

Longevity 18, London

Robust mortality forecasting in the presence of outliers

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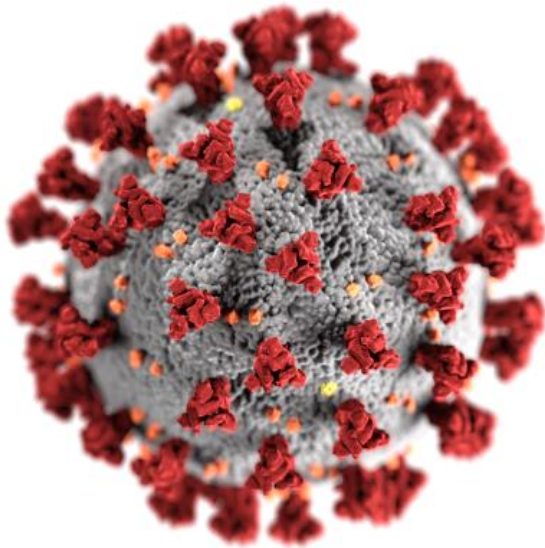


1. Motivation
2. Univariate forecasts
3. Multivariate forecasts
4. 2D P -spline model
5. Conclusions

Fast introduction to robust mortality forecasting.

Further details in Richards [2023], freely available at:

www.longevity.co.uk/robust-forecasting

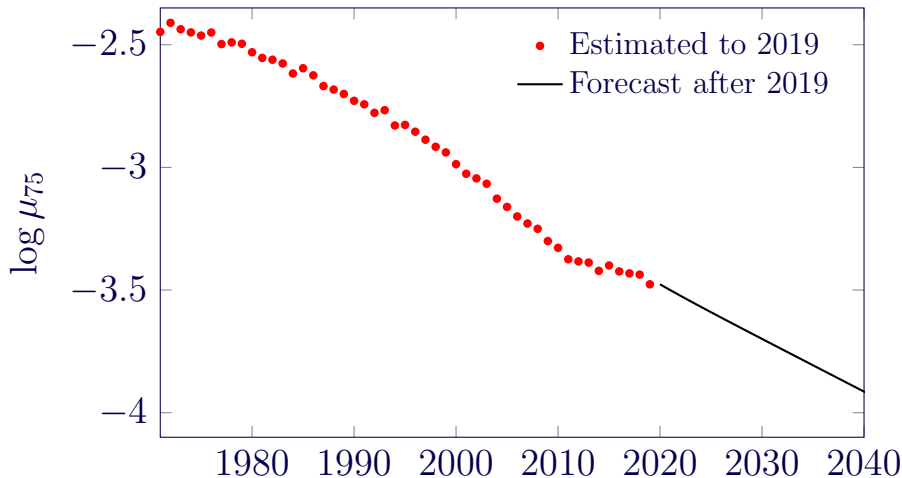


Covid-affected data cause:

1. Broken forecasts.
2. Biased starting points.
3. Inflated variance.

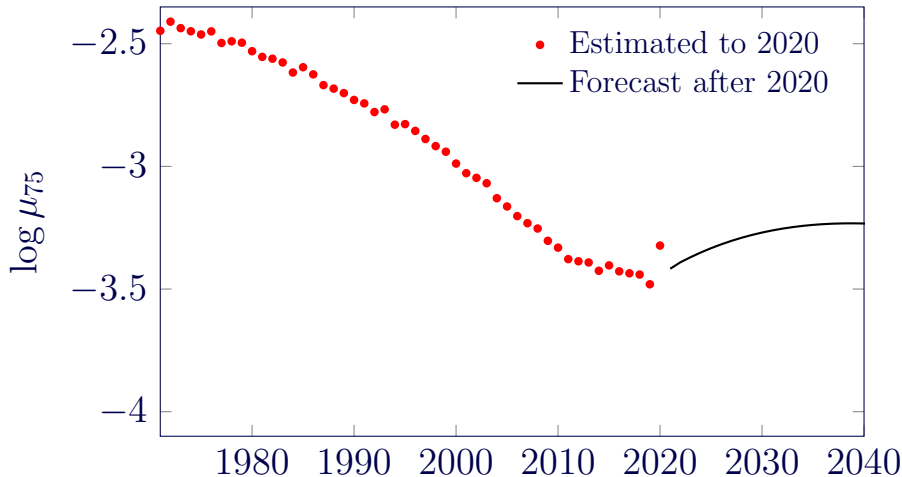
Covid-19 distorts central projections...

ARIMA forecast of time index in Lee-Carter model:



Source: Data for males in England & Wales, ages 50–105, 1971–2019.

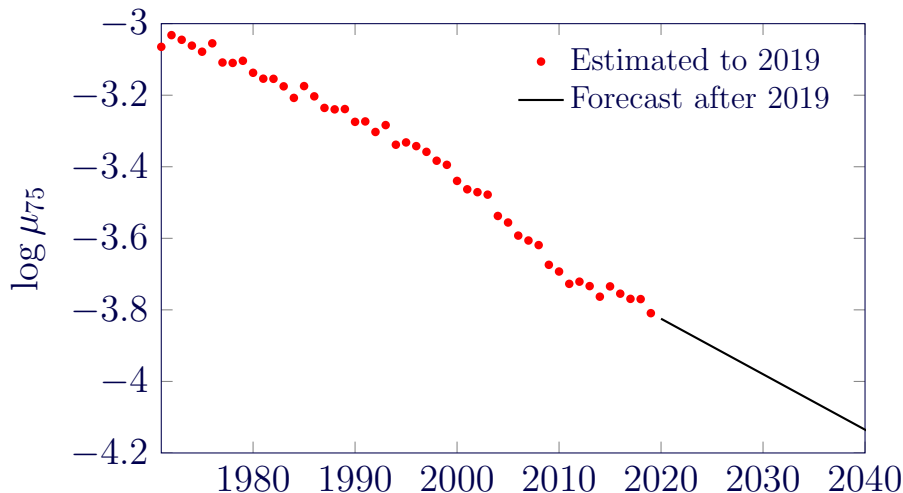
ARIMA forecast of time index in Lee-Carter model:



Source: Data for males in England & Wales, ages 50–105, 1971–2020.

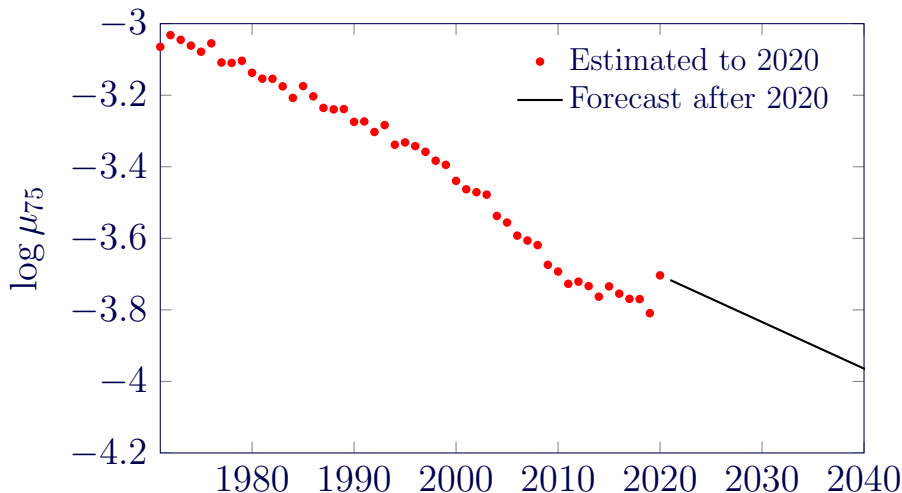
Covid-19 leads to biased starting points...

Bivariate random-walk forecast under M5 model:



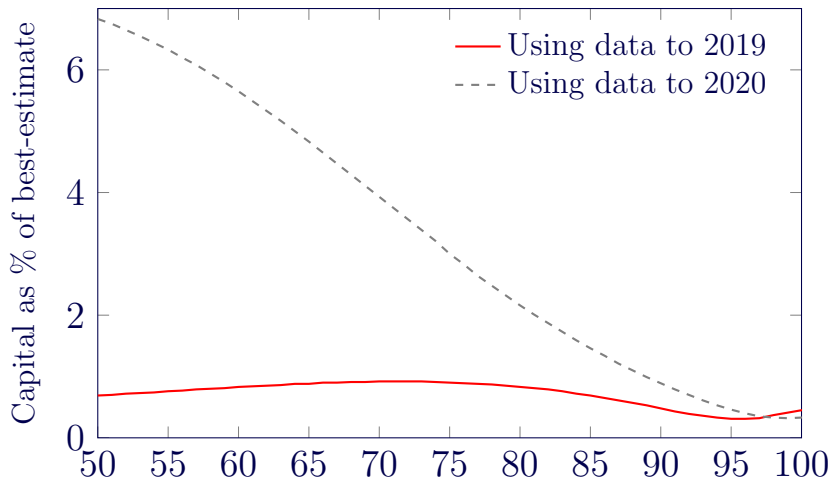
Source: Data for females in England & Wales, ages 60–105, 1971–2019.

Bivariate random-walk forecast under M5 model:



Source: Data for females in England & Wales, ages 60–105, 1971–2020.

Outliers increase VaR capital requirements. . .



Source: 10,000 recalibrations of Lee-Carter model using data for males in England & Wales. Annuity cashflows discounted at 0% per annum.

- Covid-19 breaks forecasting models in three important ways.
- How can we robustify forecasts for actuarial tasks?

1. Remove distortion in parameter estimates.
2. Calculate “clean” starting points for forecasts.
3. Estimate variance robustly.
4. Need objective methodology for (1)-(3) to allow repeated recalibration under VaR-style simulations.

- Identify outliers with statistical tests.
- Co-estimate outlier effects with other parameters.

2 Univariate forecasts

- A univariate model has multiple parameter vectors, but only one represents a time index to forecast.
- Example from Lee and Carter [1992]:

$$\log \mu_{x,y} = \alpha_x + \beta_x \kappa_y$$

- $\hat{\alpha}_x$ and $\hat{\beta}_x$ are held constant in the forecast.
- An ARIMA model is fitted to the $\hat{\kappa}_y$ time index to forecast the trend.

Outlier

An observation that is further from the one-year-ahead forecast than is consistent with the noise variance.

To robustify an ARIMA model, Chen and Liu [1993]:

1. Proposed test statistics to identify outliers.
2. Proposed further test statistics to *classify* outliers.

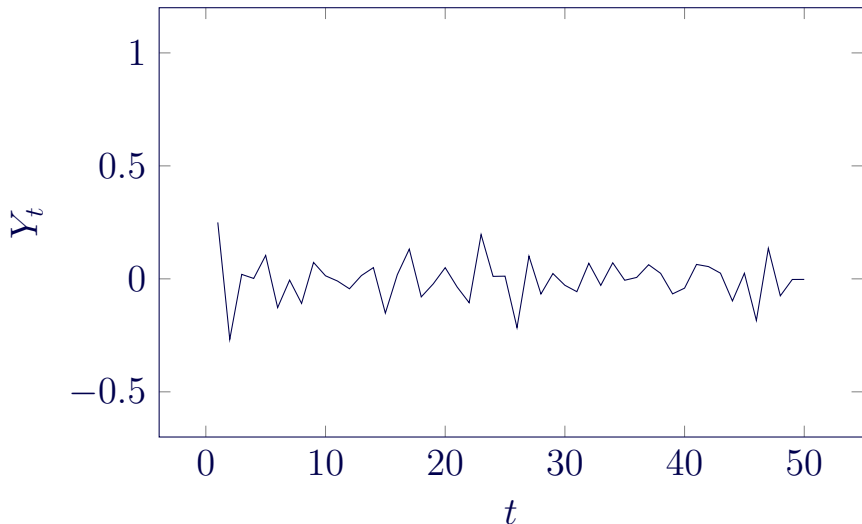
2 Four outlier types

- IO** Innovation outlier
- AO** Additive outlier
- TC** Temporary change
- LS** Level shift

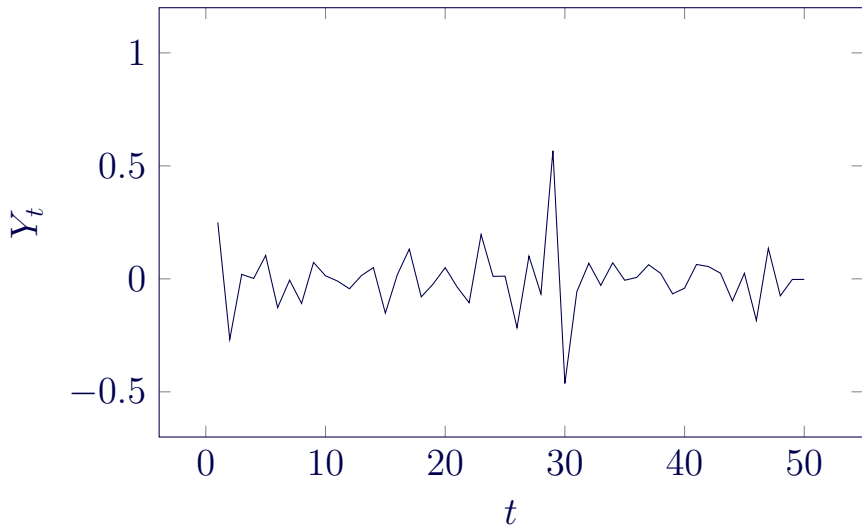
Consider a moving-average (MA) process:

$$Y_t = \epsilon_t - 0.8\epsilon_{t-1} \quad (1)$$

2 Uncontaminated MA process; LONGEVITAS



Source: Richards [2023, Figure 3].



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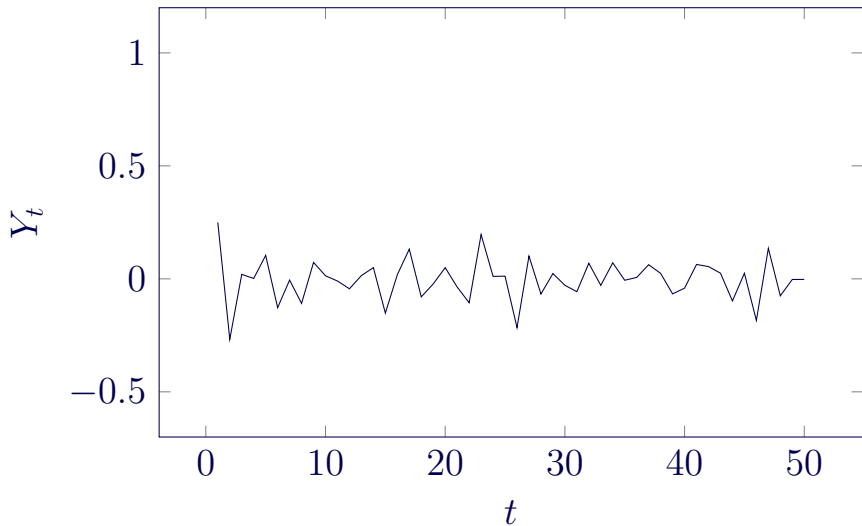
A modest outlier that is nevertheless integrated into the process.

Example

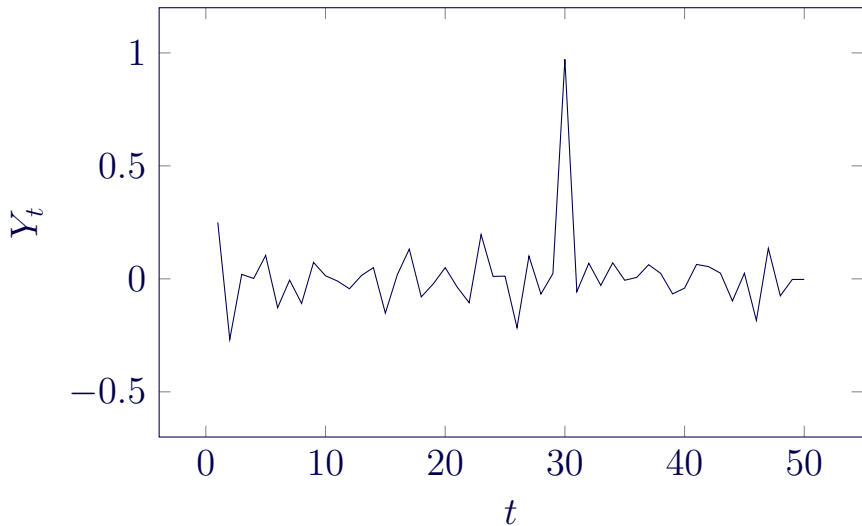
A year with heavy winter mortality due to influenza, possibly with lighter mortality the following year.

Handling: leave alone.

2 Uncontaminated MA process; LONGEVITAS



Source: Richards [2023, Figure 3].



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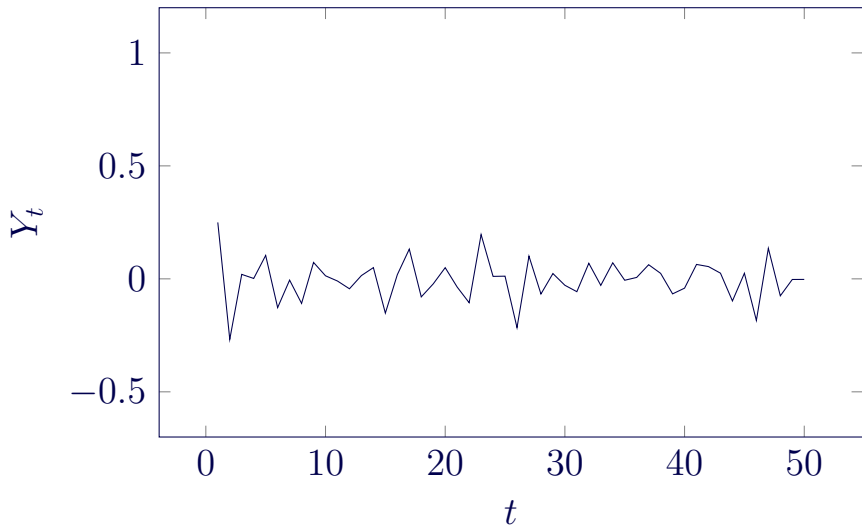
A more extreme outlier that is not integrated into the process.

Example

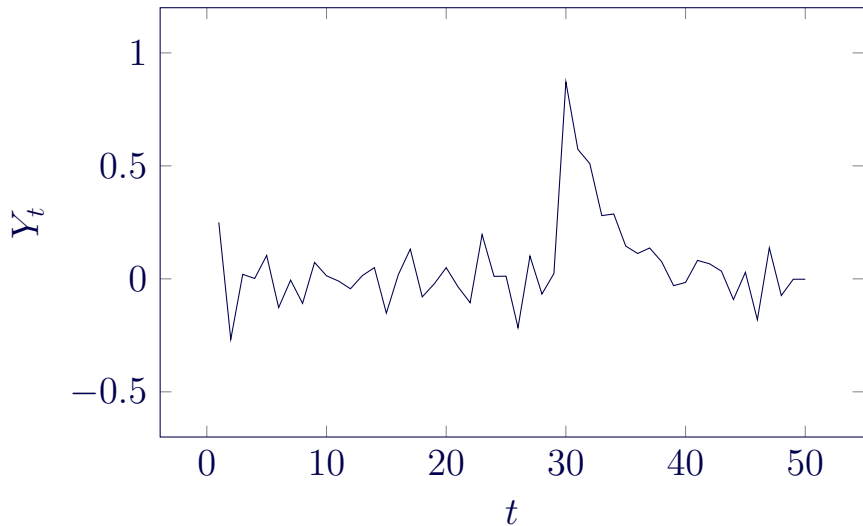
War or pandemic in a single year.

Handling: co-estimate the outlier effect to remove bias in other parameters.

2 Uncontaminated MA process; LONGEVITAS



Source: Richards [2023, Figure 3].



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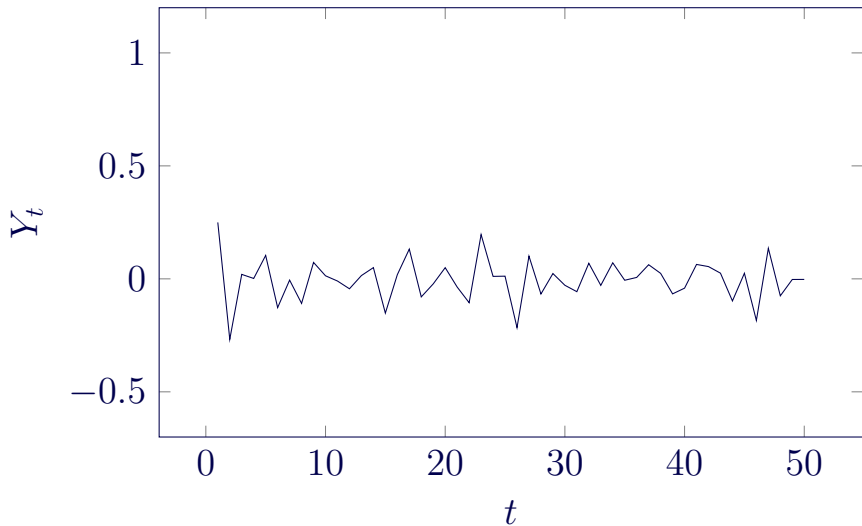
Two or more consecutive outliers that are not integrated into the process.

Example

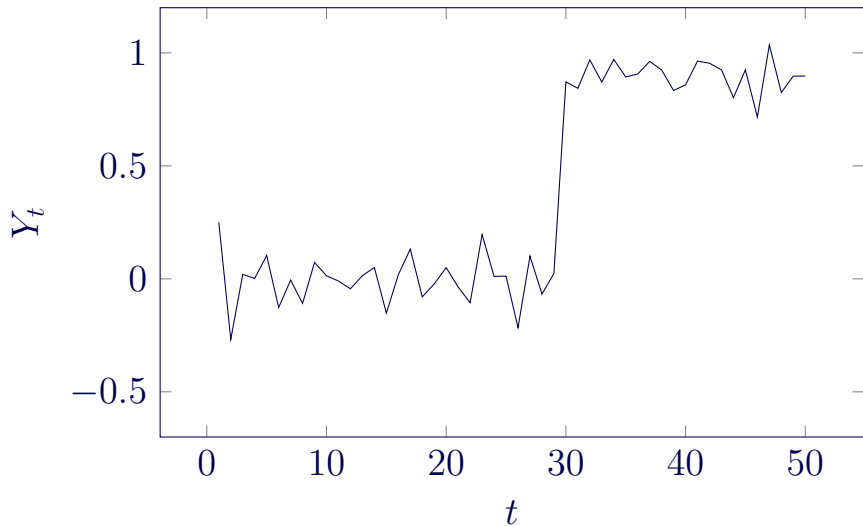
War or pandemic spread over more than one year.

Handling: co-estimate the outlier effects to remove bias in other parameters.

2 Uncontaminated MA process; LONGEVITAS



Source: Richards [2023, Figure 3].



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Permanent change in level of process.

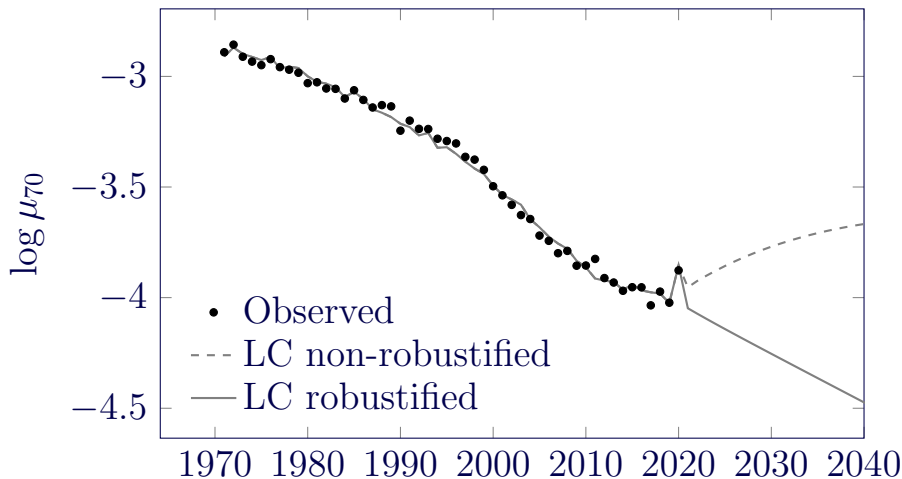
Example

After German reunification in 1990, old-age mortality in East converged rapidly on levels in the West [Grigoriev et al., 2021].

Handling: review model or data period.

Note

An outlier can be detected anywhere, but “it is impossible to empirically distinguish the type of an outlier at the very end of a series” [Chen and Liu, 1993, page 286].



Source: Richards [2023, Figure 4(b)].

3 Multivariate forecasts

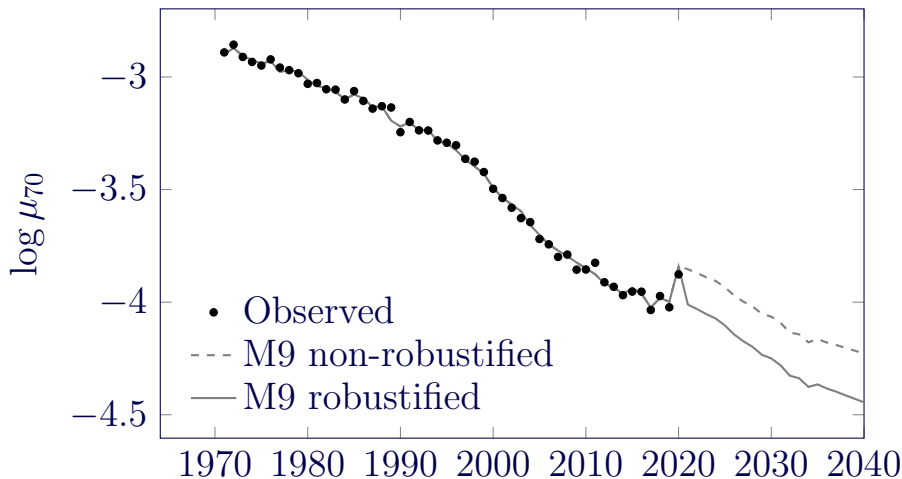
- A multivariate model has two or more time indices.
- Example from Cairns et al. [2006]:

$$\log \mu_{x,y} = \kappa_{0,y} + (x - \bar{x})\kappa_{1,y}$$

- $\hat{\kappa}_{0,y}$ and $\hat{\kappa}_{1,y}$ are forecast jointly as a bivariate random walk with drift.

- Use approach of Galeano et al. [2006].
- Robustify first differences [Richards, 2023, Appendix C].

3 Robust M9 forecast

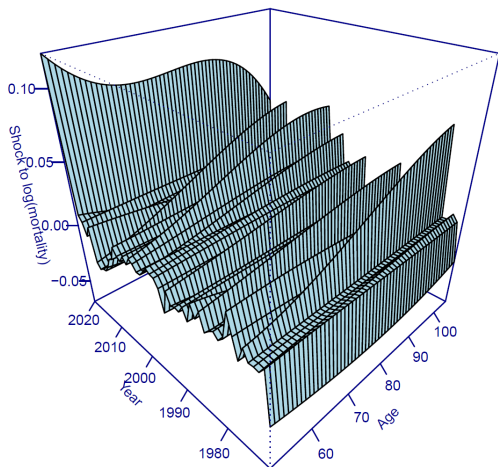


Source: Richards [2023, Figure 9(b)].

Other approaches to identifying outliers in multivariate data, e.g. Hadi [1994].

4 2D P -spline model

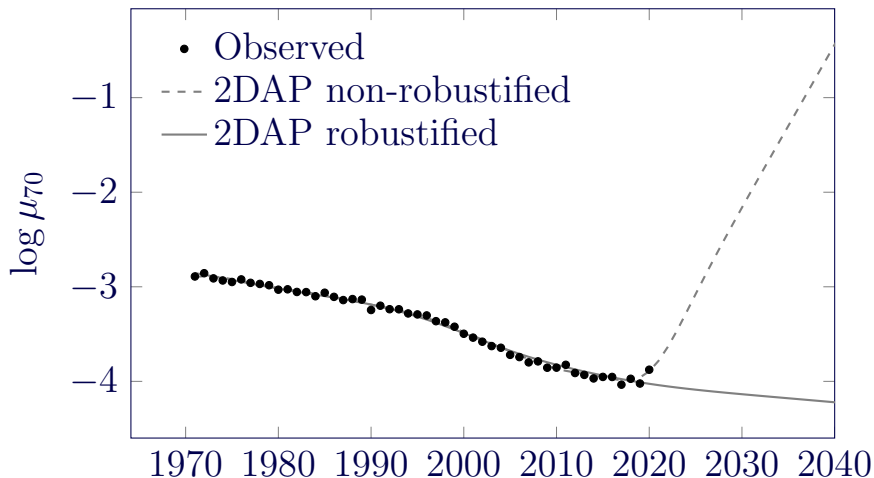
- Introduced by Currie et al. [2004].
- Extended by Kirkby and Currie [2010] to estimate period shocks. . .



Source: Richards [2023, Figure 12].

- Forecast using *penalty function*.
- Estimating period shocks robustifies penalty forecast...

4 Robust 2DAP forecast



Source: Richards [2023, Figure 13(b)].

5 Conclusions

Co-estimation of outliers and parameters:

1. Reduces bias in forecasting parameters.
2. Yields better starting points for forecasts.
3. Reduces variance in capital requirements.

Univariate forecasting

- Lee-Carter and APC models.
- Use approach of Chen and Liu [1993].

Multivariate forecasting

- Cairns-Blake-Dowd & Tang-Li-Tickle models.
- Use approach of Galeano et al. [2006].


2D P -spline

- Currie-Durban-Eilers model.
- Use approach of Kirkby and Currie [2010].

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- J. G. Kirkby and I. D. Currie. Smooth models of mortality with period shocks. *Statistical Modelling*, 10(2):177–196, 2010. doi: 10.1017/1471082X0801000204.
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- S. J. Richards. Robust mortality forecasting in the presence of outliers. Longevity working paper, 2023.
- Coronavirus graphic  from CDC

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