Introduction to demographic & mortality forecasting

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As part of IMPRS-PHDS course on Population Health
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Today's class in the morning: Introduction to demographic & mortality forecasting

- **Demographic forecasting**
  - What they are about
  - How they can look like in real life
  - What they are good for
  - How they are generated in general
  - What might be potential sources of error and how to account for them
- **Mortality forecasting**
  - What kind of methods there are
  - The Lee-Carter method
  - How to validate mortality forecast methods

Today's class in the afternoon:
Hands-on experiences in mortality forecasting with R

- Load mortality data from the Human Mortality Database
- Implement and use the Lee-Carter method
  - to fit and forecast US mortality
  - and, if time allows, to validate its performance
- Analyze LC mortality forecasts for US women and men, 2018-2067,
  - based on base periods of different length
  - and examining crucial parameters

  Present and discuss your findings.

Please make sure to have installed R package `fds`. And to have at hand your username and password for the Human Mortality Database.

What is: Demography & Forecasting

- **Demography** is the science of populations (*demos*) and their measurement (*graphy*).

- **Forecasting** is the process of making statements about likely future development of variable(s) of interest.

What is: Demographic forecasting

- **Demographic forecasts** predict how populations will develop over time in the future
- Population balance equation:

$$P_{t+n} = P_t + B_{[t,t+n]} - D_{[t,t+n]} + I_{[t,t+n]} - E_{[t,t+n]}$$

Population forecasts   Fertility forecasts   Mortality forecasts   Migration forecasts

$\rightarrow$ Demographic forecasting comprises all these components

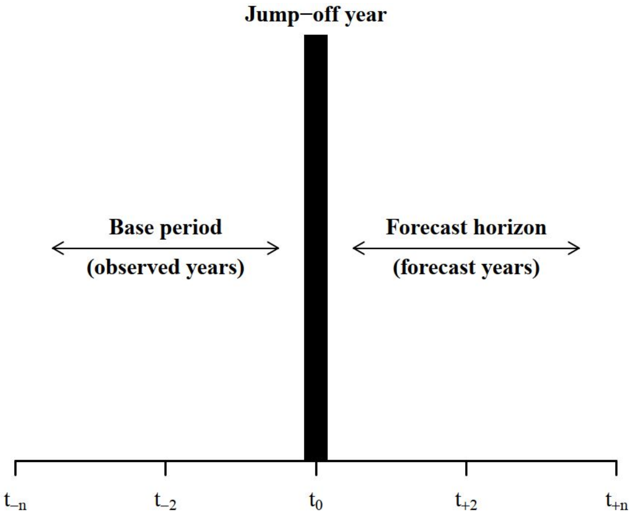
Typical questions

- How long will people live?
- How many of the remaining years of life will people spend in good health, in poor health, or in work and in retirement?
- How many children will people have in 5 and in 50 years from now?
- How many people will live worldwide in upcoming years?
- *What if ...?*

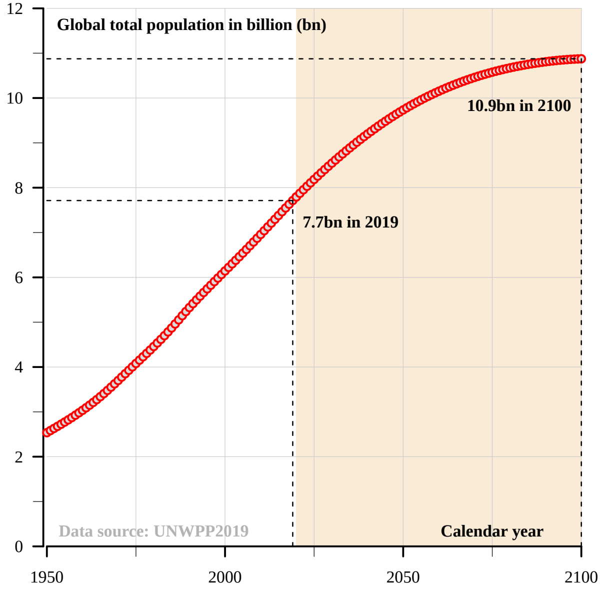
Demographic forecasts in the real world

Example: United Nations World Population Prospects 2019
($\longrightarrow$ published only in June this year)

Some terminology first...



Global population size and growth

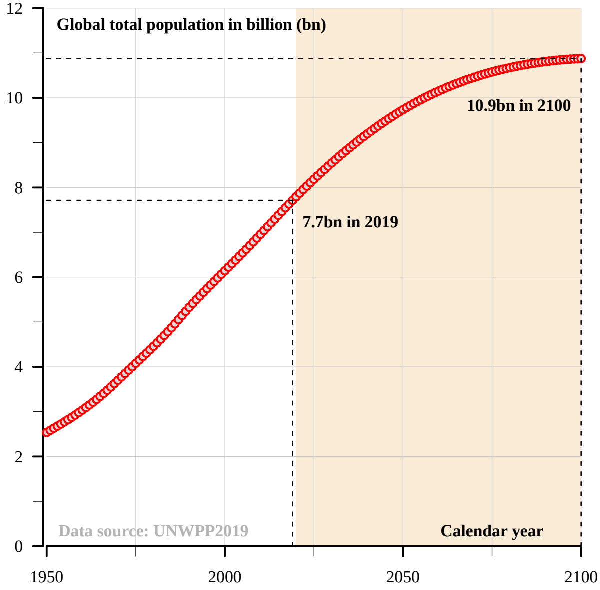


[one billion is equal to one thousand million]

1

2

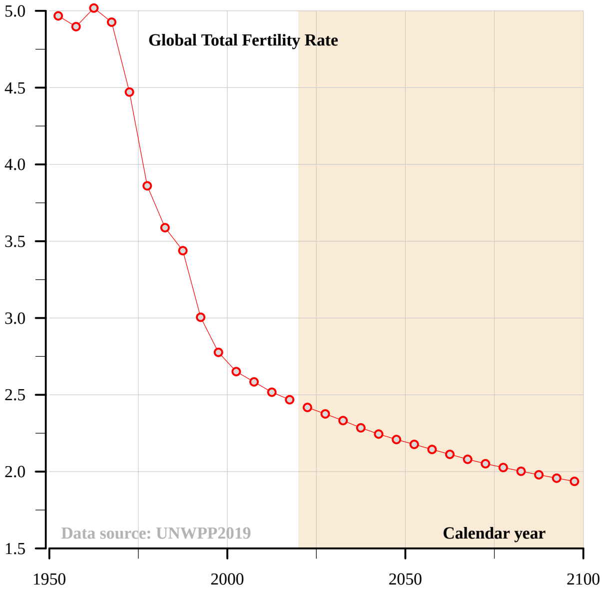
Global population size and growth



[one billion is equal to one thousand million]

1. Global population size is forecasted to increase
2. ...but less and less with each forecast year

Global Total Fertility Rate



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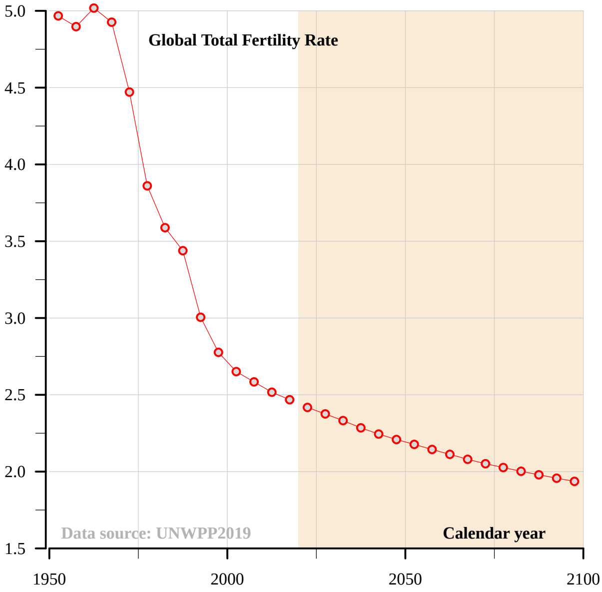
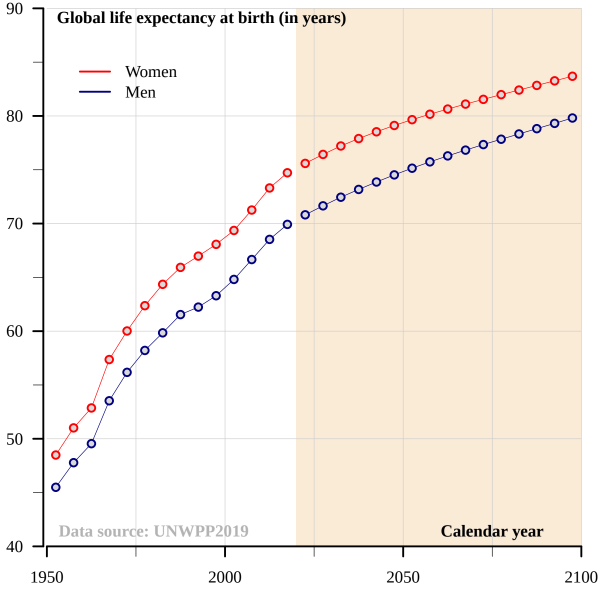


1. Global TFR is forecasted to decline ...but less and less with each forecast year

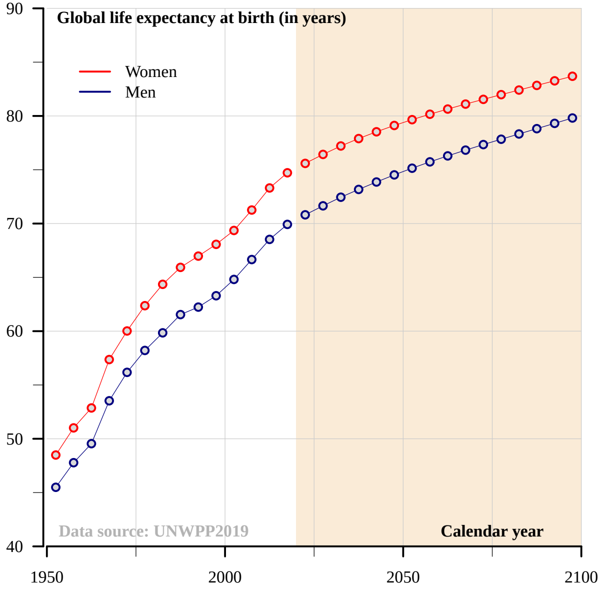
Global life expectancy at birth



1

2

Global life expectancy at birth



1. Global e_0 is higher for women than for men
2. Global e_0 is forecasted to increase ...but less and less with each forecast year

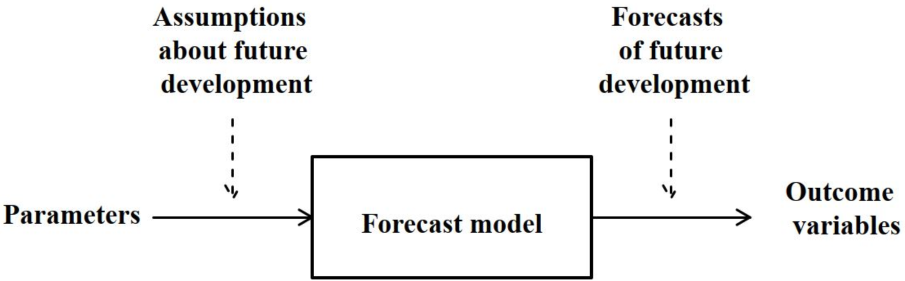
Societal relevance

Reliable demographic forecasts lead to informed decisions, policies, and programs affecting e.g. people's social & economic welfare

- They serve as basis for further analysis
  (that predict demand for resources and services in upcoming years)
- Assist in planning, decision making, and creating goals
  in areas such as health care, education, housing,
  energy consumption, transport, retirement planning

$\longrightarrow$ applies to different geographical levels and types of organization

Basic procedure



Basic procedure

Demographic forecasting is a form of prediction
(that you already know from regression analysis / statistics).

Demographic forecast methods often:

- extrapolate past developments into the future
- take time into account
- assume that future is a continuation of the past
- assume that functional relationships between model parameters (expressed in the forecast model) are valid throughout time

$\longrightarrow$ underlying assumptions might be questionable?

Potential sources of error

"Prediction is very difficult, especially about the future."
attributed to Niels Bohr

Forecast errors are deviations between forecasts and their true realizations.

What are potential sources of error?
What could possibly go wrong?

Potential sources of error

- model misspecification (all models are wrong)
- missing / incorrect data (as input for forecast model)
- errors in model implementation
- unexpected events (leading to gross shifts in demographic behavior)
- ...

$\longrightarrow$ contribute to forecast uncertainty

Potential sources of error

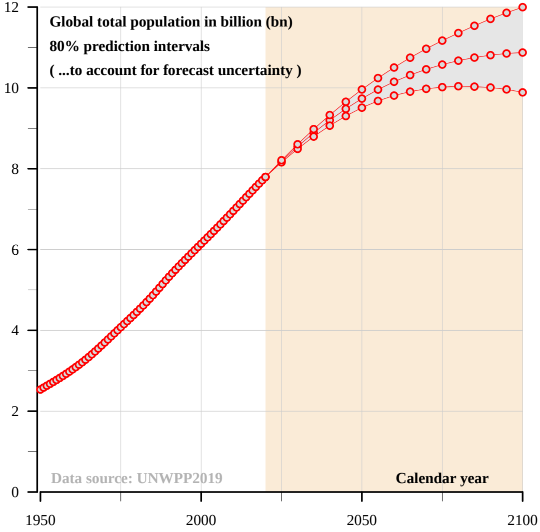
Anecdote about the inductivist chicken:

"The man who has fed the chicken every day throughout its life at last wrings its neck instead, showing that more refined views as to the uniformity of nature would have been useful to the chicken."

Bertrand Russell (1912)

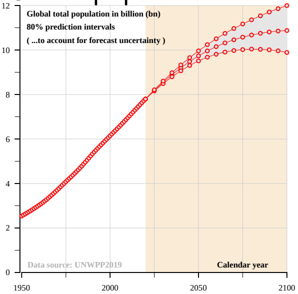
Probabilistic forecasts

...quantify forecast uncertainty

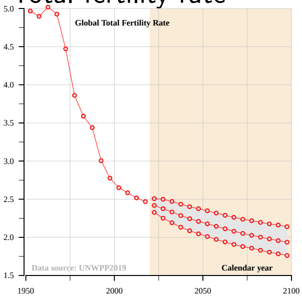


Probabilistic forecasts quantify forecast uncertainty

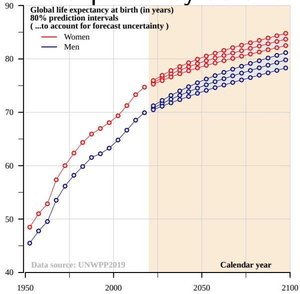
Global population



Total fertility rate



Life expectancy at birth



$\longrightarrow$ deterministic forecasts versus probabilistic forecasts

What you have learned today about demographic forecasting

- Define demographic forecasting
- List typical questions
- Apply basic terminology of demographic forecasting
- Describe UN forecast of the global population
- Describe societal relevance
- Describe basic procedure how to generate demographic forecasts
- Describe potential sources of error
  and know that they can be accounted for in probabilistic forecasts

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  - The Lee-Carter method
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Mortality forecasting

- Extrapolation methods
  - Model trends in mortality over age and time
  - Are objective & data-driven but assume basic trends in mortality to be regular and to continue in years ahead
- Explanation methods
  - Take into account mortality that is e.g. attributable to health-related behavior (such as tobacco smoking) and/or causes of death
  - Consider explanatory mechanisms / risk factors of mortality but are prone to model misspecification (due to high complexity)
- Expert-based methods
  - Use expert opinion to e.g. interpolate mortality between start and target value
  - Are subjective & opinion-driven and might be biased (as experts tend to be overly confident)
- Mixture of methods above

$\longrightarrow$ Overview in e.g. Booth (2006) and Booth and Tickle (2008)

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The Lee-Carter method

Modeling and Forecasting U.S. Mortality

RONALD D. LEE and LAWRENCE R. CARTER*

Time series methods are used to make long-run forecasts, with confidence intervals, of age-specific mortality in the United States from 1990 to 2065. First, the logs of the age-specific death rates are modeled as a linear function of an unobserved period-specific intensity index, with parameters depending on age. This model is fit to the matrix of U.S. death rates, 1933 to 1987, using the singular value decomposition (SVD) method; it accounts for almost all the variance over time in age-specific death rates as a group. Whereas e_0 has risen at a decreasing rate over the century and has decreasing variability, $\mathbf{k}(t)$ declines at a roughly constant rate and has roughly constant variability, facilitating forecasting. $\mathbf{k}(t)$, which indexes the intensity of mortality, is next modeled as a time series (specifically, a random walk with drift) and forecast. The method performs very well on within-sample forecasts, and the forecasts are insensitive to reductions in the length of the base period from 90 to 30 years; some instability appears for base periods of 10 or 20 years, however. Forecasts of age-specific rates are derived from the forecasts of $\mathbf{k}$, and other life table variables are derived and presented. These imply an increase of 10.5 years in life expectancy to 86.05 in 2065 (sexes combined), with a confidence band of plus 3.9 or minus 5.6 years, including uncertainty concerning the estimated trend. Whereas 46% now survive to age 80, by 2065 46% will survive to age 90. Of the gains forecast for person-years lived over the life cycle from now until 2065, 74% will occur at age 65 and over. These life expectancy forecasts are substantially lower than direct time series forecasts of e_0, and have far narrower confidence bands; however, they are substantially higher than the forecasts of the Social Security Administration's Office of the Actuary.

KEY WORDS: Demography; Forecast; Life expectancy; Mortality; Population; Projection.

From 1900 to 1988, life expectancy in the United States rose from 47 to 75 years. If it were to continue to rise at this same linear rate, life expectancy would reach 100 years in 2065, about seventy five years from now. The increase would

Next we fit the demographic model to U.S. data and evaluate its historical performance. Using standard time series methods, we then forecast the index of mortality and generate associated life table values at five-year intervals. Because we

Google Scholar | Modeling and forecasting US mortality

Artikel — Ungefähr 101.000 Ergebnisse (**0,10** Sek.)

Beliebige Zeit
Seit 2019
Seit 2018
Seit 2015
Zeitraum wählen...

Modeling and forecasting US mortality
RD Lee, LR Carter - Journal of the American statistical association, 1992 - Taylor & Francis
Time series methods are used to make long-run forecasts, with confidence intervals, of age-specific mortality in the United States from 1990 to 2065. First, the logs of the age-specific death rates are modeled as a linear function of an unobserved period-specific intensity ...
☆ 99 Zitiert von: 2888 Ähnliche Artikel Alle 17 Versionen »

1. Golden standard to forecast mortality.
2. Published in 1992 and widely used since then.
3. Extrapolation method. Simple and robust.
4. Many extensions since 1992.

Use Lee-Carter model to fit and forecast US female mortality

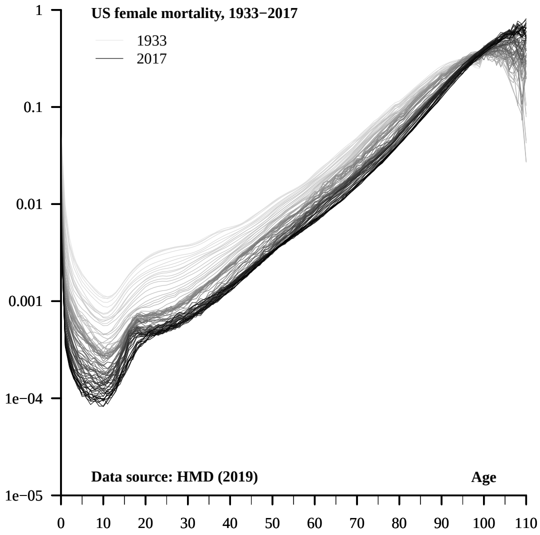
We will look at the broad idea first
before we will also briefly look at methodological and technical details.

Example of US female mortality.

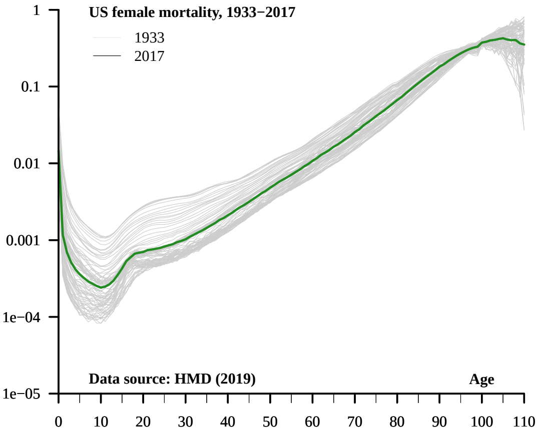
Two-step procedure:

1. **Fit** Lee-Carter **model to** US female **mortality** by age and over time **in base period**.
2. **Forecast** US female **mortality** over time **in upcoming years**.

1. Fit Lee-Carter model to US female mortality, 1933-2017

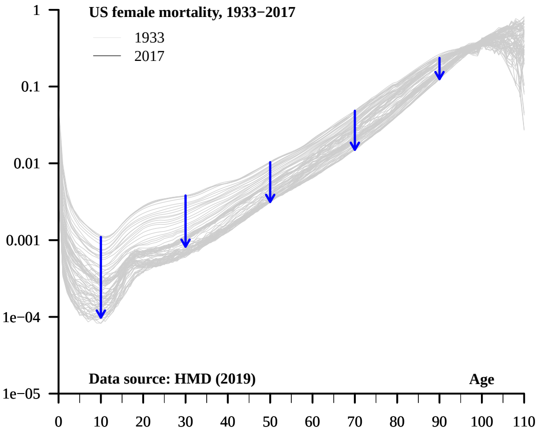


...with only few model parameters



$$\log m_{x,t} = \alpha_x + \beta_x \kappa_t$$

...with only with few model parameters



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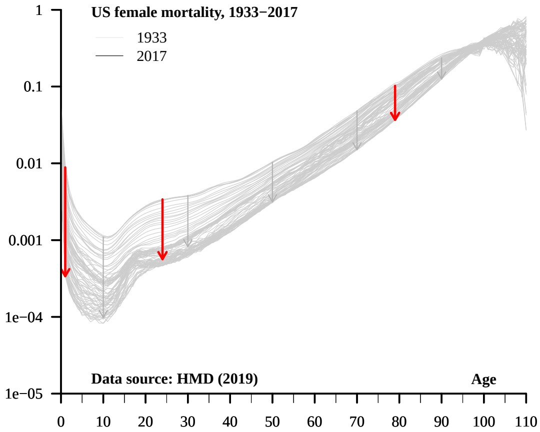
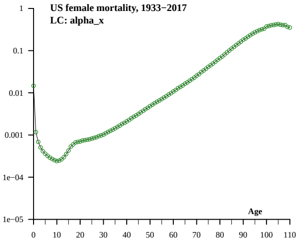
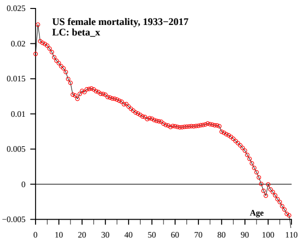


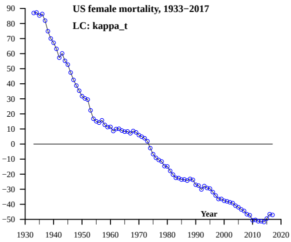
$$\log m_{x,t} = \alpha_x + \beta_x \kappa_t$$

Lee-Carter model fitted to US female mortality in base period 1933-2017

$$\log m_{x,t} = \alpha_x + \beta_x \kappa_t$$





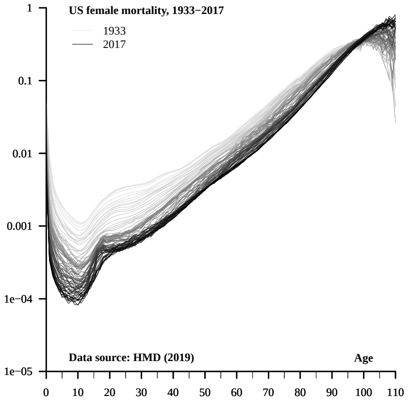


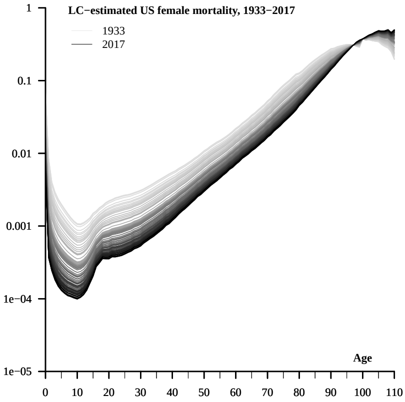
- α_x is the general shape of mortality across age x

- β_x is the change of mortality at age x
- $\beta_x > 0$: mortality decline, $\beta_x < 0$: mortality increase

- κ_t is an index of the level of mortality over time t
- direction and slope indicate strong mortality decline

...and one more thing

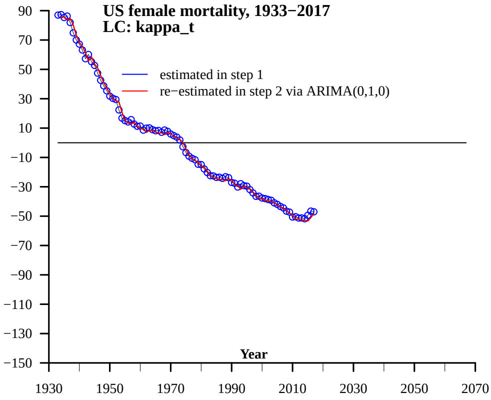




to account for residuals between LC-estimated and observed mortality:

$$\log m_{x,t} = \color{green}{\alpha_x} + \color{red}{\beta_x}\color{blue}{\kappa_t} + \epsilon_{x,t}$$

2. Use fitted LC-model to forecast US female mortality s years ahead via time index k_t



- κ_t is an index of the level of mortality over time t
- **Fit** estimated κ_t in base period using a time series model, e.g. ARIMA(0,1,0)
  - Random walk with drift: $\kappa_t = \kappa_{t-1} + \delta + \epsilon_t$
    - with δ being a drift term
    - and ϵ_t being an error term

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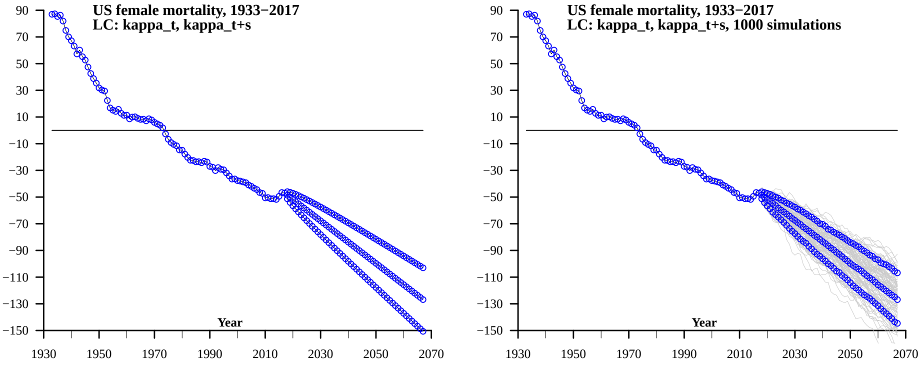
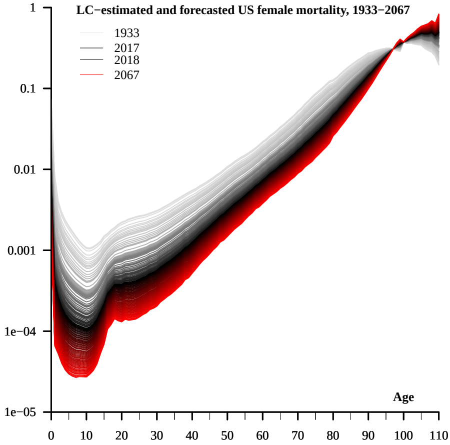
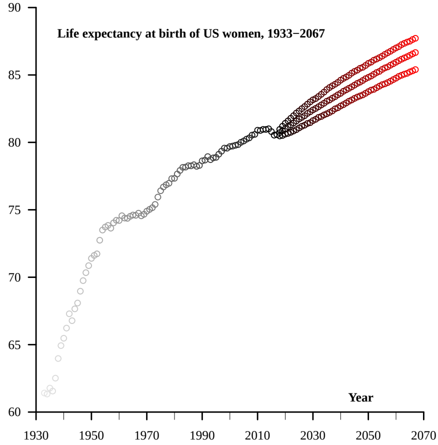


ARIMA(0,1,0), random walk with drift: $\kappa_t = \kappa_{t-1} + \delta + \epsilon_t$

80% **prediction intervals** based on statistical theory (left) & simulation (right)

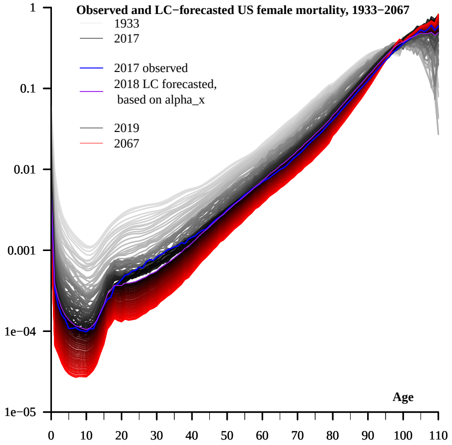
Forecasting US female mortality 50 years ahead using base period 1933-2017

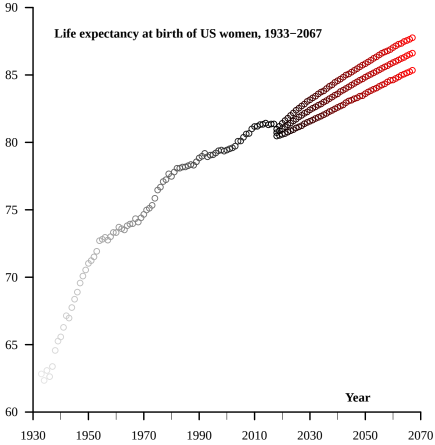




κ_t point estimates are based on median of 1000 simulated trajectories

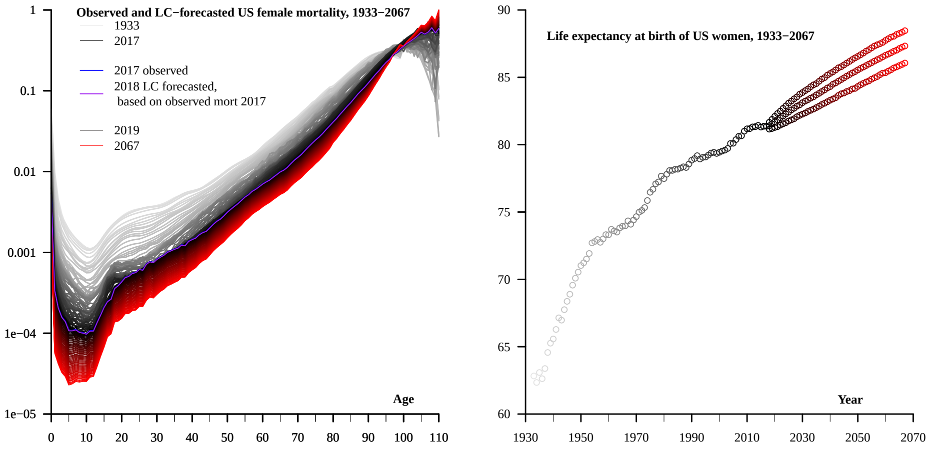
Forecasting US female mortality 50 years ahead using base period 1933-2017, **jump-off-bias**





κ_t point estimates are based on median of 1000 simulated trajectories

Forecasting US female mortality 50 years ahead using base period 1933-2017, **corrected for jump-off-bias:** $\log m_{x,t} = m_{x,2017} + \beta_x \kappa_t^* + \epsilon_{x,t}$



κ_t point estimates are based on median of 1000 simulated trajectories

Think about it.

What does the Lee-Carter model do?

What are the main steps?

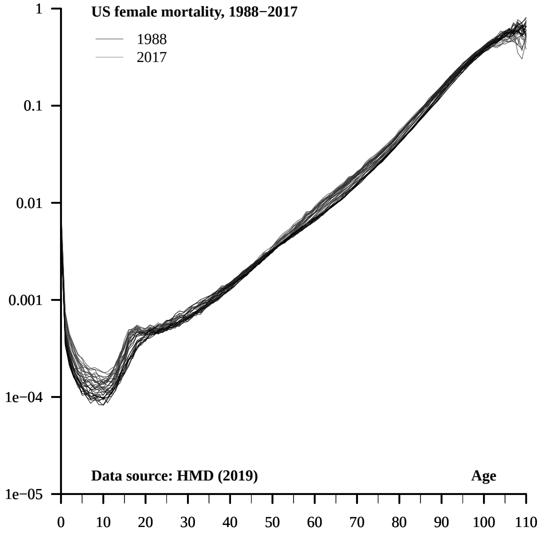
Could we forecast US female mortality differently
although we always use the Lee-Carter model?

What are high-impact parameters of the LC model?

What impacts US female mortality forecast with LC model?

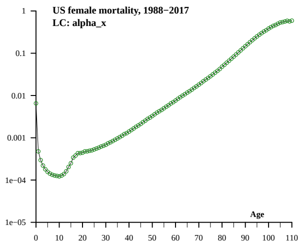
- Observed levels and trends in base period (α_x, β_x, and κ_t)
- Fitting procedure (e.g. singular value decomposition, maximum likelihood)
- Forecast time index κ_t
  - Time series model
  - Prediction intervals (based on e.g. simulation or statistical theory)
- Implementation (e.g. different R-packages)

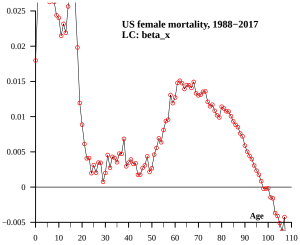
Impact base period: fit LC model to US female mortality, 1988-2017

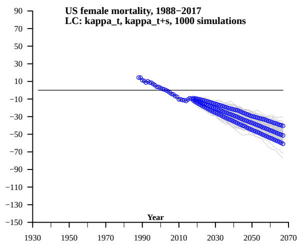


Lee-Carter model fitted to mortality in base period: 1988-2017 (focus on more recent trends)

$$\log m_{x,t} = \alpha_x + \beta_x \kappa_t + \epsilon_{x,t}$$







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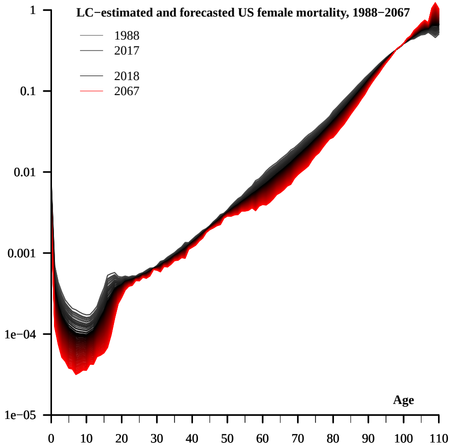
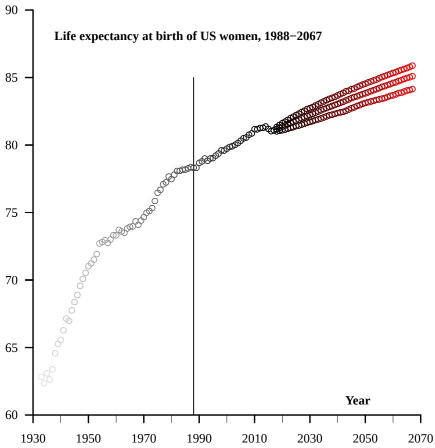
Forecasting US female mortality 50 years ahead using base period 1988-2017





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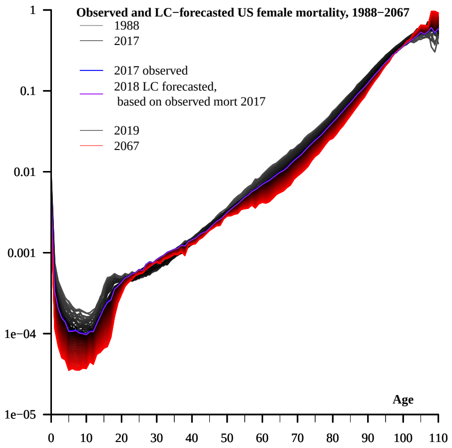
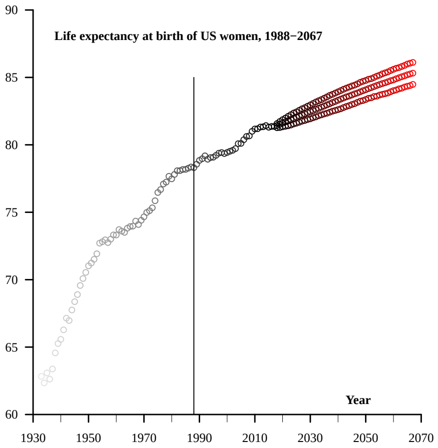
Forecasting US female mortality 50 years ahead using base period 1988-2017, **corrected for jump-off-bias:** $\log m_{x,t} = m_{x,2017} + \beta_x \kappa_t^* + \epsilon_{x,t}$





Think about it.

What are the benefits of the Lee-Carter model?

What trends does the Lee-Carter model capture?

What are the caveats concerning the Lee-Carter model?

What trends does it not capture?

Methodological and technical details on generating mortality forecasts with the LC method

1. Fit the Lee-Carter model to mortality by age and time in base period.
2. Forecast mortality by age s years ahead.

1. Fit LC model to mortality in base period in 8 steps

1. Put mortality rates $m_{x,t}$ in matrix by age (rows) and year (columns)
2. Calculate natural logarithm of mortality rates: $\ln m_{x,t}$
3. Calculate α_x as mean mortality over time for each age x
4. Calculate central (or normalized) log mortality rates $M_{x,t}$ as difference between $\ln m_{x,t}$ and α_x
5. Estimate β_x and κ_t applying singular value decomposition (SVD) to central log mortality rates $(M_{x,t})$

1. Fit LC model to mortality in base period in 8 steps

5. Estimate β_x and κ_t applying singular value decomposition (SVD) to central log mortality rates $(M_{x,t})$
    1. $svd(M_{x,t}) = UDV$; with $M[x,t]$, $U[t,t]$, $D[1,t]$, and $V[x,x]$
    2. $\beta_x = \frac{V[,1]}{\sum V[,1]}$
    3. $\kappa_t = D[1,1]U[,1]sumV[,1]$
    4. Check that $\sum \beta_x = 1$ and $\sum \kappa_t = 0$

1. Fit LC model to mortality in base period in 8 steps

6. Plot α_x, β_x, κ_t for plausibility checks
7. If desired, re-fit κ_t to e.g. total death counts, deaths counts by age, life expectancy with iterative process.
8. Fit mortality in base period putting parameter values into LC model function: $\log \hat{m}_{x,t} = \alpha_x + \beta_x \kappa_t$

2. Forecast mortality by age s years ahead in 3 steps

1. **Fit estimated κ_t in base period** using a time series model, e.g. ARIMA(0,1,0)
   - Lee and Carter suggest random walk with drift, ARIMA(0,1,0): $\kappa_{t+s} = \kappa_{t-1} + \delta + \epsilon_t$
     - δ is a drift term
     - ϵ_t is an error term

2. Forecast mortality by age s years ahead in 3 steps

2. **Forecast κ_t s years ahead** with fitted time series model:
   $\kappa_{t+s} = \kappa_{t-1} + \delta + \epsilon_t$
   - Point and interval forecasts of κ_t can be based on simulation:
     - ★ Simulate N trajectories for κ_{t+s}
       using estimate of δ (of fitted ARIMA(0,1,0) model)
     - ★ Draw $\epsilon_t \sim \mathcal{N}(0, \sigma^2_{\epsilon_t})$
       for each trajectory and year t,
       with $\sigma^2_{\epsilon_t}$ being the estimated variance of the residuals
       of the fitted ARIMA(0,1,0) model
     - ★ Determine median and 80% prediction intervals for κ_{t+s}
       using quantiles (0.1, 0.5, and 0.9)
       of the distribution comprising the N trajectories

2. Forecast mortality by age s years ahead in 3 steps

3. **Forecast age-specific mortality** s **years ahead**
   inserting parameter values into LC model function:
   $\log m_{x,t+s} = \alpha_x + \beta_x \kappa_{t+s} + \epsilon_{x,t}$

Many R implementations of the Lee-Carter model out there

R-packages and related functions (non-exhaustive):

- `demography`: `lca()`, `forecast.lca()`
- `StMoMo`:
  Vignette available at https://cran.r-project.org/web/packages/StMoMo/vignettes/StMoMoVignette.pdf
- `MortalityForecast`: `model.LeeCarter()`, `predict()`
- `ilc`
- `LifeMetrics`
  available at http://www.macs.hw.ac.uk/~andrewc/lifemetrics/

→ helpful to apply LC method but please do not use them as black box

→ to **really understand LC method** it is good to **implement it yourself**!

Think about it again.

What are the benefits of the Lee-Carter method?

What trends does the Lee-Carter method capture?

What are the caveats concerning the Lee-Carter method?

What trends does it not capture?

How could it be improved?

Extensions of the LC method

- Re-fit κ_t in step 1.7 to match
  - Total death counts (e.g. Lee and Carter (1992))
  - Life expectancy at birth (e.g. Lee and Miller (2001))
  - Death counts by age and time (e.g. Booth et al. (2002))
  - ...
- Consider mortality of multiple populations (e.g. Li and Lee (2005))
- Consider cohort effects (e.g. Renshaw and Haberman (2006))
- Consider multiple functional principal components to capture non-random patterns (e.g. Hyndman and Ullah (2007))
- Consider time-variant age pattern of mortality change (e.g. Li et al. (2013))
- ...

$\longrightarrow$ Overview of some LC extensions in e.g. Booth (2006)

Other directions in mortality forecasting

Coherent forecasting to consider developments of other populations:

- Multiple countries (e.g. Li and Lee (2005))
- Women and men (e.g. Hyndman et al. (2013))
- Bayesian methodology of recent UNWPP (e.g. Raftery et al. (2013))

Approaches to consider mortality attributable to health-related behavior:

- Smoking (e.g. Janssen et al. (2013))
- ...

Approaches to capture more closely mortality by age over time:

- Rates of mortality improvement (e.g. Bohk-Ewald and Rau (2017))
- Distribution of ages at death (e.g. Basellini and Camarda (2019))
- ...

...

Validate forecast performance of the Lee-Carter method

...to know if method accurately forecasts mortality...

...in particular mortality setting...

...and also compared to other methods...

$\longrightarrow$ Bohk and Rau (2016), Bohk-Ewald et al. (2017), Bohk-Ewald et al. (2018)

Validate forecast performance of the Lee-Carter method

Basic procedure:

- Withhold observed data and compare them to forecast
- *Single* validation forecast can be sensitive towards mortality levels and trends of selected time period and population

  $\rightarrow$ $\rightarrow$ Validate forecast performance of a method across multiple mortality levels and trends
- Calculate forecast error as deviation between forecast and corresponding observations

  $\rightarrow$ $\rightarrow$ aggregate error across e.g. time periods, populations to quantify overall forecast performance

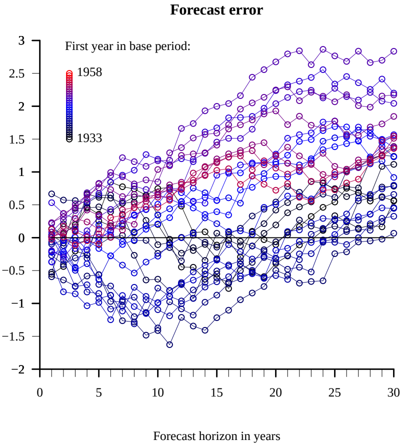
$\rightarrow$ Bohk and Rau (2016), Bohk-Ewald et al. (2017), Bohk-Ewald et al. (2018)

Validate forecast performance of the Lee-Carter method

...based on US female mortality of the HMD, 1933-2017

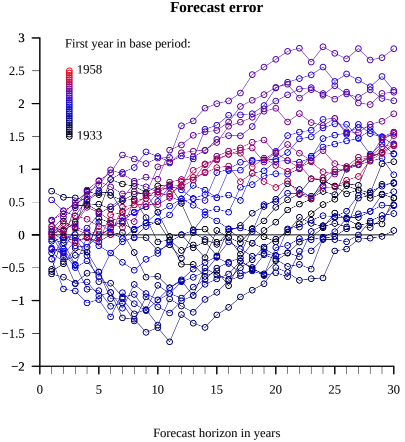
...with as many base periods and forecast horizons comprising 30 years each

...and jump-off years covering 1962 through 1987



Validate forecast performance of the Lee-Carter method

...based on US female mortality of the HMD
...with as many base periods and forecast horizons comprising 30 years each
...and jump-off years covering 1962 through 1987



- Forecast error increases with length of forecast horizon
- Partly underestimation of e_0 in early base periods
- Overestimation of e_0 in more recent base periods
- Forecast error in most recent base periods tends to decline (purple to red)

What you have learned today about mortality forecasting

- List different types of approaches to forecast mortality
- Describe the conceptual idea behind
  - the Lee-Carter method to fit and forecast mortality
  - validating forecast performance of the Lee-Carter method
- List technical and methodological details
  - of the Lee-Carter method
  - validation forecasts

Today's class in the afternoon:
Hands-on experiences in mortality forecasting with R

- Load mortality data from the Human Mortality Database
- Implement and use the Lee-Carter method
  - to fit and forecast US mortality
  - and, if time allows, to validate its performance
- Analyze LC mortality forecasts for US women and men, 2018-2067,
  - based on base periods comprising 30, 50, 70, and 85 years
  - examining crucial parameters such as α_x, β_x, κ_t, δ, ...

  Present and discuss your findings.

Please make sure to have installed R package `fds`. And to have at hand your username and password for the Human Mortality Database.

Recommended learning material for today's class

- **Lee, R. D., & Carter, L. R. (1992)**
  Modeling and forecasting U.S. mortality. Journal of the American Statistical Association, 87(419), 659-671.
- **Booth, H. (2006)**
  Demographic forecasting: 1980 to 2005 in review. International Journal of Forecasting, 22(3), 547-581.
- **Booth, H., & Tickle, L. (2008)**
  Mortality modelling and forecasting: A review of methods. Annals of Actuarial Science, 3(1-2), 3-43.

Recommended learning material for today's class

- **Bohk, C., & Rau, R. (2016)**
  Changing mortality patterns and their predictability: the case of the United States. In Dynamic Demographic Analysis (pp. 69-89). Springer, Cham.
- **Rau, R., Bohk-Ewald, C., Muszyńska, M., & Vaupel, J. (2017)**
  Visualizing Mortality Dynamics in the Lexis Diagram (Vol. 44). Springer.
- **Bohk-Ewald, C., Ebeling, M., & Rau, R. (2017)**
  Lifespan disparity as an additional indicator for evaluating mortality forecasts. Demography, 54(4), 1559-1577.
- **Bohk-Ewald, C., Li, P., & Myrskylä, M. (2018)**
  Forecast accuracy hardly improves with method complexity when completing cohort fertility. Proceedings of the National Academy of Sciences, 115(37), 9187-9192.

Recommended learning material for today's class

- **UNWPP2019**: `https://population.un.org/wpp/`
  Publications, Graphs, & Data files.

- **Raftery, A. E., Gerland, P., and Ševčíková, H. (2013)**
  Bayesian probabilistic projections of life expectancy for all countries. Demography, 50(3), 777–801.
- **Alho, J. and Spencer, B. (1997)**
  The practical specification of the expected error of population forecasts. Journal of Official Statistics, 13(3), 203–225.
- **Preston, S., Heuveline, P., and Guillot, M. (2000)**
  Demography: measuring and modeling population processes
  Blackwell Publishers Ltd.
- **Alho, J. and Spencer, B. (2006)**
  Statistical demography and forecasting
  Springer Science & Business Media.

Thank you for your attention!

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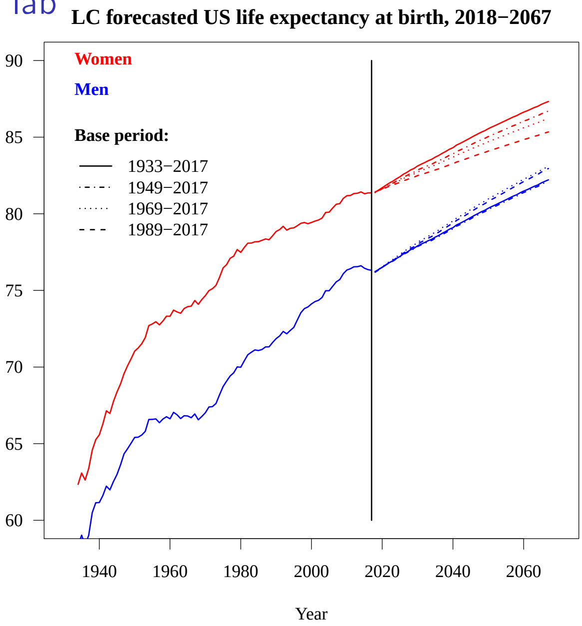
Afternoon lab

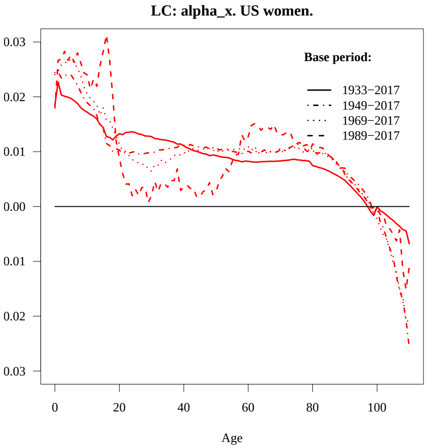
- Implement LC method in R
  $\rightarrow$ document *hands-on-experience-forecasting-mortality-with-LC.pdf*
- Analyze LC mortality forecasts for US women and men, 2018-2067,
  - based on base periods comprising 30, 50, 70, and 85 years
  - examining crucial parameters such as α_x, β_x, κ_t, δ, ...

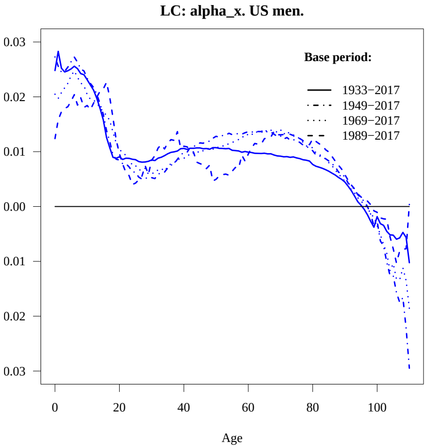
  Present and discuss your findings.
- Validate LC method (if time allows)

Afternoon lab



Afternoon lab



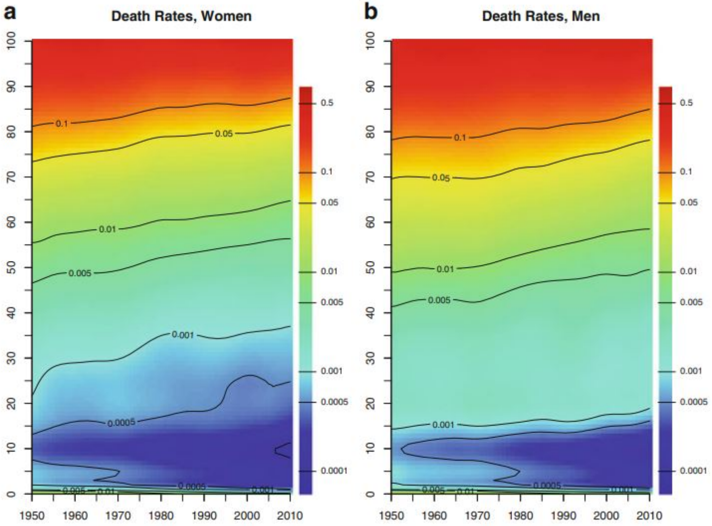


US mortality level and trends

Bohk and Rau (2016) and Rau et al. (2017):

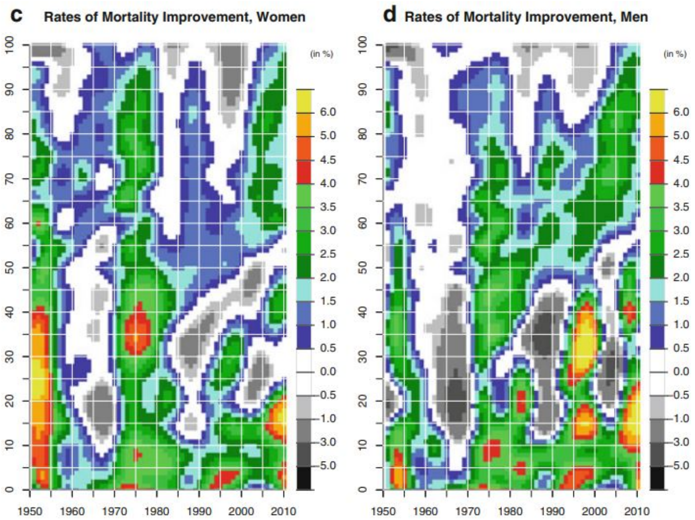
- Rates of mortality improvement
  $\rightarrow \rho_{x,t} = -\left(\frac{m_{x,t+1}}{m_{x,t}} - 1\right)$
- for lung cancer related mortality
  $\rightarrow$ lifestyle risk factor cigarette smoking
- for diabetes related mortality
  $\rightarrow$ link to obesity?
- ...

US mortality level and trends



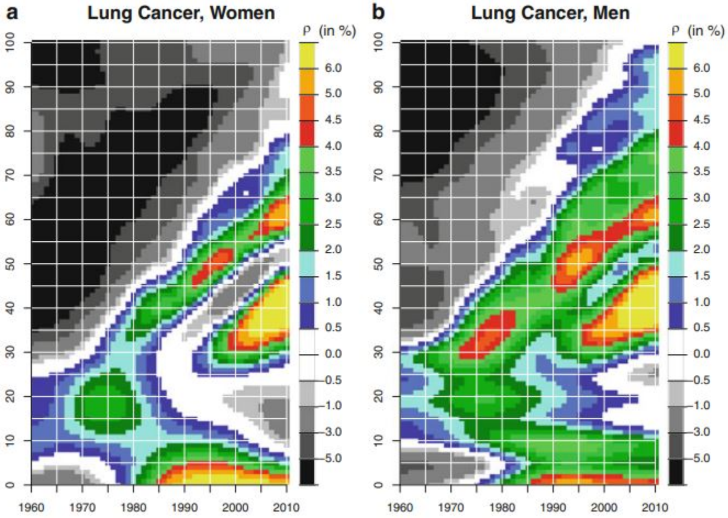
Bohk and Rau (2016, p. 72)

US mortality level and trends



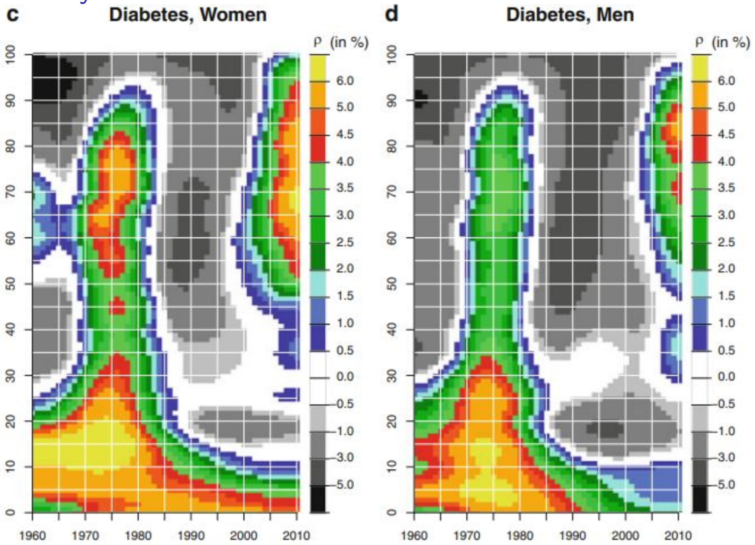
Bohk and Rau (2016, p. 72)

US mortality level and trends



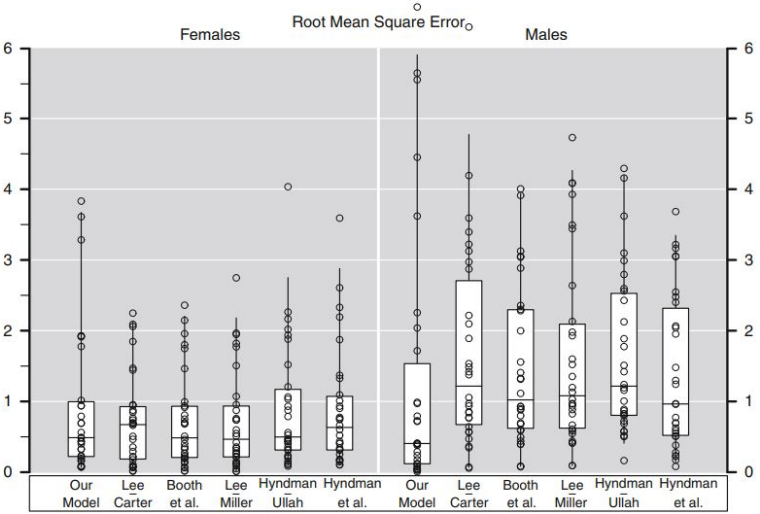
Bohk and Rau (2016, p. 74)

US mortality level and trends



Bohk and Rau (2016, p. 74)

Validate LC forecast performance across HMD countries



Bohk and Rau (2016, p. 84)