Forecasting Hospitalization Trends in Europe

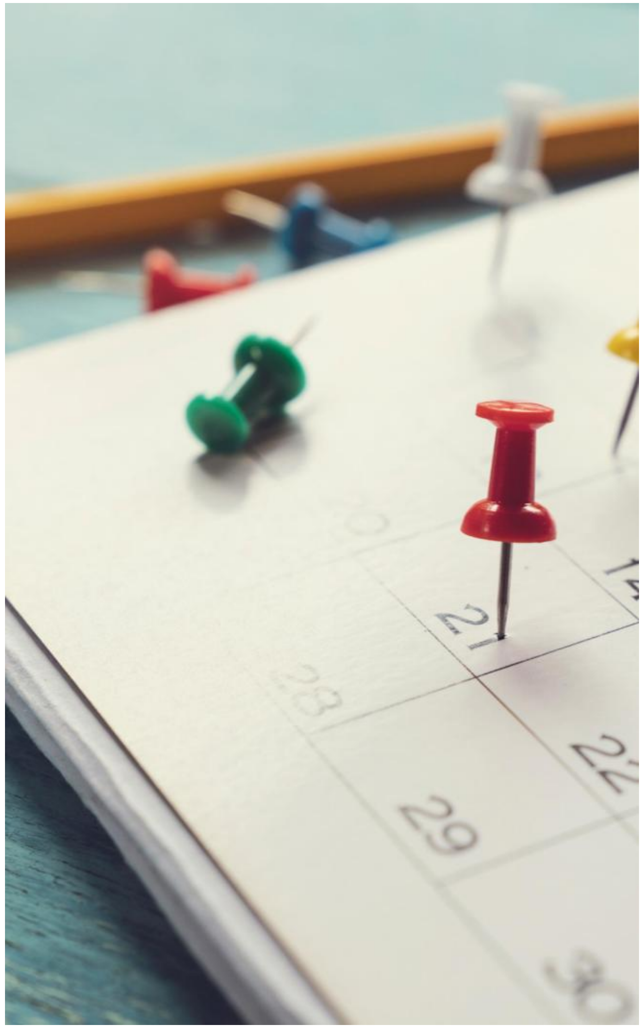
Nicolas Zimmer, Gen Re

6th European
Congress of Actuaries
www.eca2026.org

2026 ECA

Overview

- Introduction to Hospital cash insurance products
- Eurostat data and high-level trends
- Application of Lee-Carter methodology to hospitalization data
  - Performance comparison of different model variants
  - Hospitalization projections and trends



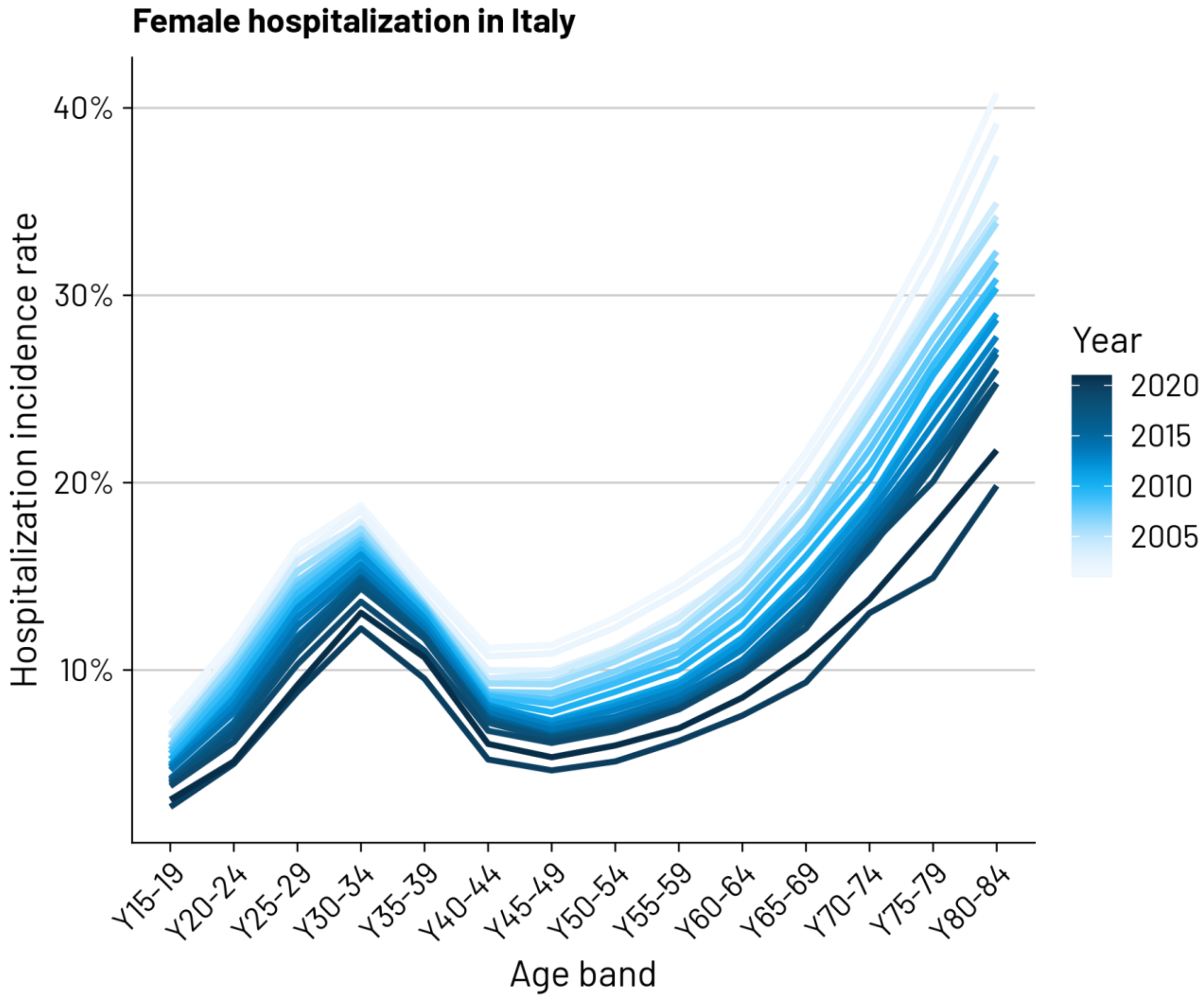
Hospital Cash Insurance

- Hospital cash insurance pays a fixed daily benefit during hospitalization
  - Purpose: compensate for loss of income during illness periods, provide funding for treatment
- Product is sold worldwide
- Pricing depends on covered causes of claims, hospitalization incidence rates and distribution of lengths of stay
  - Premium for 1€ of benefit = incidence rate x expected length of stay
  - Deferment periods and limits often part of the product
- Challenges:
  - Granular hospitalization data often not available
  - Insured portfolio data either not available or not credible enough
  - Experience may be affected by political interventions in the healthcare system

Hospitalization Data

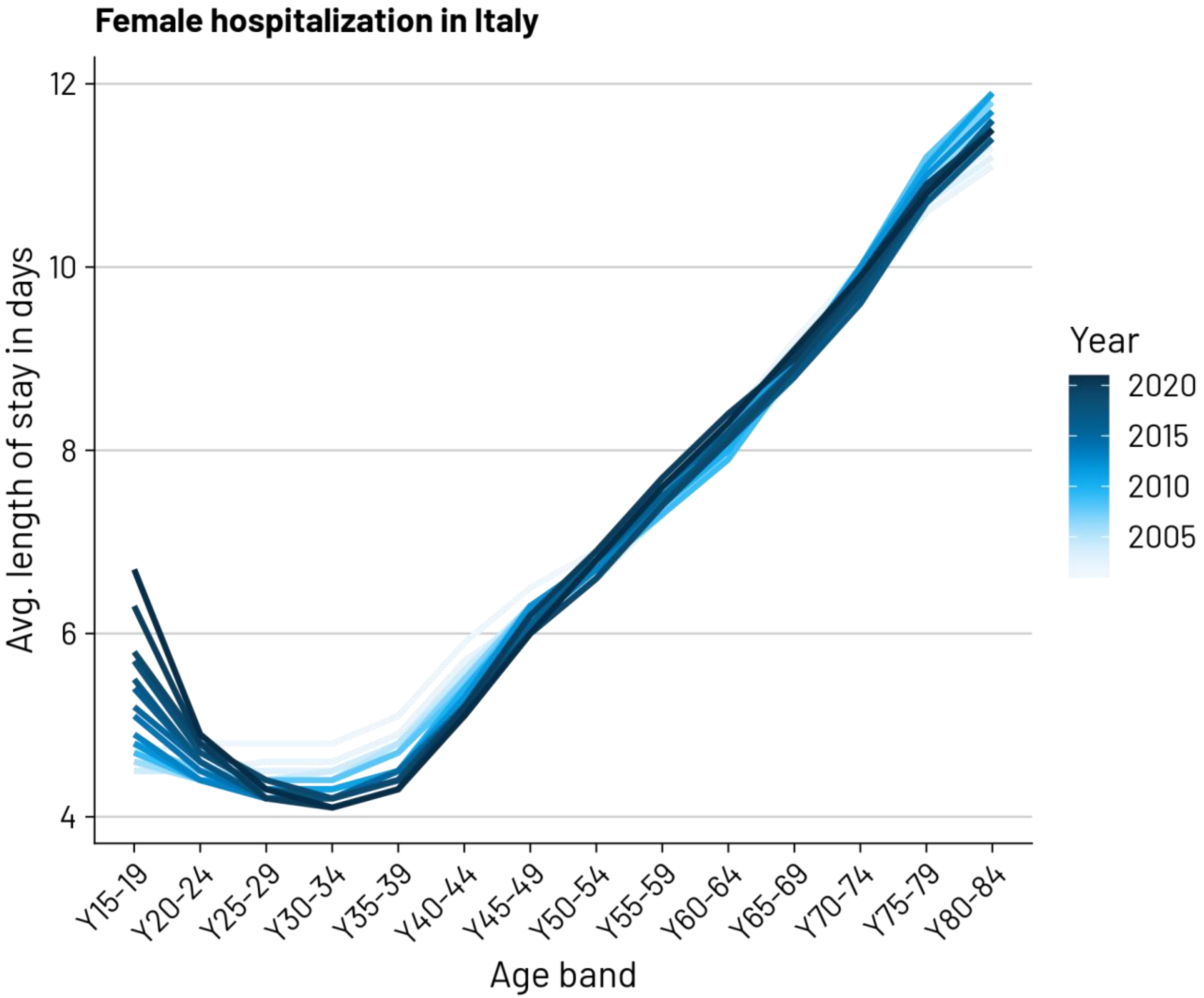
- For this presentation we use Eurostat data:
  - Hospital discharges (hlth_co_disch2)
  - Inpatient average length of stay (hlth_co_inpst)
  - 36 European countries
  - Time span: 1995 – 2021, for most countries slightly shorter
  - Focus on: all causes of diseases (A00–Z99), excluding V00–Y98 and Z38

Hospitalization Incidence Rates (IR) in Italy



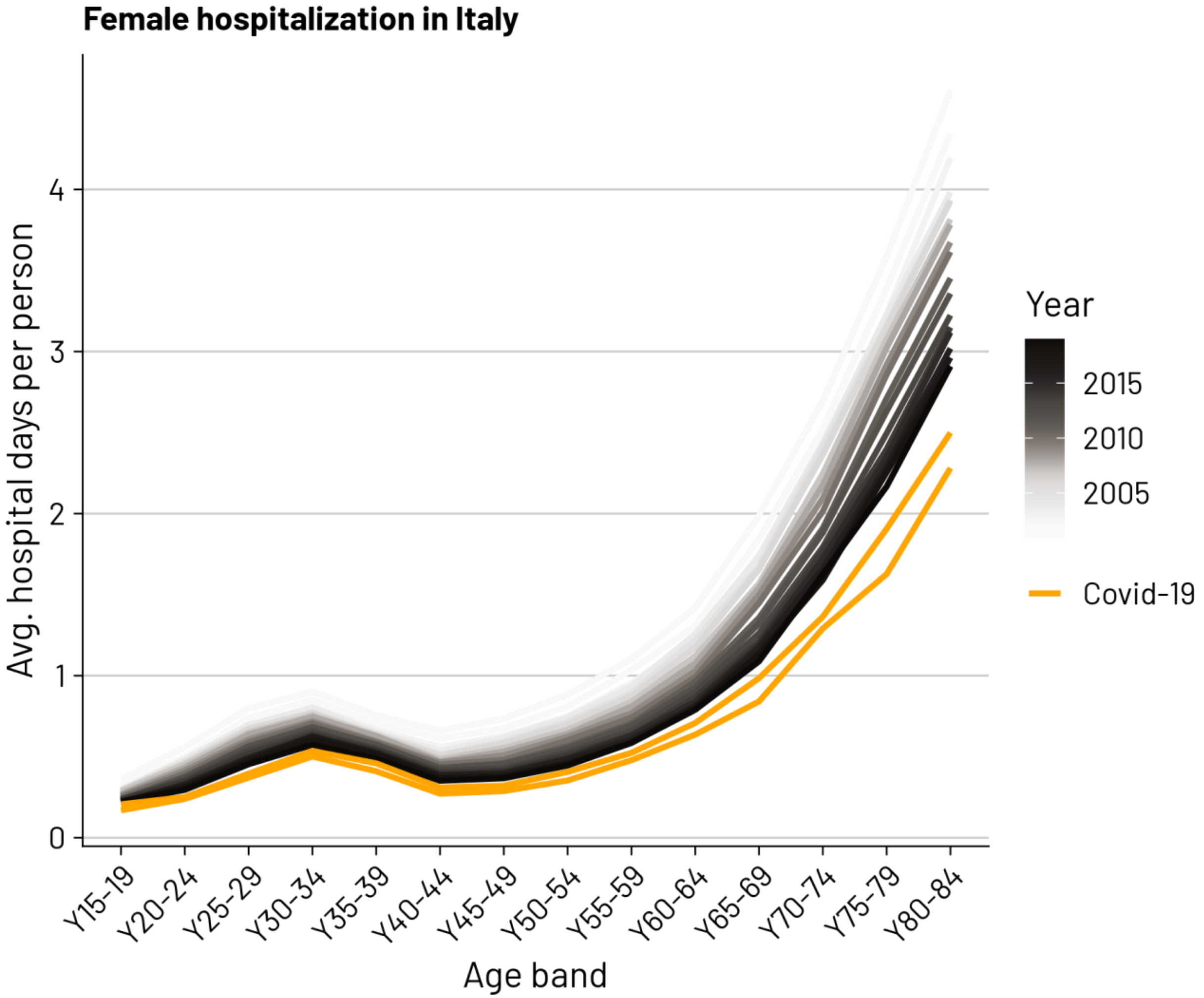
- Incidence = number of hospital visits / population
  - Event-based incidence
- Negative time trend: hospitalizations are decreasing over time
- Pronounced pregnancy bump, although ICD10 Z38 is excluded
- Steep increase for higher ages

Average Length of Stay (ALoS) in Italy



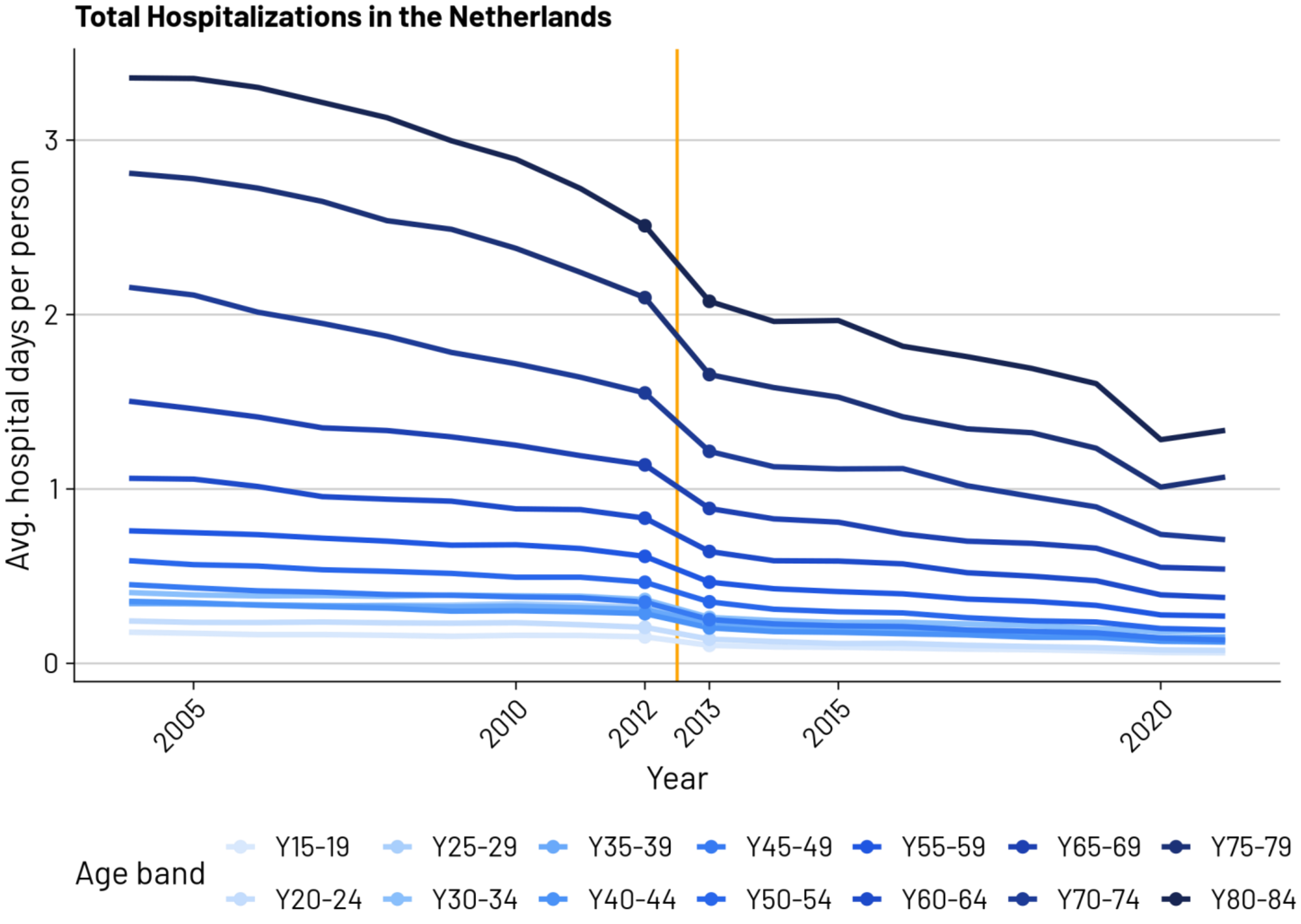
- Pattern is substantially different from incidence patterns
- No clear time trend
- Young age bands (15-24) have fewer, but longer hospital visits
- No pregnancy bump
- Very steep increase for higher ages

Average Hospital Days (HD) per Person



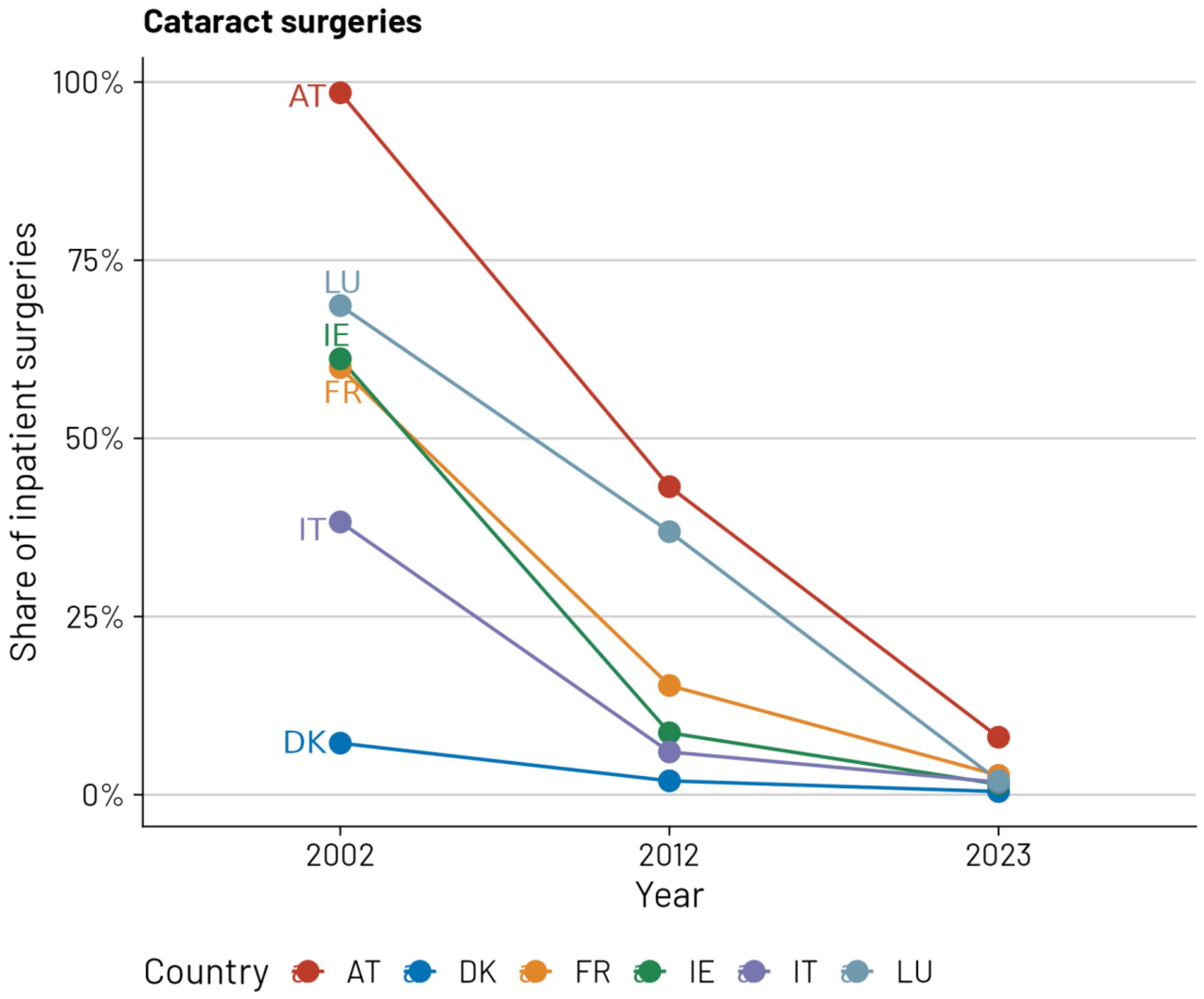
- Average Hospital Days $= IR \cdot ALoS$
- HD highly age dependent
- Significant trend over time
- Covid-19 had heterogeneous effects on hospital days across countries:
  - Decrease because of delay of treatment
  - Increase because of Covid-19 admissions
  - Years 2020 and 2021 will be excluded from the modeling exercise

Changes in Healthcare Systems



- Needs to be considered in model, pricing and product design
- Example Netherlands ~2012:
  - introduction of macro-level expenditure controls
  - Reforms are described in detail in Schut et al. (2013)
- Sharp decline of hospital days per person from 2012 to 2013: -22.4%

Shift Towards Outpatient and Day-Case Surgeries



- Hospital days per person are declining for many European countries over time
- Overnight inpatient care is increasingly substituted by same-day treatments and outpatient surgeries
- Example: Cataract surgeries have transitioned from inpatient care to predominantly outpatient settings
  - Data: Eurostat, hlth_co_proc3 series

Modeling Hospitalizations (1/3)

- Various applications of Lee-Carter type models in the actuarial literature:
  - Mortality/longevity (Lee & Carter, 1992)
  - Medical costs (Christiansen et al., 2018)
  - Morbidity rates (Yue et al., 2024)
  - Disability rates (Levantesi & Menzietti, 2012)
- Average hospital days per person follow similar patterns as mortality rates, medical costs, and morbidity rates:
  - High values at birth
  - Pregnancy and accident-related peaks
  - Steady increase at middle and older ages

Modeling Hospitalizations (2/3)

- We compared different Lee-Carter models:

Model	Implementation
M1: Classical Lee-Carter (Lee & Carter, 1992)	`demography` (Hyndman, 2025)
M2: Poisson Lee-Carter (Brouhns et al., 2002)	`StMoMo` (Villegas et al., 2018)
M3: Negative Binomial Lee-Carter (Delwarde et al., 2007)	`gnm` (Turner & Firth, 2007)

- All models use a similar specification, e.g. for model 1:
  - $\log(HD_{x,t}) = \alpha_x + \beta_x \, \kappa_t + \epsilon_{x,t},$

  where α_x is the age profile, κ_t is the time index and β_x is the age-specific sensitivity
- Model 2 and 3 make use of a log link function and the same predictors (α_x, κ_t and β_x) as model 1.
- The time index κ_t is projected using an ARIMA model.

Modeling Hospitalizations (3/3)

- Performance metrics are computed using mid-year population weights
  - Mean absolute error (MAE) $= \frac{1}{\sum_{x,t} pop_{x,t}} \sum_{x,t} pop_{x,t} \cdot |\widehat{HD_{x,t}} - HD_{x,t}|$
  - Mean absolute percentage error (MAPE) $= \frac{1}{\sum_{x,t} pop_{x,t}} \sum_{x,t} pop_{x,t} \cdot \left|\frac{HD_{x,t} - \widehat{HD_{x,t}}}{HD_{x,t}}\right|$
  - Root mean squared error (RMSE) $= \sqrt{\frac{1}{\sum_{x,t} pop_{x,t}} \sum_{x,t} pop_{x,t} \cdot \left(\widehat{HD_{x,t}} - HD_{x,t}\right)^2}$
- Included countries (n = 11):
  - AT, BE, CH, CZ, DE, IE, IT, LT, HR, NL, SK
  - Training data: 2000-2015, test data: 2016-2019.
  - Gender-specific models estimated for ages 15–84

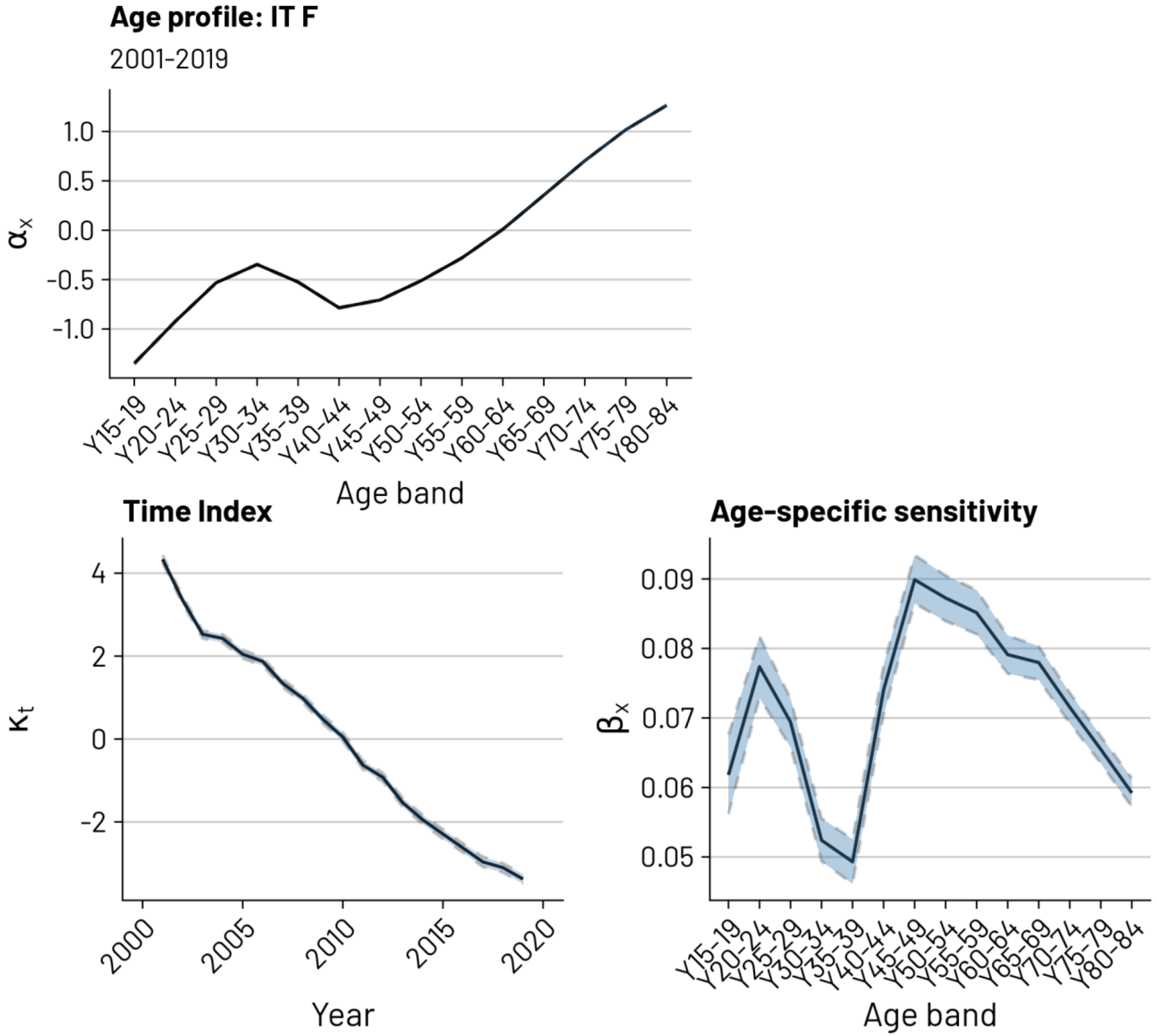
Model Performance

- Results reported as cross-country averages across 11 countries:

Split	Model	MAPE	RMSE	MAE
Train 2000-2015	Classical LC	2.5836%	0.0620	0.0396
	Poisson LC	2.1813%	0.0518	0.0312
	Negative Binomial LC	2.1834%	0.0602	0.0348
Test 2016-2019	Classical LC	5.3537%	0.1034	0.0711
	Poisson LC	5.1474%	0.0908	0.0615
	Negative Binomial LC	5.0947%	0.0971	0.0632

- Poisson LC performs best in most metrics and is therefore selected for further analysis.
- We refit the Poisson LC model to the full range of data (2000-2019).

Poisson LC Model Results for Italian Females



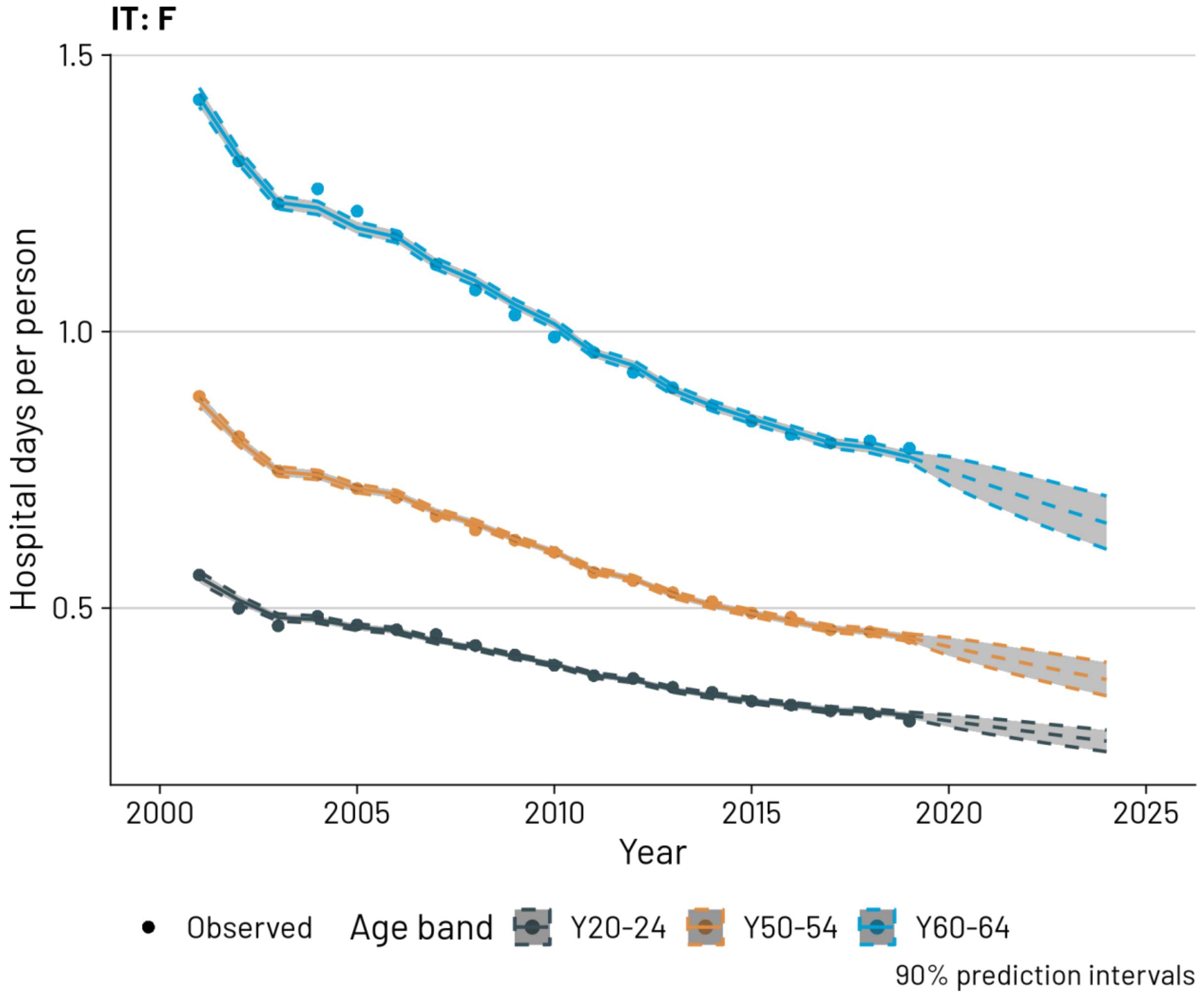
- Model captures the age shape, including a pronounced pregnancy-related peak
- Persistent decreasing time trend
- Fastest decline in hospital days at middle ages
- Slowest decline in hospital days at pregnancy-related ages and at very high ages

Alternative: Separate Models for IR and ALoS

- Alternatively, one can model the hospitalization incidence and length of stay separately and combine the results
  - Expected Hospital Days $= IR \cdot ALoS$
- Performance is worse than that of a single model for hospital days when benchmarked using the 11-country average:

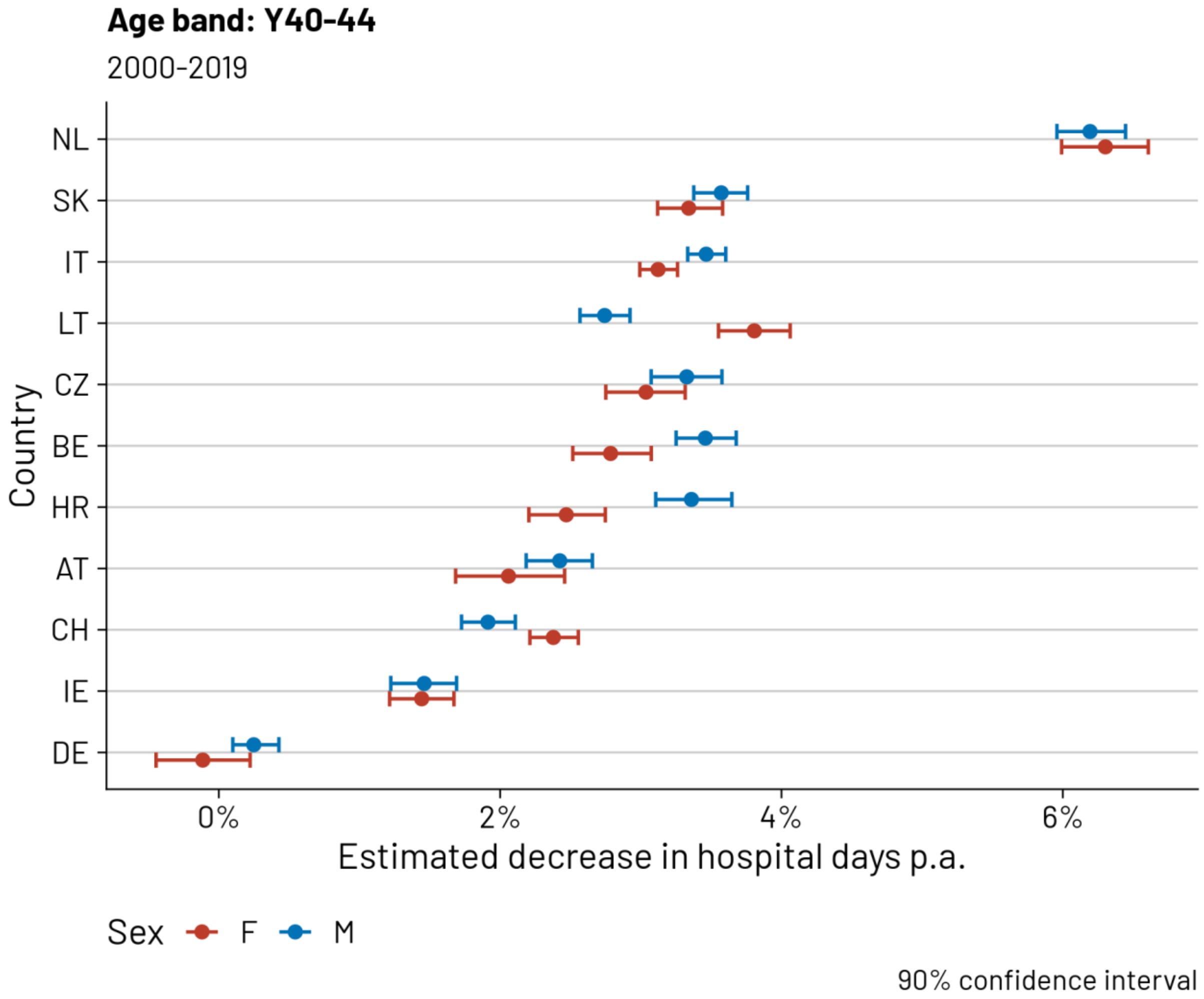
Split	Model	MAPE	RMSE	MAE
Train 2000-2015	Poisson LC – HD model	2.1813%	0.0518	0.0312
	Poisson LC – ALoS/IR model	2.6216%	0.0697	0.0426
Test 2016-2019	Poisson LC – HD model	5.1474%	0.0908	0.0615
	Poisson LC – ALoS/IR model	5.7751%	0.1004	0.0719

Uncertainty in Trends and Projections



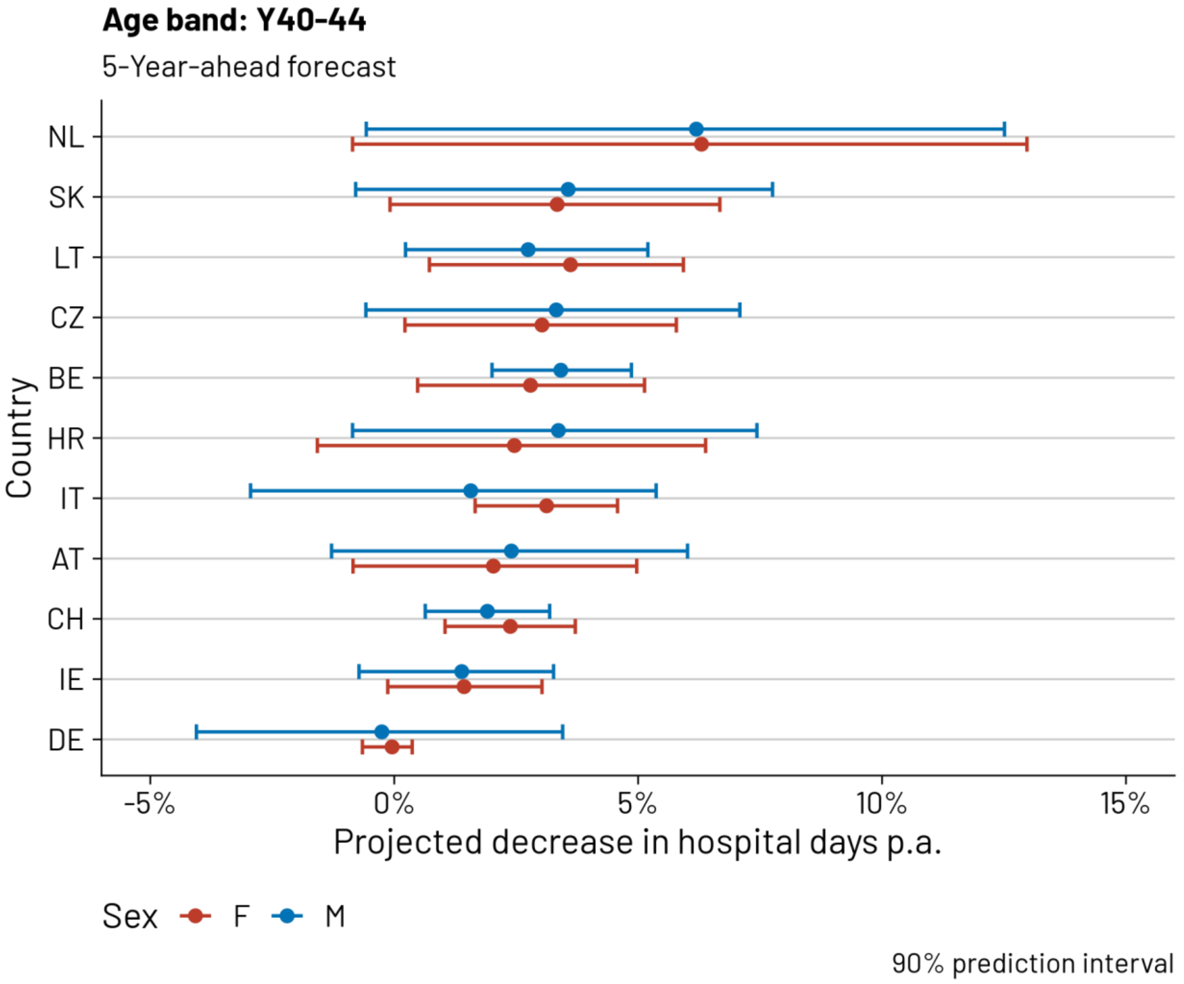
- Residual bootstrap (Renshaw & Haberman, 2008) is used to quantify the uncertainty of the model results and projections
- 90% prediction intervals have been estimated with 2000 bootstrap samples and 1000 simulated trajectories of the time index

Hospitalization Trends in Europe



- Model output and bootstrap samples can be used to quantify the historic trends
- Focus on age band 40-44, as magnitude of the time trend depends on the age band
- Most countries show a decreasing historic trend

Hospitalization Forecasts in Europe



- Model can be used to project the future trend
- 90% prediction interval based on bootstrap sampling
- Forecast uncertainty varies significantly across countries

Summary of Results

- Most European countries show a persistent decrease in hospital days per person over time
  - Magnitude varies by age and gender
  - Shift towards outpatient and day-case surgeries
- Lee-Carter models effectively capture hospitalization dynamics
  - Poisson LC delivers best results
  - Single model for hospital days is preferred performance-wise over two separate models for IR and ALoS
- Substantial uncertainty in projections, with large variation across countries

References

- Villegas, A. M., Kaishev, V. K., & Millossovich, P. (2018). StMoMo: An R package for stochastic mortality modeling. *Journal of Statistical Software*, *84*, 1-38.
- Hyndman R (2025). demography: Forecasting Mortality, Fertility, Migration and Population Data. R package version 2.0.1.9000, https://pkg.robjhyndman.com/demography/.
- Turner, H., & Firth, D. (2007). Generalized nonlinear models in R: An overview of the gnm package.
- Schut, E., S. Sorbe and J. Høj (2013), Health Care Reform and Long-Term Care in the Netherlands, *OECD Economics Department Working Papers*, No. 1010
- Lee, R. D., & Carter, L. R. (1992). Modeling and forecasting US mortality. *Journal of the American statistical association*, 87(419), 659-671.
- Brouhns, N., Denuit, M., & Vermunt, J. K. (2002). A Poisson log-bilinear regression approach to the construction of projected lifetables. *Insurance: Mathematics and economics*, *31*(3), 373-393.
- Renshaw, A. E., & Haberman, S. (2008). On simulation-based approaches to risk measurement in mortality with specific reference to Poisson Lee–Carter modelling. *Insurance: Mathematics and Economics*, *42*(2), 797-816.
- Delwarde, A., Denuit, M., & Partrat, C. (2007). Negative binomial version of the Lee–Carter model for mortality forecasting. *Applied Stochastic Models in Business and Industry*, *23*(5), 385-401.
- Christiansen, M., Denuit, M., Lucas, N., & Schmidt, J. P. (2018). Projection models for health expenses. *Annals of Actuarial Science*, *12*(1), 185-203.
- Levantesi, S., & Menzietti, M. (2012). Managing longevity and disability risks in life annuities with long term care. *Insurance: Mathematics and Economics*, *50*(3), 391-401.
- Yue, J. C., Wang, H. C., & Chang, T. C. (2024). Application of type II diabetes incidence and mortality rates for insurance. *PloS one*, *19*(9), e0307508.

Nicolas Zimmer
Senior Data Scientist
Gen Re Life/Health R&D

- Gen Re delivers reinsurance solutions to the Life and Non-Life insurance industry
- A Berkshire Hathaway Company
- https://www.genre.com