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Modeling Trend Processes in Parametric Mortality Models

- Johannes Schupp
- joint work with Matthias Börger
- Longevity 11 Conference, Lyon, 7th-9th September 2015



Agenda

Motivation

New Stochastic Trend Process

Parameter Estimation

Stochastic Start Trend

Comparison with other Trend Processes

Summary

Motivation

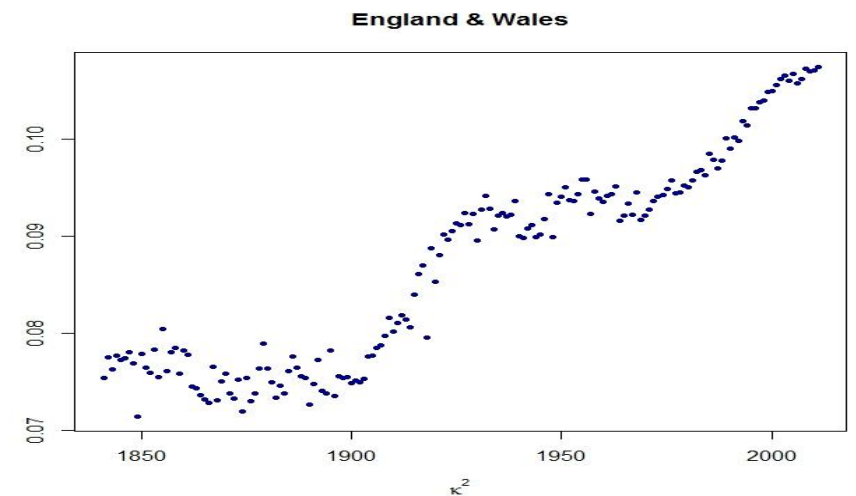
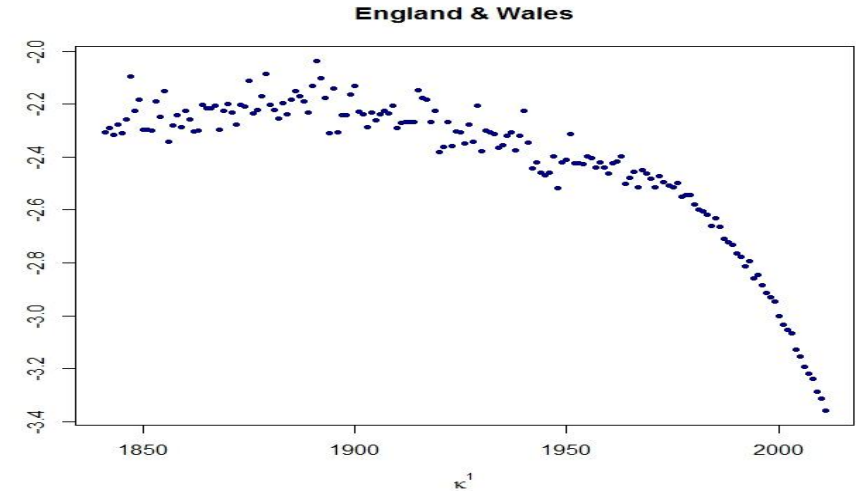
Uncertainty about the evolution of mortality

- increasing attention on longevity risk
- measure longevity risk in pension or annuity portfolios with stochastic mortality models
- parametric mortality models
- one or more time dependent parameter
- projection of these parameter processes with stochastic processes
 - stochastic forecasts of future mortality
- focus here: A new stochastic trend process to model the parameter processes in parametric mortality models

Motivation

Stochastic processes:

- popular choice: (multivariate) random walk with drift (RWD)
 - one constant drift
 - simple estimation
- curves are unlikely to be generated by a RWD (Börger et al. 2014)
- new trend process
 - continuous and piecewise linear trends
 - random changes in the trend's slope
 - random fluctuations around the trend



New Stochastic Trend Process

Trend process with multiple breakpoints:

- modeling the trend with random noise:

$$\kappa_t = \tilde{\kappa}_t + \epsilon_t$$

- extrapolation with most recent trend:

$$\tilde{\kappa}_t = \tilde{\kappa}_{t-1} + d_t$$

- inclusion of a possible trend change with a trend change probability p

$$d_t = d_{t-1} + \lambda_t$$

and with no trend change with a probability $1 - p$

$$d_t = d_{t-1}$$

- trend change intensity:

$$\lambda_t = S_t \cdot M_t$$

- absolute magnitude of trend change M_t

- sign of the trend change S_t

Parameter Estimation

Parameters to be estimated:

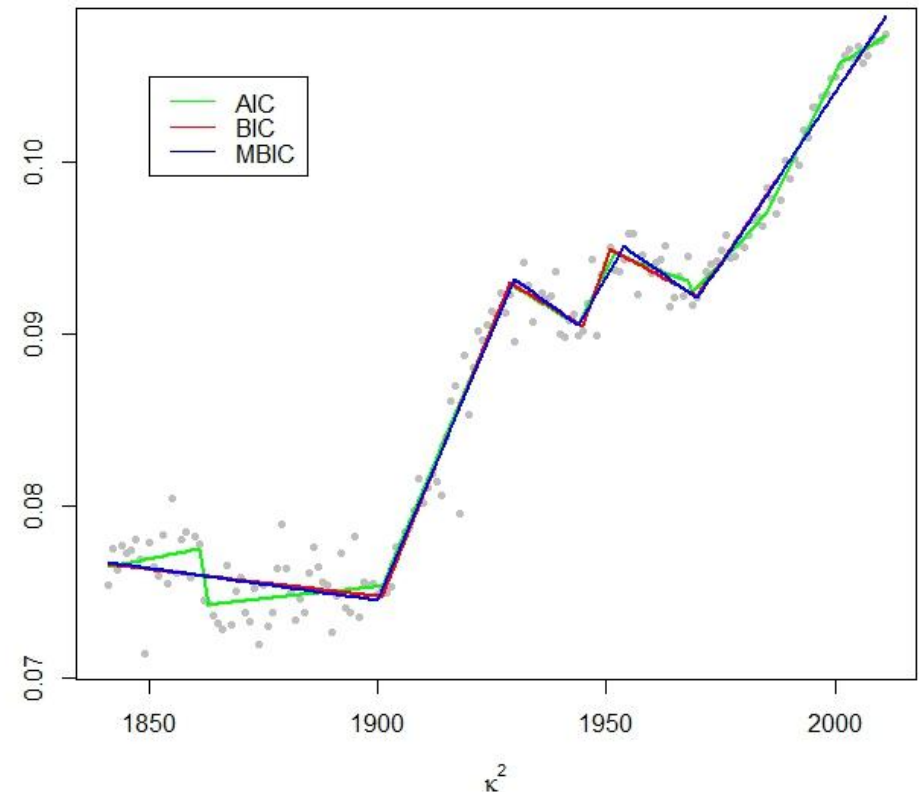
- trend change probability p
- decomposed trend change intensity $\lambda_t = S_t \cdot M_t$
 - S_t bernoulli distributed with values -1 and 1 each with probability $\frac{1}{2}$.
 - M_t lognormally distributed with parameters μ, σ^2
 - Other approaches use a normal distribution or a Pareto distribution
- values of $\tilde{\kappa}_t$ and d_t for the starting value and trend
- variance of the error terms $\epsilon_t \sim \mathcal{N}(0, \sigma_t^2)$

Parameter Estimation

Idea: Estimation based on historical trend changes

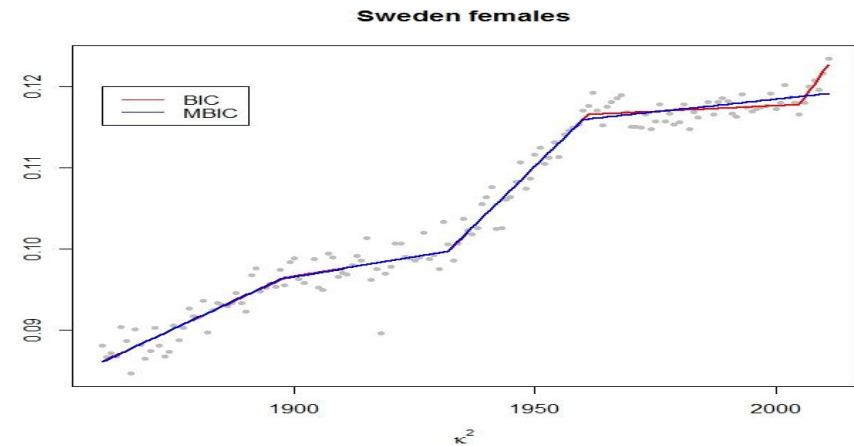
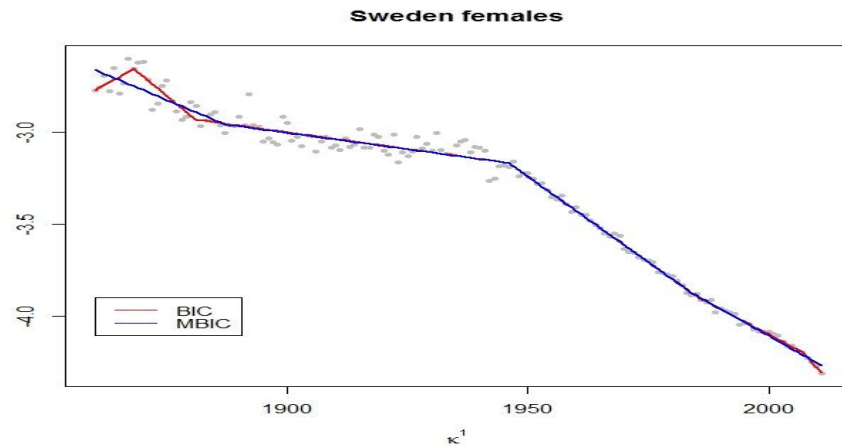
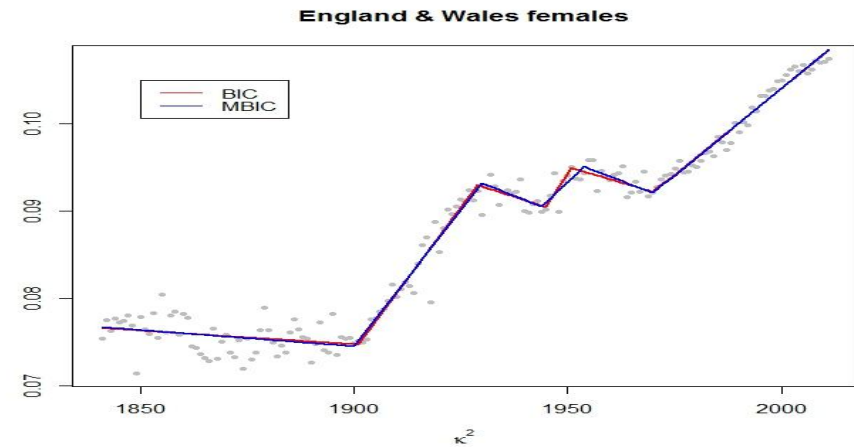
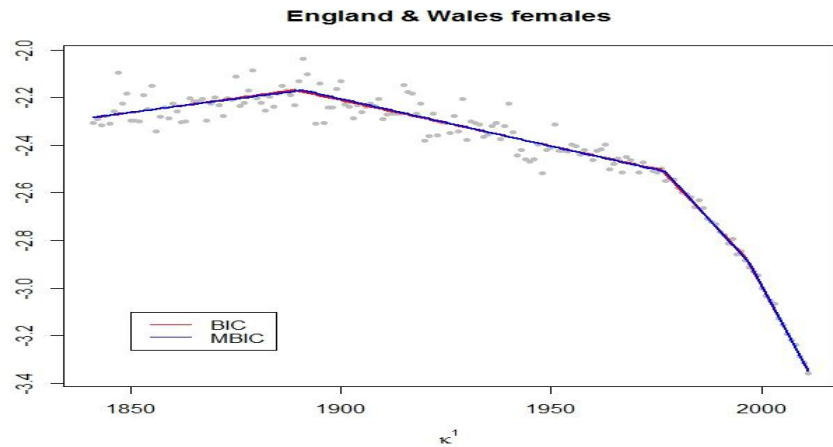
- Use an iterative 'segmented' method proposed by Muggeo (2003).
- comparison and selection of models with information criteria, e.g.:
 - Akaike Information Criterion (AIC)
 - Bayesian Information Criterion (BIC)
 - Modified Bayesian Information Criterion (MBIC)
- Consider changing variance in ϵ_t with a CUSUM test.

England & Wales females



Parameter Estimation

Historic trend processes for females in England & Wales and Sweden

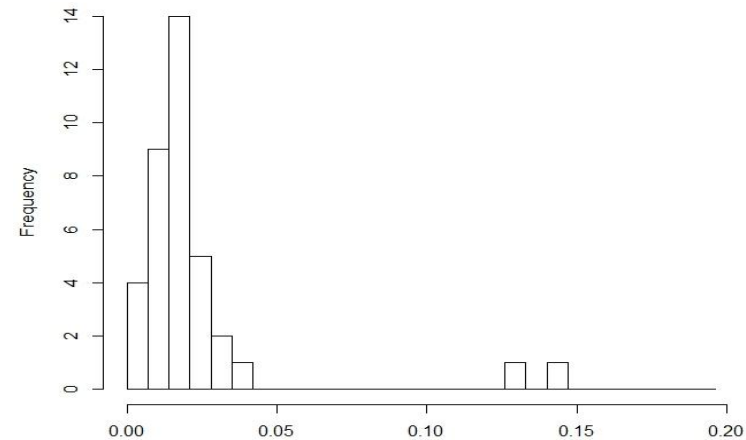


Parameter Estimation

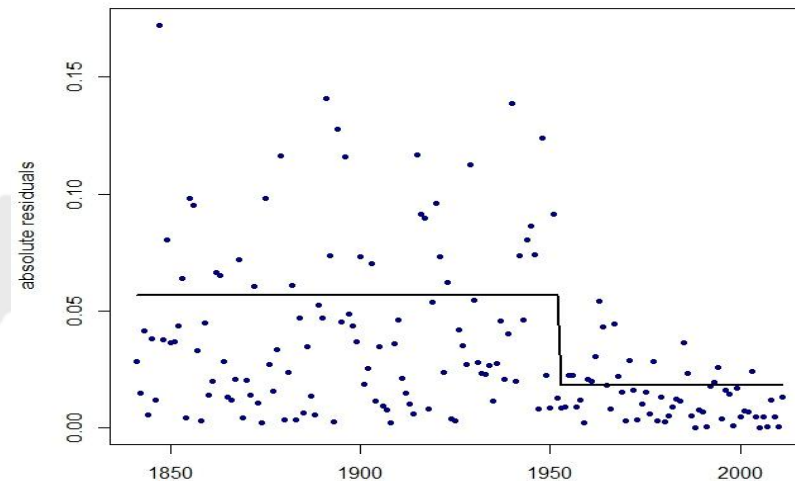
Estimate parameters based on historical trend changes:

- trend change probability $p = \frac{\#breaks}{data\ length}$
- trend change intensity:
 - use historic absolute trend changes to estimate the parameters of the lognormal distribution μ, σ^2
 - optional: sampling of absolute trend changes for different countries
- values of $\tilde{\kappa}_t$ and \tilde{d}_t for the starting value and trend based on historic trends
- variance of the error term with CUSUM test

Histogram of sampled absolute trend changes



England & Wales females

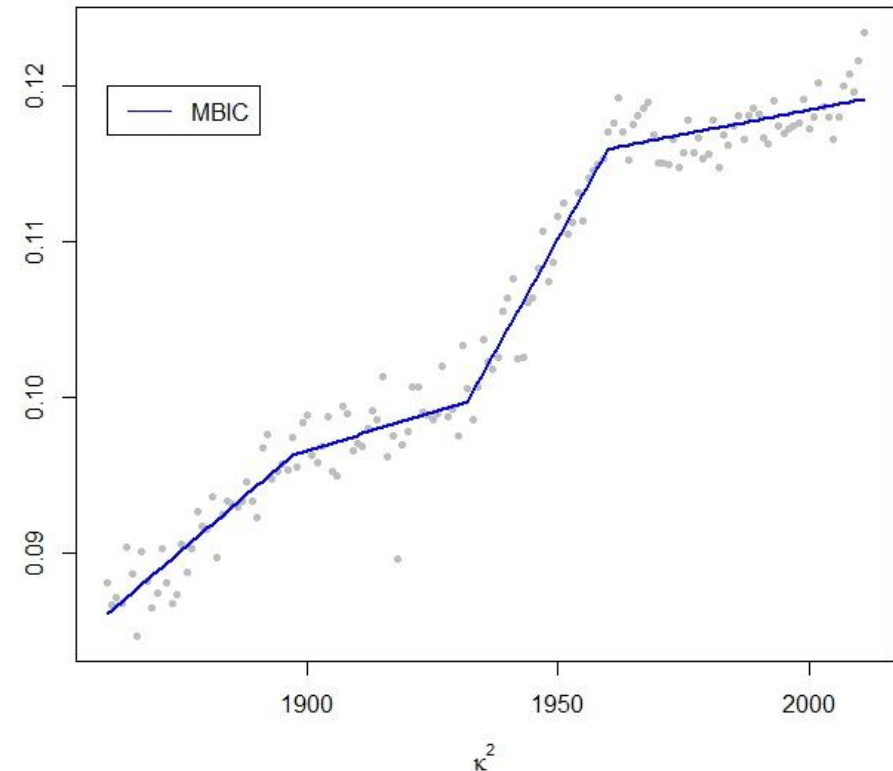


Stochastic Start Trend

Uncertainty about the most recent trend and the starting point of simulation

- breakpoint which was not detected yet?
 - possible different actual trend?
 - possible different starting value?
- Idea: include a stochastic distribution for the most recent trend d_t and for the starting point of simulation $\tilde{\kappa}_t$.
- Include another last breakpoint after the last detected breakpoint in the historic trend.
- Use relative likelihood to estimate a discrete distribution for the models with an additional last breakpoint.

Sweden females



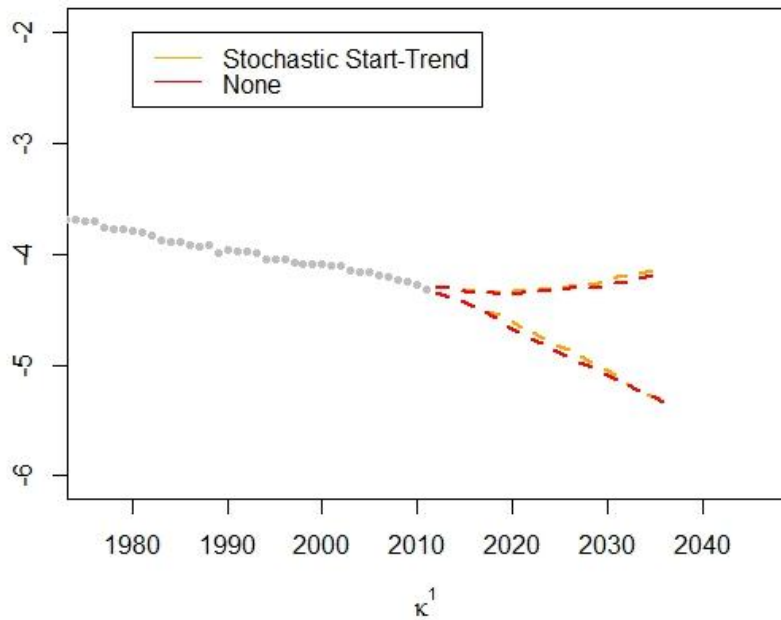
Stochastic Start Trend

Uncertainty about the most recent trend

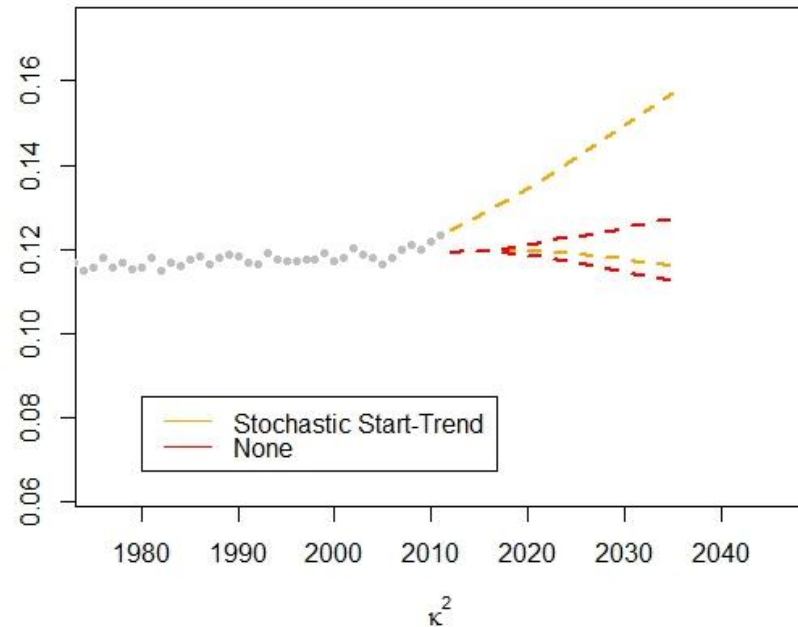
- stochastic start trend considers latest evolution
- extrapolation with the most recent trend which is set to be stochastic
- here : upward movement of confidence interval and increase of uncertainty



Sweden females



Sweden females



Comparison with other Trend Processes

Random walk with drift (RWD) and models of Sweeting and Li et al.

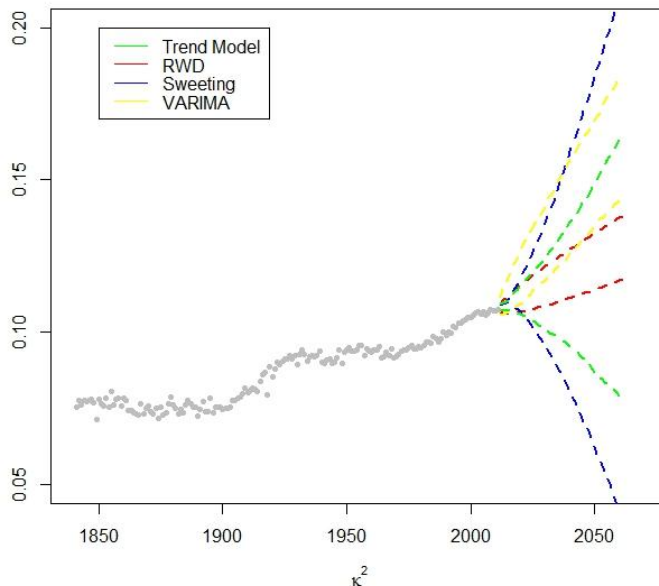
- RWD:
 - bivariate random walk with one constant drift
 - preselection of data history; here: data since last breakpoint
- Sweeting (2011):
 - identification of trend model with Chow-test
 - magnitude of changes normally distributed with mean 0
- Li et al. (2014):
 - VARIMA process
 - extrapolation of trends and errors
 - fitted to total data history

Comparison with other Trend Processes

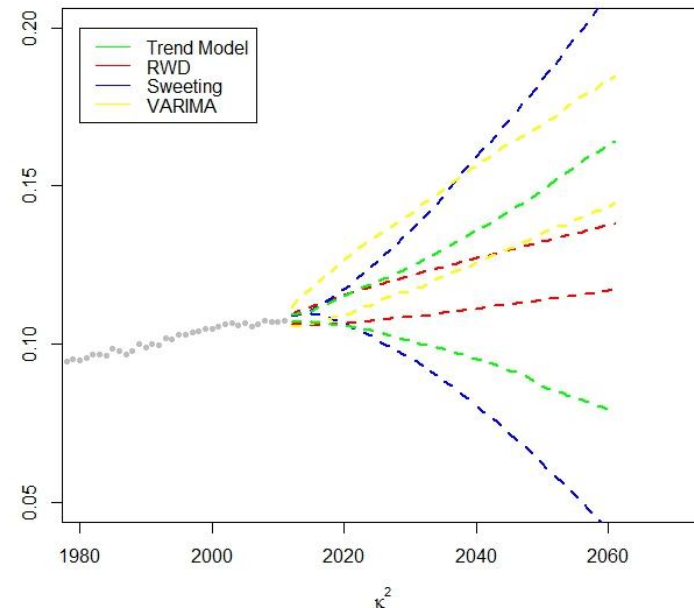
RWD and models of Sweeting and Li

- rather small confidence intervals for RWD and VARIMA; location seems questionable
 - preselection on data history
 - large uncertainty in nearby future and moderate increases in more distant future
- trend process indicates larger uncertainty in the future
- extremely wide confidence intervals with the approach of Sweeting

England & Wales females



England & Wales females



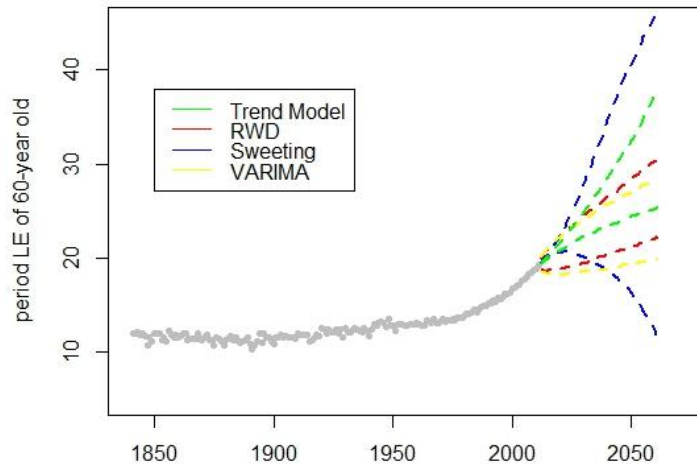
Comparison with other Trend Processes

RWD and models of Sweeting and Li

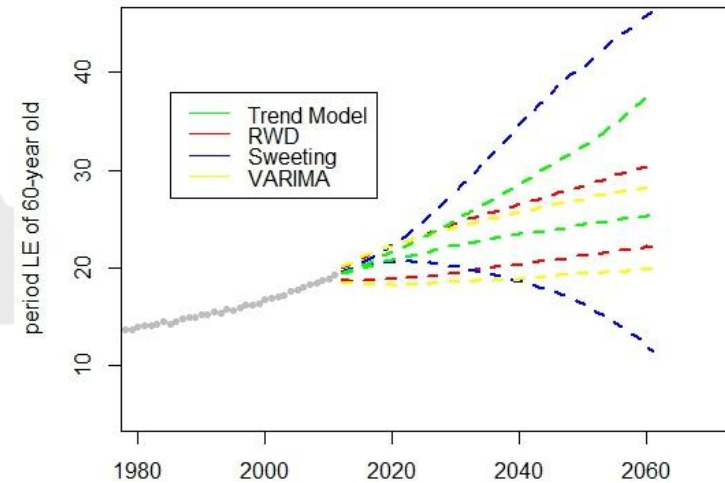
- same result for the period life expectancy at age 60
- rather small upside potential for RWD and VARIMA
- trend process includes uncertainties in the future, i.e.:
 - possible continuation of latest improvements
- extremely wide confidence intervals with the approach of Sweeting



England & Wales females



England & Wales females



Summary

- Standard random walk with drift does not always extrapolate historic evolution.
 - one constant drift only for limited period of time
- new trend model with:
 - continuous and piecewise linear trends
 - random changes in the trend's slope
 - random fluctuations around the trend
- parameter estimation based on historic trends
- reasonable trend models for all countries with long data histories provided by the HMD
- Uncertainty in current trend can be accounted for by a stochastic start trend distribution.
- comparison with other approaches including trends
 - reasonable results with the new trend process
 - adequate extrapolation of historic evolution
 - large uncertainty in the more distant future

Literature

- Börger, M., Fleischer, D., Kuksin, N., 2014. Modeling Mortality Trend under Modern Solvency Regimes. *ASTIN Bulletin*, 44: 1–38.
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