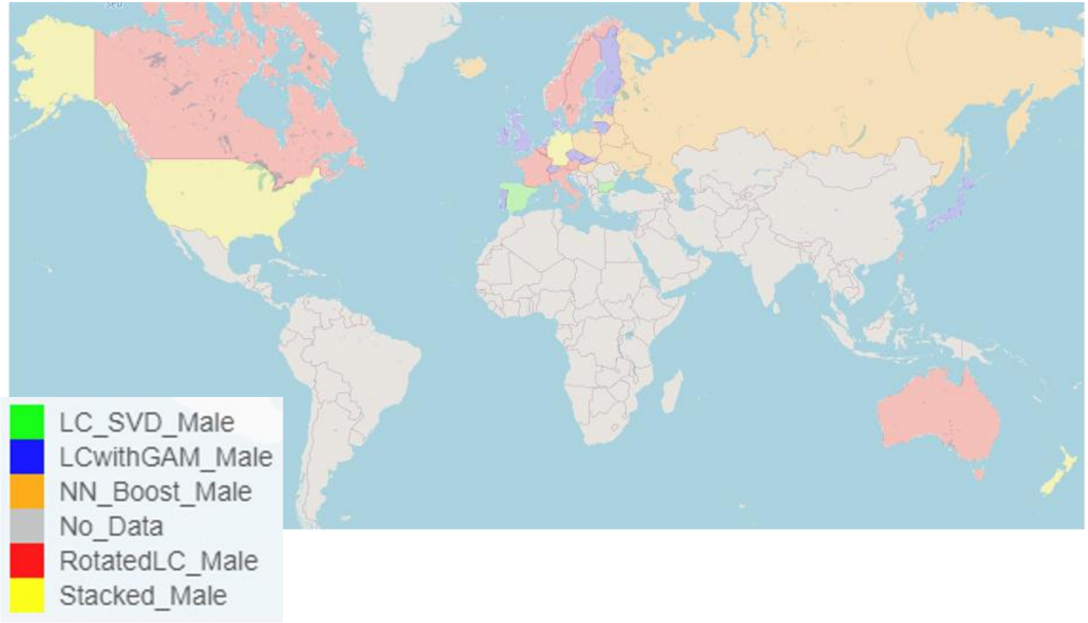
# Stacking

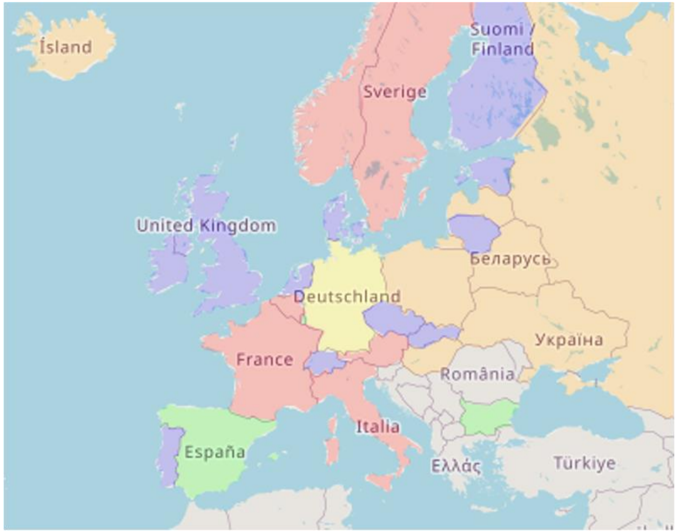
- Simple unweighted average of predictions of other three models (robust ensemble, Jose and Winkler, 2008).

# Number of wins by method and gender

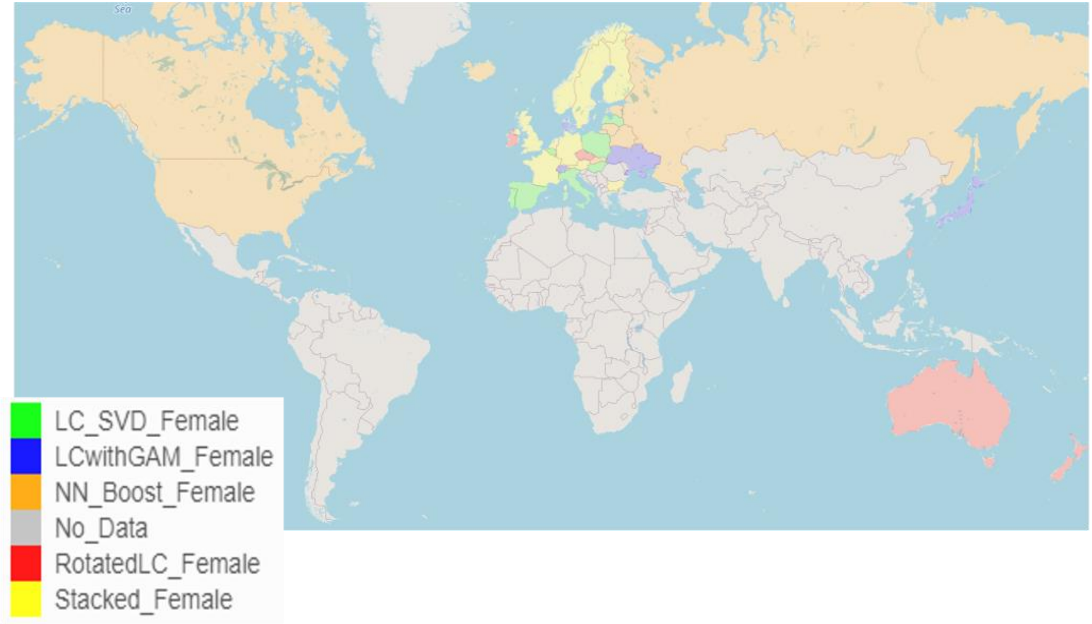
| Method | Female | Male | Total |
|---|---|---|---|
| Vanilla LC | 7 | 3 | 10 |
| Rotated LC | 7 | 9 | 16 |
| LC-GAM | 4 | **14** | **18** |
| LC-ANN (boosted) | 9 | 7 | 16 |
| Stacking | **11** | 5 | 16 |
| Total | 38 | 38 | 76 |

# Best models for males



# Best models for females




# Takeaways

- Mortality improvement shifting from younger to older ages (rotation).
- This significantly affects long-term forecasts and increases longevity risk.
- Lee−Carter ignores this and can thus be very inaccurate in long run.
- Rotation should be assessed before picking a forecasting method.
- COVID-19 makes long-term forecasts go haywire (age pattern of decline, slope and volatility!).
- Several ways to (or not to) incorporate it into forecasts.
- New AI methods capturing rotation can greatly outperform LC.
- Various techniques work best for different countries.

Thank you for your attention!

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