

The Gender Mortality Gap: Unlocking Future Patterns via Neural Network Models

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- 1 Motivation
- 2 Aim and methodological framework
- 3 Gender Mortality Gap: stylized evidence over the past
- 4 Gender Mortality Gap: long-term trends
- 5 References

Gender gap in mortality: motivation

- Differences in the survival prospects between genders.
- Demographic transition and healthy ageing:
 - greater longevity and morbidity risks for women than for men,
 - different needs in silver ages.
- Gender patterning of COVID-19 pandemic:
 - *gender health paradox*,
 - economic and health inequalities between men and women.
- Our focus: gender mortality gap patterns over time and over age.

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Step 1

Stylized evidence on the peculiar **age pattern** of the gender gap in mortality.

→ verified in both COVID-19 and non COVID-19 times.

Based on: *G. Apicella, E Navarro, P Requena, M Sibillo, The age pattern of the gender gap in mortality: stylized evidence across COVID-19 pandemic times. Annals Oper. Res. (2024).*

Our methodological approach

Literature

Graduation methods applied to raw mortality rates: → smooth change of mortality rates over age and preservation of the underlying pattern:

- mortality laws;
- non-parametric graduation methods, such as splines.

Our method

Cubic spline functions for sex-specific crude mortality rates;

- ages: 1-99;
- years: 2018-19, 2020, 2021;
- countries: France, Italy and Spain (data from Eurostat).

Measures of mortality

Crude mortality rates

$$\hat{q}_{x,t} = \frac{\theta_{x,t}}{E_{x,t}} \quad (1)$$

$\theta_{x,t}$: observed number of deaths, $E_{x,t}$: initial exposure to risk.

- $\hat{q}_{x,t}$ is an unbiased estimate of the probability $q_{x,t}$, that is the actual mortality rate at age x and period t ,
- It is based on raw data $\rightarrow$ randomness of stochastic mortality $\rightarrow$ irregular pattern,
- $y_{x,t} = \log \hat{q}_{x,t}$.

Graduated mortality rates

It can be assumed that there is an **unknown functional relationship** between the mortality rate and the age x :

$$y_{x,t} = s_t(x) + \epsilon,$$

where ϵ is a random error variable, with zero mean and σ^2 variance.

- The $s(x)$ function could be a formula such as Gompertz and Makeham laws. Alternatively, it could be based on splines (piecewise polynomial functions).
- Trade-off between fit and roughness, tuning parameters:
 - degree of the underlying polynomials (3),
 - choice of basis functions (B-Spline basis of degree 3),
 - number of inner knots (9).

Gender Gap Ratio (GGR)

$\tilde{y}_{x,t}$: graduated logarithmic death rate for age x and year t ;

$\tilde{q}_{x,t} = \exp(\tilde{y}_{x,t})$;

$$GGR_{x,t} = \frac{\tilde{q}_{x,t}^M}{\tilde{q}_{x,t}^F}, \quad (2)$$

M stands for males, and F stands for females.

Outcomes:

Continuous curves of the GGR that smooth out irregularities from random variation.

→ Such curves reveal the **fundamental age pattern** of the GGR.

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Graphical evidence

A. Gender Gap Ratio curves in 2018-19, 2020, 2021.

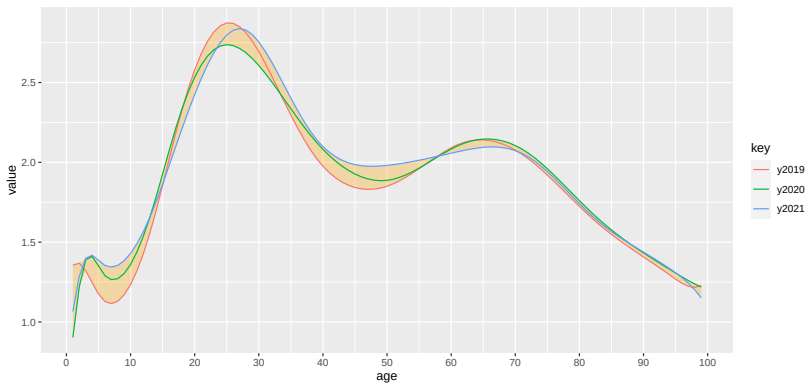


Figure: France

Graphical evidence

B. Gender Gap Ratio curves in 2018-19, 2020, 2021

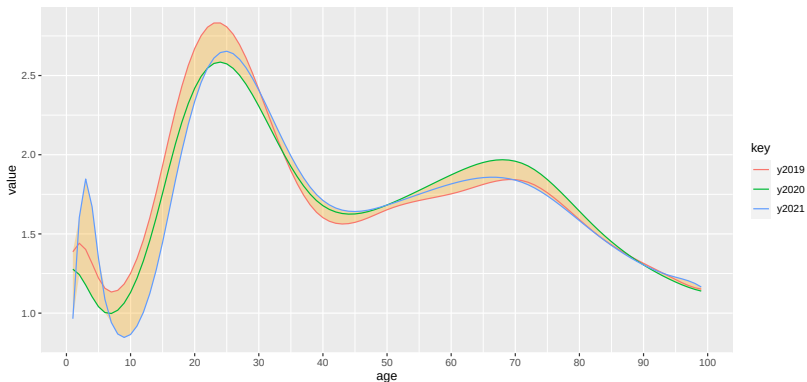


Figure: Italy

Graphical evidence

C. Gender Gap Ratio curves in 2018-19, 2020, 2021

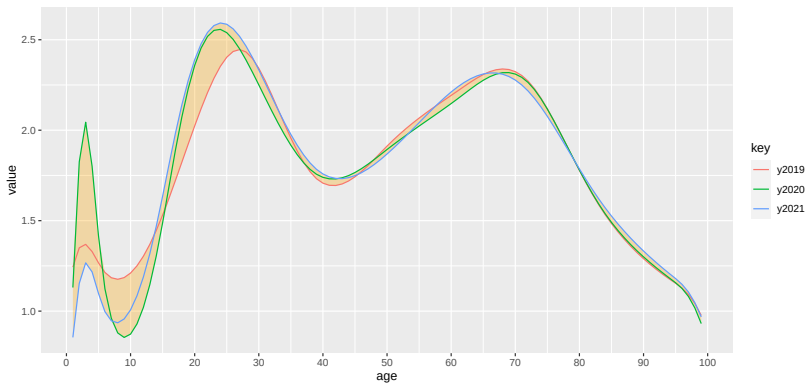


Figure: Spain

Relevant remarks:

- 1 magnitude of the GGR across countries;
- 2 change of the GGR in COVID-times;
- 3 stylized shape of the GGR curve → peculiar age profile.

Local maximizers

Occur at ages being remarkably close to each other for the countries under study. [2, 3], [24, 27], and [65, 69].

Local minimizers

Age ranges [7, 8] and [42, 47], and age 98 for France.

COVID-19 effects

Any enduring and structural change in the age-dependent shape of the GGR curve?

- Only mild changes to the stylized shape (e.g., narrower age intervals where extreme points occur);
- the GGR curve declines almost linearly toward the value of 1 with age.
- [68, 79]: the GGR increased by 2.24% in 2020 and decreased by 2.70% in 2021, on average.

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Step 2

- **AIM:** forecasts of the age pattern of the GGR*;
- **MORTALITY MODEL:**
Lee-Carter (LC) mortality model.

LC predictor structure:

a single stochastic time-varying index k_t expresses the level of mortality and thus drives its evolution, as follows:

$$\log m_{x,t} = a_x + b_x k_t + e_{x,t}. \quad (3)$$

a_x and b_x : age-specific parameters; $e_{x,t}$, with mean 0 and variance σ_e^2 : residual age-specific historical effects.

$m_{x,t}$: crude death rate; under given standard assumptions

$$q_{x,t} = 1 - \exp(-m_{x,t}).$$

*Based on: Apicella, G., La Rocca, M., Perna, C., and Sibillo, M. (2025) Neural network Lee-Carter model and the actuarial relevance of longevity risk assessment. Scand. Actuar. J. 2025, 549–573, and on further ongoing work on the topic.

- **METHODS APPLIED TO THE TIME INDEX k_t :**

- autoregressive integrated moving average (ARIMA) models, as in Lee and Carter 1992);
- autoregressive exogenous neural network (ARX-NN) models, in Apicella et al. (2025).

ARX-NN models: proven advantages

- they capture possible non-linear dynamics of the time index;
- they outperform time-series linear models;
- they smooth the uncertainty around central forecasts over time.

Graphical evidence

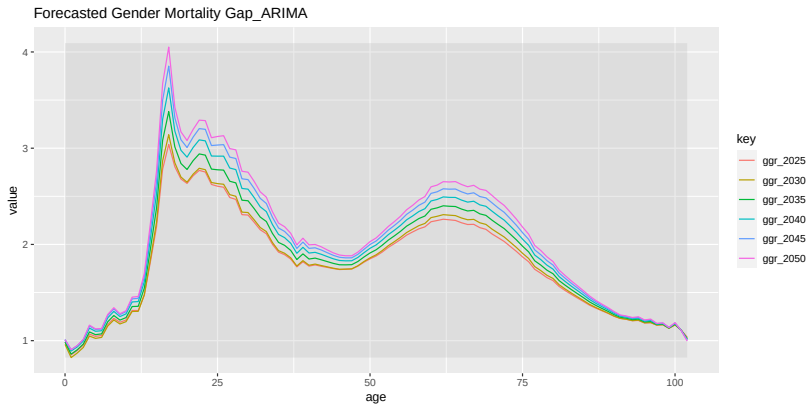


Figure: Autoregressive linear models

Graphical evidence

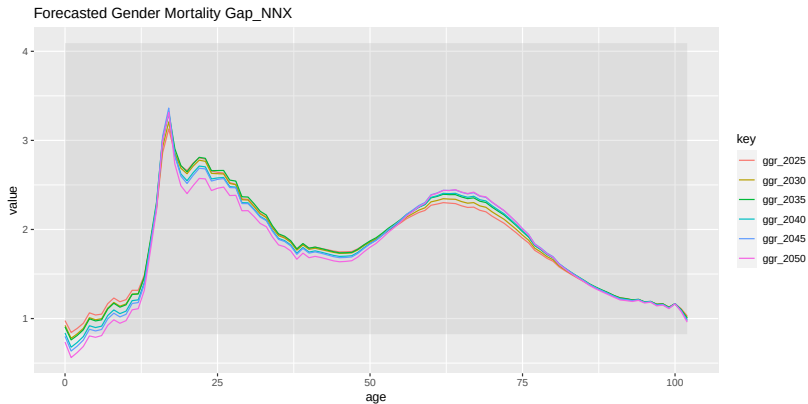


Figure: Neural network approach

Relevant remarks

- The overall shape of the GGR curve is consistent between the two forecasting methods;
- linear time series models: involve projections of the GGR curve over age that are **almost regularly inflated**;
- ARX-NN models: clear age-specific prospective trends and reasonable amount of variation of the GGR over time;
- average relative change of the GGR curve of 12.4% between 2025 and 2050 (ARIMA models) against -3.9%, according to the neural network-based approach.

Conclusions

- Capturing the age pattern of the gender gap in mortality is important for a quantitative description of such a phenomenon.
- Important implications for scientists in many fields, e.g., in the context of social insurance and health public policy.
- While the gender gap has noticeably increased during most of the 20th century in most Western countries, recent studies reveal a reverse trend.
- Our analysis, based on the use of a neural **network-based approach**, aims to uncover **age-specific long-run trends** of the Gender Gap Ratio (GGR).
- We can notice that the magnitude and the direction of the GGR change over time is highly sensitive to the choice of the underlying mortality modeling (e.g., models' ability to capture non-linearities).

Thank you very much for your kind attention!

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- Forfar, D. O., McCutcheon, J. J., and Wilkie, A. D. (1988). On graduation by mathematical formula. *Journal of the Institute of Actuaries* (1886-1994), 115(1):1–149.
- Kaishev, V. K., Dimitrova, D. S., Haberman, S., and Verrall, R. J. (2016). Geometrically designed, variable knot regression splines. *Comput Stat*, 31:1079–1105.