

Inferences for Maximum country life expectancy using Provincial data

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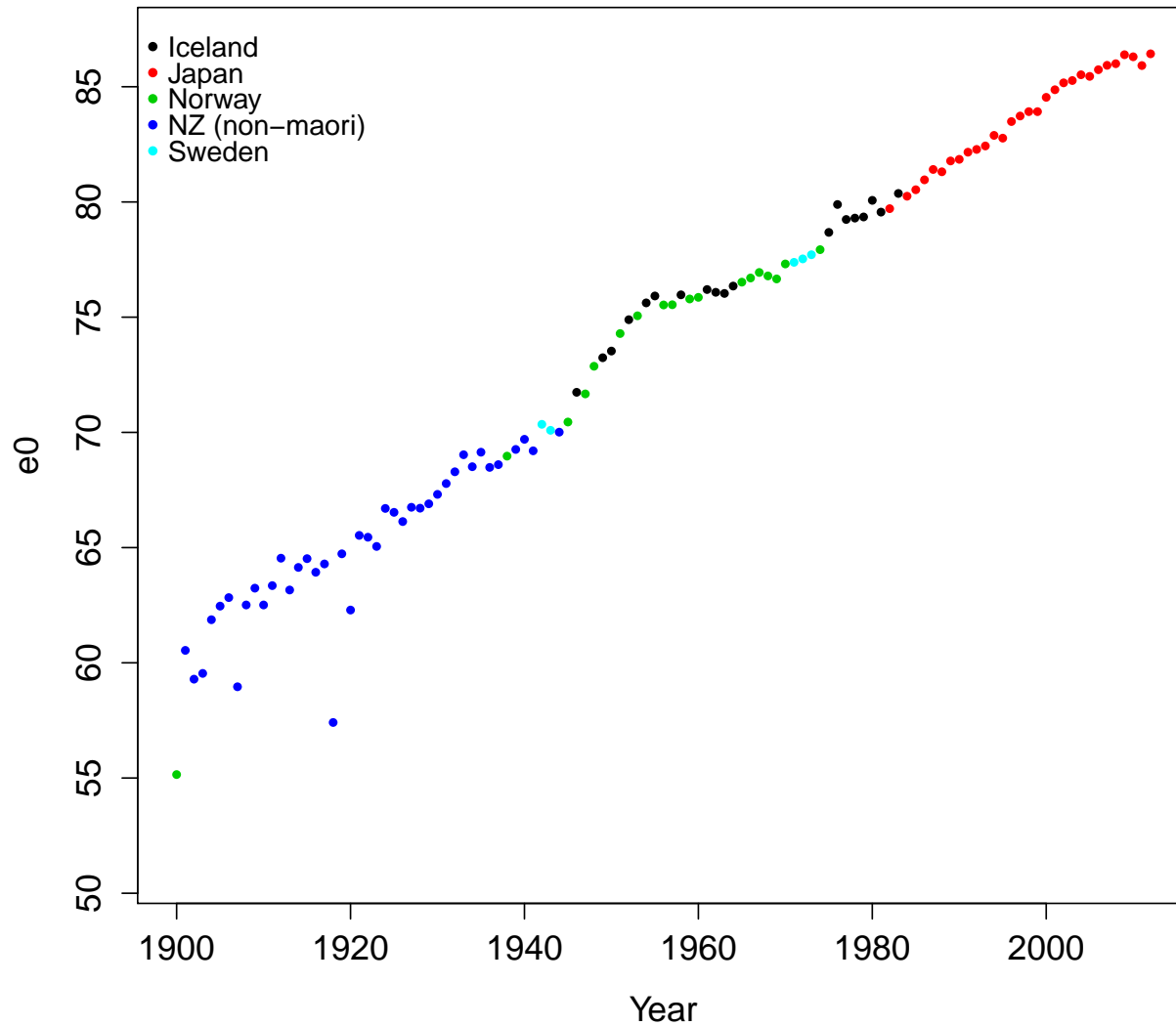
- 1 Intro
- 2 Global BPLE
 - Breakpoints
- 3 Model for BPLE?
 - Empirical motivation
 - Theoretical motivation
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- 4 Regional BPLE
 - Data
 - The Model
- 5 Results
- 6 Conclusions
 - Ongoing work
 - Take Aways

Overview

- What is Global Best practice Life expectancy?
- Extreme Value Theory in brief and its relation to Best practice Life expectancy
- Regional Best practice Life expectancy and inference

Females e_0

Female Best Practice e_0



Global Best Practice Life Expectancy

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- At birth, has been increasing almost linearly - beginning in Scandinavia c. 1840 - at about 3 months per year (Oeppen and Vaupel, 2002).

Global Best Practice Life Expectancy

- Global Best Practice Life Expectancy (BPLE) is the maximum life expectancy observed among nations at a given age.
- At birth, has been increasing almost linearly - beginning in Scandinavia c. 1840 - at about 3 months per year (Oeppen and Vaupel, 2002).
- Life expectancy trends may fit better than individual-country trends in age-standardized (log) death rates (White, 2002).

Global Best Practice Life Expectancy

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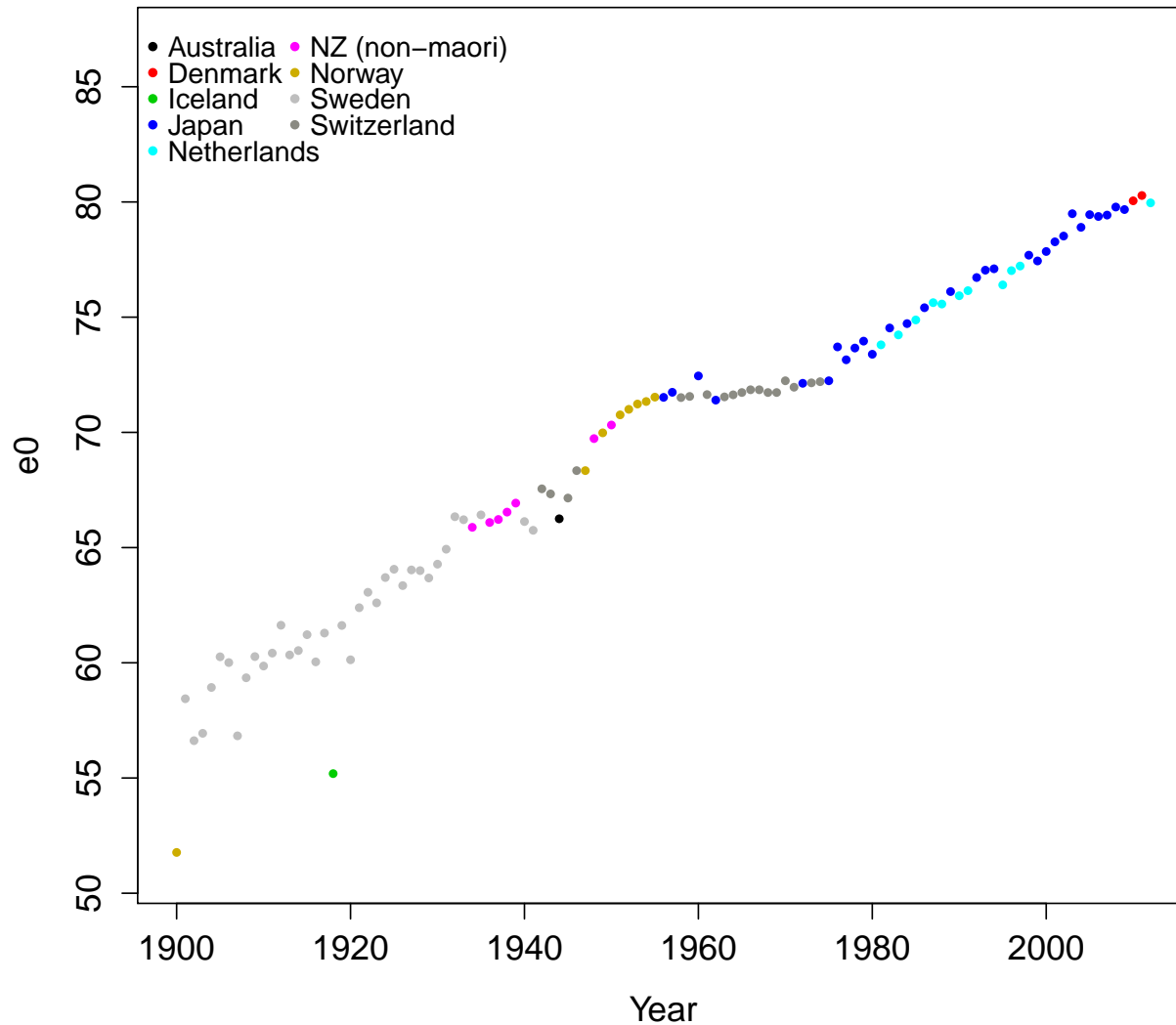
- Nations experience more rapid life expectancy gains when they are farther below BPLE and tend to converge towards BPLE (Torri and Vaupel, 2012).

Global Best Practice Life Expectancy

- Nations experience more rapid life expectancy gains when they are farther below BPLE and tend to converge towards BPLE (Torri and Vaupel, 2012).
- It is sensible to consider national mortality trends in a larger international context rather than individual projections (Lee, 2006; Wilmoth, 1998).

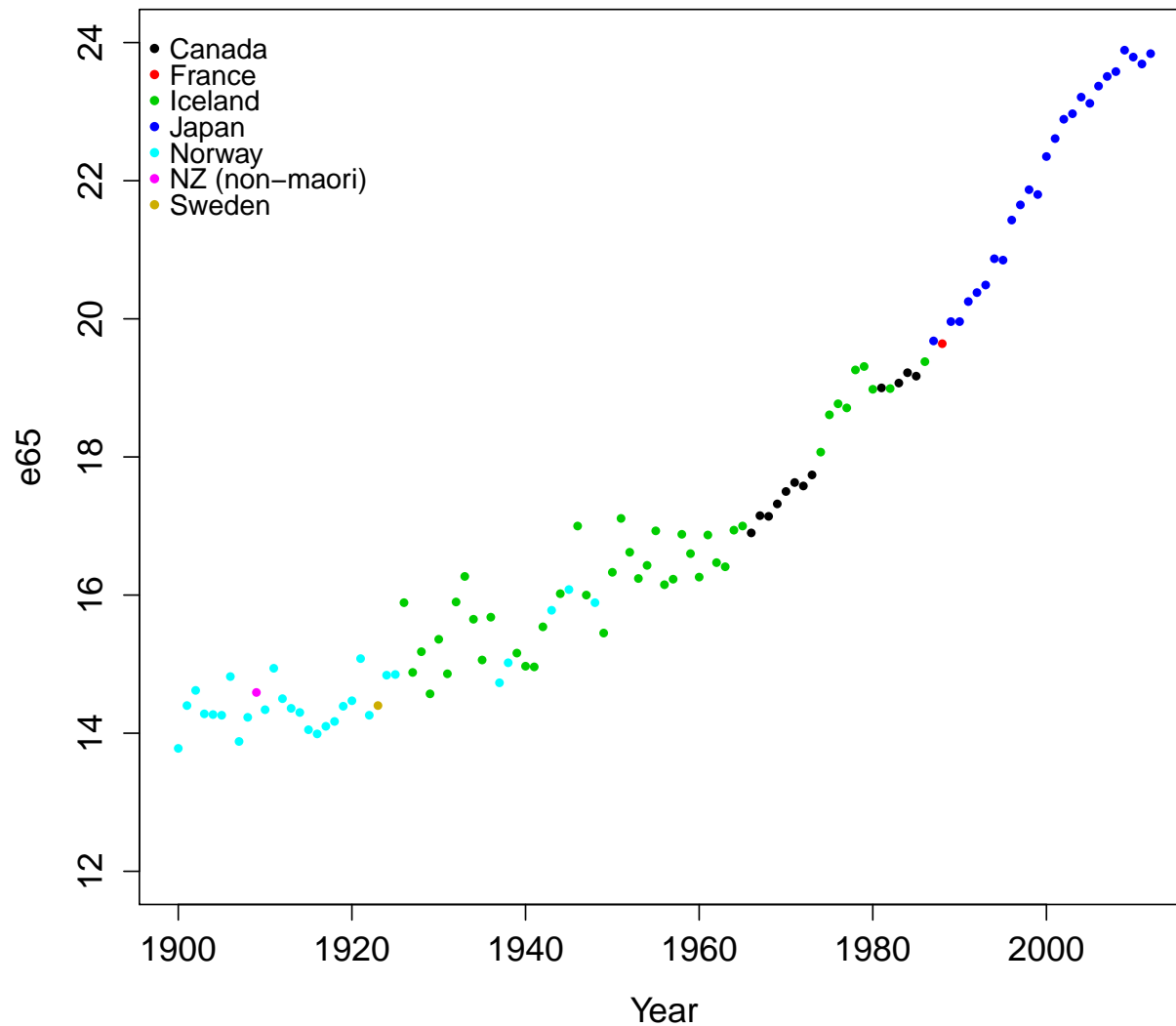
Males e_0

Male Best Practice e_0



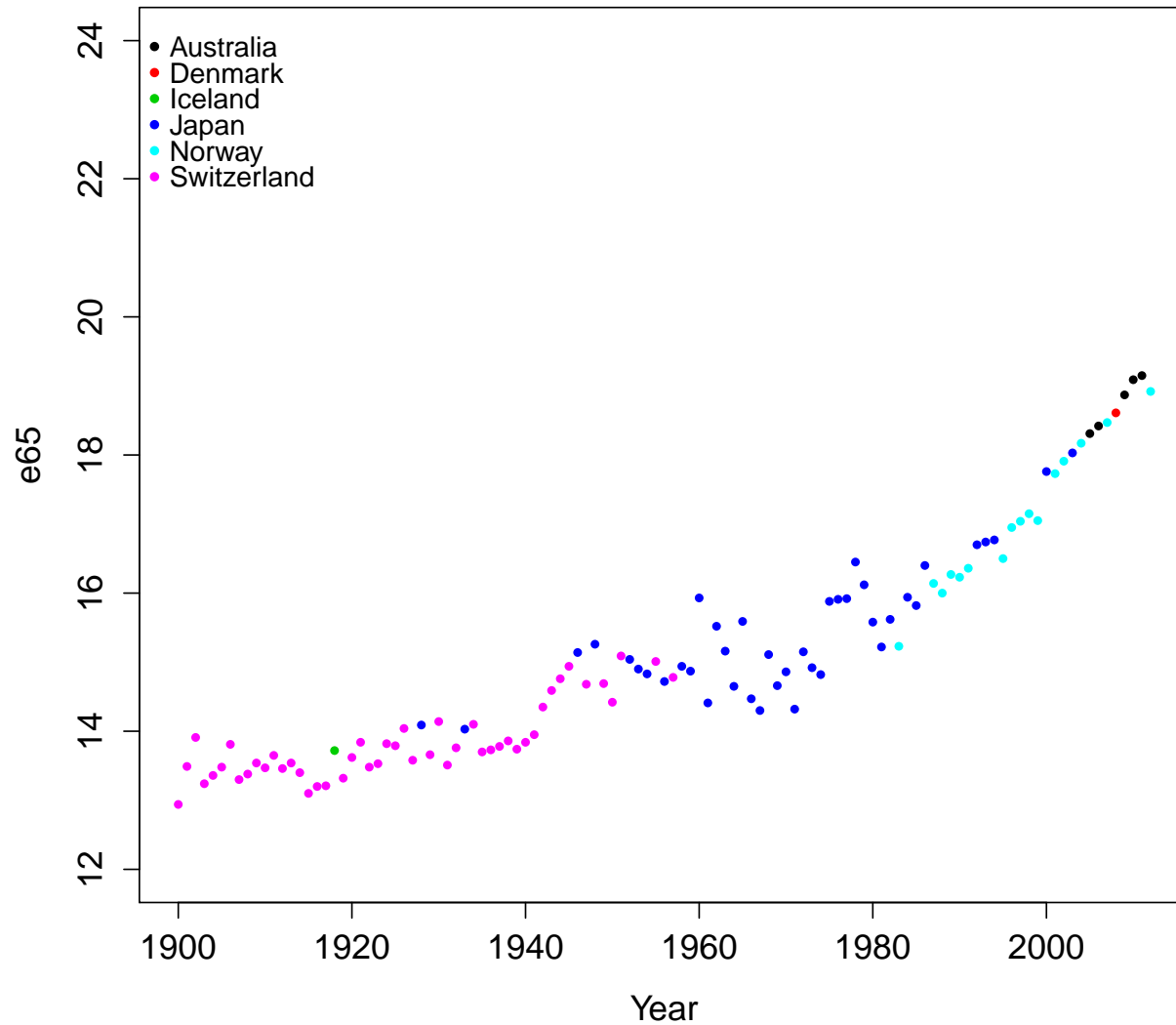
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Breakpoints

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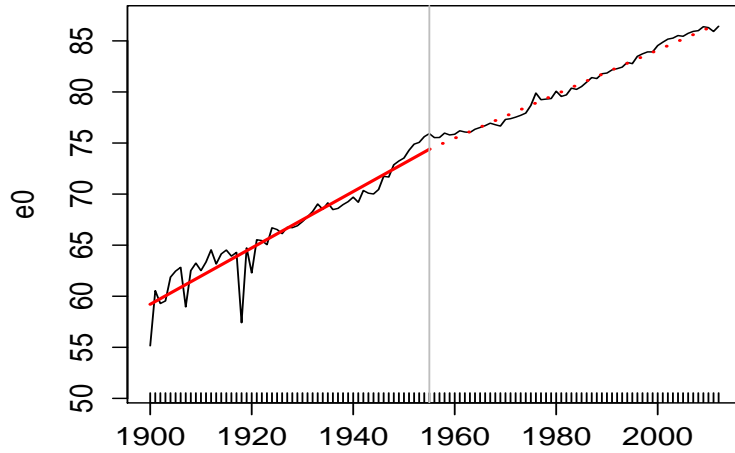
- Vallin and Meslé (2009) expanded on work of Oeppen and Vaupel and argued that BPLE trend may comprise multiple segments

Breakpoints

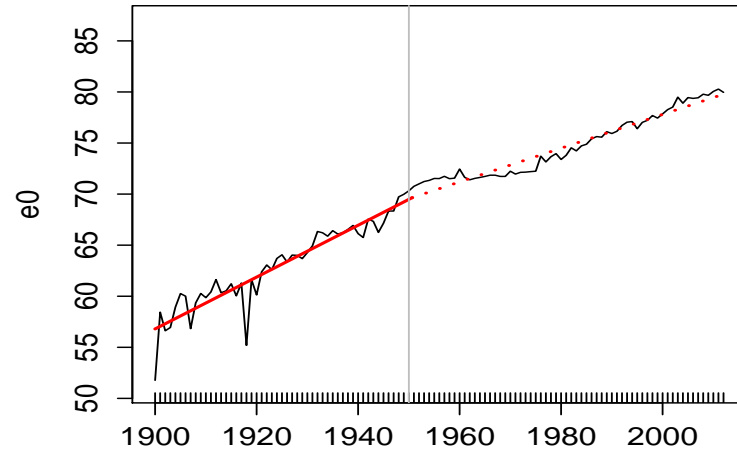
- Vallin and Meslé (2009) expanded on work of Oeppen and Vaupel and argued that BPLE trend may comprise multiple segments
- Each segment corresponds to distinct health transition phases

Breakpoints

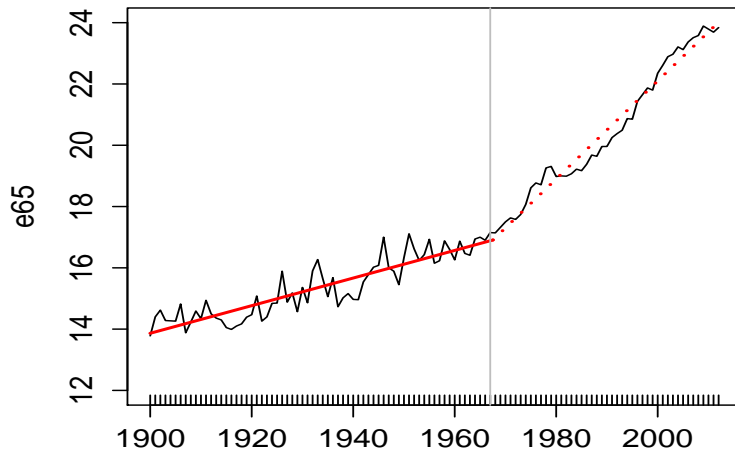
Females



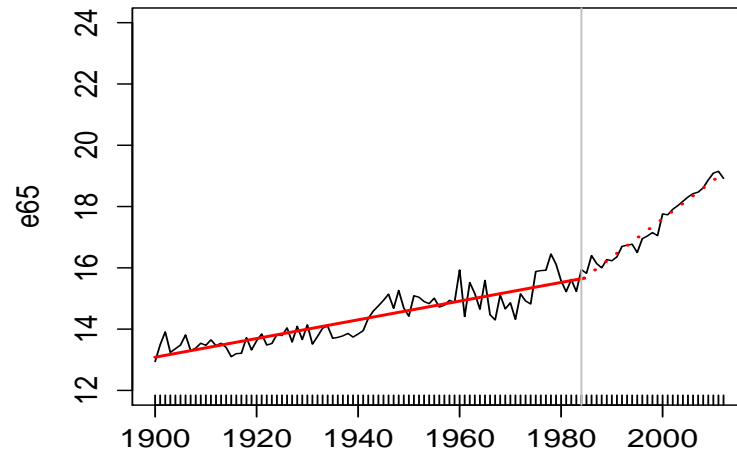
Males



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Males

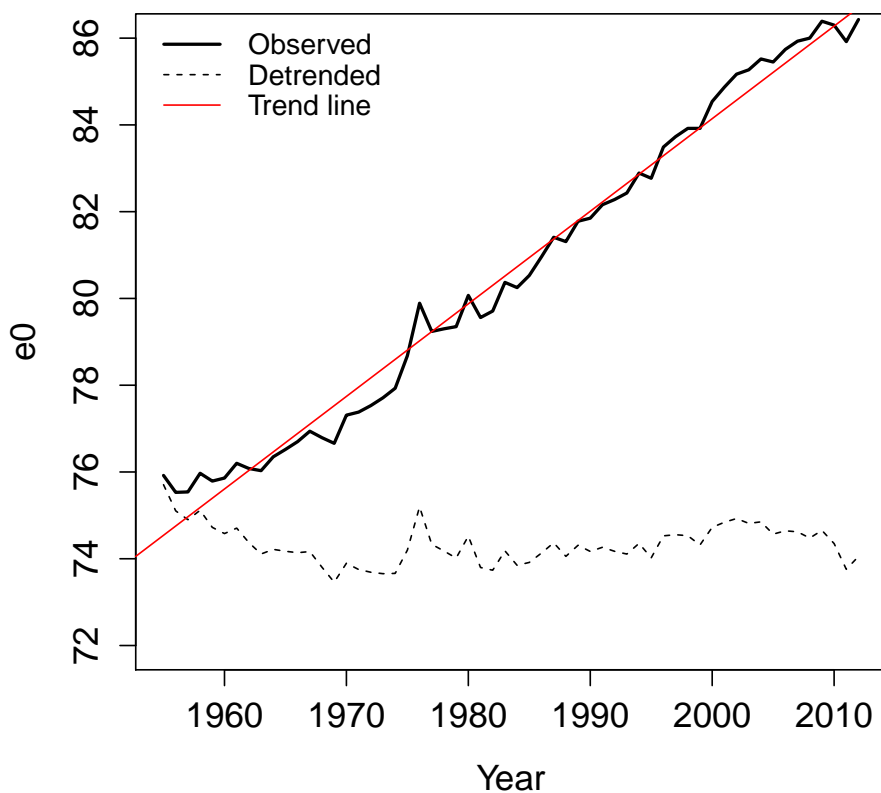


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Can we model Global BPLE?

Female Best Practice e0



Kernel Density and fitted GEV

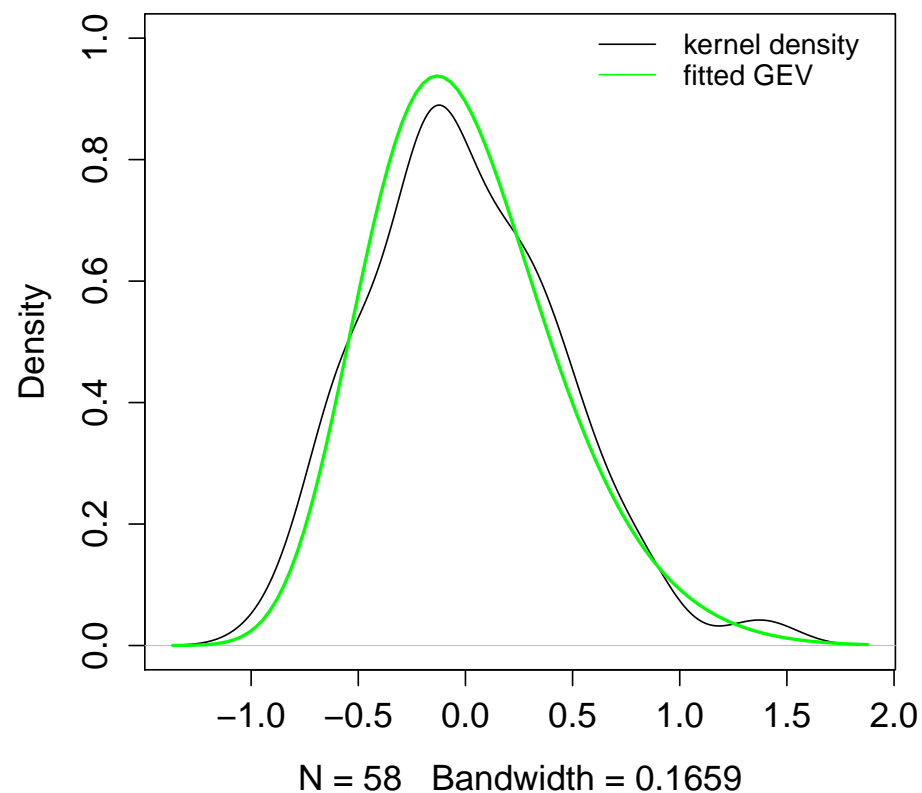


Figure: Left panel: raw and detrended data. Right panel: kernel density and fitted GEV distribution.

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Suppose that X_1, X_2, \dots, X_n is a sequence of independent, identically distributed random variates all having a common distribution function $F(x)$.

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Let $M_n = \max\{X_1, X_2, \dots, X_n\}$.

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Let $M_n = \max\{X_1, X_2, \dots, X_n\}$.

The distribution of the maxima, M_n , converges (for large n) to the Generalized Extreme Value (GEV) Distribution.

Theoretical motivation

Extremal Types theorem

If there exists sequences of constants $\{a_n > 0\}$ and $\{b_n\}$, such that as $n \rightarrow \infty$,

$$P\left(\frac{M_n - b_n}{a_n} \leq z\right) \rightarrow G(z) \tag{1}$$

where $G(z)$ is a non-degenerate distribution function, then G **must** be a member of the Generalized Extreme Value (GEV) family of distributions (Fisher and Tippett, 1928; Gnedenko, 1943).

Theoretical motivation

Extremal Types theorem

- This is a remarkable result because regardless of the underlying distribution, the distribution of the maxima (or minima) converges to one of the Generalized Extreme Value family of distributions.
- Can maximum period life expectancies be approximately modeled as a GEV?

The Generalized Extreme Value Distribution

$$G(z) = \exp\left\{ - \left[1 + \xi \left(\frac{z - \mu}{\sigma} \right) \right]_+^{\frac{-1}{\xi}} \right\} \quad (2)$$

where $b_+ = \max(0, b)$. The situation where $\xi = 0$ is not defined in (2), but taken as the limit as $\xi \rightarrow 0$, given by

$$G(z) = \exp\left\{ -\exp\left[- \left(\frac{z - \mu}{\sigma} \right) \right] \right\}. \quad (3)$$

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- μ is the location parameter

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- ξ is the shape parameter, which determines the tail behaviour
 - $\xi > 0$: polynomial tail decay and the Fréchet Distribution
 - $\xi = 0$: exponential tail decay and the Gumbel Distribution
 - $\xi < 0$: bounded upper finite end point and the Weibull Distribution

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Inference

Quantiles

Inverting the GEV distribution function:

$$z_p = \mu - \frac{\sigma}{\xi} \left[1 - \{-\log(1 - p)\}^{-\xi} \right],$$

where p is the tail probability and $G(z_p) = 1 - p$

Inference

Quantiles

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Return Levels

- Simply a different way of thinking about the quantiles.
- If data are annual the $(1 - p)$ th quantile would be exceeded on average once every $1/p$ years.

Regional Best Practice Life Expectancy?

THE IDEA

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- Can the notion of BPLE be extended to regions smaller than the global whole?

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- If we find BPLE over an arbitrary region - itself comprised of smaller subregions - would there also be a regular temporal evolution e.g. strong (piecewise) linear trends?

Regional Best Practice Life Expectancy?

THE IDEA

- Can the notion of BPLE be extended to regions smaller than the global whole?
- If we find BPLE over an arbitrary region - itself comprised of smaller subregions - would there also be a regular temporal evolution e.g. strong (piecewise) linear trends?
- What sort of inferences can we perform?

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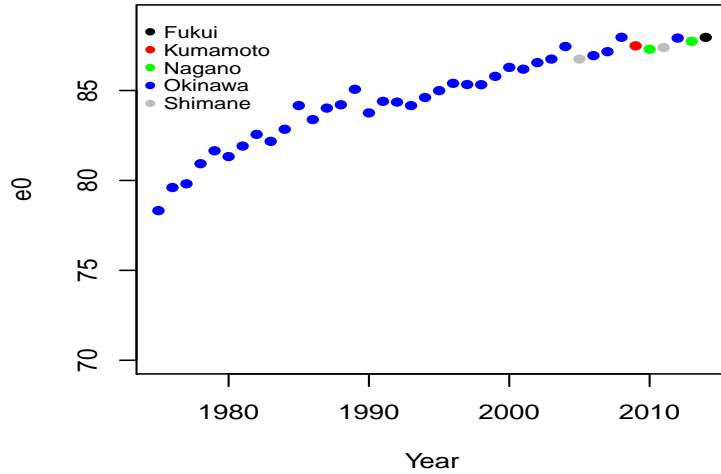
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 - Life expectancy data broken down by province
 - Covers period from 1921 to 2011 (but Newfoundland from 1949)

Data

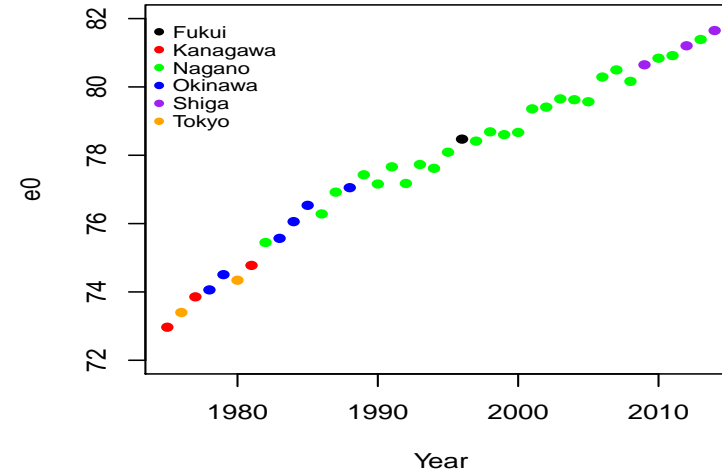
- Canadian Human Mortality Database (CHMD)
 - Life expectancy data broken down by province
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- Japanese Mortality Database (JMD)
 - Life expectancy data broken down by prefecture
 - Covers period from 1975 to 2014

Japan - Maximum e_x by Prefecture

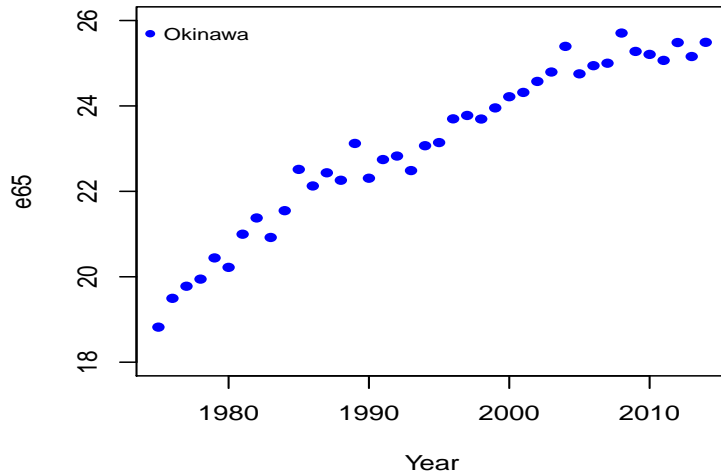
Female Best Practice e_0



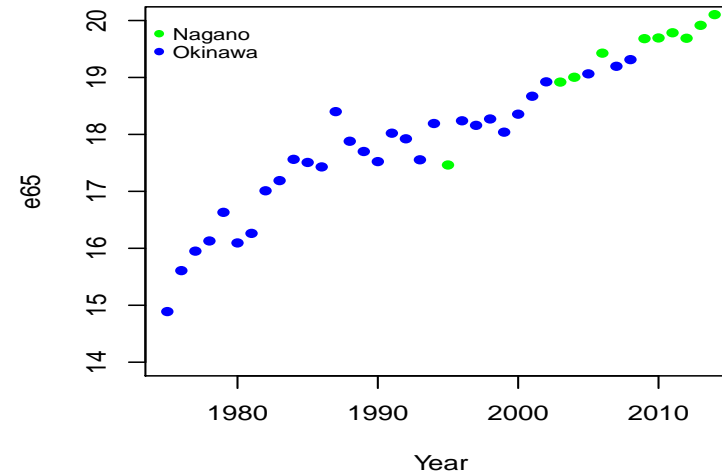
Male Best Practice e_0



Female Best Practice e_{65}

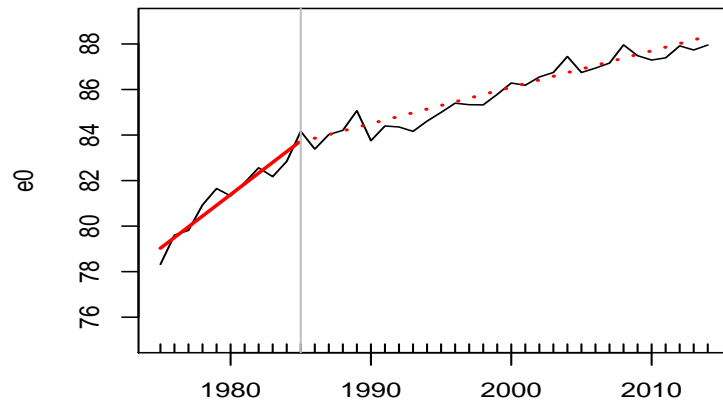


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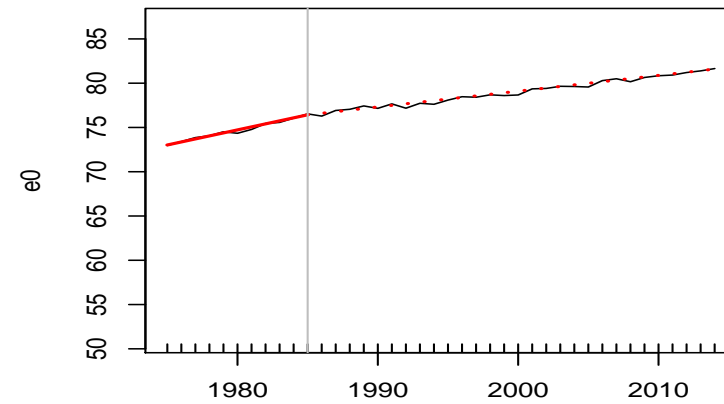


Japan - Maximum e_x by Prefecture

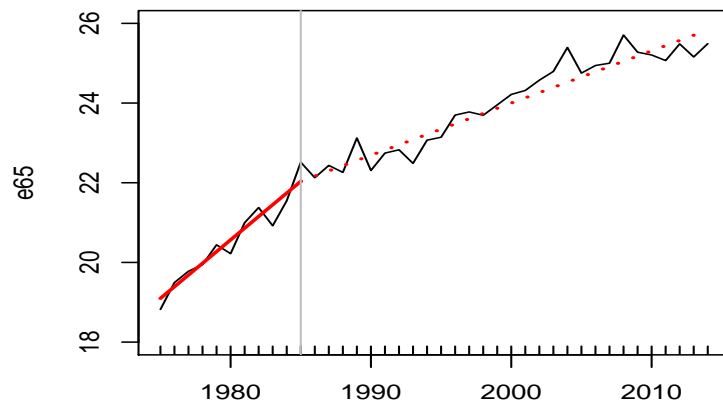
Females



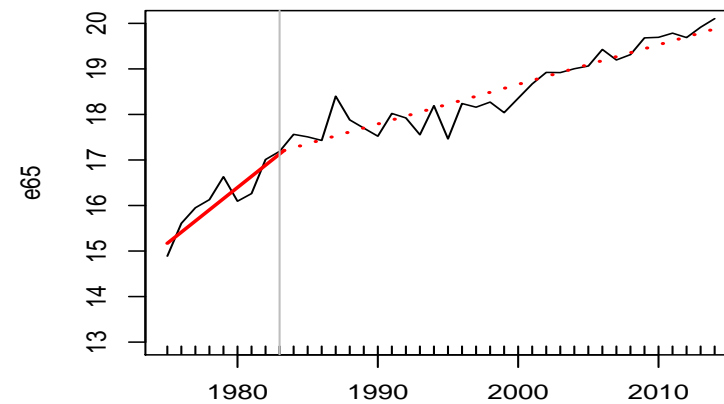
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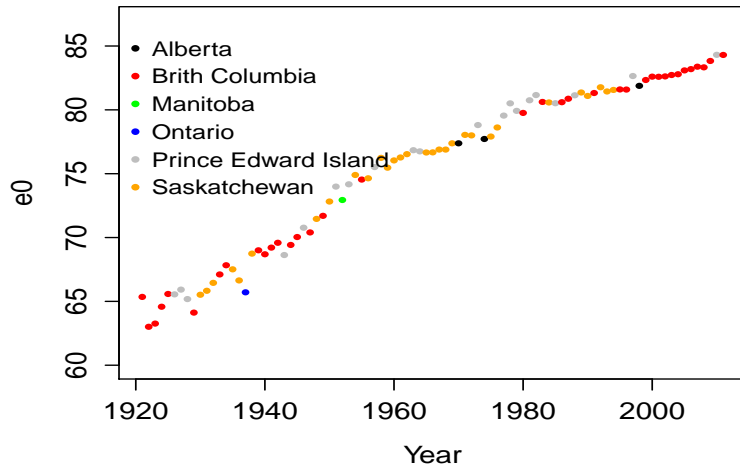


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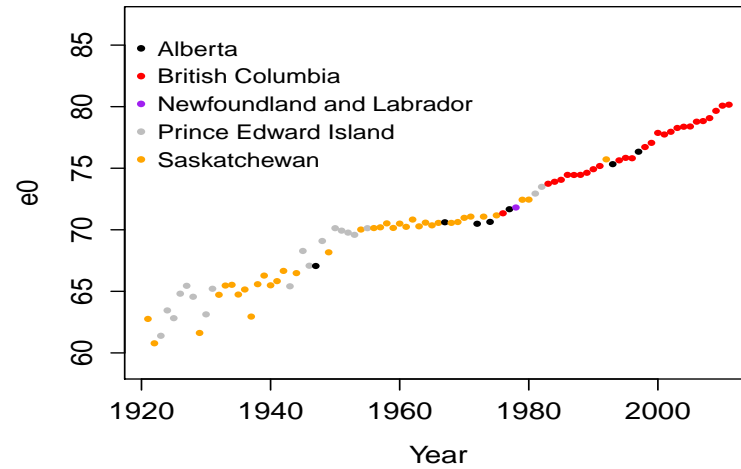


Canada - Maximum e_x by Province

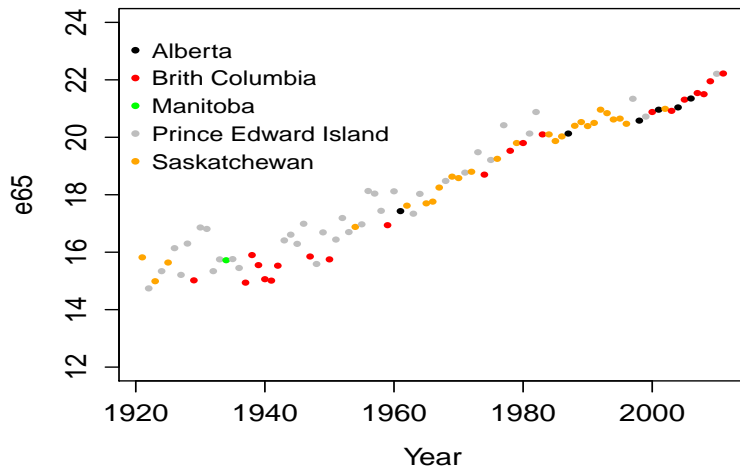
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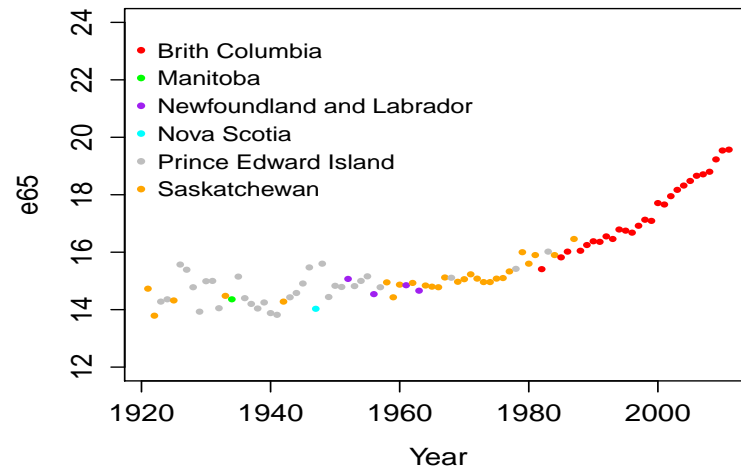
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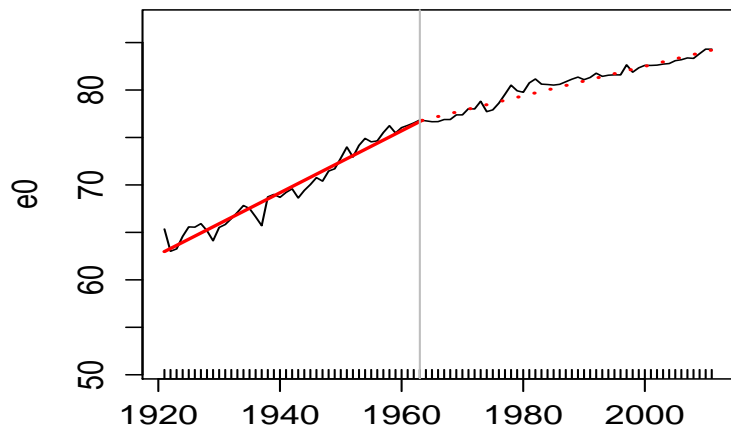


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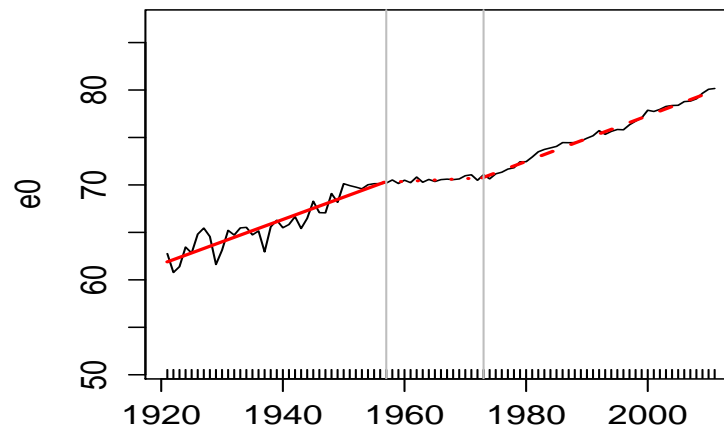


Breakpoints in Canadian e_x

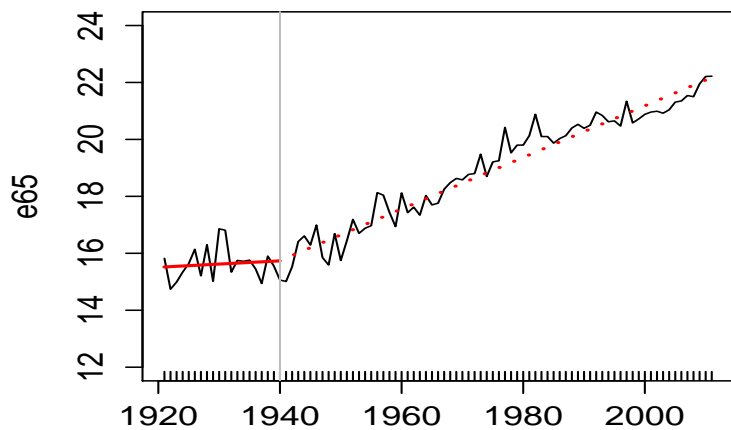
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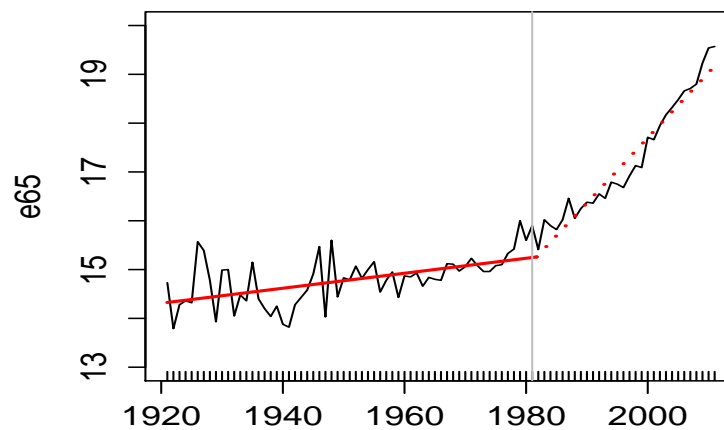
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The Model

Time-dependent GEV model to annual maximum provincial e_x :

$$GEV(\mu_t, \sigma_t, \xi_t) \quad \text{with} \quad \mu_t = \beta_0 + \beta_1 t; \quad \sigma_t = \sigma; \quad \xi_t = \xi$$

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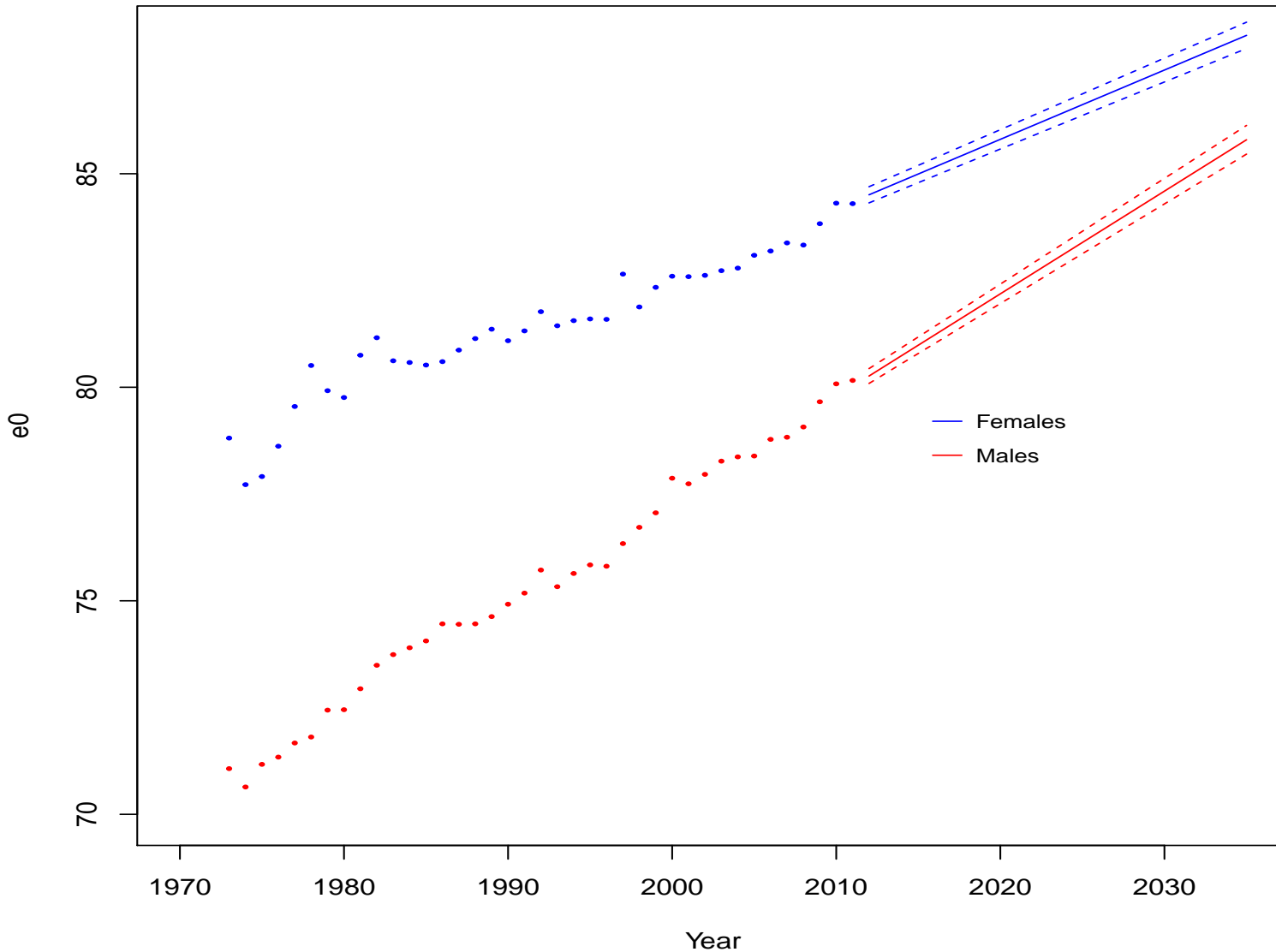
- Other forms of time dependence possible but linearity in μ reasonable and parsimonious choice.
- Parameters estimated jointly using maximum likelihood

Parameter estimates - Canada

	Neg. Likelihood	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\sigma}$	$\hat{\xi}$
Female e_0	30.8	76.4(0.11)	0.16 (0.003)	0.37 (0.030)	0.10
Male e_0	3.9	70.6 (0.10)	0.24 (0.004)	0.27 (0.03)	-0.34 (0.15)
Female e_{65}	45.2	15.4 (0.11)	0.09 (0.002)	0.42 (0.040)	-0.15 (0.08)
Male e_{65}	-3.60	15.1 (0.11)	0.13 (0.006)	0.27 (0.04)	-0.29 (0.14)

Table: Maximized negative log-likelihoods, parameter estimates and standard errors (in parentheses) of the Block Maxima Model

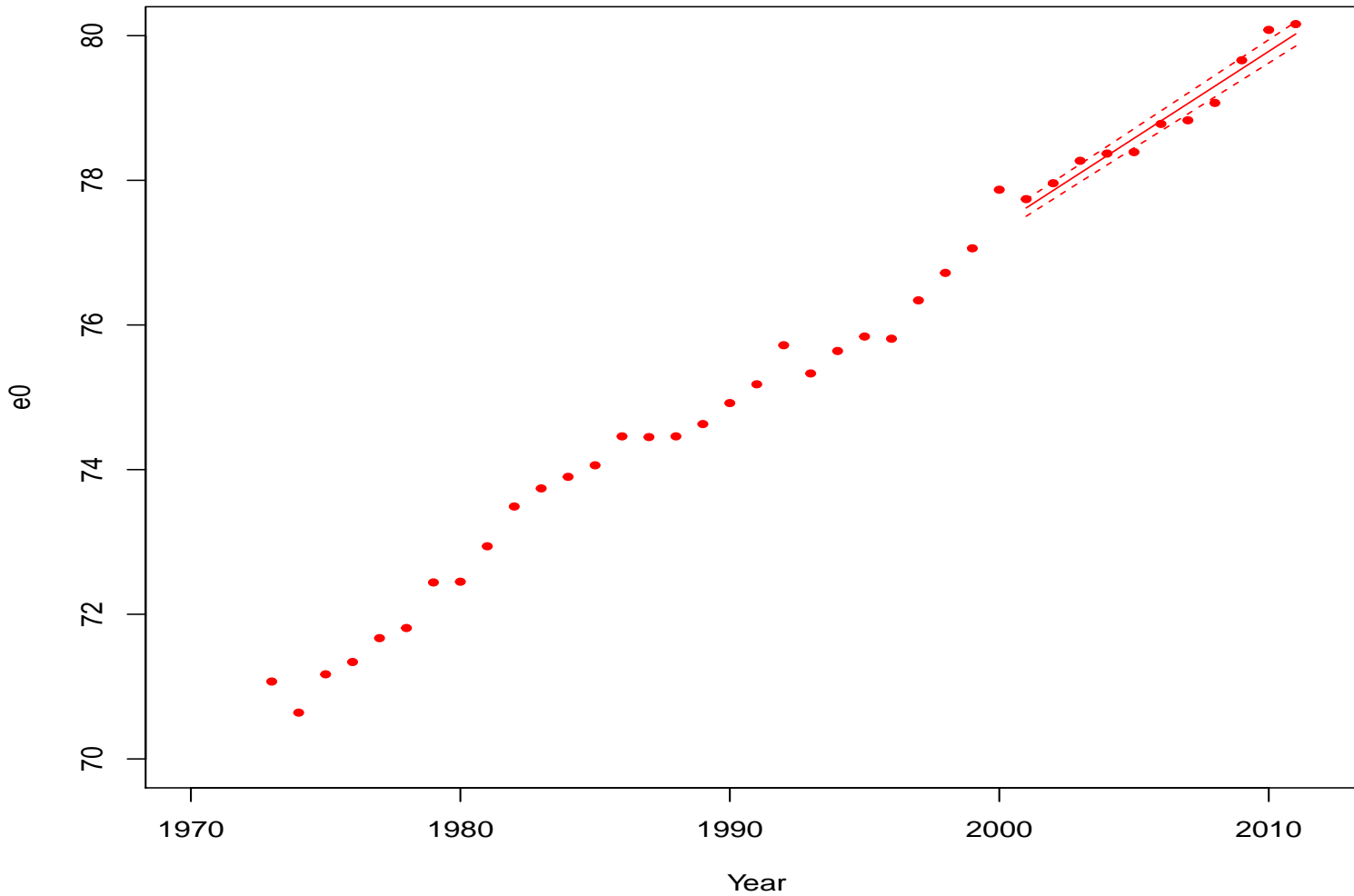
Projected e_0 - Canada



Probability statements - Canada

Year	$P(e_{0,f}^{max} > 87.5)$	$P(e_{0,f}^{max} > 89)$
2030	0.44	0.02
2035	0.99	0.11

Forecast Performance e.g. Canadian Males e_0



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- Data wastage?

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- Relax linearity assumption for time dependence to allow any time-varying shape for GEV parameters
- More flexible Dynamic Linear Model for time-varying parameters for forecasting
- Flexible GLM type framework for modelling
 - Vector Generalized Linear Models (Yee & Hastie, 2003), or
 - Generalized Additive Models for Location, Scale and Shape (Rigby & Stasinopoulos, 2001, 2005)

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- Since a probability distribution is fitted, it is straightforward to obtain probabilities

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- Since a probability distribution is fitted, it is straightforward to obtain probabilities
- Ancillary benefit: if provinces with maxima also have high proportion of population then projecting median gives a workable estimate of overall country e_x
- Underlying theoretical model assumptions may be hard to achieve in practice but acid test is usually good assessment of empirical fit

References

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