The Future of Death in America

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Institute for Quantitative Social Science
Harvard University

joint work with Samir Soneji

(talk at the Center for Population and Development Studies, Harvard University, 12/15/08)

Citations

- Gary King and Samir Soneji. 2008. "The Future of Death in America"

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- copies at `http://gking.harvard.edu`

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    - Including demographic knowledge (smooth over time and age)
    - Including biological knowledge (smoking, obesity)

How (Some) Existing Mortality Forecasts Work

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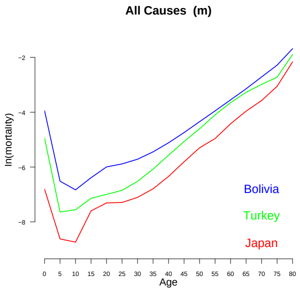
- We bring statistics to demography

Existing Method 1: Parameterize the Age Profile



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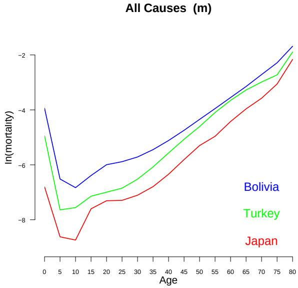

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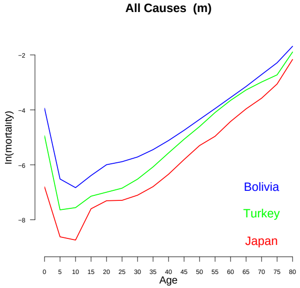

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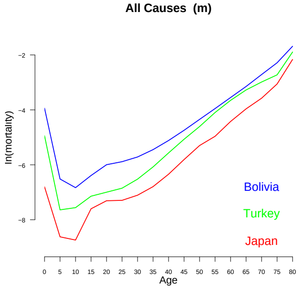

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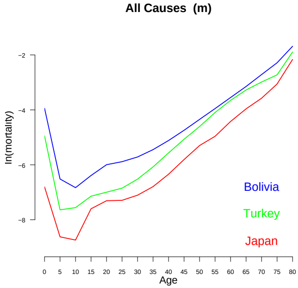

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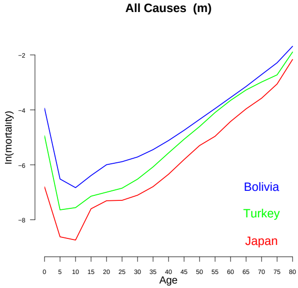

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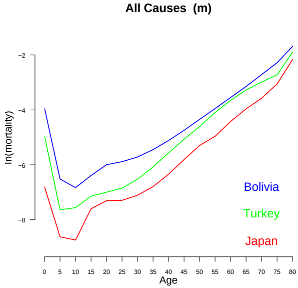

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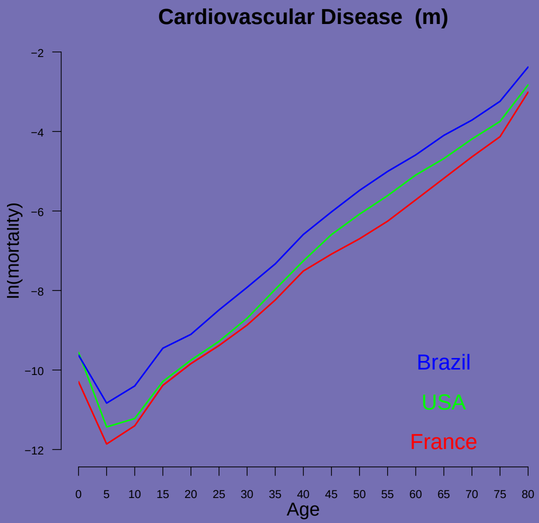
- Dozens of more general functional forms proposed since 1825
- But does it fit anything else?

Mortality Age Profile: The Same Pattern?



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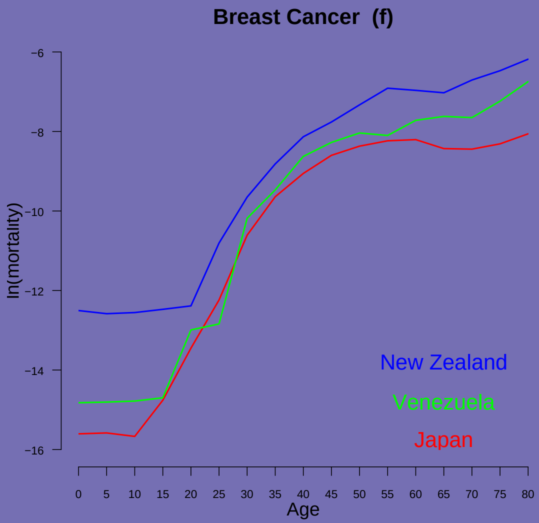

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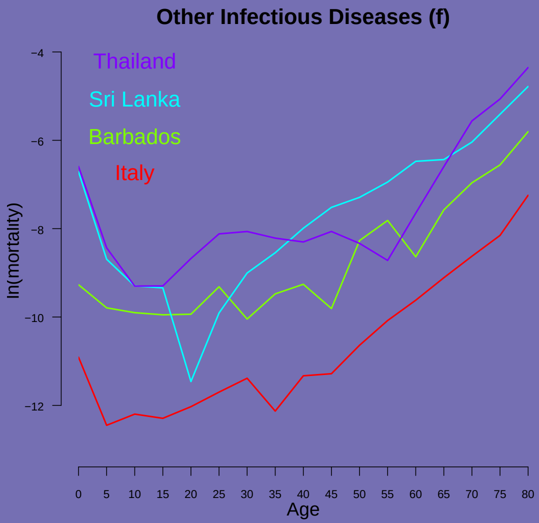

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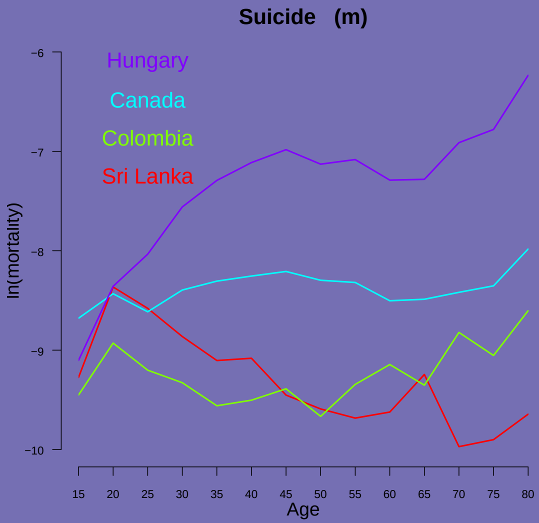

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- Ignores covariate information

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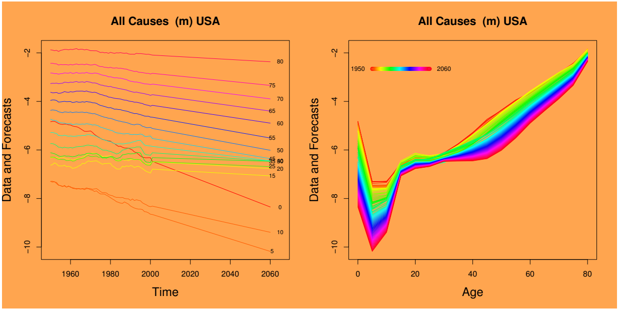

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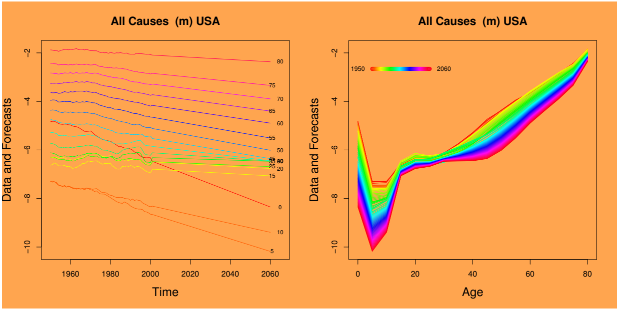

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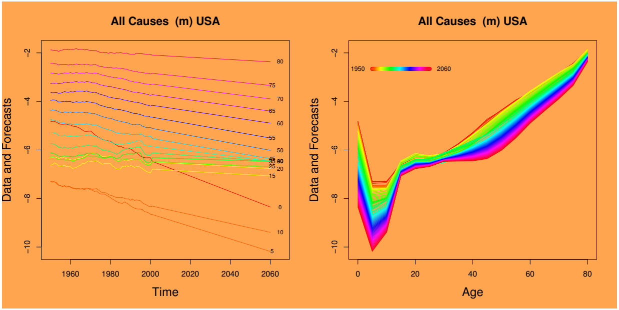

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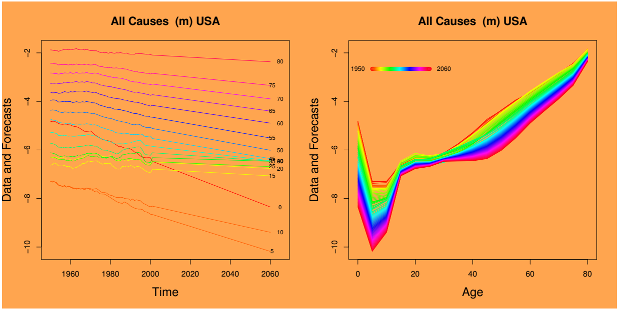

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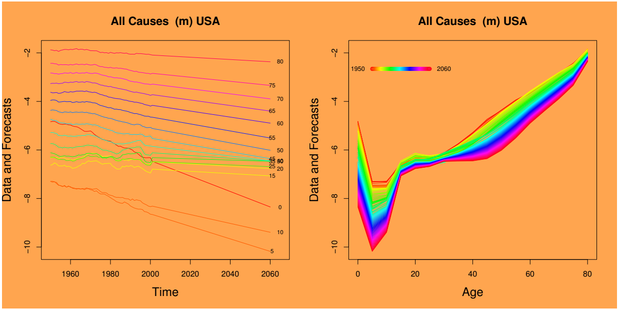

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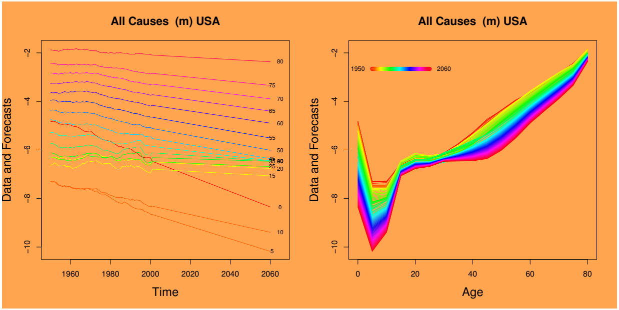

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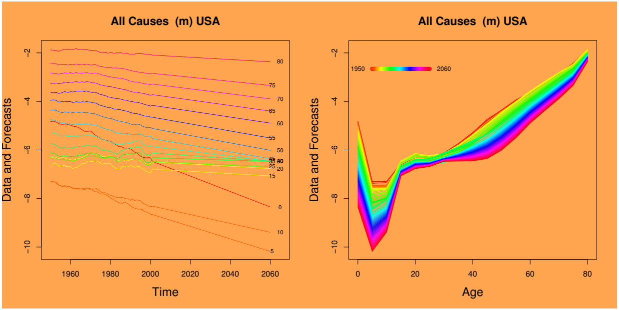

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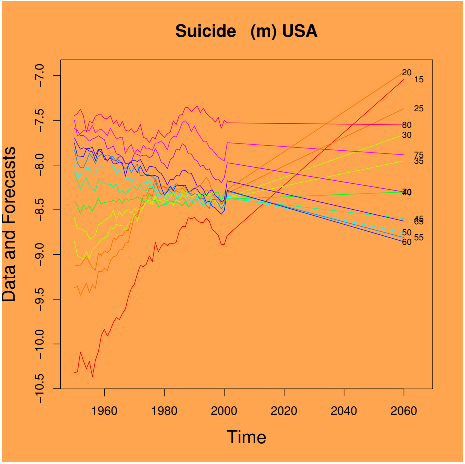

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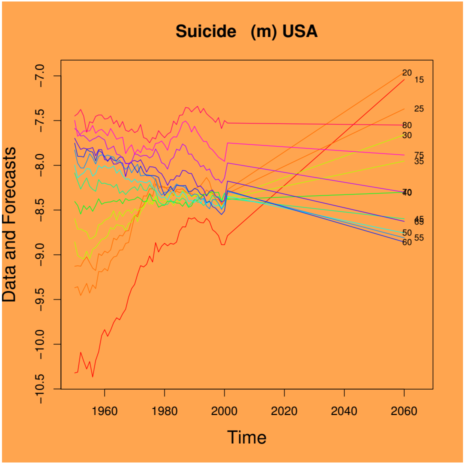

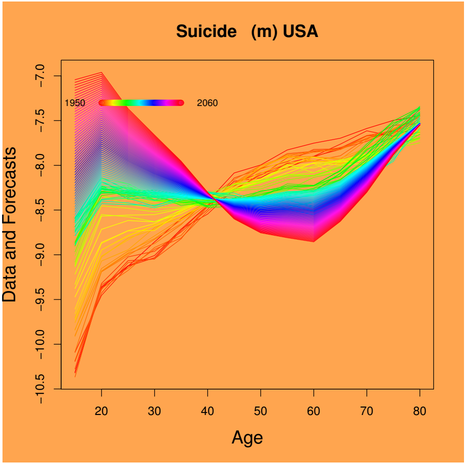

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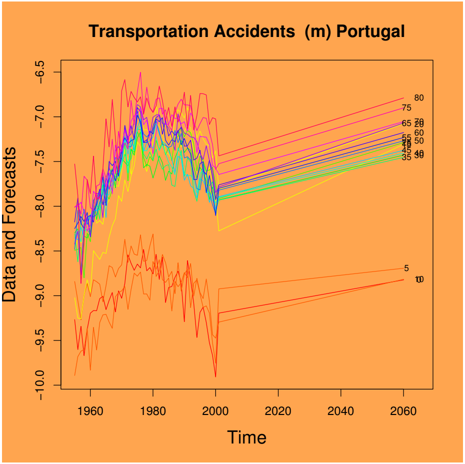

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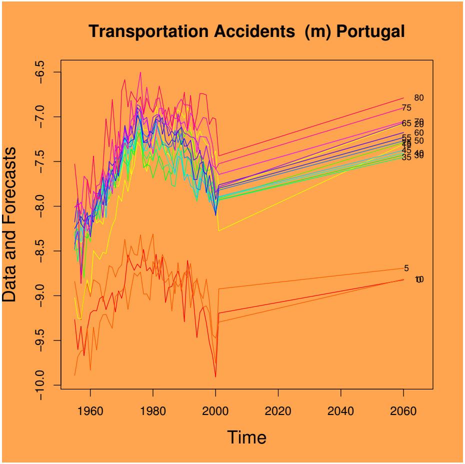

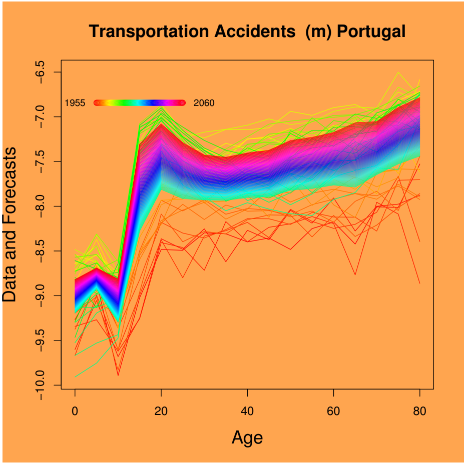

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- (It always seems ok to pool over variables outside your own field.)

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- $\rightsquigarrow$ An easy-to-use software program, YourCast

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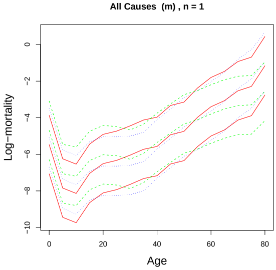

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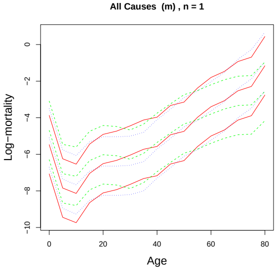
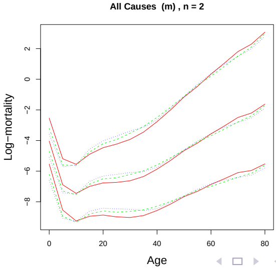


Level and slope indifference



Mortality from Respiratory Infections, Males

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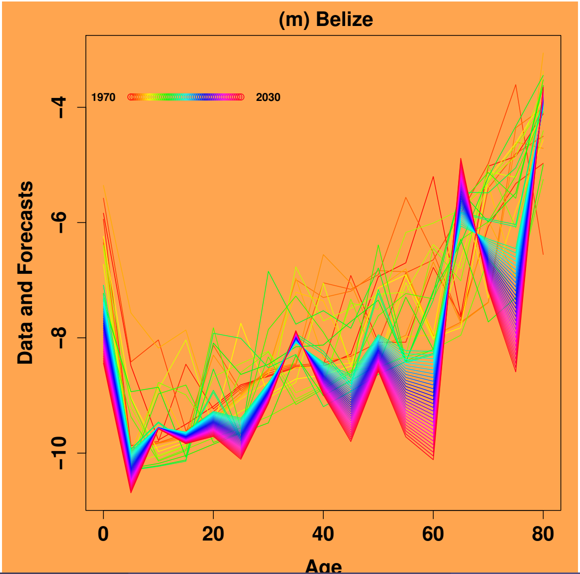
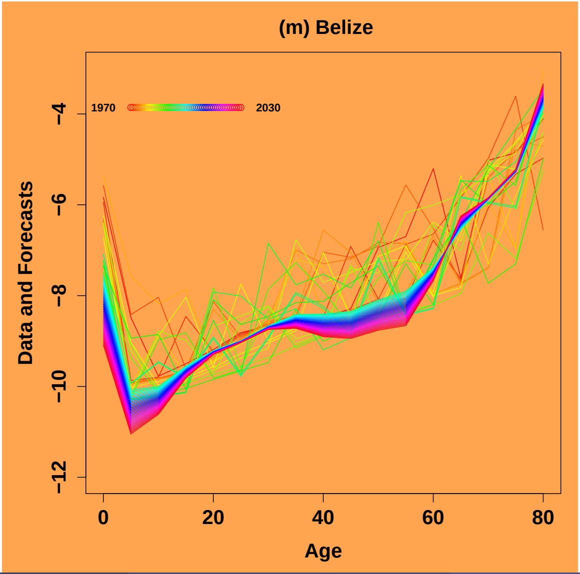


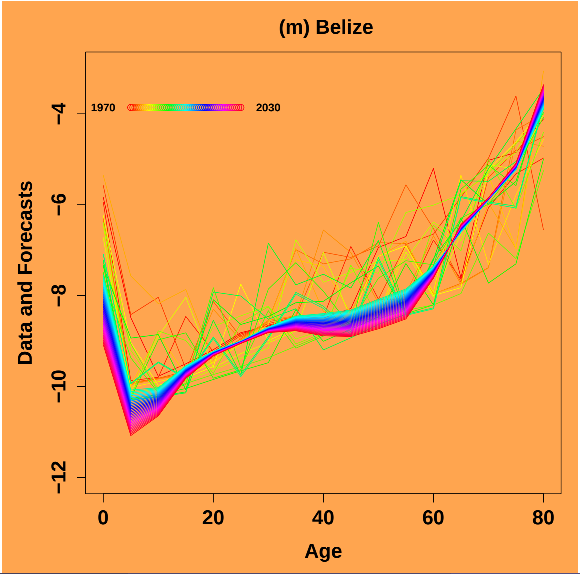
Mortality from Respiratory Infections, males, $\sigma = 2.00$

Smoothing over Age Groups



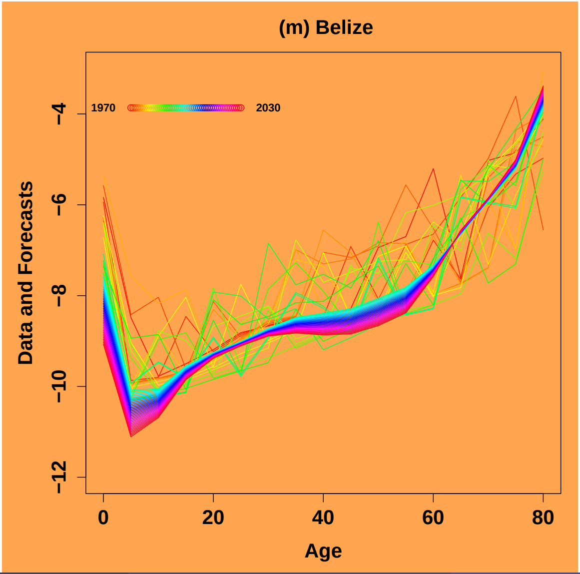
Mortality from Respiratory Infections, males, $\sigma = 1.51$

Smoothing over Age Groups



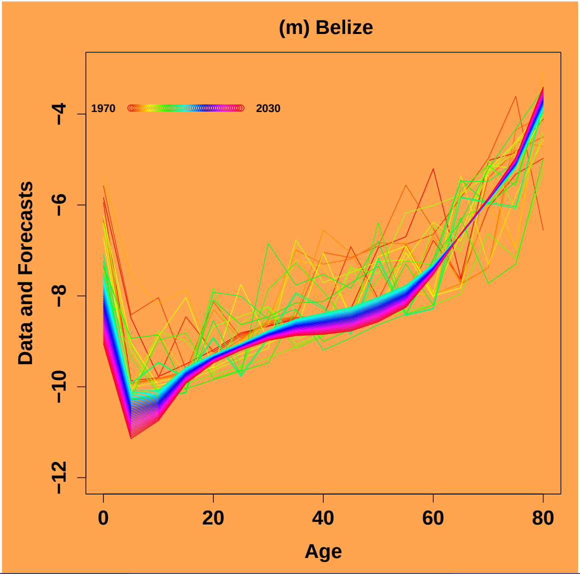
Mortality from Respiratory Infections, males, $\sigma = 1.15$

Smoothing over Age Groups



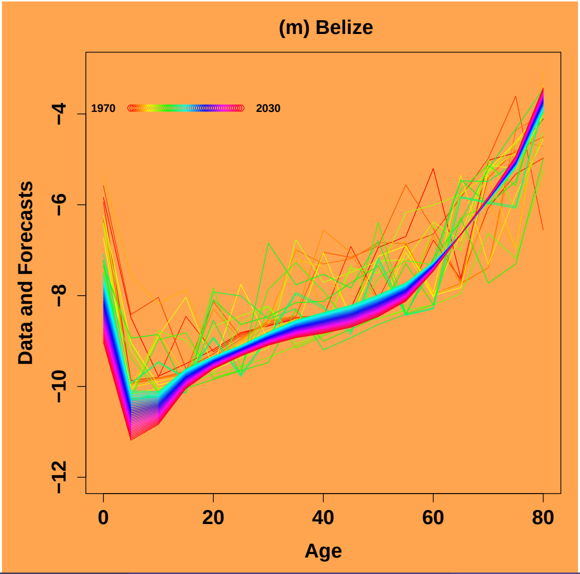
Mortality from Respiratory Infections, males, $\sigma = 0.87$

Smoothing over Age Groups



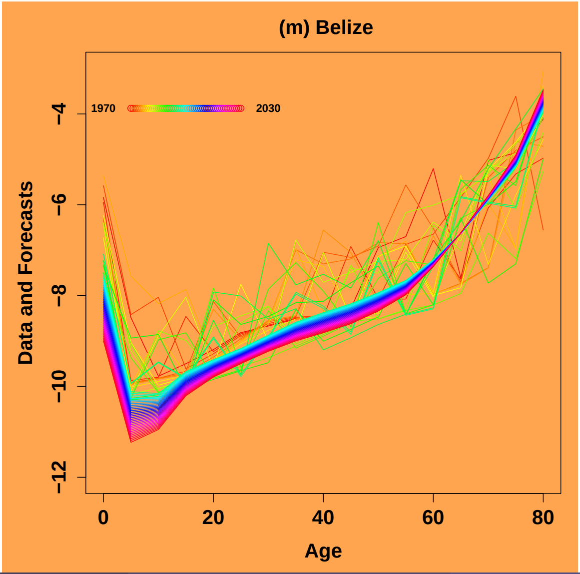
Mortality from Respiratory Infections, males, $\sigma = 0.66$

Smoothing over Age Groups



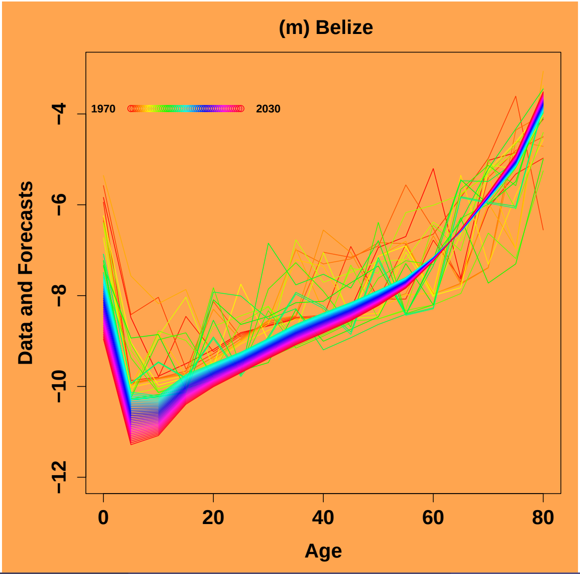
Mortality from Respiratory Infections, males, $\sigma = 0.50$

Smoothing over Age Groups



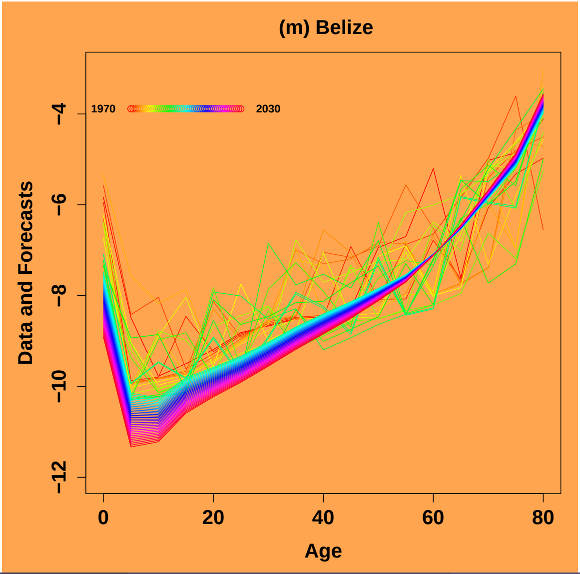
Mortality from Respiratory Infections, males, $\sigma = 0.38$

Smoothing over Age Groups



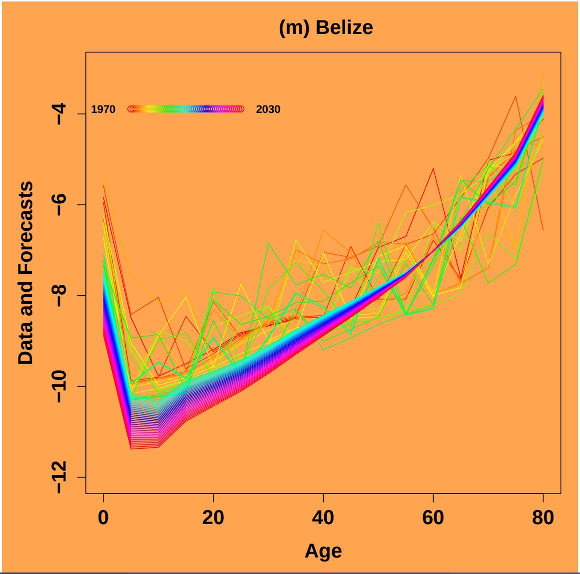
Mortality from Respiratory Infections, males, $\sigma = 0.28$

Smoothing over Age Groups



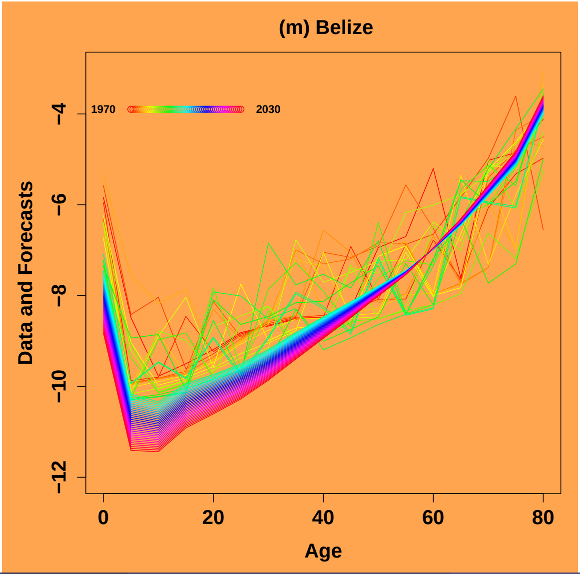
Mortality from Respiratory Infections, males, $\sigma = 0.21$

Smoothing over Age Groups



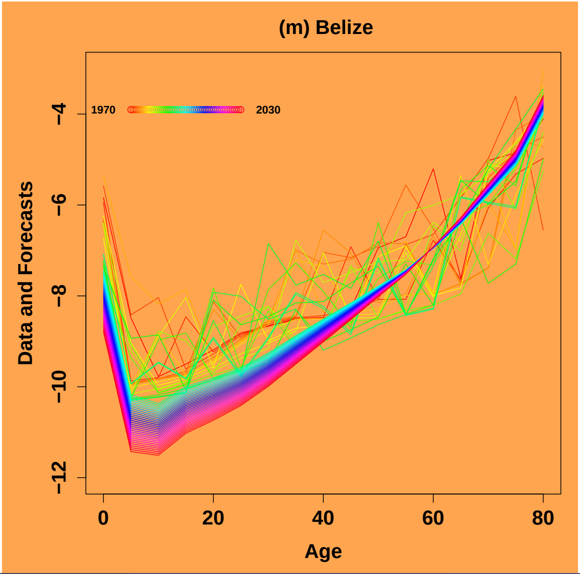
Mortality from Respiratory Infections, males, $\sigma = 0.16$

Smoothing over Age Groups



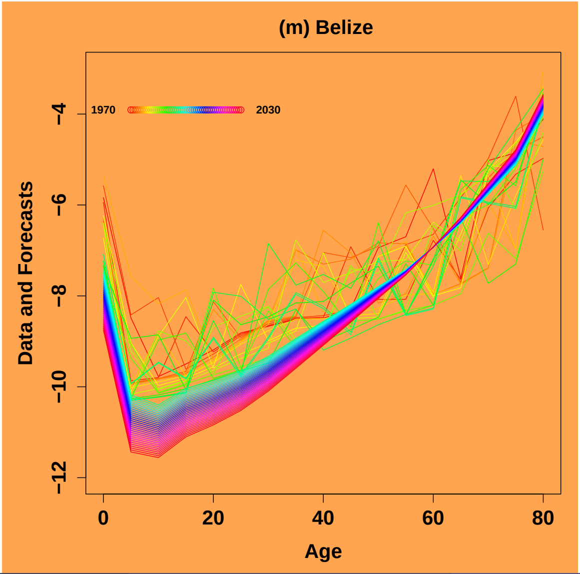
Mortality from Respiratory Infections, males, $\sigma = 0.12$

Smoothing over Age Groups



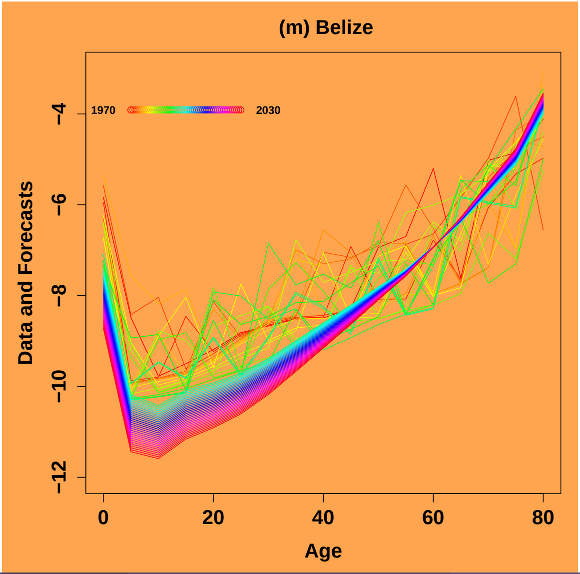
Mortality from Respiratory Infections, males, $\sigma = 0.09$

Smoothing over Age Groups



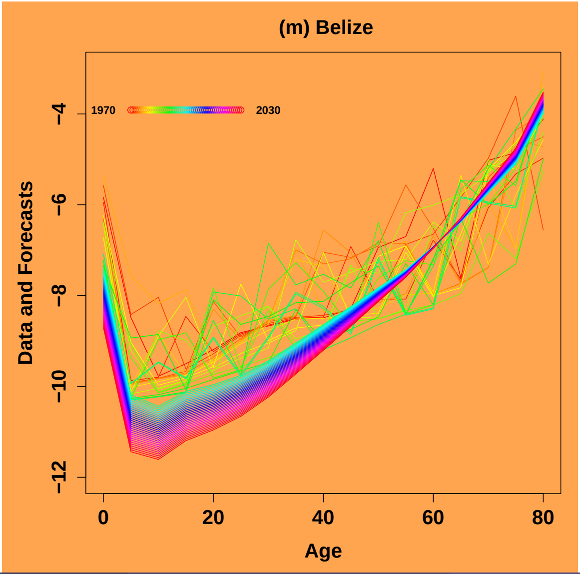
Mortality from Respiratory Infections, males, $\sigma = 0.07$

Smoothing over Age Groups



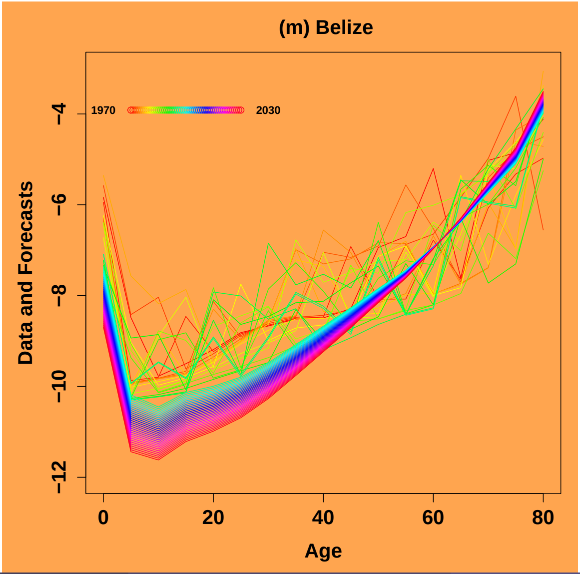
Mortality from Respiratory Infections, males, $\sigma = 0.05$

Smoothing over Age Groups



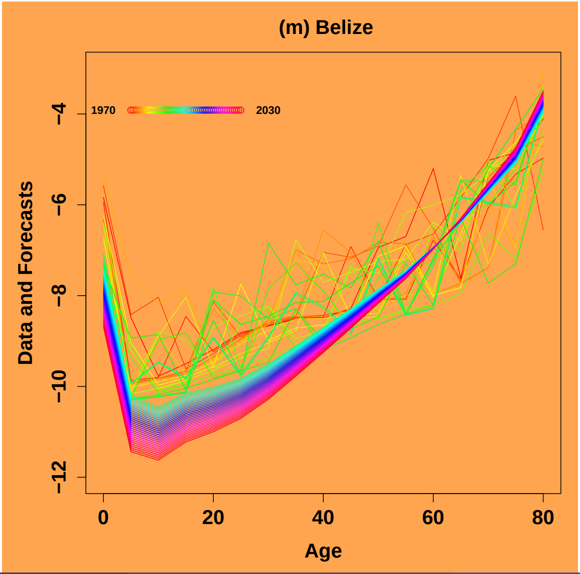
Mortality from Respiratory Infections, males, $\sigma = 0.04$

Smoothing over Age Groups



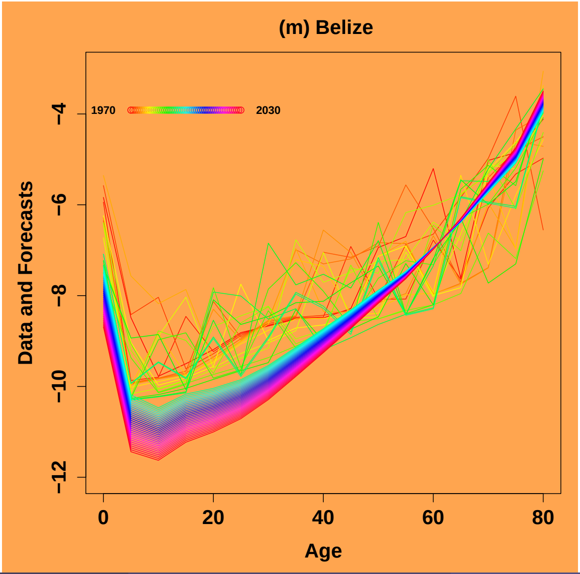
Mortality from Respiratory Infections, males, $\sigma = 0.03$

Smoothing over Age Groups



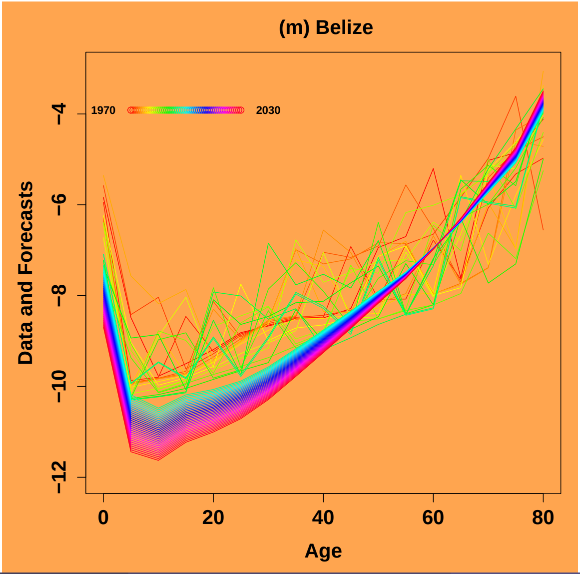
Mortality from Respiratory Infections, males, $\sigma = 0.02$

Smoothing over Age Groups



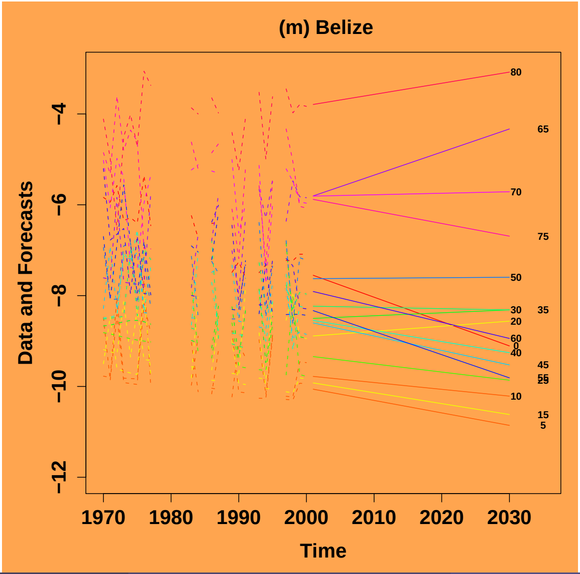
Mortality from Respiratory Infections, males, $\sigma = 0.01$

Smoothing over Age Groups



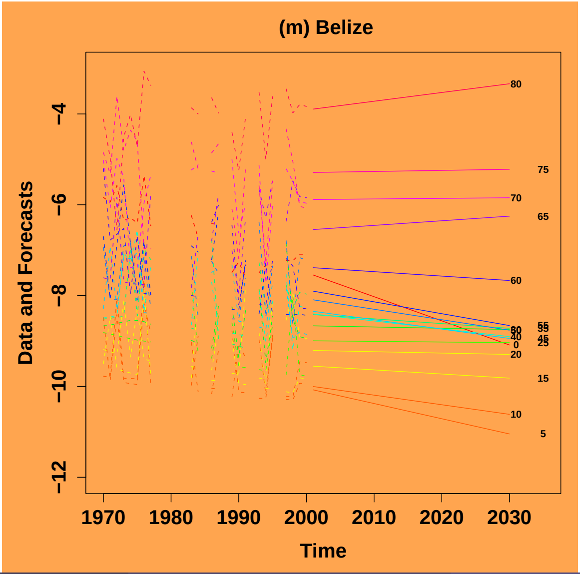
Mortality from Respiratory Infections, males

Least Squares



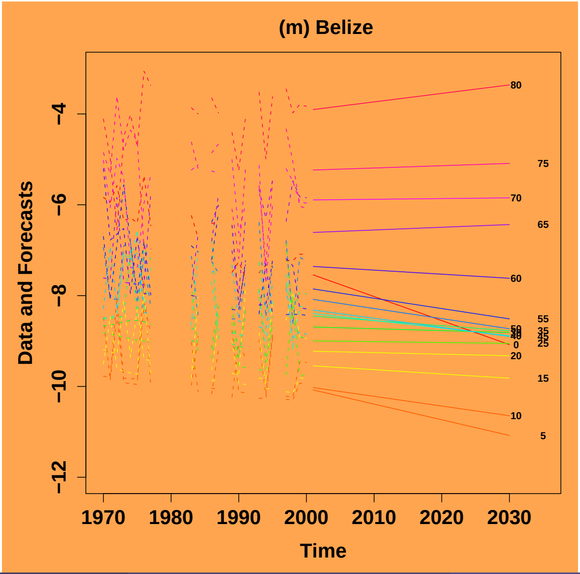
Mortality from Respiratory Infections, males, $\sigma = 2.00$

Smoothing over Age Groups



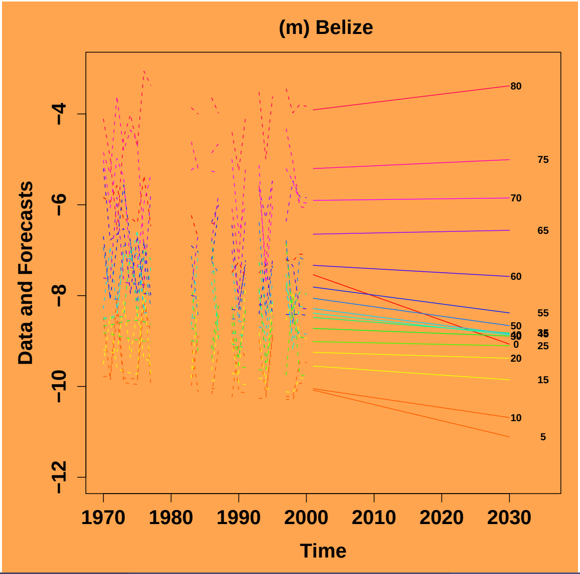
Mortality from Respiratory Infections, males, $\sigma = 1.51$

Smoothing over Age Groups



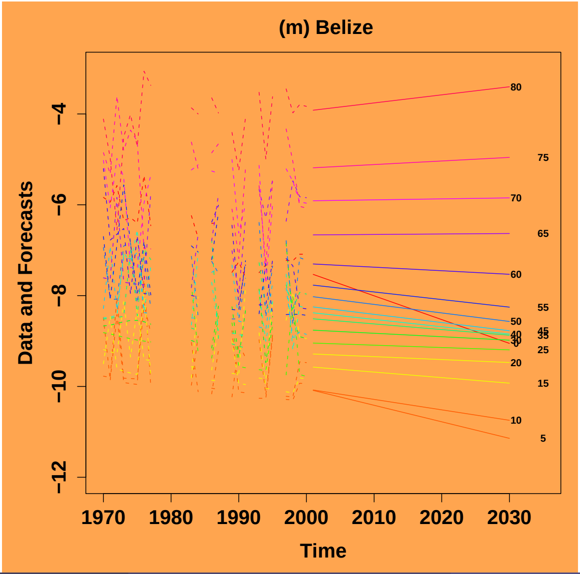
Mortality from Respiratory Infections, males, $\sigma = 1.15$

Smoothing over Age Groups



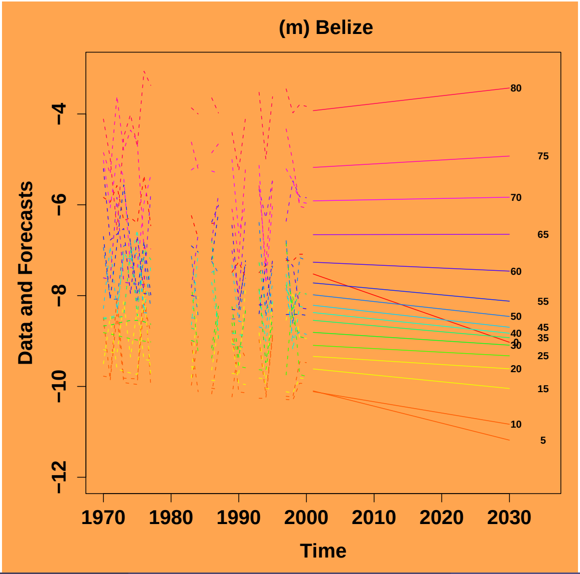
Mortality from Respiratory Infections, males, $\sigma = 0.87$

Smoothing over Age Groups



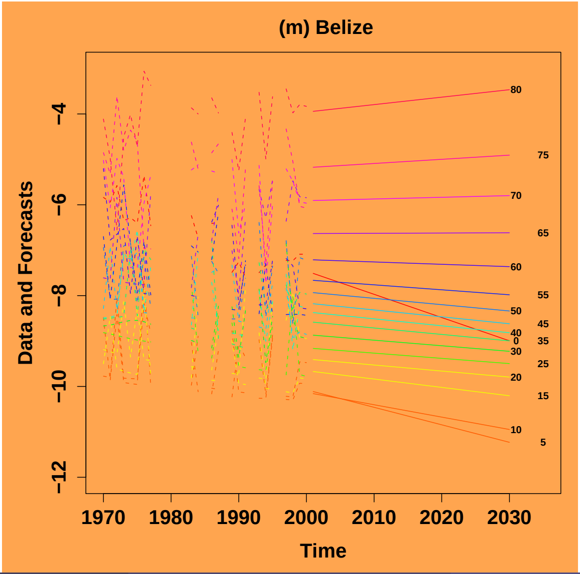
Mortality from Respiratory Infections, males, $\sigma = 0.66$

Smoothing over Age Groups



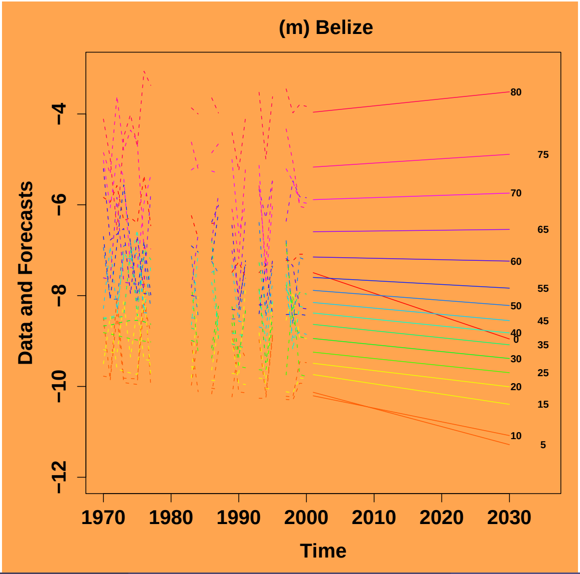
Mortality from Respiratory Infections, males, $\sigma = 0.50$

Smoothing over Age Groups



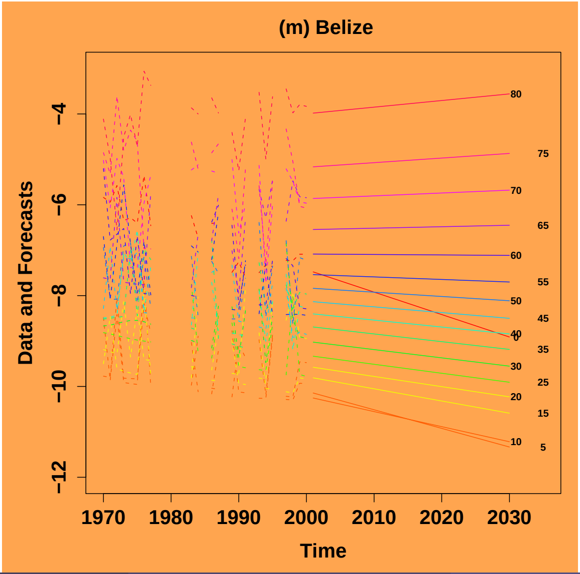
Mortality from Respiratory Infections, males, $\sigma = 0.38$

Smoothing over Age Groups



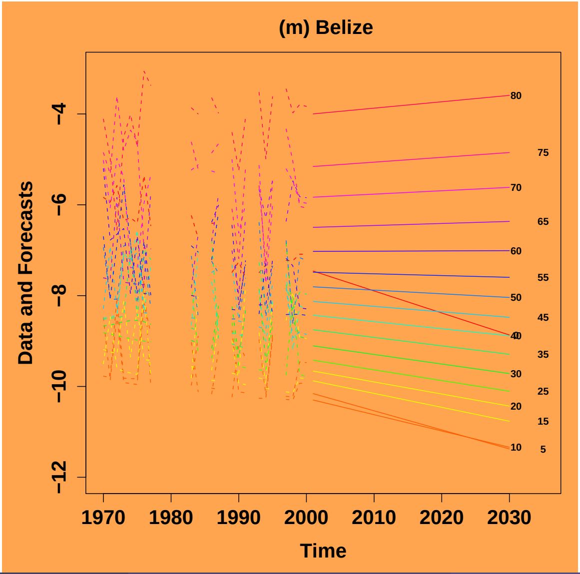
Mortality from Respiratory Infections, males, $\sigma = 0.28$

Smoothing over Age Groups



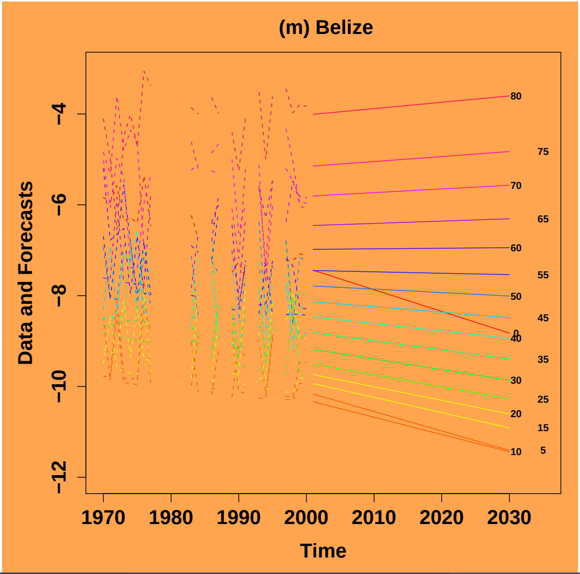
Mortality from Respiratory Infections, males, $\sigma = 0.21$

Smoothing over Age Groups



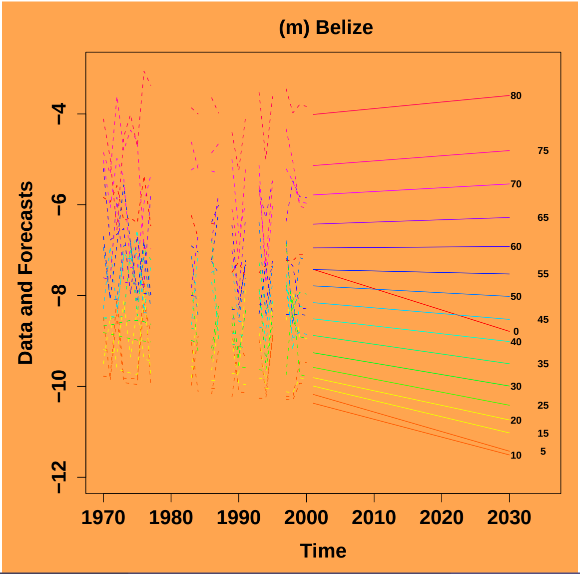
Mortality from Respiratory Infections, males, $\sigma = 0.16$

Smoothing over Age Groups



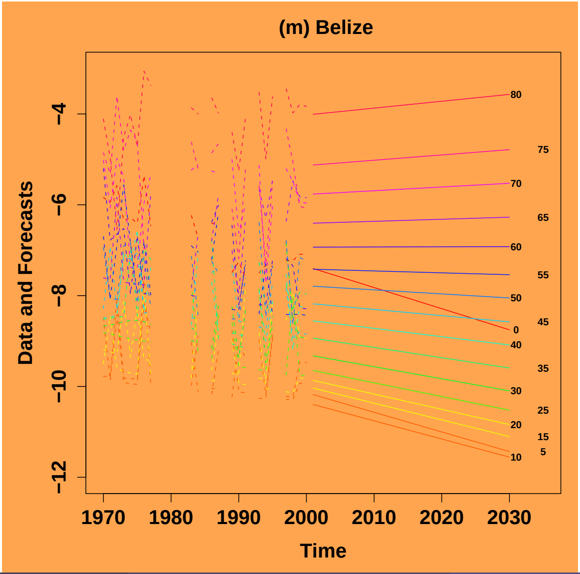
Mortality from Respiratory Infections, males, $\sigma = 0.12$

Smoothing over Age Groups



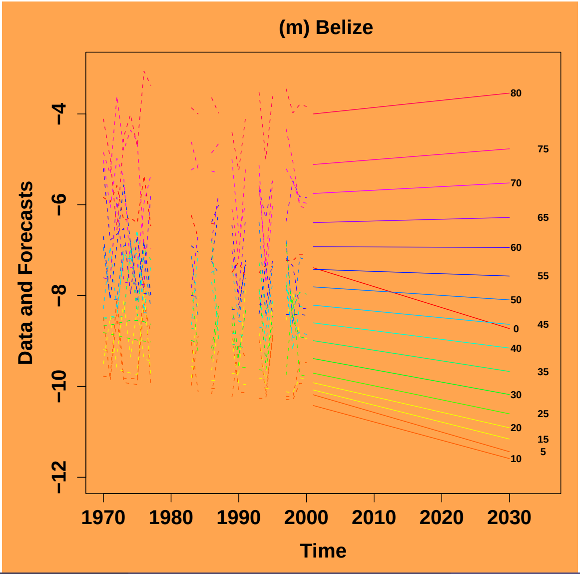
Mortality from Respiratory Infections, males, $\sigma = 0.09$

Smoothing over Age Groups



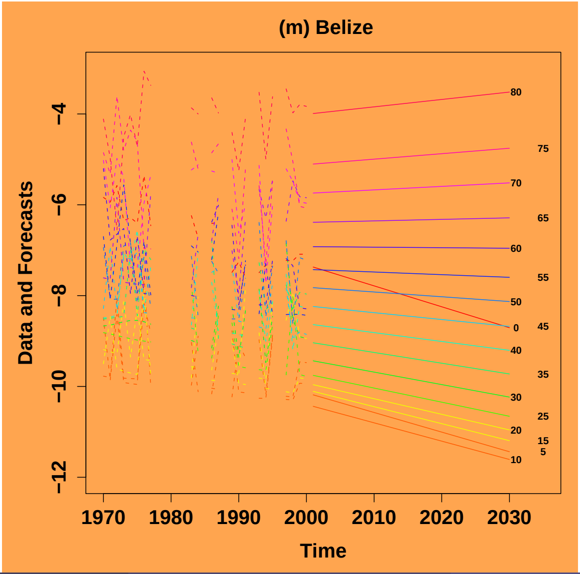
Mortality from Respiratory Infections, males, $\sigma = 0.07$

Smoothing over Age Groups



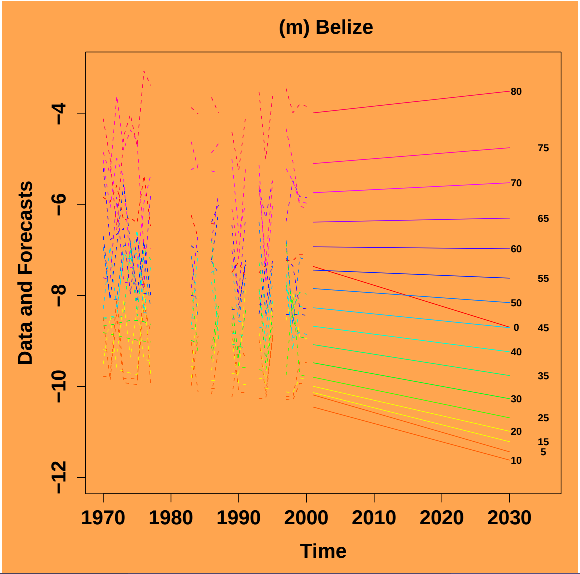
Mortality from Respiratory Infections, males, $\sigma = 0.05$

Smoothing over Age Groups



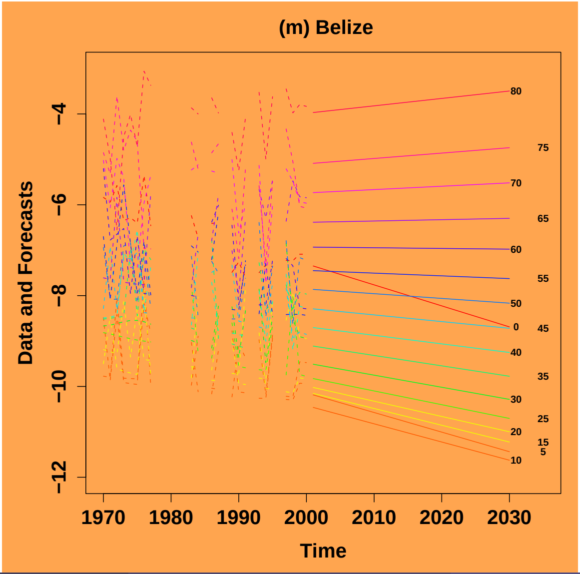
Mortality from Respiratory Infections, males, $\sigma = 0.04$

Smoothing over Age Groups



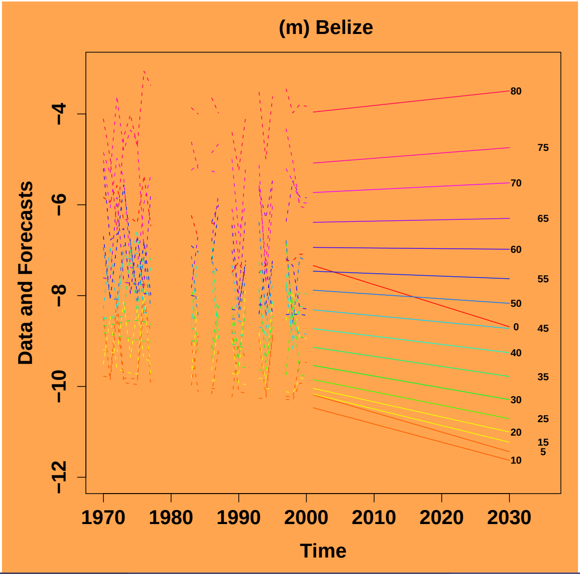
Mortality from Respiratory Infections, males, $\sigma = 0.03$

Smoothing over Age Groups



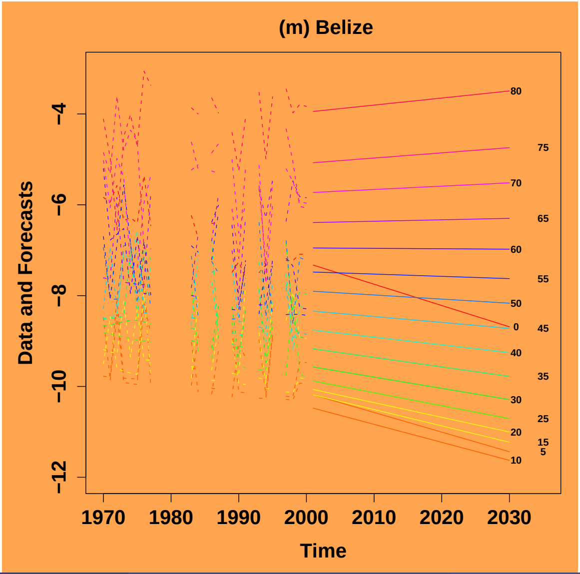
Mortality from Respiratory Infections, males, $\sigma = 0.02$

Smoothing over Age Groups



Mortality from Respiratory Infections, males, $\sigma = 0.01$

Smoothing over Age Groups



Smoothing Trends over Age Groups

Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

Smoothing Trends over Age Groups

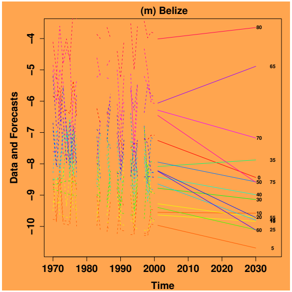
Log-mortality in Belize males from respiratory infections

Least Squares

Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

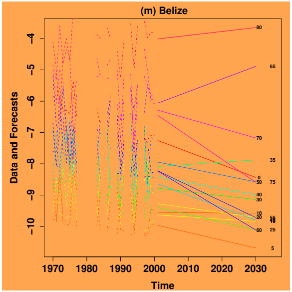
Least Squares

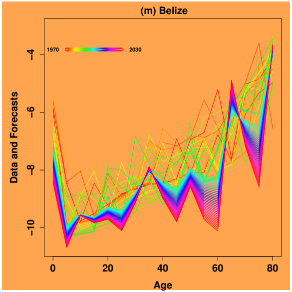


Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

Least Squares

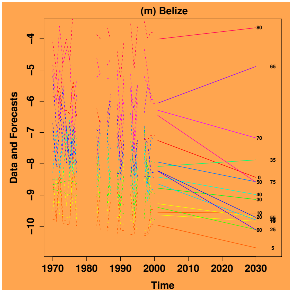


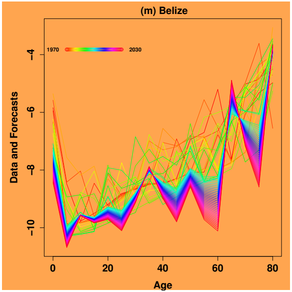


Smoothing Trends over Age Groups

Log-mortality in Belize males from respiratory infections

Least Squares



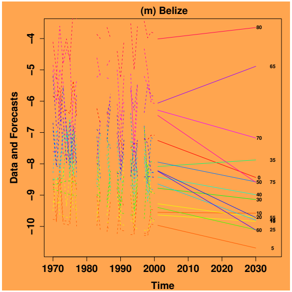


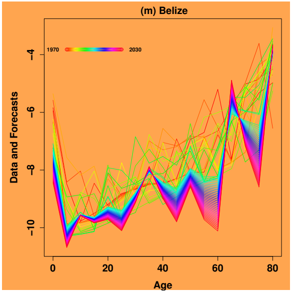
Smoothing
Age Groups

Smoothing Trends over Age Groups

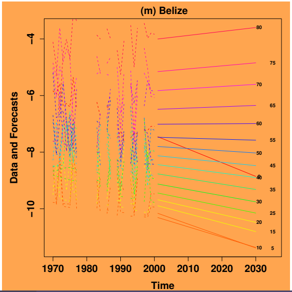
Log-mortality in Belize males from respiratory infections

Least Squares





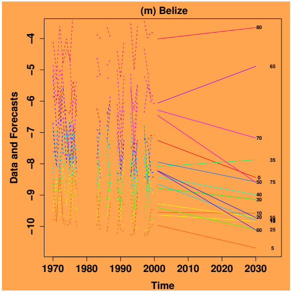
Smoothing Age Groups

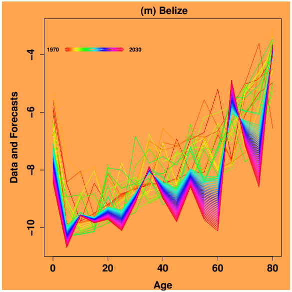


Smoothing Trends over Age Groups

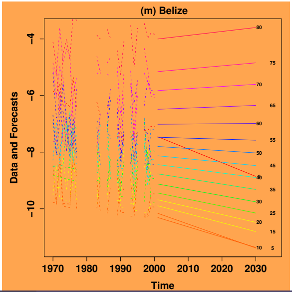
Log-mortality in Belize males from respiratory infections

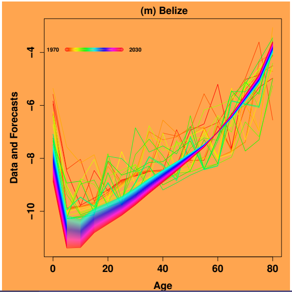
Least Squares





Smoothing
Age Groups





Smoothing Trends over Age Groups and Time

Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

Smoothing Trends over Age Groups and Time

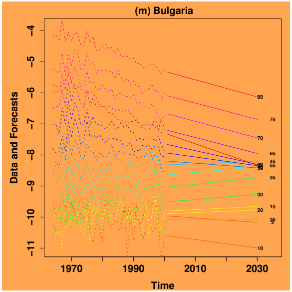
Log-Mortality in Bulgarian males from respiratory infections

Least Squares

Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

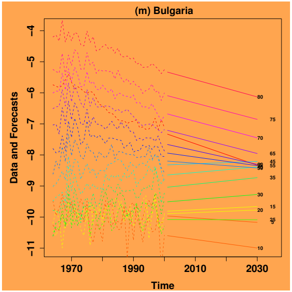
Least Squares

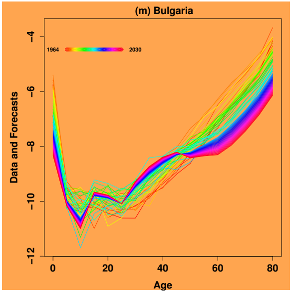


Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

Least Squares

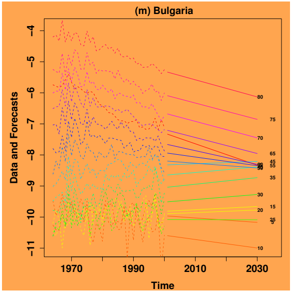


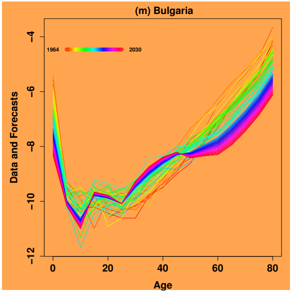


Smoothing Trends over Age Groups and Time

Log-Mortality in Bulgarian males from respiratory infections

Least Squares



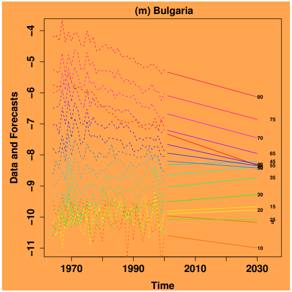


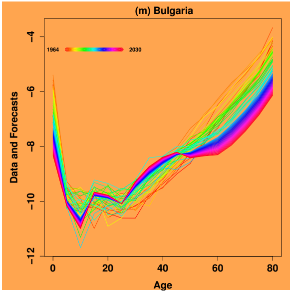
Smoothing
Age and Time

Smoothing Trends over Age Groups and Time

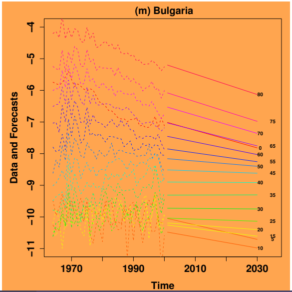
Log-Mortality in Bulgarian males from respiratory infections

Least Squares





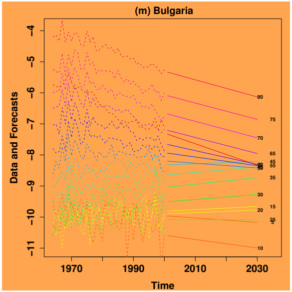
Smoothing
Age and Time

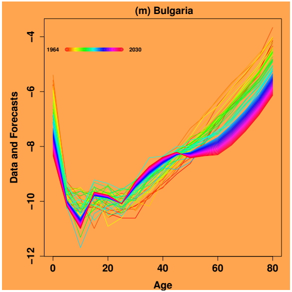


Smoothing Trends over Age Groups and Time

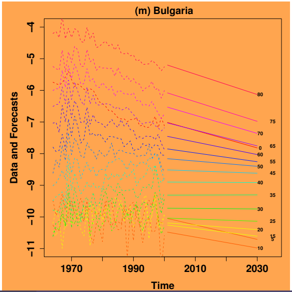
Log-Mortality in Bulgarian males from respiratory infections

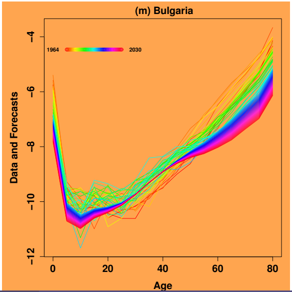
Least Squares





Smoothing
Age and Time





Using Covariates (GDP, tobacco, trend, log trend)

Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Using Covariates (GDP, tobacco, trend, log trend)

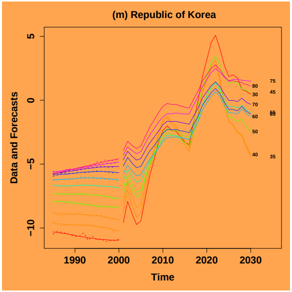
Lung cancer in Korean Males

Least Squares

Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

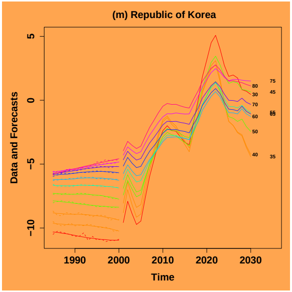
Least Squares

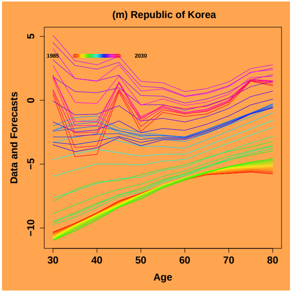


Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Least Squares

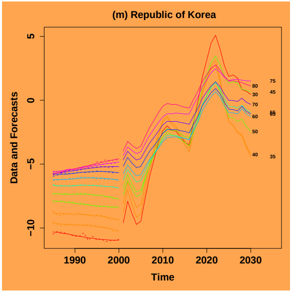


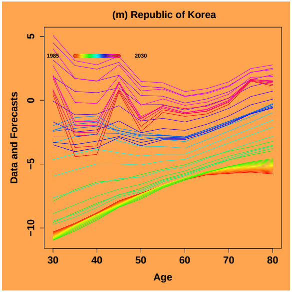


Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Least Squares



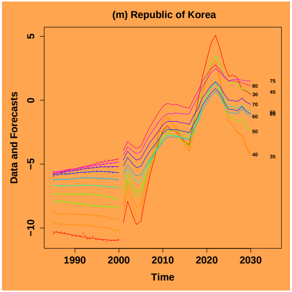


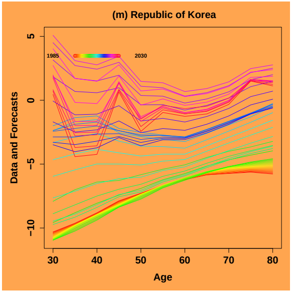
Smooth over age, time, age/time

Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Korean Males

Least Squares





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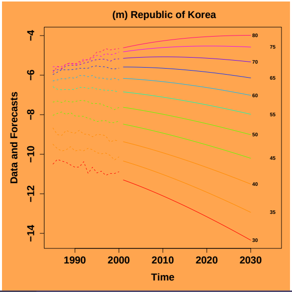

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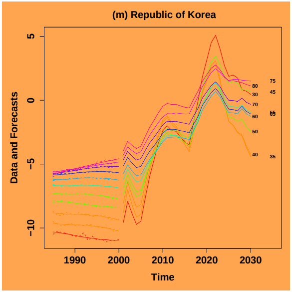

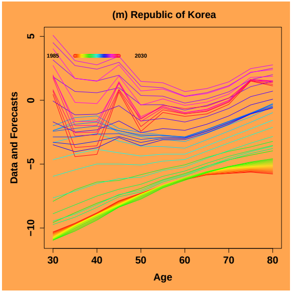

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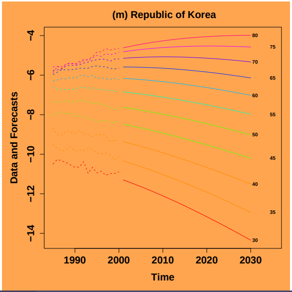

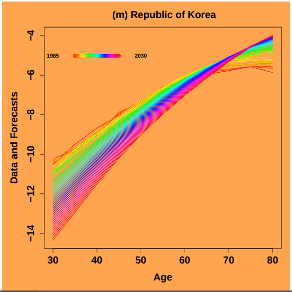

Using Covariates (GDP, tobacco, trend, log trend)

Using Covariates (GDP, tobacco, trend, log trend)

Lung cancer in Males, Singapore

Using Covariates (GDP, tobacco, trend, log trend)

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Least Squares

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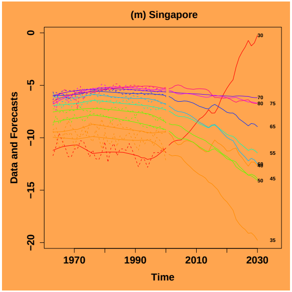

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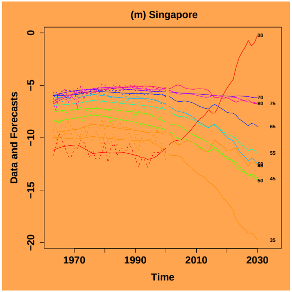
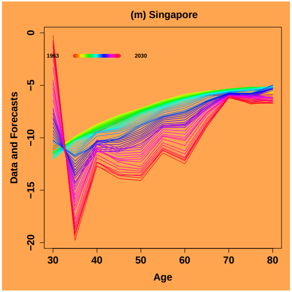
Lung cancer in Males, Singapore

Least Squares





Using Covariates (GDP, tobacco, trend, log trend)

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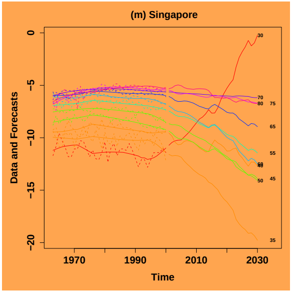
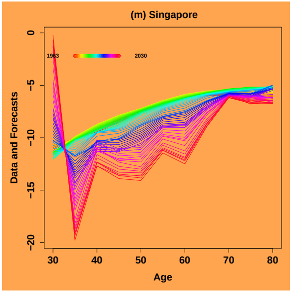
Least Squares





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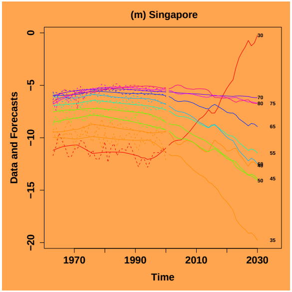

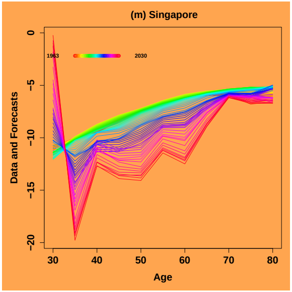

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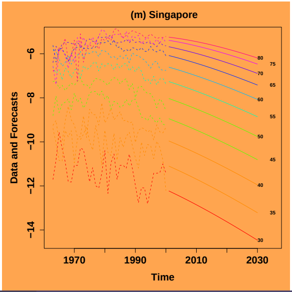

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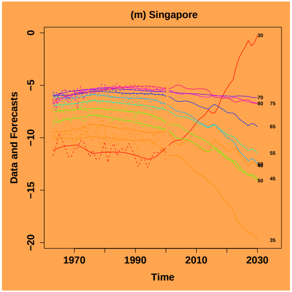

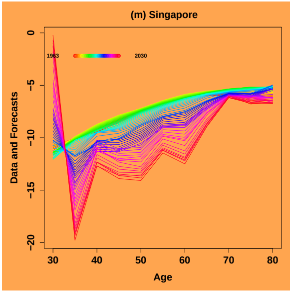

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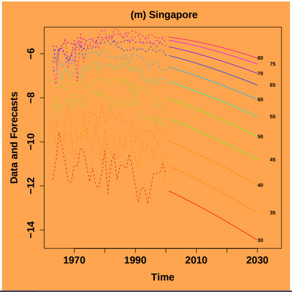
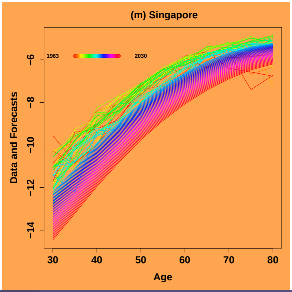
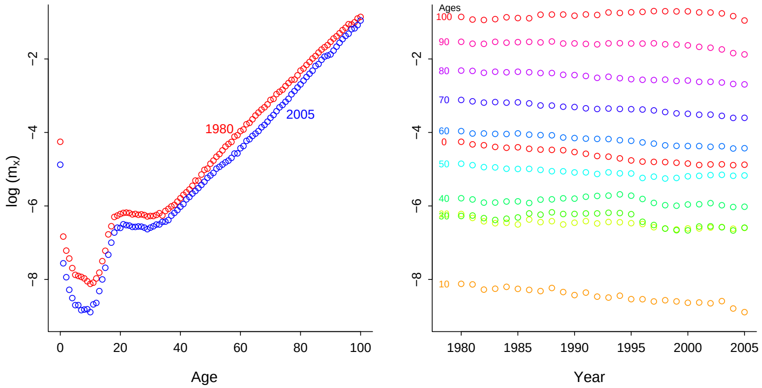


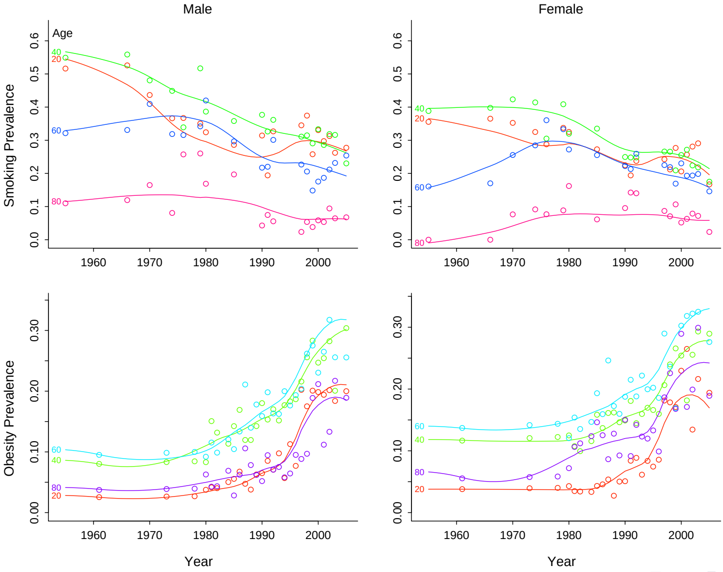


U.S. Male Mortality over Age and Time

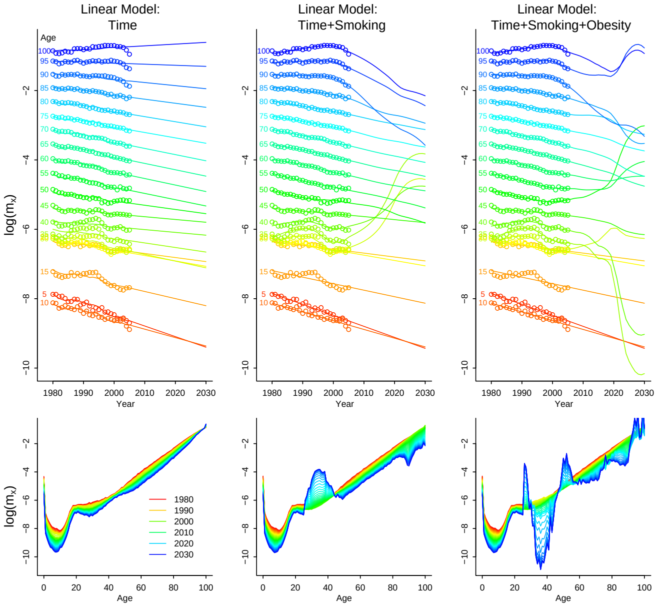
Demographic Facts: Smoothness in both dimensions



Biological Risk Factors in U.S. Data



Linear Models: Biology vs. Demography



Forecasts: Biology *and* Demography

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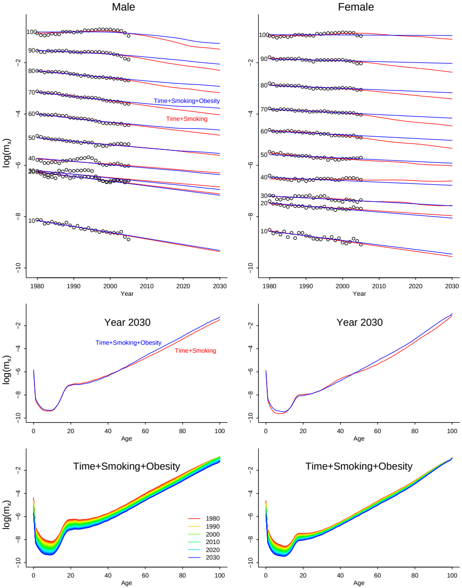
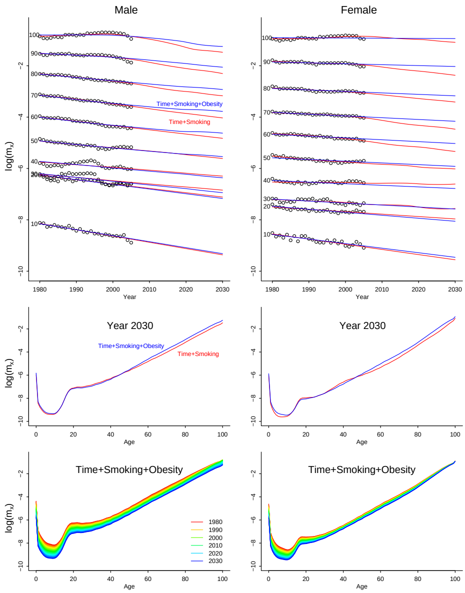
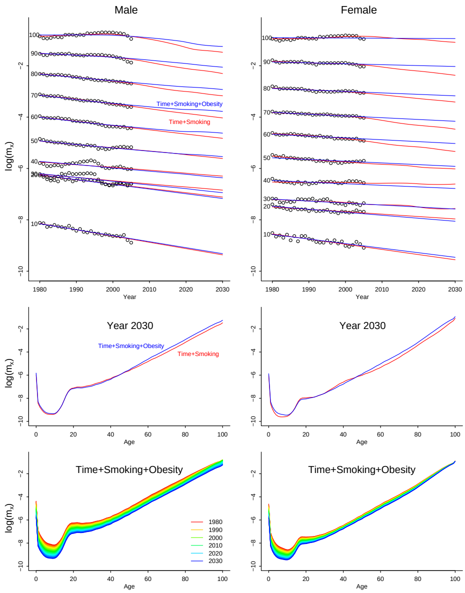


Forecasts: Biology *and* Demography

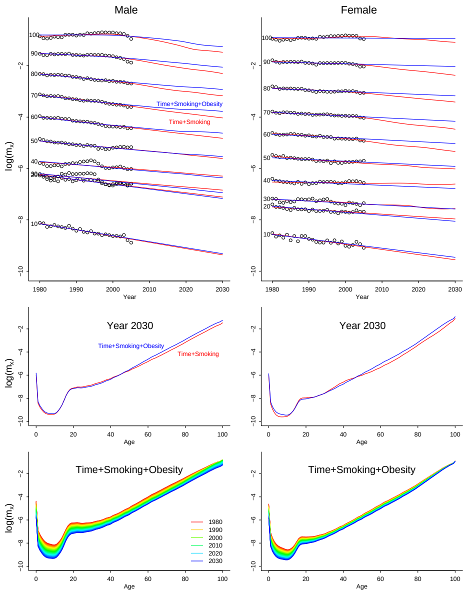


- Forecasts retain smoothness over age and time

Forecasts: Biology *and* Demography



- Forecasts retain smoothness over age and time
- After age 50, age-specific mortality increases when adding obesity.



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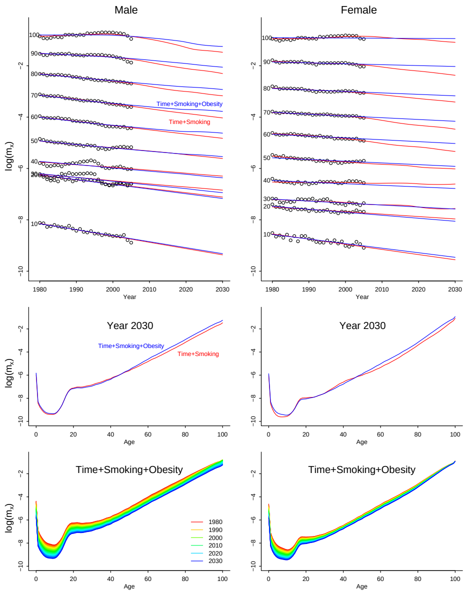

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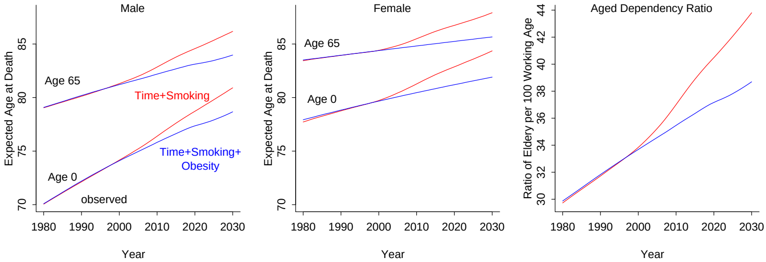
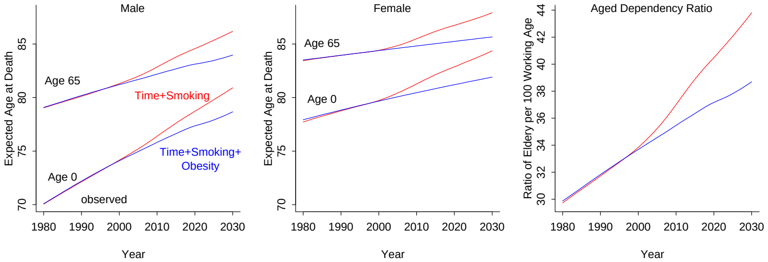
- At ages over 90, model forecasts converge faster for females than males.

Life Expectancy and Aged Dependency Ratios



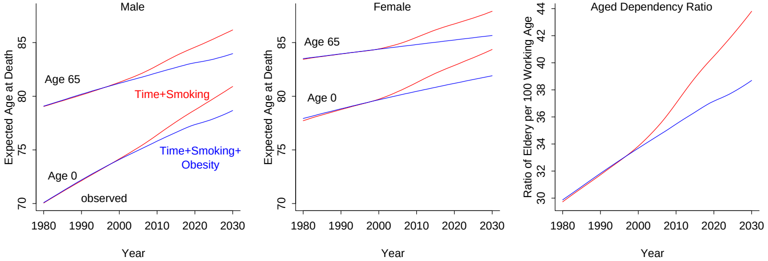
- Male Life Expectancy (±25 years)

Life Expectancy and Aged Dependency Ratios

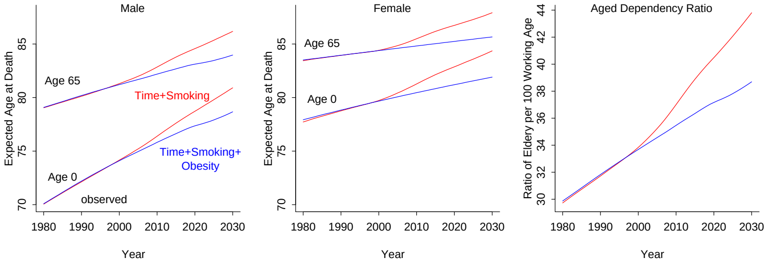


- Male Life Expectancy (±25 years)
  - Past: +5.1 years ⇝ 75.2

Life Expectancy and Aged Dependency Ratios



- Male Life Expectancy ($\pm$25 years)
  - Past: $+5.1$ years $\rightsquigarrow$ 75.2
  - Future: $+5.7$ years $\rightsquigarrow$ 80.9 (excluding obesity)



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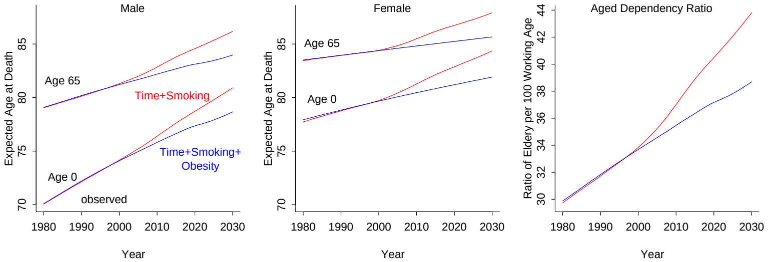

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- Female Life Expectancy ($\pm$25 years)

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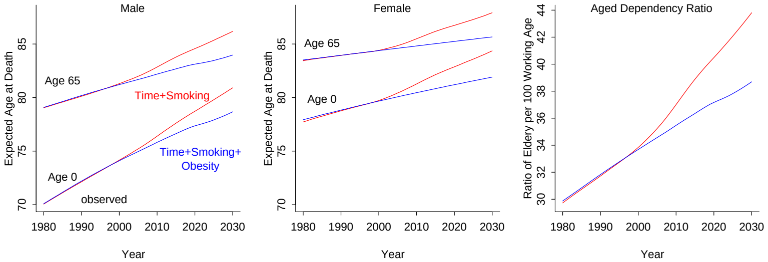

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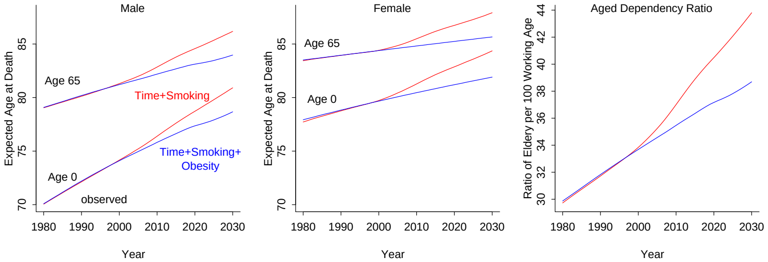
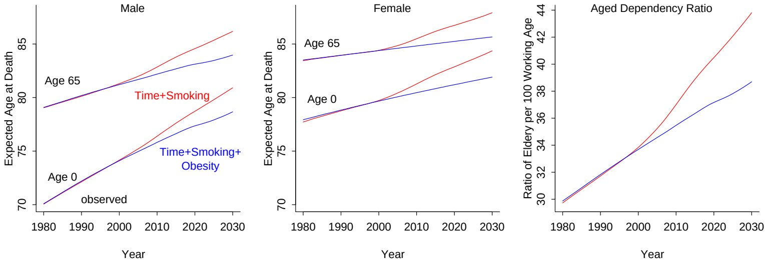
- Female Life Expectancy (±25 years)
  - Past: +2.7 years ⇝ 80.4

Life Expectancy and Aged Dependency Ratios



- Male Life Expectancy (±25 years)
  - Past: +5.1 years ⇝ 75.2
  - Future: +5.7 years ⇝ 80.9 (excluding obesity)
  - Future: +3.5 years ⇝ 78.7 (a 35% drop)
- Female Life Expectancy (±25 years)
  - Past: +2.7 years ⇝ 80.4
  - Future: +3.9 years ⇝ 84.4 (excluding obesity)

Life Expectancy and Aged Dependency Ratios



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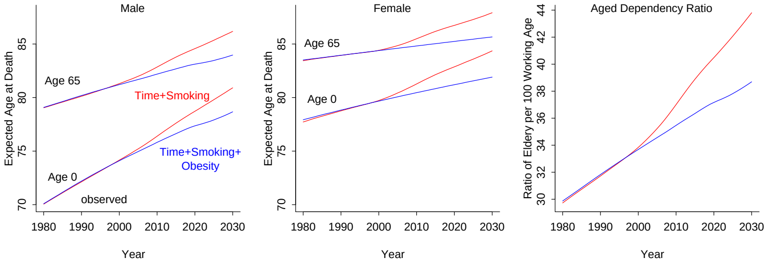
Life Expectancy and Aged Dependency Ratios



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  - Future: $+3.9$ years $\rightsquigarrow$ 84.4 (excluding obesity)
  - Future: $+1.8$ years $\rightsquigarrow$ 81.9 (a 53% drop)
- $\rightsquigarrow$ 1/2 trillion dollar difference for Social Security

For papers, software, etc.

http://GKing.Harvard.edu